Do more chargers mean more electric cars?

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Abstract
To reverse the trend of rising CO\(_2\) 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\(_2\) emissions has long been impeded by the transportation sector. Transportation is the only sector in the EU in which CO\(_2\) 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 threefold, 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 Nejad 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. 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 ($N = 50 172$). 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.

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 as 1.157 PHEVs. In about 31% of the month-county

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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.

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 workplace. 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
maintain measurement in levels rather than logarithms to avoid missing values.

The data is completed by a suite of regional, time-varying control variables taken from the RWI-GEO-GRID km² 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.

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

$$ ev_{it} = \beta + \beta_{i} \text{charge}_{it} + \beta_{t} X_{it} + \theta_{i} + \mu_{t} + \nu_{it}, $$

(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 $X_{it}$ 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
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.

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 of 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. 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 transformer, while 95% of counties have at least one transformer.

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. $\text{cov}(Z_{it}, CHARGE_{it}) \neq 0$, and (ii) they are not correlated with the error term $\nu_{it}$, i.e. $\text{cov}(\nu_{it}, Z_{it}) = 0$. 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 presents results using the transformers instrument, which has a slightly narrower confidence interval. 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).

Fast chargers are seen to have a considerably stronger influence on BEV uptake, with an FE estimate of 0.103. 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. 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 nonlinear 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 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 estimates 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 \(0.062 \times 12 / 2500 = 0.298\) BEVs per year per €1000, while the subsidy for fast chargers leads to \(0.273 \times 12 / 12000 = 0.273\) 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.

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

\[\text{probability of success} = \frac{\text{number of new EVs}}{\text{number of EVs on the road}}\]

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

\[\text{percentage increase in EV uptake} = \frac{\text{probability of success}_{\text{with subsidies}} - \text{probability of success}_{\text{without subsidies}}}{\text{probability of success}_{\text{without subsidies}}} \times 100\%\]
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 Groceries | Normal Transformers | Fast 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) | —                   | —                |
| Population density | 137.818** (58.543) | —                   | —                |
| No. of houses | —               | —                   | 2.218 (5.995)    |
| Fuelprice | —               | 54.614** (26.865) | —                |
| Constant | —               | 0.000*** (0.000)   | —                |

Year-month fixed effects: Yes
Individual fixed effects: Yes
Cragg–Donald Wald F-statistic: 7422
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 A2.** Second stage estimation results for the uptake of BEVs.

|                | Normal Groceries | Normal Transformers | Fast Gas stations |
|----------------|------------------|---------------------|------------------|
|                | 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 | —               | —                   | —                |
| Purchase power pc | −0.163** (0.083) | −0.039 (0.127)     | −0.022 (0.132)   |
| Population density | −0.757 (3.893) | −1.934 (7.629)     | −2.096 (8.118)   |
| No. of houses | 0.704*** (0.085) | 0.422*** (0.156)   | 0.383*** (0.146) |
| Fuelprice | 5.246*** (1.835) | 4.337** (2.074)    | 4.212** (2.010)  |
| Constant | 2.260*** (0.113) | 2.260*** (0.113)   | 2.260*** (0.113) |

Year-month fixed effects: Yes
Individual fixed effects: Yes
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 A3. Second stage estimation results for the uptake of BEVs with grouped charging points.

|                | FE Coeff. | FE Std. err. | IV Coeff. | IV 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)      |

|                | FE         | FE         | IV          | IV          |
|----------------|------------|------------|-------------|-------------|
| Year-month fixed effects | Yes | Yes | Yes | Yes |
| Individual fixed effects | Yes | Yes | Yes | Yes |
| Cragg–Donald Wald F-Statistic | — | — | 1212 | — |

|                |            |            |            |            |
|----------------|------------|------------|------------|------------|
| 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 A4. Placebo estimation results.

|                | Groceries Coeff. | Groceries Std. err. | Transformers Coeff. | Transformers Std. err. | Stations Coeff. | Stations 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) |

|                | Groceries | Groceries | Transformers | Transformers | Stations | Stations |
|----------------|-----------|-----------|--------------|--------------|----------|----------|
| Year-month fixed effects | Yes | Yes | Yes | Yes | — | — |
| Individual fixed effects | Yes | Yes | Yes | Yes | — | — |

|                |            |            |            |            |            |            |
|----------------|------------|------------|------------|------------|------------|------------|
| No. of observations | 1230 | 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 chargers | Normal chargers × Normal chargers | Fast chargers | Fast chargers × Fast chargers | Purchase power pc | Population density | No. of houses | Fuel price | Normal chargers × Purchase power pc | Normal chargers × Population density | Normal chargers × # Houses | Normal chargers × Fuel price | Fast chargers | Fast chargers × Purchase power pc | Fast chargers × Population density | Fast chargers × # Houses | Fast chargers × Fuel price | Year-month fixed effects | Individual fixed effects | Cragg–Donald Wald F-Statistic |
|------------------------|-----------------|----------------------------------|--------------|-------------------------------|-------------------|--------------------|---------------|-----------|-----------------------------------|-------------------------------|-----------------------------|-----------------------------|--------------|-----------------------------------|-------------------------------|-----------------------------|-----------------------------|--------------------------|--------------------------|-----------------------------|
| FE Transformers        | Coeff.          | Std. err.                        | Coeff.       | Std. err.                     | Coeff.            | Std. err.          | Coeff.       | Std. err. | Coeff.                            | Std. err.                      | Coeff.                      | Std. err.                    | Coeff.       | Coeff.                            | Std. err.                      | Coeff.                      | Std. err.                    | Yes                      | Yes                      | Yes                         |
| FE Stations            |                 |                                  |              |                               |                   |                    |              |           |                                   |                               |                             |                             |              |                                   |                               |                             |                             | Yes                      | Yes                      | Yes                         |
| Normal chargers        | 0.031***        | (0.003)                          | 0.061***     | (0.006)                       | —                 | —                  | —            | —         | —                                 |                               |                             |                             | —            | —                                 |                               |                             |                             | —                        | —                        | —                           |
| Normal chargers ×      | —               | (0.000)                          | —            | (0.000)                       | —                 | —                  | —            | —         | —                                 | —                             |                             |                             | —            | —                                 |                               |                             |                             | —                        | —                        | —                           |
| Fast chargers          | —               | —                                | —            | —                             | —                 | —                  | —            | —         | —                                 | —                             |                             |                             | —            | —                                 |                               |                             |                             | —                        | —                        | —                           |
| 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)   | —                                 | —                             |                             |                             | —            | —                                 |                               |                             |                             | —                        | —                        | —                           |
| Fuel price             | 5.160***        | (1.862)                          | 4.074***     | (1.955)                       | 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                           | Yes               | Yes                | Yes          | Yes       | Yes                              | Yes                           |                             |                             | Yes          | Yes                              | Yes                           |                             |                             | Yes                      | Yes                      | Yes                         |
| Individual fixed effects | Yes             | Yes                             | Yes          | Yes                           | Yes               | Yes                | Yes          | Yes       | Yes                              | Yes                           |                             |                             | Yes          | Yes                              | Yes                           |                             |                             | Yes                      | Yes                      | Yes                         |
| Cragg–Donald Wald      | —               | 663                             | —            | —                             | —                 | 981                | —            | —         | —                                 | —                             |                             |                             | —            | —                                 |                               |                             |                             | —                        | —                        | —                           |
| F-Statistic            |                 |                                  |              |                               |                   |                    |              |           |                                   |                               |                             |                             | —            | —                                 |                               |                             |                             | —                        | —                        | —                           |
| 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 |
|------------------------|--------------|----------|
| FE Transformers        | Coeff.       | Std. err. |
| FE Stations            |              |          |
| Normal chargers        | 0.073***     | (0.014)  |
| Purchase power pc      | 0.241        | (0.228)  |
| Population density     | -12.859      | (8.669)  |
| # Houses               | 0.264        | (0.232)  |
| Fuel price             | 1.532        | (2.346)  |
| Normal chargers ×      | -0.073       | (0.070)  |
| Normal chargers ×      | 1.131*       | (0.601)  |
| Normal chargers × #    | -0.001       | (0.008)  |
| Normal chargers × Fuel | 0.263***     | (0.079)  |
| Fast chargers          | —            | —        |
| Fast chargers ×        | —            | —        |
| Fast chargers × #      | —            | —        |
| Fast chargers × Fuel   | —            | —        |
| Year-month fixed effects | Yes         | Yes      |
| Individual fixed effects | Yes         | Yes      |
| Cragg–Donald Wald      | 20           | 282      |

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 Transformers FE | Normal Transformers Std. err. | Fast Stations FE | Fast Stations Std. err. |
|----------------------|-------------------------|-------------------------------|-----------------|-------------------------|
| Normal chargers      | 0.005 (0.004)           | 0.020*** (0.004)             | —               | —                       |
| Fast chargers        | —                       | —                             | —               | —                       |
| 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)        |

|                      | Normal Transformers FE | Normal Transformers Std. err. | Fast Stations FE | Fast Stations Std. err. |
|----------------------|-------------------------|-------------------------------|-----------------|-------------------------|
| 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 |

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 FE | Normal Std. err. | Fast FE | Fast 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)       |

|                      | Normal FE | Normal Std. err. | Fast FE | Fast Std. err. |
|----------------------|-----------|------------------|---------|---------------|
| Year-month fixed effects | Yes       | Yes              | Yes     | Yes           |
| Individual fixed effects | Yes      | Yes              | 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.

|                      | Normal Poisson FE | Normal Poisson Std. err. | Hurdle (second stage) FE | Hurdle (second stage) Std. err. |
|----------------------|-------------------|--------------------------|--------------------------|---------------------------------|
| Normal chargers      | 0.009*** (0.001) | —                        | —                        | —                               |
| Fast chargers        | —                 | —                        | —                        | —                               |
| 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)                |

|                      | Normal Poisson FE | Normal Poisson Std. err. | Hurdle (second stage) FE | Hurdle (second stage) Std. err. |
|----------------------|-------------------|--------------------------|--------------------------|---------------------------------|
| 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.

| Normal chargers       | Coeff. | Std. err. |
|-----------------------|--------|-----------|
| Purchase power pc     | 0.057*** | (0.011)   |
| Population density    | −0.046 | (0.123)   |
| No. of houses         | −1.862 | (7.384)   |
| Fuelprice             | 0.439*** | (0.150)   |
| Constant              | 4.393**  | (2.050)   |
|                       | 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 chargers       | Coeff. | Std. err. |
|-----------------------|--------|-----------|
| Purchase power pc     | −0.014 | (0.135)   |
| Population density    | −2.166 | (8.362)   |
| No. of houses         | 0.366** | (0.148)   |
| Fuelprice             | 4.158** | (2.026)   |
| Constant              | 2.260*** | (0.113)   |

| Fast chargers         | Coeff. | Std. err. |
|-----------------------|--------|-----------|
| Purchase power pc     | 0.279*** | (0.090)   |
| Population density    | −0.360*** | (0.105)   |
| No. of houses         | 0.887*** | (0.216)   |
| Fuelprice             | 4.937**  | (2.233)   |
| Constant              | 2.260*** | (0.113)   |

Year-month fixed effects: Yes
Individual fixed effects: Yes
Cragg–Donald Wald F-Statistic: 48
Hansen J-Statistic: 34.51 (p = 0.185), 42.601 (p = 0.038)

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 A12. Second stage estimation results for the uptake of BEVs when using two instruments.

| Normal chargers       | Coeff. | Std. err. |
|-----------------------|--------|-----------|
| 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.
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