No Place Like Home: Charging Infrastructure and the Environmental Advantage of Plug-in Hybrid Electric Vehicles*

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Abstract

The environmental impact of many energy-saving technologies depends on user behavior. For Plug-in Hybrid Electric Vehicles (PHEVs), consumer choices regarding how much to drive and which source of energy to use (fossil fuels vs. electricity) impact CO_2 emissions. This paper leverages quasi-experimental variation in the availability of home charging stations to quantify the impact of this technology on energy use and CO_2 emissions of 836 PHEV company cars. Fuel and charging expenditures for these cars are covered by the employer so that, to the employee, home charging changes only the non-monetary costs of charging the car. We find that access to home charging increases electricity consumption by 298.88 ($\pm$25.9) kWh per quarter and decreases fuel consumption by 102.34 ($\pm$38.0) liters, reducing CO_2 emissions by 39 %. Moreover, access to home charging increases the employee's propensity to choose a Battery Electric Vehicle (BEV) upon renewal of the lease. We use these estimates to compute (private) levelized abatement costs and payback times of home charging for a range of scenarios characterizing the diffusion of BEVs. With current tax-inclusive energy prices, home charging stations break even within six to eight years.

Keywords: home charging, plug-in hybrid electric vehicles, company cars

JEL-code: D12, L91, Q52, R42

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1 Introduction

The true environmental impact of many potentially energy-saving technologies depends on consumer behavior. Plug-in Hybrid Electric Vehicles (PHEVs) are an important case in point because they can run on either electricity or petroleum-based fuels. Therefore, consumer choices of how much to drive and which source of energy to use have a major impact on the environmental externalities emitted by the vehicle. Because real-world electric driving shares are systematically lower than what is technically feasible, or assumed in official testing procedures (Chakraborty et al., 2020; Plötz et al., 2022; Tsanko, 2023), the true environmental impact of PHEVs is higher than necessary. One explanation for low electric driving shares is the additional time needed to recharge the car (Krishna, 2021). The provision of charging infrastructure in convenient locations could increase electric utilization by lowering that time cost, yet so far this hypothesis has not been tested empirically.

This paper leverages quasi-experimental variation in the adoption of home chargers to estimate their effect on the electric driving share of PHEV company cars (and several other outcomes). To encourage employees holding a Battery Electric Vehicle (BEV) or a PHEV company car to charge their cars at home, the cooperating company introduced a program that (i) subsidized the installation cost of a home charger and (ii) automatically reimbursed electricity expenditures for home charging. To be eligible for participation in the program, employees must hold a BEV or PHEV and participate in the company's fuel cost compensation scheme. Under this scheme, refueling and charging the company car has no variable monetary cost for employees (but a monthly fixed cost in terms of a deduction from the monthly salary), even if the car is used for private trips. Employees in our sample applied for home chargers between January 2021 and December 2022. For various reasons, e.g., because of delays in the delivery and installation due to supply chain disruptions in the aftermath of the COVID-19 pandemic, the program roll-out was staggered over time. In particular, the waiting times for employees varied considerably despite similar application dates for the home chargers.

Our sample consists of 836 PHEVs, for which our partner company provided us with transaction data on fuel and electricity consumption. Besides the date and time of refueling (or recharging), the data contains the amount of fuel in liters (electricity in kWh), employee-reported odometer readings, and information on the vehicle's make and model. Using emission factors for the different energy sources (Juhrich, 2022; Icha & Lauf, 2022), we also estimate CO_2 emissions.

The setting described above allows us to study the effect of installing charging infrastructure at home using a Difference-in-Differences (DiD) estimator. As two-way fixed effects estimators can suffer from severe biases under staggered treatment adoption, we employ the estimator developed by Callaway & Sant'Anna (2021) and use as the control group not-yet-treated PHEV users who receive a home charger at a later point in time. The difference in contemporaneous outcomes between these groups identifies the average treatment effect on the treated. Outcomes of primary interest are the amount of electricity charged, the amount of fuel used, the mileage driven, and the implied CO_2 emission changes.

We find that the availability of home charging increased electricity consumption by 298.9 (±25.9) kilowatt-hours (kWh) per quarter while decreasing consumption of gasoline or diesel by 102.3 (±38.0) liters per quarter. This translates into a 39 % reduction in tailpipe emissions, corresponding to 248.1 (±130.1) kg of CO_2. The average employee's mileage increased by 606.6 (±498.1) km per quarter, which can be interpreted as a 14 % rebound effect in terms of vehicle kilometers traveled.

The reduction in tailpipe CO_2 emissions is statistically and economically significant and, as we argue, translates into real emissions abatement for the planet. For one, the type-approval-based CO_2 emission ratings of PHEVs assume zero on-road CO_2 emissions for electric driving. More importantly, however, CO_2 emissions from electricity generation in Germany, where this study took place, are covered under the emissions cap of the European Emissions Trading System for CO_2 and may thus be reasonably considered as non-additional.

In addition to intensive-margin effects, we also find an extensive-margin effect on the adoption of Battery Electric Vehicles (BEVs) following the installation of home chargers. In particular, employees with a PHEV who receive access to home charging at least half a year before replacing their company car are 30 % more likely to choose a BEV. This choice eliminates the option of refueling in the future, thus further contributing to future emissions reductions.

In a cost-benefit analysis using different assumptions about the diffusion of BEVs in the initial PHEV fleet, we find that total abatement per employee from adopting a home charger ranges from between four to 20 tons of CO_2 emissions. What is more, in most scenarios the installation of the home charger already pays off for the company after six to eight years. Given that the useful lifetime of a home charger should be considerably longer than that, the program can be said to yield substantial benefits in terms of emissions abatement but also financially.

2 Literature

Our paper bridges a gap between the literature on the effect of financial incentives on electric vehicle *use* and charging behavior on one hand and the literature on the impact of infrastructure provision and monetary incentives on electric vehicle *adoption* on the other hand.

Concerning the former literature, studies show that higher home electricity prices and lower potential cost savings from charging are related to *not* plugging in a PHEV (Chakraborty et al., 2020) and that electric vehicle households respond to changing electricity pricing signals by increasing their charging in lower-priced off-peak hours (Qiu et al., 2022). Chakraborty et al. (2019) find that costs of charging play an important role in the demand for charging location (at home vs. at the place of work) for PHEV commuters. Grigolon et al. (2024) show that PHEV drivers respond to fuel price increases more than drivers of gasoline and diesel cars, making fuel prices an effective instrument for improving the environmental performance of PHEVs, given their low electric driving share. Bailey et al. (2023) find for BEV drivers that financial rewards mimicking time-of-use pricing are effective at shifting charging behavior to off-peak hours, while a moral suasion nudge is not. Both Grigolon et al. (2024) and Bailey et al. (2023) find no evidence of habit formation when fuel prices fall or financial incentives are removed. Nehiba (2024) studies the role of residential electricity prices and the availability of public charging stations on the mileage of BEVs. In particular, a 10 % increase in residential electricity prices reduces mileage by 1 %. In our setting, there are no differences in actual costs for PHEV users between charging at the firm, at home or at public charging stations.

The second strand of literature focuses on the BEV or PHEV adoption decision and how this decision is influenced by the provision and availability of (mostly public) charging infrastructure and monetary incentives. He et al. (2023) exploit a quasi-experimental setting to show that for the US, PHEV sales increased by an average of 2.7 % following a $2,000 tax credit incentive and that sales remained stable after the incentive's termination. Bailey et al. (2015) show that awareness of public chargers is not a strong predictor of PHEV interest and that the availability of charging at home is more important. Li et al. (2017), Springel (2021) and Remmy (2022) study the interdependence between electric vehicle adoption and public charging stations (indirect network effects). The first study finds that a 10 % increase in the number of public charging stations would increase PHEV sales by about 8 %. Springel (2021) shows for Norway that subsidies on public charging stations resulted in more than twice as many electric vehicle purchases than the same amount spent on subsidies on purchase prices. By contrast, Remmy (2022) finds that

German purchase subsidies generated more electric vehicle sales than charging station subsidies. Illmann & Kluge (2020) also find a positive but small effect of charging infrastructure on monthly electric vehicle registrations for Germany. Ou et al. (2020) show in a simulation study that public charging infrastructure is more effective at promoting PHEV sales in emerging markets than in mature markets. Lee et al. (2023) show that PHEV adopters' replacement choices when deciding between a conventional car, a BEV, or (again) a PHEV correlate with charging convenience and home charging access. Hardman & Tal (2021) study the purchase decisions of PHEV owners and find that PHEV discontinuance in California is related to dissatisfaction with the convenience of charging and not having 240-volt charging at home. Finally, Li (2023) shows that unifying three incompatible charging standards would induce car manufacturers to build more charging stations and sell more electric vehicles.

Using fuel and charging expenditure transaction data on company cars, we can track an employee's driving behavior across multiple energy sources and link this data to information on the availability of a company-provided home charging station. Our paper is the first to causally estimate the impact of home charging on charging behavior and CO_2 emissions.

Lastly, our paper is related to the literature on behavioral reactions to the adoption of energy-efficient technology. This line of research shows that inefficient consumption behavior (Salvo & Huse, 2013) and increased consumption ("rebound" - Davis et al., 2014) can offset the anticipated reductions in environmental externalities following the adoption of energy-efficient technology. We contribute to this literature by showing that technological solutions reducing the non-monetary cost of using energy-efficient durable goods can counteract this effect.

3 Research Design

We exploit quasi-experimental variation in the timing of adoption of home chargers by PHEV holders to identify causal impacts on charging and several other outcomes. Linking adoption time to rich microdata on charging, refueling, and driving behavior, we are able to estimate average treatment effects on the treated (ATT) in an event-study framework. A unique feature of our setting is that the switch to home charging has no pecuniary consequences for the subjects in our sample. That is, our ATT estimates speak to non-financial channels that drive behavior with respect to electric vehicle usage and charging. In what follows, we describe the data-generating process in detail, explain our identification strategy, and describe the estimation framework.

3.1 Quasi-Experimental Roll-Out of Home Charging

We study the roll-out of home chargers among employees of a large German firm that operates a large fleet of company cars. In Germany and other EU countries, company cars are commonly offered as a fringe benefit to employees. In exchange for a fixed monthly pay deduction of pre-tax income, employees get a car that they can use for business-related trips but also private trips. For an additional lump-sum deduction, employees can enroll in a fuel cost compensation scheme that covers the costs of all fuel and electricity consumed by the vehicle.[1]

Employees of our partner company can choose a car from a large set of makes and models. Vehicles with an internal combustion engine (ICEVs) are the most popular choice, but PHEVs have been on the rise and some employees have switched to fully electric battery vehicles (BEVs). For PHEVs, the electric utilization rate is typically measured by the so-called utility factor (Plötz et al., 2021), which is defined as the ratio between kilometers traveled using electricity and total vehicle kilometers traveled.[2] Although electric vehicles can be charged at no extra cost to the holder under the above scheme at public charging points and in the company parking lots, the utility factor for employees without access to home charging is low. Employees receiving a home charger in 2021 and 2022 exhibited an average utility factor of 0.29 in 2020. This is much lower than the average utility factor of 0.69 assumed in type-approval ratings under the New European Driving Cycle (NEDC) but higher than the average utility factor of 0.18 found for German PHEV company cars (Plötz et al., 2020).

To encourage holders of PHEV and BEV company cars to charge at home, the company introduced a program that subsidized the installation cost of a home charger (at 100 %) and automatically reimbursed expenditures for the electricity consumed by that home charger. The program was rolled out in January 2021 and open to all employees (i) driving a PHEV or BEV company car and (ii) participating in the fuel cost compensation scheme.

Several features of the application and installation process caused the roll-out to be staggered over time. First, during the first eight months of the program, participants could order a home charger only via the employer and not directly from the provider. The employer collected applications and forwarded them in batches to the company installing the home chargers. Second, throughout the first two years of the program, supply-side

[1]See Appendix B for background on the German company car scheme.

[2]Since we can only observe the total number of kilometers traveled, we need to impute the utility factor based on the rated fuel consumption per 100 km of the vehicle according to testing procedures. The imputation is taken from Plötz et al. (2022), and described in more detail in Appendix C.

frictions in the aftermath of the COVID-19 pandemic caused delays in the delivery and installation of home chargers. Third, employees only become eligible for participation in the home charger program once they hold or have ordered an electric company car (BEV or PHEV). They typically become eligible to order a company car after three years of being employed with the company, regardless of whether they need a company car for business-related travel. Employees who order a company car must hold on to it for four years before they can order a new one or opt out of the program (which rarely happens). This implies that each month, a new group of employees can decide to order an electric company car and, potentially, participate in the home charger program.

All of these factors delayed the installation dates of the home chargers in ways that varied considerably across participants, as can be seen in Figure 1. Panel (a) shows cumulative applications for and deliveries of home chargers over time, pointing to a time-varying gap between the time of application and the time of first usage. Panel (b) shows the cross-sectional distribution of waiting times between the application for a home charger and its date of first usage. We observe that the mode of the average waiting time is two months but some employees also waited more than 12 months for the installation of their home charger. Panel (c) shows that the waiting times varied considerably over the sample period. The average waiting times by month of application lie between two and more than five months.

3.2 Econometric framework

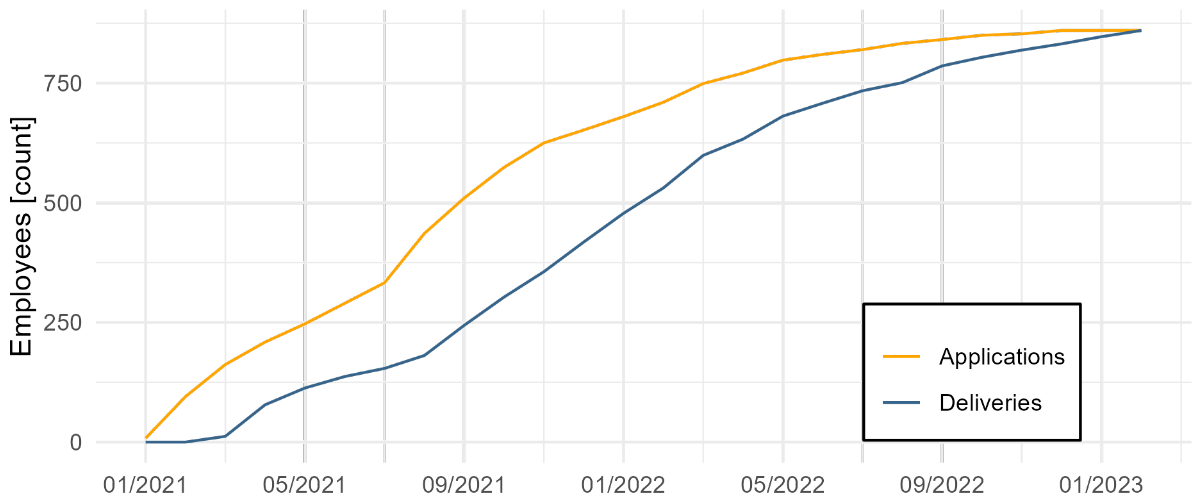
The setting described above allows us to study the effect of installing home chargers using a generalized Difference-in-Differences (DiD) estimator. The traditional approach would implement a two-way fixed-effects estimator based on the equation

$$Y_{it} = \beta_1 \, \mathcal{I}(t \geq HC_i) + \eta_i + \mu_t + \epsilon_{it} \tag{1}$$

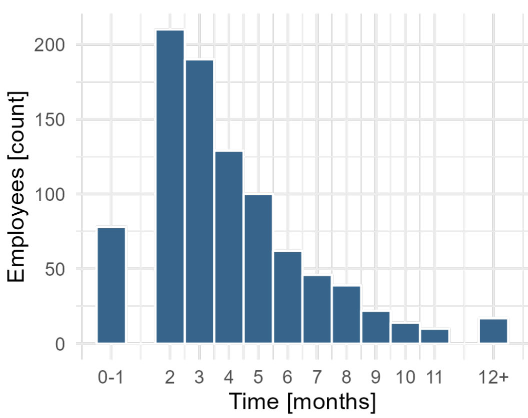
where the variable Y_{it} measures relevant outcome variables of employee respectively vehicle i in quarter t, HC_{it} denotes the quarter t in which the home charger (HC) becomes available for use for employee i, and η_i and μ_t are car and quarter fixed effects.

Since this two-way fixed effects estimator can suffer from severe biases under staggered treatment adoption, as is the case in our setting, we employ the alternative estimator developed by Callaway & Sant'Anna (2021). We use not-yet-treated PHEV users as the control group, i.e., users who receive a home charger at a later point in time. By comparing their outcomes to the contemporaneous outcomes of PHEV users who have already received a home charger, we estimate the ATT on different outcome variables.

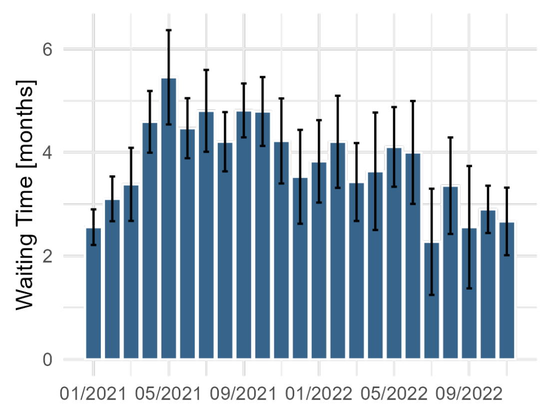
Figure 1: Home Charger Applications and Distribution of Waiting Times



(a) Applications and Deliveries over Time



(b) Distribution of Waiting Times across Employees



(c) Average Waiting Times by Month of Application

Notes: Figure (a): Cumulative applications and deliveries of home chargers over the sample period. Figure (b): Cross-sectional distribution of waiting times between the date of application and the date of first use of a home charger. Figure (c): Average waiting times by month of application. 95 % confidence interval of the mean indicated. Source: Own computations.

We use the estimator in equation 3.11 in Callaway & Sant'Anna, 2021 to aggregate the group $\times$ time-specific estimates of the ATT into one summary measure for the average treatment effect of home charger adoption. This estimator assigns equal weight to each employee in our sample, independent of the number of post-treatment observations. The analysis is clustered at the level of the participating employee. Furthermore, we allow for an unbalanced panel, which is necessary, since each month, some employees could potentially order a new car. To estimate event study coefficients for treatment effects as a function of the length of treatment exposure, we use the estimator in equation 3.4 in Callaway & Sant'Anna, 2021 to aggregate the group $\times$ time-specific estimates of the ATT into an estimator of the treatment effect at differential temporal exposure to the treatment. As Callaway & Sant'Anna (2021) point out, interpreting differences in the estimator $\theta_{es}(e)$ as dynamic effects hinges on the assumption of homogeneous effects of treatment exposure across groups with different timing of home charger adoption since the composition of groups observed with a given exposure time might change.

Our primary interest is with the outcome variables amount of electricity charged, amount of fuel used, total amount of energy used, mileage of the PHEV, and the implied CO_2 emission changes. The next section describes how we measure those outcomes at the worker level.

3.3 Data

Sample Composition. Our analysis considers all home charger applications between January 2021 and December 2022. Fuel efficiency and mileage outcomes are computed based on automatically collected transaction data on charging and refueling, but also on employee-reported odometer readings. Employees report their vehicles' odometer readings only when refueling their cars. Starting with transaction data for 1,021 PHEVs held by 939 employees during our sample period (i.e., some employees renewed their lease during the sample period), we drop 63 cars with less than two odometer readings. To the remaining odometer readings, we apply a data cleaning algorithm that identifies implausible (infeasible) mileages and interpolates between odometer readings that were deemed feasible to impute a plausible measure of mileage. We explain the details of this imputation in Appendix C. As part of the cleaning procedure, we drop 50 cars for which we do not observe at least three feasible odometer readings. We drop two cars that had more than 30 % of their quarterly mileages above the 99.9th percentile of quarterly mileages, and we additionally drop all quarterly observations where i) the mileage exceeded the 99.9th percentile of quarterly mileages or ii) the ratio between the observed mileage and an approximation of the mileage based on the vehicles fuel and electricity consumption was below 0.005 (the 0.5th percentile of the ratio) or exceeded 4.68 (the 99.5th percentile of the ratio).[3] Finally, we drop all observations after September 2022, since for many cars, we observe the second to last refueling event and thus odometer reading before September 2022. The final analysis sample comprises 908 PHEVs held by 836 employees.

Note that we aggregate the data to quarterly observations. This is because weekly and monthly observations would be too noisy, as some subjects in the sample refuel their car only every couple of weeks, which would imply that we do not have reliable data for short time periods. Furthermore, the estimator by Callaway & Sant'Anna (2021) relies on the estimation of a generalized propensity score, which requires a minimum size for treatment groups (i.e. employees receiving access to home charging in the same time period), which was not attained in a monthly aggregation.

Summary Statistics. Transaction data on fuel and electricity consumption between January 2020 and December 2022 contains automatically registered information on the date and time of refueling (or recharging), the amount of fuel in liters (electricity in kWh), the employee-reported odometer readings, and administrative information on the vehicle model, which we merged with vehicle efficiency data published by the General German Automobile Club (Allgemeiner Deutscher Automobil-Club e.V. (ADAC), nd) . We estimate CO_2 emissions using appropriate emission factors for each energy source (gasoline, diesel, and electricity) published by the German Environment Agency (Umweltbundesamt) (Juhrich, 2022; Icha & Lauf, 2022). Appendix Table A.1 provides comprehensive summary statistics on driving and charging behavior, vehicle attributes, and employee characteristics for this sample, following the adoption of a home charger.

Selection into Treatment. Employees who applied for the home charger program might differ systematically from those who drove a PHEV and did not apply during the period of analysis. Those differences might be correlated with potential outcomes associated with home charger adoption. To guard against such selection bias, our identification strategy discards non-applicants and relies entirely on quasi-experimental variation in the installation time among program participants. This strengthens the internal validity of our approach, yet the external validity hinges on how different applicants are from non-applicants.

During the analysis period, 836 employees holding a PHEV company car participated

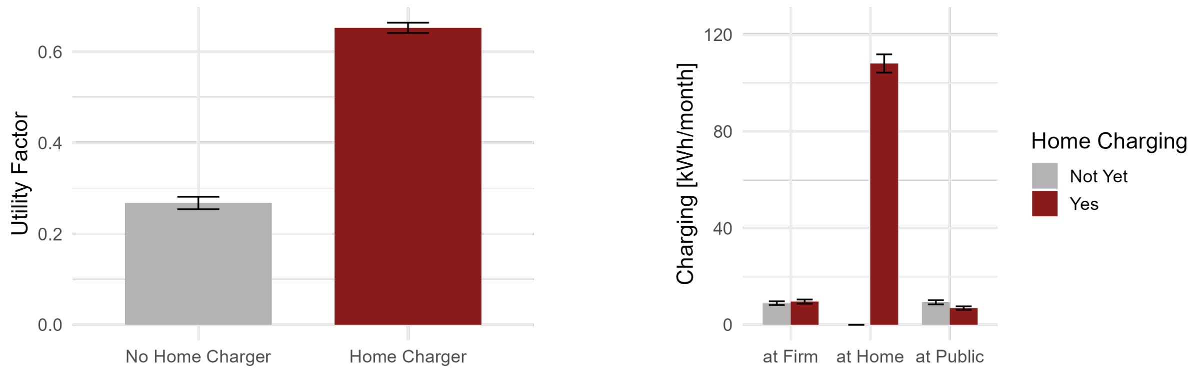
[3]Only three cars had a very high mileage ($\geq$ 19,770 km per quarter) in more than 30 % of all observed quarters. Two of them are observed in the sample period.

Table 1: Home Charger Sample vs. Population of PHEV Drivers

Variable	Home Charger Mean	Home Charger Sd	No Home Charger Mean	No Home Charger Sd
Panel A: Vehicle Use in 2020				
Mileage per quarter [km]	4358.644	(2904.99)	4258.238	(2762.52)
Emissions [kg CO2]	654.973	(564.69)	709.286	(581.34)
Tailpipe Emissions [kg CO2]	636.078	(570.88)	695.018	(587.41)
Electricity per quarter [kWh]	49.334	(82.34)	37.254	(73.84)
Fuel per quarter [l]	263.416	(237.34)	289.477	(245.01)
Fuel consumption [l/100 km]	5.792	(3.2)	6.534	(3.08)
Electricity consumption [kWh/100 km]	1.518	(2.83)	1.213	(2.53)
Utility factor [km elec./km total]	0.287	(0.38)	0.187	(0.38)
Energy expenditures [euro]	347.345	(301.51)	379.198	(312.62)
Panel B: Vehicle Characteristics				
Fuel efficiency [l/100 km WLTP]	1.591	(0.35)	1.537	(0.36)
Electric efficiency [kWh/100 km WLTP]	17.469	(3.16)	16.645	(2.49)
Price [euro]	32164.160	(4198.59)	30286.348	(4765.73)
Weight [kg]	1999.109	(255.61)	1896.169	(210.85)
Panel C: Employee Characteristics				
Age [years]	48.215	(0.46)	43.188	(0)
Tenure [years]	17.431	(1.07)	12.888	(0)
Female [%]	0.156	(0.02)	0.235	(0)

Notes: Comparison of the sample of employees selecting into the home charger program between January 2021 and December 2022 (N = 836 employees) to the group of employees not selecting into the home charger program during that period (N = 2683 employees). Both samples are restricted to the employees holding at least one PHEV during the sample period and opting into the fuel cost compensation scheme of the company. Panel A shows summary statistics for vehicle use in the year 2020 in which none of the employees in the home charger sample has received a home charger yet. The sample sizes are reduced to N = 388 employees that are using their PHEV during that period for the home charger sample and N = 1533 employees in the no home charger sample. Panel B displays vehicle characteristics obtained from the General German Automobile Club's car catalog. Panel C displays employee characteristics which are only available in terms of group averages. WLTP stands for "Worldwide Harmonised Light Vehicle Testing Protocol".

Figure 2: Average Differences in Electric Utilization Between Treated and Not-yet-treated Employees



(a) Utility Factor

(b) Charging by Source

Notes: Based on transaction data for the period 2020 - 2022. Utility factors are calculated based on the observed on-road fuel consumption and the vehicle's fuel consumption in the charge-sustaining mode in the NEDC testing procedure. For details on the calculation, see Appendix C. Charging by source is calculated based on the observed amount charged at each source. Both measures compare employees who have already received home chargers with employees who selected into the program but have not yet received home chargers. Thus, some employees switch between the two samples as time proceeds. 95 % confidence intervals are indicated.

in the program, while 2,683 employees holding a PHEV company car did not. Table 1 shows the differences in means of all the key variables for these groups in 2020, i.e., the year before the launch of the program.[4] Home charger applicants are more frequently male, they are older and have longer tenure with the company than non-applicants. That applicants are, on average, older than non-applicants seems plausible, as it is easier to have a home charger installed when an employee owns a home than when she rents a home, and home ownership increases with age. With a two percent higher mileage per quarter, applicants use nine percent less fuel and 24 percent more electricity than non-applicants. Given those differences, a naïve estimate based on never-takers of the home charger would likely induce bias in the results.

Average Outcomes for Treated and Not-yet-treated Subjects. Within the group of employees eventually receiving a home charger, Figure 2 compares average outcomes between employees who have a company-sponsored home charger and those who do not yet have it, for the years 2020 to 2022. Panel (a) shows that home charging users exhibited

[4]Since PHEV adoption grew very fast during this period, both groups were considerably smaller in 2020, with 317 and 1,623 cars, respectively. The proportion between these groups remained stable over time.

a utility factor almost three times as high as for non-users, despite similar overall mileages. This difference is mainly driven by charging at home, which dwarfs charging at the firm or at public places (Panel b). The next section investigates whether these findings continue to hold in a causal evaluation framework.

4 Treatment Effects of Home Charger Adoption

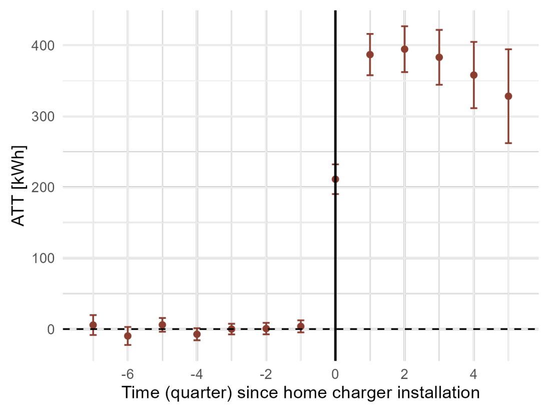
In this section, we first consider the effects of access to home charging on several outcome variables in event studies. In the second part of this section, we aggregate these quarterly treatment effects into one ATT over the full sample period,using a weighted average of the DiD estimates. Furthermore, we also consider treatment effects on the extensive margin of buying a BEV instead of a PHEV, and intensive-margin treatment effects for BEVs only (i.e., their electricity consumption).

4.1 Treatment Effects by Quarter

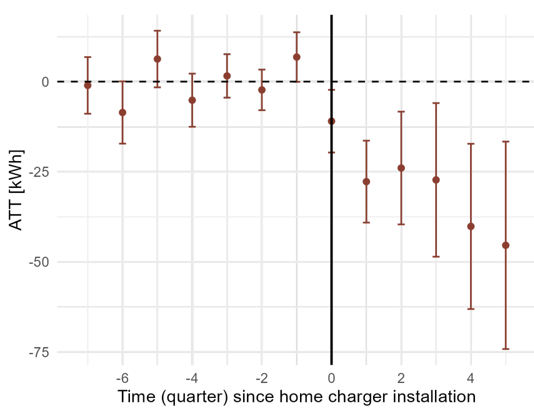
We begin our discussion of the results by looking at the margin of charging vs. refueling. Figure 3 displays the ATTs per quarter obtained with the event-study design discussed above. Quarter 0 refers to the quarter in which the home charger was installed, quarter 1 is the first quarter after the adoption quarter, and so on. Two general comments apply. First, the point estimates in quarter zero are lower in absolute value than those for subsequent quarters because subjects receive the home charger on different dates during that quarter. Second, point estimates get noisier for higher treatment lags because the size of the control group (not-yet-treated employees) falls over time. Panel (a) of Figure 3 shows that the total electricity consumption of the PHEVs held by employees receiving a home charger increases sharply at the time of adoption by between 200 and 400 kWh per quarter. The effect is relatively stable over time, with a slight decrease in total charging beginning in quarter 3 after adoption. Panel (b) shows that treated subjects reduce charging at public stations, to an increasing extent, by up to around 60 kWh per quarter. We observe from panel (c) that there is no significant impact on charging at the firm, though this estimate points in the expected direction of less charging at the firm's premises.

Figure 4 displays various outcomes concerning fuel consumption and mileage. We observe that the increase in electric charging is accompanied by a drop in fuel use (Panel a), which is driven by reductions in both the number of refueling transactions per quarter (Panel b) and the average quantity of fuel per transaction (Panel c). On average, treated

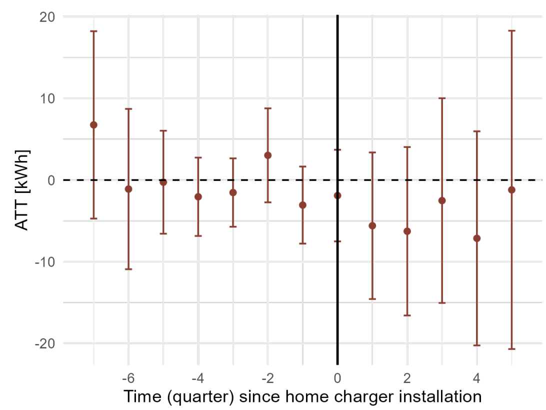
Figure 3: Treatment Effects on Electric Charging Per Quarter



(a) Total Charging



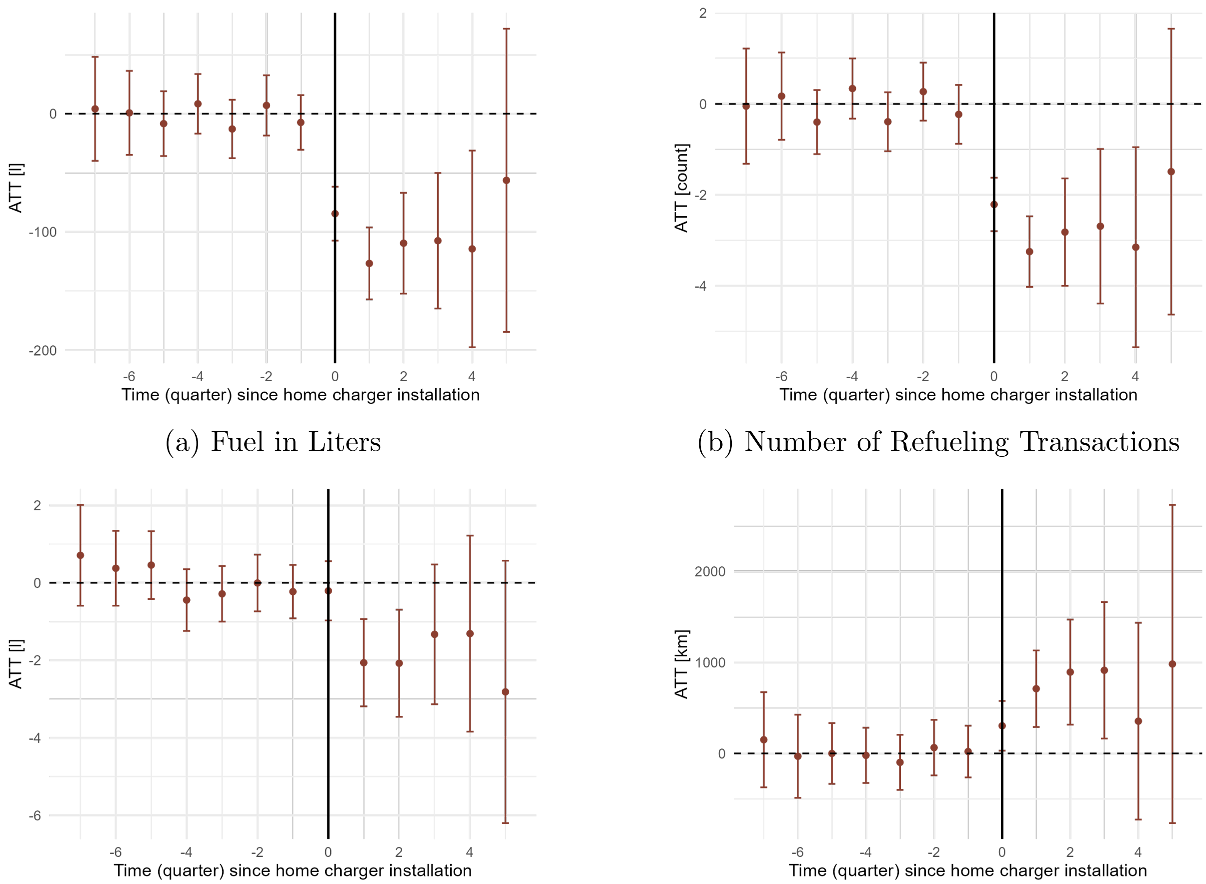
(b) At Public Station



(c) At Firm

Notes: Doubly-robust estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021). 95 % confidence intervals are indicated.

Figure 4: Treatment Effect on Fuel Consumption and Mileage



(a) Fuel in Liters

(b) Number of Refueling Transactions

(c) Liters per Refueling Transaction

(d) Kilometers Traveled

Notes: Doubly-robust estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021). 95 % confidence intervals are indicated.

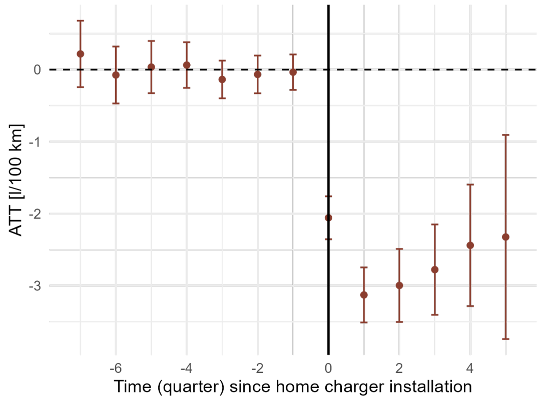
subjects reduce quarterly fuel consumption by slightly more than 100 liters in the first few quarters after adoption. These results indicate a high substitutability of electricity for gasoline among treated subjects. As before, the precision of these estimates falls with the length of the event window.

Five quarters after the installation date for the home charger, the treatment effect on fuel consumption appears to vanish whereas the increase in electric charging is sustained (see Figure 3a). This begs the question of whether treated workers end up driving more. The estimated treatment effects on total kilometers driven per quarter are plotted in Panel (d) of Figure 4. While a positive effect on the vehicle kilometers traveled is observed in the first three quarters after the adoption of home charging (mileage increases by up to 1000 km per quarter), this effect seems to become somewhat smaller in quarter 4 after adoption and it becomes statistically insignificant from that quarter onwards. The observed increase in mileage in the first quarters after adoption is equivalent to an increase of roughly 20 % as compared to 2020 levels. This rebound effect might have several reasons. First, as charging becomes more convenient with a home charger and potentially also less time-consuming for treated subjects, this lowers the non-monetary cost of driving the PHEV, leading to higher mileage. Second, treated subjects might feel morally licensed to use their PHEV more often, as charging is associated with lower CO_2 emissions than refueling. In other words, they might have less of a bad conscience when driving the car electrically (for moral licensing in the environmental domain, see, e.g., Tiefenbeck et al., 2013). As a consequence, using the PHEV becomes more attractive relative to using another car that may be available in the household, or to using other environmentally friendly modes of transport.

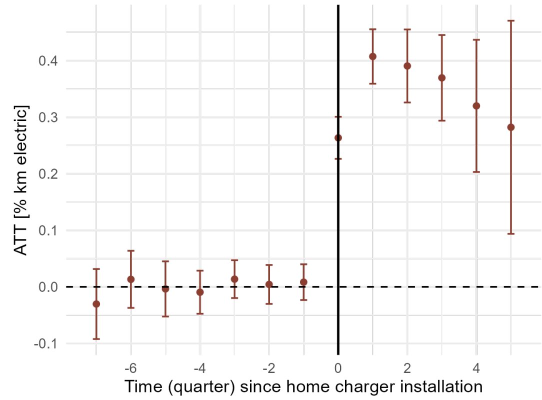
Turning to environmental outcomes, Figure 5 shows that the treatment reduced average fuel consumption per 100 km by up to three liters (Panel (a)) as it increased the electric driving share of PHEVs by up to 40 percentage points (Panel (b)). How this translates into CO_2 emissions abatement depends on the assumptions about the emissions caused by electricity generation for charging. We argue that the most reasonable assumption about these emissions is that no additional emissions are generated. The reason for this is that any emissions from charging are regulated under the total emissions cap implied by the EU's Emissions Trading System (EU ETS). Hence, any additional emissions from charging must reduce emissions elsewhere under the cap. Under this realistic scenario, the reduction in fuel consumption translates into reduced CO_2 emissions of up to 300 kg per quarter (Panel c). For comparison, panel (d) shows the treatment effect on net CO_2 emissions if the additional electricity charged gave rise to unregulated CO_2 emissions at the prevailing average CO_2 intensity in the German electricity grid (cf. Appendix D.1). Under this scenario, emissions abatement is still about half of the abatement under the other scenario, though the corresponding coefficient becomes statistically insignificant already shortly after the adoption of home charging infrastructure.

Finally, panel (e) of Figure 5 plots the quarterly treatment effects on the energy costs of charging or refueling the vehicle. This outcome aggregates the pecuniary costs of gasoline or diesel bought at the pump and of electricity charged at home, at the firm's premises or at public stations. We find that home charger adoption significantly lowered energy costs. Recall that, within the fringe benefit scheme considered here, this is a benefit that accrues to the firm, not to the holder of the car.

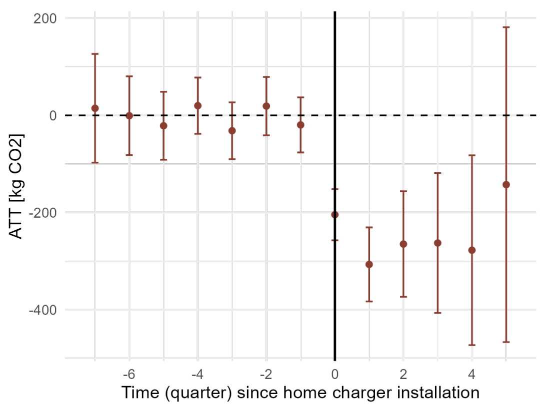
Figure 5: Treatment Effects on Fuel Efficiency, CO_2 Emissions and Energy Costs



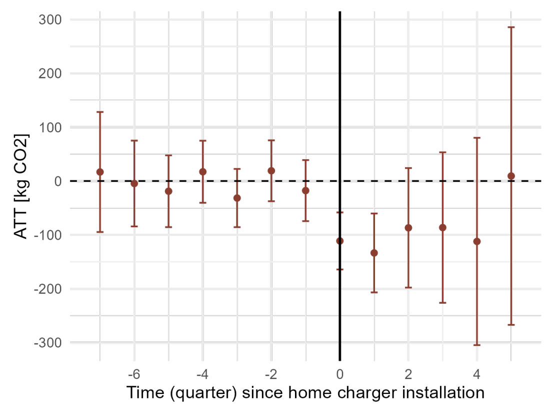
(a) Fuel Consumed per 100km



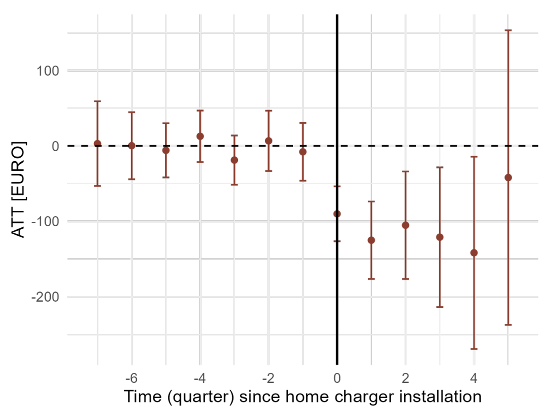
(b) Electric Driving Share



(c) CO_2 Emissions (EU ETS Cap)



(d) CO_2 Emissions (No EU ETS Cap)



(e) Company Energy Costs

Notes: Doubly-robust estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021). Total CO_2 emissions in Panel (c) are computed under the realistic assumption that charging is not associated with any CO_2 emissions under the cap implied by the EU's emissions trading scheme (EU ETS). By contrast, total CO_2 emissions in Panel (d) are computed under the (counterfactual) assumption that additional electricity charged by the treated group leads to unregulated CO_2 emissions at the average CO_2 intensity in the German electricity grid (cf. Appendix D.1). 95 % confidence intervals are indicated.

4.2 Overall Treatment Effects

Following Callaway & Sant'Anna (2021), we compute the ATT as a weighted average of the DiD estimates obtained for different cohorts and time horizons, assigning equal weight to each employee in our sample (alternatively, we could assign equal weight to each post-treatment employee × quarter observation, which would assign a larger weight to employees joining the program earlier). Table 2 reports the resulting ATT estimates for quarterly outcomes, all of which are statistically significant at the 5 % or 1 % level. Home charger adoption increased electricity consumption by 298.9 (±25.9) kWh and decreased consumption of gasoline or diesel by 102.3 (±37.9) liters per quarter. The net effect on emissions is a reduction of 248.1 (±88.6) kg of CO_2 under the assumption of non-additionality of emissions under the EU ETS. Emissions would drop by only 112.7 (±90.7) kg if additional charging induced higher CO_2 emissions from electricity generation at the average emissions rate in the German electricity grid. Home charger adoption caused a reduction in energy costs of 117.4 (±62.8) euros for the company. Finally, the average employee's mileage increased by 606.6 (±498.1) km per quarter, which can be interpreted as a 14 % rebound effect in terms of vehicle kilometers traveled.

4.3 Treatment Effects on Vehicle Choice

Employees entitled to a company car get to choose a new vehicle every four years. This allows us to investigate whether the availability of home charging makes it more likely that employees choose a BEV. We identify this treatment effect using quasi-experimental variation in exposure to home charging infrastructure among PHEV holders. The estimation sample for this analysis contains all PHEV holders whose renewal decisions were scheduled between July 2021 and June 2022. All these employees could have adopted a home charger at least two quarters before the renewal, and some of them did. Due to the delays in the ordering and installation of home chargers described above, however, other employees did not receive the home charger before choosing their new company car. We thus compare PHEV holders who had access to home charging for at least one full quarter before obtaining a new company car to PHEV holders who obtained access to at-home charging only after ordering a new company car. This identifies the treatment effect of home chargers on the choice probabilities for BEV and PHEV company cars, respectively.[5] Note that selection into the home-charging program does not affect these choice probabilities, since both groups select into the program eventually.

[5]For this distinction to work, we drop 33 employees who received access to home charging less than a full quarter before obtaining a new company car.

Table 2: Aggregate ATT for Different Outcomes

	Energy		Mileage	Emissions		Cost
	Electricity [kWh]	Fuel [l]	Mileage [km]	No EU ETS Cap [kg CO_2]	EU ETS Cap [kg CO_2]	Energy [euro]
Treated	298.88***	-102.34***	606.65**	-112.72**	-248.14***	-117.39***
	(12.97)	(18.98)	(244.54)	(45.37)	(44.33)	(31.42)
Employees	836	836	836	836	836	836
Groups	6	6	6	6	6	6
Periods	11	11	11	11	11	11
Employee FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X

Notes: Doubly-robust ATT estimator (Callaway & Sant'Anna, 2021). "Periods" are quarters. "Groups" are groups of employees receiving home charging in the same quarter. "No EU ETS Cap" stands for CO_2 emissions being computed under the (counterfactual) assumption that additional electricity charged by the treated group leads to unregulated CO_2 emissions at the average CO_2 intensity in the German electricity grid (cf. Appendix D.1). "EU ETS Cap" stands for CO_2 emissions being computed under the realistic assumption that charging is not associated with any CO_2 emissions under the cap implied by the EU's emissions trading scheme (EU ETS). *, **, *** means that the corresponding estimated parameter is different from zero at the 10 %, 5 %, and 1 % significance level, respectively.

Table 3: Access to Home Charger and BEV Adoption

	(1)	(2)
Treatment	0.393***	0.298***
	(0.108)	(0.100)
Observations	75	75
RMSE	0.46	0.43
AIC	95.0	93.8

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Probit regressions, coefficients transformed into marginal effects. Bootstrapped standard errors (1000 draws). In model (2), the following covariates were included: A dummy for working at the headquarters and energy consumption with previously held PHEV (fuel in liters and electricity by source in kWh). *, **, *** means that the corresponding estimated parameter is different from zero at the 10 %, 5 %, and 1 % significance level, respectively.

Our hypothesis is that employees who already had access to at-home charging with their previous vehicle are more likely to decide for a BEV company car.[6] We test this by regressing an indicator for BEV adoption on a treatment indicator, as defined above. This is a cross-sectional regression since we observe at most one vehicle choice per employee. Our preferred specification controls for location-specific effects (in particular the availability of charging stations at the employee's location of work and the density of the public charging network) using a headquarters dummy, and for employee-specific mobility preferences by including the total amount of energy consumed with the previously held PHEV company car.[7] Table 3 reports the estimated treatment effects on choice probabilities. Having access to a home charger increases the probability of ordering a BEV by 29.8%-points in the preferred specification. This suggests that home charger adoption induces some PHEV holders to go all electric and switch to a BEV, thus eliminating the option of refueling in the future.

Table 4: ATT across different Outcomes for BEVs

	Electricity consumption				
	Total [kWh]	Firm [kWh]	Public [kWh]	Emissions [kg CO_2]	Expenditures [euro]
Home charger	172.05**	-52.38**	-247.73***	79.84**	23.03
	(73.02)	(24.16)	(62.58)	(32.16)	(24.84)
Employees	407	407	407	407	407
Groups	5	5	5	5	5
Periods	10	10	10	10	10
Employee FE	X	X	X	X	X
Time FE	X	X	X	X	X

Notes: Doubly-robust ATT estimator (Callaway & Sant'Anna, 2021). "Periods" are quarters. "Groups" are groups of employees receiving home charging in the same quarter. *, **, *** means that the corresponding estimated parameter is different from zero at the 10 %, 5 %, and 1 % significance level, respectively.

4.4 Treatment Effects on Charging of Battery Electric Vehicles

For employees obtaining a BEV at some point during the sample period,[8] we estimate the effect of home charging on electricity consumption and expenditures. Table 4 reports aggregate ATT estimates. We find that home charging increases total electricity consumption by 172.05 kWh per quarter, after netting out significant decreases in both charging at the firm's premises (-52.3 kWh) and, especially, on the public grid (-247.73 kWh). Since public charging is more expensive than charging at home,[9] the resulting increase in charging expenditures is economically and statistically insignificant. If there was no cap on electricity sector emissions, the increase in charging would lead to incremental CO_2 emissions of 79.84 kg.

These effects are unlikely to be driven by systematic differences between adopters of home chargers and non-adopters. As shown in Table A.2, electricity consumption per quarter prior to treatment is very similar across the two groups, and differences in the electric efficiency, weight and price of the respective BEVs are minor. As in the larger sample of EV holders, treated BEV holders tend to be male, older than non-participants,

[6]In theory, access to at-home charging should also affect choice probabilities for vehicle ownership and ICEV ownership. These margins play a limited role in our sample. We observe only four employees in the treated and none in the not-yet-treated group that either do not get a new company car at all or choose an ICEV instead.

[7]Note that all PHEV company cars were held for approximately four years. Thus, the total amount of fuel and electricity consumed can be interpreted as reflecting driving behavior over a four-year period.

[8]Due to the smaller sample of employees holding a BEV company car and since we rely on not-yet-treated units as our control group, we had to cut our sample period off after July 2022 (Q2 2022). In Q2 2022, the control group still comprised 28 employees holding a BEV company car.

[9]In 2021, the charging price at the median supplier and normal charger was 0.39 € per kWh, compared to 0.28 € per kWh at the average employee's home and 0.15 € per kWh on the firm premises.

and have longer tenure with the company.

5 Cost-Benefit Analysis

Building on the estimated treatment effects at the intensive and extensive margins, we conduct a cost-benefit analysis of home charger adoption which relates total emissions abatement to the associated costs. Simulating emissions trajectories over the expected 20-year lifetime of a home charger requires us to combine intensive-margin and extensive-margin impacts of its adoption. This is because adopters are more likely to switch to BEVs, and BEV holders use the home charger differently than PHEV holders. We address this by adapting the method by Dugoua & Gerarden (2023, Appendix H) to our potential outcome framework (using conditional expectations instead of derivatives). The basic idea is to first consider a one-off vehicle choice and then forward-simulate the path of the outcome variable over a 20-year period with repeated vehicle choices. A detailed description of how we simulate the paths of energy costs and emissions, as well as formal derivations of the ATTs is relegated to Appendix E. We simulate these outcomes under alternative assumptions about employees' vehicle choices, subsumed in scenarios. Across scenarios, we rely on a set of common assumptions. First, emissions from electricity generation are non-additional due to a binding cap of the EU ETS. Second, the initial fleet of PHEVs in the first four years is equal to the fleet observed in the data. Third, all employees choose a new company car simultaneously in four-year increments.[10]

5.1 Scenarios

Scenario 0: Baseline This scenario is based on the following assumptions:

A1 There is no exit from vehicle ownership.

A2 BEV adoption is an absorbing state (employees do not go back to ICEVs or PHEVs).

A3 Home charging does not decrease the probability of BEV adoption among employees currently holding a PHEV and does not decrease the probability of BEV adoption among employees currently holding a BEV

The choice probabilities for different vehicle types are then given by the transition matrix in equation (E.15), and the ATT over different time horizons can be calculated using the formula in equation (E.10).

[10] This reflects the time employees have to hold on to their company car at our partner company. In reality, this schedule implies that roughly a quarter of employees chooses a new company car every year.

Scenario 1: Treatment does not affect vehicle choice We replace assumption **A3** with the assumption that access to home charging does not change vehicle choice, thus shutting down extensive-margin effects of the treatment. The choice probabilities for different vehicle types are thus given by the following transition matrix:

$$\begin{aligned}\mathbf{E}(\delta_i(1)|k_{it}) \quad &= \mathbf{E}(\delta_i(0)|k_{it}) \\ &= \begin{pmatrix} (1 - \mathbf{E}(\delta_i^{EV}(0)|PHEV)) & 0 \\ \mathbf{E}(\delta_i^{EV}(0)|PHEV) & 1 \end{pmatrix}\end{aligned} \tag{2}$$

Since the treatment no longer affects vehicle choice, we only need to consider the intensive-margin treatment effects for the ATTs:

$$ATT(Y_{it}) = \sum_{t=1}^{5} \gamma^t \mathbf{E}(\delta_{it}^{PHEV}(1))\mathbf{E}(\Delta Y_i^{PHEV}) \tag{3}$$

Scenario 2: Randomly assigned access to home charging Like scenario 1, but also replacing assumption **A2** with the assumption that the vehicle choice probabilites among employees in the home charger program are the same as in the population of all employees having to replace their company car in the near future (within the next two years). We elicited these choice probabilities in a company-wide survey in February 2023. Employees who were going to choose a new company car within two years from the survey reported the engine types of the company car they currently had and the car they were planning to choose next. Assuming that the choice probabilities of employees who were still undecided at the time of the survey would follow the same distribution as the sample we observe, we obtain the following transition matrix:

$$\begin{aligned}&\mathbf{E}(\delta_i(1)|k_{it}) \\ &= \begin{pmatrix} 1779/3038 & 105/598 & 15/300 \\ 643/3038 & 277/598 & 8/300 \\ 661/3038 & 216/598 & 277/300 \end{pmatrix}\end{aligned} \tag{4}$$

and consider only the intensive-margin treatment effects for the period-ATTs:

$$ATT(Y_{it}) = \sum_{t=1}^{5} \gamma^t \mathbf{E}(\delta_{it}^{PHEV}(1))\mathbf{E}(\Delta Y_i^{PHEV}) \tag{5}$$

Scenario 3: Permanent PHEV ownership Like scenario 1, but with the simplifying assumption that employees do not change their vehicle type over time after their initial choice in period 1. Under these assumptions, the ATTs are simply given by the net present value of the period treatment effects on PHEV use:

$$ATT(Y_{it}) = \sum_{t=1}^{5} \gamma^t \mathbf{E}(\Delta Y_i^{PHEV}) \tag{6}$$

Scenario 4: Forced Transition to BEVs Like scenario 1, but with the additional assumption that the company only allows BEV company cars from the second four-year period onwards. The dynamic ATTs then correspond to the ATTs during the first four-year period:

$$ATT(Y_{it}) = \gamma \mathbf{E}(\Delta Y_i^{PHEV}) \tag{7}$$

This gives us all the ingredients needed to approximate the ATT on CO_2 emissions and energy costs, combining intensive- and extensive-margin reactions. We collect the required parameters in Table 5.

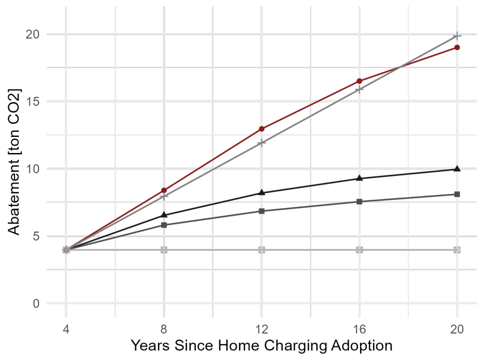
Table 5: Coefficients and Parameters for the Back-of-the-Envelope Calculation

Parameter	Source
Panel A: Estimated ATTs	
$\mathbf{E}(\Delta\delta_i^{EV}) = 0.298$	Table 3
$\mathbf{E}(\Delta E_i^{PHEV}) = -248.14$ kg CO_2 per quarter	Table 2
$\mathbf{E}(\Delta C_i^{PHEV}) = -117.39$ € per quarter	Table 2
$\mathbf{E}(\Delta C_i^{EV}) = 0$ € per quarter	Table 4
Panel B: Observed population averages	
$\mathbf{E}(E_i^{PHEV}(0)) = 636.08$ kg CO_2 per quarter	Table 1
$\mathbf{E}(C_i^{PHEV}(0)) = 347.35$ € per quarter	Table 1
$\mathbf{E}(C_i^{EV}) = 63.40$ € per quarter	Table A.2
Panel C: Parameter assumptions	
$\mathbf{E}(\delta_{it}^{PHEV}(0), \delta_{it}^{EV}(0), \delta_{it}^{ICEV}(0)) = (1,0,0)$	Starting from PHEV users
$\mathbf{E}(E_i^{EV}) = 0$	Assumption given EU ETS Cap
$\gamma = \sum_{y=1}^{4}(1.03)^y$ for abatement cost	Ad hoc
$\gamma = 4$ for emissions	Ad hoc
$\mathbf{E}(\delta_i(1)\|k_{it})$	See scenarios

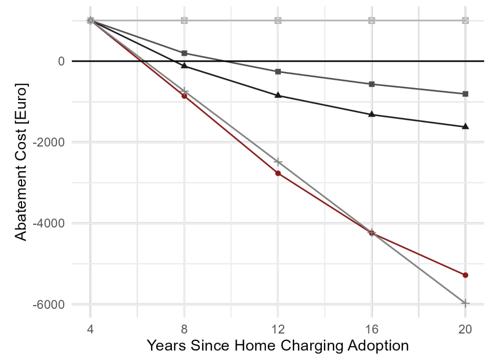
5.2 Simulation Results

Figure 6 displays cumulative treatment effects of home charging adoption over time for various outcomes, starting from the end of year four when the leases for the initial PHEV

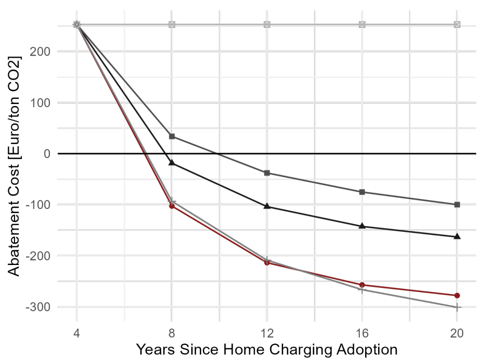
Figure 6: Simulation of Cumulative Treatment Effects over Time



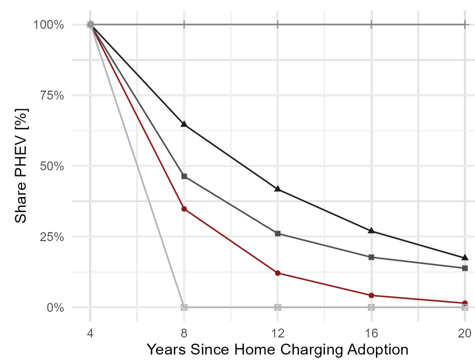
(a) Cumulative Emissions Abatement



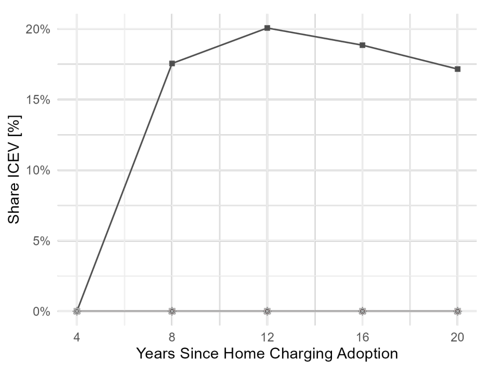
(b) Cumulative Abatement Cost



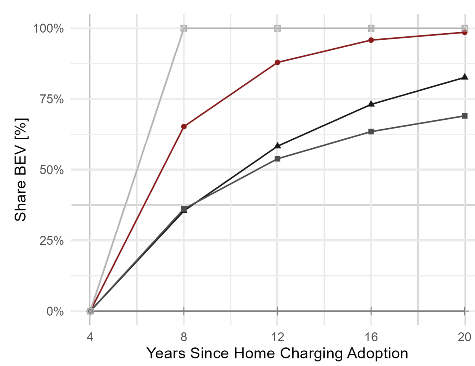
(c) Abatement Cost



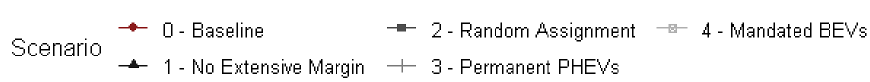
(d) Employees Holding PHEV



(e) Employees Holding ICEV



(f) Employees Holding BEV



Notes: Estimates for the dynamic ATT.Scenario 0 is the baseline scenario. In scenario 1, treatment does not affect vehicle choice. In scenario 2, access to home charging is randomly assigned to employees. In scenario 3, employees keep a PHEV company car for the full 20-year period. In scenario 4, all employees are forced to choose a BEV after four years.

fleet need to be renewed. Panel (a) shows cumulative CO_2 emissions abatement per employee, which ranges from about four tons of CO_2 in scenario 4 (BEVs) to almost 20 tons of CO_2 in the baseline scenario and scenario 3 (PHEVs), with the other two scenarios lying somewhere in between these polar cases. The reason for low abatement in scenario 4 is that there are no further emissions reductions from adopting a home charger after the first four years. After that, the forced transition to a pure BEV fleet means that all vehicles run at 100% electric utility factor and hence adding chargers has no impact on emissions.

In all other scenarios, the program generates emissions reductions in all years because not everyone transitions to BEVs. Depending on the scenario, employees may stick with PHEVs or even go back to an ICEV (see panels d, e, and f for the shares of employees holding PHEVs, ICEVs, and BEVs, respectively).

Panel (b) displays the cumulative total abatement cost from adopting home chargers, i.e., installation costs minus cost savings resulting from the substitution from fuel (gasoline or diesel) to electricity. We observe that the abatement cost per employee is highest if the company mandates BEV company cars from the second four-year period onwards since home chargers do not result in additional emissions reductions, and it is lowest in the baseline scenario and scenario 4 in which the program also generates future benefits. Note that an abatement cost of zero implies that the home charger installation has paid off and that lower, in particular, a negative abatement cost results when there is more to be gained from the home charger program. This is the case when (i) more PHEVs remain in the fleet, as in scenario 3 or (ii) access to charging at home has a positive impact on BEV adoption, as in the baseline scenario. The break-even point is reached already after slightly more than six years in the baseline and in scenario 4. For the remaining two scenarios, the break-even point is approximately two to four years later, either because the transition to BEVs is proceeding more slowly (see panel f), or because we assumed the extensive margin effect of experience with the program to be zero (to understand the magnitude of the extensive margin effect, compare the baseline scenario to scenario 1 in Panel a). Per ton of CO_2 emissions, we estimate levelized abatement costs of around 250 euros after four years, but these decrease to between -100 and -300 euros after 20 years (see Panel c).

6 Conclusion

This paper contributes the first causal evidence on the effects of home charger adoption on the use of Plug-in Hybrid Electric Vehicles. We find that CO_2 emissions from Plug-in

Hybrid Electric Vehicles fall by 38 % when the vehicle holder obtains access to home charging infrastructure under the assumption that electric charging does not cause additional emissions under the EU's Emissions Trading System. Home charging predominantly replaces refueling with conventional gasoline or diesel rather than other charging options, and hence it reduces CO_2 emissions, despite a 14 % rebound effect via increased mileage. Even under a more pessimistic assumption that electric charging leads to emissions equal to the average emissions in the German electricity mix, total CO_2 emissions are significantly lower after installing a home charger. Furthermore, home charger adoption leads to a 30 % higher likelihood of choosing a Battery Electric Vehicle when employees choose a new company car under the periodical renewal of their lease.

In a cost-benefit analysis, we find that in most scenarios the installation of the home charger already pays off (for the company) after six to eight years. The longer is the assumed time span that the home charger lasts, the larger are the net benefits from installing it, with negative levelized abatement costs. Per employee, total abatement from adopting a home charger ranges from between four to 20 tons of CO_2 emissions.

Since PHEVs accounted for 9.4 % of new vehicle registrations in the European Union in 2022 (European Environment Agency, 2023), our results bear high policy relevance. They identify and quantify a powerful lever for decreasing emissions from a large segment of the vehicle fleet. While our research design relies on data from a subsidy scheme implemented by a private company in a company car fleet, we reckon that government subsidies on home charging infrastructure could have similar effects for a broader segment of PHEV holders, with expected pay-back times that are similar to the ones found in this study. Take-up by private vehicle owners will require that the subsidy be high enough to offset the as yet relatively high cost of the technical equipment. Falling cost of the equipment, a longer useful lifetime, increasing carbon taxes on fossil fuels and decarbonization of the electricity grid will all work in the direction of a faster diffusion of at-home charging, and thereby leverage the environmental benefits of electric vehicles.

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Appendix (For Online Publication)

A Additional Tables

Table A.1: Summary Statistics

Variable	Mean	Sd	Min	Pctl. 25	Median	Pctl. 75	Max
Panel A: Driving Behavior							
Mileage [km]	5138	2896	21.8	3021	4739	6824	19343
Emissions [g CO_2]	501	384	2.49	252	401	649	3764
Tailpipe Emissions [g CO_2]	323	392	0.551	63.8	179	436	3722
Fuel [l]	133	161	0.231	26.1	73.9	181	1560
Charge at home [kWh]	347	306	0	108	293	498	2504
Charge at firm [kWh]	28.6	69.5	0	0	0.005	29.7	1203
Charge public [kWh]	22.1	64.6	0	0	0	16.1	977
Fuel consumption [l/100 km]	2.52	2.28	0.0538	0.774	1.92	3.47	14.2
Electricity consumption [kWh/100 km]	8.6	6.34	0	3.71	7.5	12.6	45.7
Panel B: Vehicle Characteristics							
Price [euro]	32575	4496	0	30946	32511	35328	49631
Weight [kg]	2020	262	1480	1844	2025	2105	2655
Fuel Consumption [l/100 km WLTP]	1.59	0.343	0.8	1.4	1.4	1.7	2.9
Electricity Consumption [kWh/100 km WLTP]	17.5	3.18	13.3	15.3	16.2	18.9	24.2
Panel C: Employee Characteristics							
Age [Years]	48.2						
Tenure [Years]	17.4						
Female [%]	0.156						

Notes: Descriptive statistics on the sample of employees and their PHEVs, respectively, in the home charger program between January 2021 and December 2022 (N = 836 employees). Panel A shows summary statistics for vehicle use after the employee has received access to home charging. This reduces the size of the sample to N = 720 employees since we exclude the last-treated group. Panel B displays vehicle characteristics for the car models held by employees participating in the program. WLTP stands for "Worldwide Harmonized Light Vehicles Test Procedure". Panel C displays employee characteristics. Note that each employee is assigned the average characteristics of the group simultaneously adopting a home charger.

B Company Cars

Many companies provide generous mobility options to their employees, not only for business trips but also for the commute to work and for leisure trips. The most prominent example are company cars, which typically can also be used privately. The use of company cars is heavily subsidized in many countries, particularly in Europe (Copenhagen Economics, 2010). Furthermore, companies often reimburse up to 100 % of the car's fuel cost. These two factors make a company car much cheaper for an employee than if the same car were purchased privately. Additionally, providing a company car is often perceived as a status symbol and can make working for an employer more attractive. Therefore, companies are reluctant to take away this privilege, even though they are con-

Table A.2: Home Charger Sample with BEVs vs. Population of BEVs

	Home Charger		No Home Charger	
Variable	Mean	Sd	Mean	Sd
Panel A: Vehicle Use in 2020				
Emissions [kg CO2]	94.889	(105.5)	93.058	(99.56)
Electricity per quarter [kWh]	247.753	(275.46)	242.972	(259.96)
Energy expenditures [euro]	63.398	(87.42)	65.303	(90.68)
Panel B: Vehicle Characteristics				
Electric efficiency [kWh/100 km WLTP]	15.616	(2.11)	15.433	(2.51)
Price [euro]	32642.918	(11468.1)	31268.432	(12404.58)
Weight [kg]	1980.911	(349.8)	1901.058	(330.25)
Panel C: Employee Characteristics				
Age [years]	48.338	(0.4)	43.188	(0)
Tenure [years]	17.536	(1.05)	12.888	(0)
Female [%]	0.157	(0.02)	0.235	(0)

Notes: Comparison of the sample of employees selecting into the home charger program between January 2021 and December 2022 (N = 493 employees) to the group of employees not selecting into the home charger program during that period (N = 749 employees). Both samples are restricted to the employees holding at least one BEV during that period and opting into the fuel cost compensation scheme of the company. Panel A shows summary statistics for vehicle use in the year 2020 in which none of the employees in the home charger sample has received a home charger yet. The sample sizes are reduced to N = 63 cars that were used during that period for the home charger sample and N = 221 cars in the no-home charger sample. Panel B displays vehicle characteristics obtained from the General German Automobile Club's car catalog. Panel C displays employee characteristics which are only available in terms of group averages. WLTP stands for "Worldwide Harmonised Light Vehicle Testing Protocol".

fronted with external or internal ambitions to rapidly decrease CO_2 emissions, also from their employees' mobility.

As an alternative to a company car, some companies have started to offer a so-called mobility budget to their employees. A mobility budget is a predefined individual budget that can be used flexibly by employees during a certain time period, e.g., a year, to choose any transport mode that is available on the market or allowed to be used. In the European Union, around 30 % of the companies with at least one company car already offer this option or are considering doing so in the future; see Kantar/Arval Mobility Observatory, 2020. For an analysis of sustainability incentives within a mobility budget, see Gessner et al. (2023).

C Data Preparation

For this project, our partner company provided us with data from five different sources: i) the register of company cars, listing the employee holding the car, a description of the car model, the vehicle's fuel type, potentially the date on which the employee ordered a home charger, ii) transaction data on charging procedures at the companies premises, iii) transaction data on charging procedures at public charging stations iv) transaction data on charging procedures at the employees home, for those employees who already joined the home charger program and v) transaction data on refueling at public gas stations. For all transaction data sets, we observe the date and time at which the transaction occurred and the amount of energy charged (fuel in liters, electricity in kWh). For the refueling transactions, we additionally observe employee-recorded odometer readings, giving the total vehicle kilometers traveled up to this point.

The odometer readings imply vehicle mileages between two refueling procedures that are sometimes implausible, since i) the implied mileage is negative or ii) the mileage information is not consistent with the fuel and electricity consumption of the car and the car's efficiency. To clean the mileage variable, we assess the plausibility of the mileage observed using the two criteria. To do so, we apply the following procedure. We manually match the vehicle model descriptions in the company car register to vehicle models as listed in the model catalog of the General German Automobile Club[11].

For each PHEV model, we obtain the combined (using both electricity and fuel) fuel consumption per 100 km according to type-approval tests using the New European Driving Cycle (NEDC).The NEDC was the European Union's testing procedure for type-approval before 2017, and NEDC testing values had to be provided for all model years in Europe until 2019. For all but 63 vehicles in our sample, a NEDC fuel consumption is available. If the efficiency is only available for the newer Worldwide Harmonised Light-Duty Vehicles Test Procedure (WLTP), we use that value divided by 1.2 as an NEDC-equivalent value. To clean the data, we used the vehicle's fuel consumption in charge-sustaining mode, that is, when the PHEVs battery is (almost) depleted and the PHEV mainly uses the internal combustion engine for driving (Riemersma & Plötz, 2017). In the ADAC data, only the combined fuel consumption (average between charge sustaining and charge depleting

[11]ADAC Modellkatalog, `https://www.adac.de/rund-ums-fahrzeug/autokatalog/marken-modelle/?filter=ONLY_RECENT&sort=SORTING_DESC`, last accessed 24.02.2024, 23:28 CET.

mode, i.e. the vehicle's fuel consumption when the battery is fully charged) is available. We obtain a lower-bound estimate for the fuel consumption in charge-sustaining mode using the formula for the combined consumption under the NEDC procedure (as found in Riemersma & Plötz, 2017)

$$C^{NEDC} = \frac{C_1^{NEDC} D_e^{NEDC} + C_2^{NEDC} 25}{D_e^{NEDC} + 25} \tag{C.1}$$

$$\implies C_2^{NEDC} \geq \frac{25 C^{NEDC}}{D_e^{NEDC} + 25} \tag{C.2}$$

Finally, to account for the underestimation of fuel consumption under the NEDC testing procedure, particularly for PHEVs (Plötz et al., 2020), we multiply the NEDC consumption in charge-sustaining mode by 1.5 to obtain an estimate for the on-road fuel consumption of the vehicle, following Grigolon et al. (2024) and Plötz et al. (2021).

$$C_2^{real} = 1.5 C^{NEDC} \frac{25}{D_e^{NEDC} + 25} \tag{C.3}$$

C^{NEDC} is the combined NEDC fuel consumption, C_1^{NEDC} is the charge-depleting NEDC fuel consumption D_e^{NEDC} is the NEDC electric driving range of the PHEV, and C_2^{NEDC} and C_2^{real} are the NEDC and on-road fuel consumption in charge-sustaining mode, respectively.

We also obtain the electric efficiency of the PHEV version of the model, according to the NEDC procedure, where possible. If we only observe the WLTP electric efficiency, we divide that value by 1.2 to obtain a proxy for the NEDC electric efficiency. We assume that the NEDC testing procedure imposes an electric driving share of 80 % on the vehicle (which is at the upper end of electric driving shares assumed in testing procedures, see e.g. (Plötz et al., 2021), which implies that we obtain the efficiency of purely electric driving by dividing the combined NEDC electricity consumption by 0.8. Assuming a high NEDC utility factor will thus lead to a higher electricity consumption per 100 km in a hypothetical all-electric driving mode.

We proceed to clean the mileage variable as follows: Based on the transaction data, we calculate the total electricity consumption between two odometer readings by adding up all the electricity charged between the two corresponding refuelling dates. Based on the electric efficiency of the vehicle, we then translate the electricity consumption into kilometers, which we subtract from the mileage obtained from differencing the odometer readings. Dividing the total fuel consumption by this residual mileage multiplied by 100, we obtain an observed fuel consumption per 100 km traveled using mainly the internal combustion engine. If this observed average fuel consumption exceeds the vehicles fuel consumption in charge-sustaining mode (C_2^{real}) by more than a factor 3 or else if it is lower than 20 % of C_2^{real}, we flag the mileage as erroneous. We interpolate mileages flagged as implausible using an energy-weighted average between the last and the next correct observed mileage. To obtain the energy weights, we transform fuel consumption in liters into the equivalent electricity consumption in kWh using the vehicle's electric and fuel efficiency according to testing procedures.

We drop series with less than three non-flagged mileage observations. Such series can occur, e.g., for series with few refueling procedures, ii) for series that appear to charge their PHEV privately, such that the observed average fuel consumption is constantly below the lower bound implied by 20 % of C_2^{real}, or iii) for series in which the employee did not take entering the odometer readings seriously, such that the sequence of recorded mileages does not appear to reflect driving behavior. Note that the latter case should be rare since not entering odometer readings correctly violates corporate policies.

If flagged mileages occur at the end of a series, we extrapolate based on the last correct odometer reading and the fuel and electricity use of the vehicle after that. For each refueling procedure after the last correct odometer reading, we impute the mileage based on the vehicle's electricity and fuel consumption, translating energy consumption into kilometers traveled using the vehicle's NEDC electricity consumption per 100 km in all-electric mode (see above) and the vehicles average fuel consumption per 100 km we observe in the not-flagged transactions data (see above). To test whether this extrapolation affects our results for the vehicle's mileage, average fuel consumption per 100 km and utility factor, we run a sensitivity analysis with two alternative imputation procedures in Appendix F. We truncate all vehicle time series after the vehicle's last (correct or incorrect) mileage observation, i.e. after the second-to-last observed refueling procedure since we would be unable to obtain a mileage after the last refueling procedure (odometer readings are only recorded after refuelling the vehicle).

In contrast to the employee-recorded odometer readings, we take the amount of fuel and electricity consumed in the transactions data almost at face value. The only correction we apply is that we winsorize refueling at 100 liters per transaction since most vehicles have a tank capacity of less than 100 liters (this affects 8 out of 949406 refueling procedures) and we winsorize electric charging at 130 % of the vehicles gross battery capacity (this affects 15497 out of 949406 recharging and refueling procedures).[12]

Finally, we construct the share of vehicle kilometers traveled in electric mode, the so-called on-road utility factor following Plötz et al. (2021) and Grigolon et al. (2024) using the following formula:

$$UF = 1 - \frac{C_2^{on-road}}{C_2^{real}} \tag{C.4}$$

We obtain estimates for the on-road fuel consumption per 100 km $C_2^{on-road}$ by dividing the fuel consumption observed in the transaction data by the mileage variable (constructed as described above).

[12]The amount of electricity charged from the station is always greater than the amount of electricity stored in the battery, due to efficiency losses. Charging slightly more electricity in kWh than the net battery capacity of the vehicle is thus possible. Winsorizing charged amounts at 130 % gross battery capacity should affect only charging procedures that are technically infeasible.

D CO_2 Emissions, Energy Prices and Abatement Cost

This section outlines the assumptions made to transform the observed energy consumption in terms of electricity, or fossil fuels (either diesel or gasoline) into CO_2 emissions and energy costs. We summarize the assumptions made for energy prices, emission factors, etc. in Table D.1.

D.1 CO_2 Emissions

The PHEVs can drive using electricity and either Gasoline or Diesel fuel. We observe the amount of fuel in liters and the amount of electricity in kWh. Converting fuel consumption into CO_2 emissions is straightforward, since the amount of CO_2 emitted is proportional to the amount of fuel burned. To quantify that relationship, we use emissions factors for fossil fuels from the German Environmental Protection Agency (Juhrich, 2022).

To convert electricity consumption into CO_2 emissions, we make the simplifying assumption that the emissions intensity of electricity generation in Germany is constant for one year at a time. We can then calculate CO_2 emissions from electric charging using the average annual CO_2 intensity of the German electricity mix, as calculated by the German Environmental Protection Agency (Icha & Lauf, 2022).

D.2 Energy Prices

To calculate energy cost savings for the firm, we need to assign a monetary value to the energy consumption observed. For at-home charging, we directly observe the price per kWh of electricity. To approximate prices paid for fuel and electricity charged at the company's premises or on the public grid, we use annual average annual consumer prices for Gasoline and Diesel in Germany from the industry organization "Wirtschaftsverband Fuels und Energie e.V." (Bittkau et al., 2022), and data on industry electricity prices from the German Federal Statistical Office (DESTATIS, 2023b). To approximate the cost of charging the vehicle at public charging stations, we take the average price paid across a set of charging station providers from (Kampwirth, 2020, 2021, 2023).

D.3 Home Charging Installation Cost

Our partner company cooperated with a utility company to provide employees with subsidized at-home charging stations. The utility had a modular pricing schedule. More complex installations, e.g. for installations at underground parking needed to pay for an inspection ahead of the installation to check whether installing a home charger would be feasible. Depending on the complexity of the installation (defined by the length of needed electricity cable and the number of walls these cables needed to go through) employees were offered one of two prices for the installation. The subsidy provided by the company was capped at 2,750 Euro, which was sufficient to cover the cost of a charging station and the simple installation. For a more complex installation, employees could end up paying up to 800 euros out of their own pocket. Additionally, the subsidy for the home charger installation was subject to a flat income tax rate of 25 %.

D.4 Abatement Cost

We calculate abatement cost by assuming that the company paid the full subsidy to all employees, and this covered the full installation cost. The installation cost of the home charger is thus covered by a 2,750 Euro subsidy. To obain abatement cost, we assume a useful life of the home charger of 20 years and calculate abatement cost under different scenarios in four-year increments. Four years is the period over which an employee has to hold on to her company car. We assume that the treatment effect on the vehicle's tailpipe emissions would be constant over the useful life of the home charger. Aggregating over the useful life, we obtain the implied CO_2 emission savings. To obtain energy cost savings, we assume that the ATT on the energy costs from refueling and charging the car is also constant over time, and calculate the total cost per employee as the net present value of the initial investment (the subsidy) and the future energy cost savings. We divide this number by the CO_2 emissions reduction to obtain an estimate for the abatement cost.

Table D.1: Energy prices and CO_2 emission factors

Variable	Value	Source
Panel A: Emission factors		
Diesel	74.0 tCO_2/TJ	(Juhrich, 2022)
Gasoline	3.169 tCO_2/t	(Juhrich, 2022)
	383 g/kWh (2020)	(Icha & Lauf, 2022)
Electricity	425 g/kWh (2021)	(Icha & Lauf, 2022)
	459 g/kWh (2022)	(Icha & Lauf, 2022)
Panel B: Prices		
	1.124 EUR/l (2020)	(Bittkau et al., 2022)
Diesel	1.399 EUR/l g/kWh (2021)	(Bittkau et al., 2022)
	1.96 EUR/l (2022)	(Bittkau et al., 2022)
	1.293 EUR/l (2020)	(Bittkau et al., 2022)
Gasoline	1.579 EUR/l g/kWh (2021)	(Bittkau et al., 2022)
	1.962 EUR/l (2022)	(Bittkau et al., 2022)
	0.100 EUR/kWh (2020)	(DESTATIS, 2023b)
Electricity Firm	0.150 EUR/kWh g/kWh (2021)	(DESTATIS, 2023b)
	0.246 EUR/kWh (2022)	(DESTATIS, 2023b)
	0.38 EUR/kWh (2020)	(Kampwirth, 2020)
Electricity Public	0.39 EUR/kWh g/kWh (2021)	(Kampwirth, 2021)
	0.43 EUR/kWh (2022)	(Kampwirth, 2021, 2023)
Social Cost of Carbon	150 EUR/tCO_2 eq	(Rennert et al., 2022)
Value of Time	12.80 EUR/h	(DESTATIS, 2023a)
Cost of Home Charger	2750 EUR	Partner company

E Derivations for Cost-Benefit Analysis

E.1 Approximating the ATT for a One-off Vehicle Choice

For simplicity, we first consider a one-off decision for vehicle adoption (e.g. for a four-year lease) where employee i decides on vehicle type k given her treatment status. Treatment status D_i and vehicle type k jointly determine the outcomes CO_2 emissions $E_i^k(D_i)$ and energy costs $C_i^k(D_i)$ for employee i. We adopt the notation $Y_i^k(D_i) \in \{E_i^k(D_i), C_i^k(D_i)\}$. Employee i's outcomes can then be written as $Y_i(D_i) = \sum_k \delta_i^k(D_i) Y_i^k(D_i)$, where δ_i^k is an indicator for whether employee i adopts vehicle type $k \in \{ICEV, PHEV, EV\}$.

Using this notation, we can define the ATT as:

$$ATT(Y_i) = \mathbf{E}(Y_i(1)|D_i = 1) - \mathbf{E}(Y_i(0)|D_i = 1) \tag{E.1}$$

where $\mathbf{E}$ stands for the expectation operator. With random assignment of treatment, this simplifies to:

$$ATT(Y_i) = \mathbf{E}(Y_i(1)) - \mathbf{E}(Y_i(0)). \tag{E.2}$$

Considering the emissions given one treatment status in isolation, we can rewrite:

$$\mathbf{E}(Y_i(D_i)) = \mathbf{E}\left(\sum_k \delta_i^k(D_i) Y_i^k(D_i)\right) \tag{E.3}$$

We assume that vehicle choice δ_i^k is independent of vehicle use and thus independent of emissions E_i^k and energy costs C_i^k. We justify this assumption by the following argument: suppose a company rolls out home charging infrastructure among employees initially holding PHEVs. These employees have similar characteristics ex-ante. Changes in vehicle choice could be driven by i.i.d. shocks to employee preferences for sustainable transportation. Under the independence assumption, we can r-write:

$$\mathbf{E}(Y_i(D_i)) = \sum_k \mathbf{E}\left(\delta_i^k(D_i)\right) \mathbf{E}\left(Y_i^k(D_i)\right) \tag{E.4}$$

By definition, the CO_2 emissions of ICEVs and EVs (under the assumption of a binding cap of the EU ETS) and the energy costs of ICEVs are not affected by the treatment status. Additionally, we find in Table 4 that the energy costs of BEVs are also the same regardless of the treatment status. Thus, we can simplify our notation: $Y_i^k(1) = Y_i^k(0) = Y_i^k \; \forall \, i, \; k \in \{EV, \; ICEV\}, Y \in \{E, \; C\}$. This implies that we can re-write the ATT as:

$$\begin{aligned} ATT(Y_i) = {} & \mathbf{E}(\delta_i^{PHEV}(1))\mathbf{E}(Y_i^{PHEV}(1)) \\ & - \mathbf{E}(\delta_i^{PHEV}(0))\mathbf{E}(Y_i^{PHEV}(0)) \\ & + \sum_{k \in \{EV, ICEV\}} \mathbf{E}(\delta_i^k(1) - \delta_i^k(0))\mathbf{E}(Y_i^k) \end{aligned} \tag{E.5}$$

Adding a "smart zero" yields:

$$
\begin{aligned}
ATT(Y_i) = &\, \mathbf{E}(\delta_i^{PHEV}(1))\mathbf{E}(Y_i^{PHEV}(1)) \\
&+ \mathbf{E}(\delta_i^{PHEV}(1))\mathbf{E}(Y_i^{PHEV}(0)) \\
&- \mathbf{E}(\delta_i^{PHEV}(1))\mathbf{E}(Y_i^{PHEV}(0)) \\
&- \mathbf{E}(\delta_i^{PHEV}(0))\mathbf{E}(Y_i^{PHEV}(0)) \\
&+ \sum_{k\in\{EV,ICEV\}} \mathbf{E}(\delta_i^k(1) - \delta_i^k(0))\mathbf{E}(Y_i^k)
\end{aligned} \tag{E.6}
$$

We adopt the notation $\delta_i^k(1) - \delta_i^k(0) = \Delta\delta_i^k$ and $Y_i^k(1) - Y_i^k(0) = \Delta Y_i^k$ and rearrange terms:

$$
\begin{aligned}
ATT(Y_i) = &\, \mathbf{E}(\Delta\delta_i^{PHEV})\mathbf{E}(Y_i^{PHEV}(0)) \\
&+ \mathbf{E}(\delta_i^{PHEV}(1))\mathbf{E}(\Delta Y_i^{PHEV}) \\
&+ \mathbf{E}(\Delta\delta_i^{ICEV})\mathbf{E}(Y_i^{ICEV}) \\
&+ \mathbf{E}(\Delta\delta_i^{EV})\mathbf{E}(Y_i^{EV})
\end{aligned} \tag{E.7}
$$

To obtain an estimate of the ATT, we need to make three additional assumptions on vehicle choice. First, we assume that there is no exit from vehicle ownership over the lifetime of the home charger, implying $\mathbf{E}(\Delta\delta_i^{PHEV})+\mathbf{E}(\Delta\delta_i^{ICEV})+\mathbf{E}(\Delta\delta_i^{EV}) = 0$. Second, we assume that among the employees selecting into the home charging program, employees currently holding a PHEV or a BEV will not choose an ICEV again, even without access to company-financed home charging. Third, access to home charging does not increase the probability of ICEV adoption. Together, these assumptions imply that $\mathbf{E}(\Delta\delta_i^{ICEV}) = 0$ and $\mathbf{E}(\Delta\delta_i^{PHEV}) = -\mathbf{E}(\Delta\delta_i^{EV})$, and we can re-write:

$$
\begin{aligned}
ATT(Y_i) = &\, \mathbf{E}(\delta_i^{PHEV}(1))\mathbf{E}(\Delta Y_i^{PHEV}) \\
&+ \mathbf{E}(\Delta\delta_i^{EV})\mathbf{E}(Y_i^{EV} - Y_i^{PHEV}(0))
\end{aligned} \tag{E.8}
$$

The first term in this expression is the intensive-margin effect on the outcomes for employees holding on to their PHEVs, and the second term is the extensive-margin effect for employees choosing a BEV instead of a PHEV as their next company car. Note that we have already estimated $\mathbf{E}(\Delta E_i^{PHEV})$ and $\mathbf{E}(\Delta\delta_i^{EV})$, for our sample of employees holding a PHEV initially and selecting into the home charging program. We estimate $\mathbf{E}(E_i^{PHEV}(0))$, $\mathbf{E}(C_i^{PHEV}(0))$ and $\mathbf{E}(C_i^{EV})$ using the corresponding sample averages among not-yet-treated PHEV or BEV owners. Furthermore, $E_i^{EV} = 0$ by assumption.

E.2 Approximating the ATT with Repeated Vehicle Choices

In our setting, employees have to decide on a new company car every four years. Assuming that these decisions occur simultaneously for all employees, we obtain a new equation to extrapolate the ATT over the subsequent 20 years, which corresponds to (an upper bound on) the expected useful life of the home charging station:

$$\begin{aligned}ATT(Y_{it}) &= \sum_{t=1}^{5} \gamma^t ATT_t \\ &= \sum_{t=1}^{5} \gamma^t \left[(\mathbf{E}(\delta_{it}^{PHEV}(1))\mathbf{E}(\Delta Y_{it}^{PHEV}) + \mathbf{E}(\Delta\delta_{it}^{EV})\mathbf{E}(Y_{it}^{EV} - Y_{it}^{PHEV}(0)) \right] \end{aligned} \tag{E.9}$$

where t denotes the time period (e.g., $t = 1$ is the first four-year period) and γ^t denotes the discount factor for the respective outcome in period t. We work with an annual discount rate of three percent for energy costs and do not discount CO_2 emissions abatement. We additionally assume that (i) treatment effects are constant over time, i.e., a home charger has the same effect on vehicle adoption and charging behavior regardless of how long the employee has had access, and (ii) car usage, emissions factors, and energy prices are constant over time. The ATT the simplifies to:

$$\begin{aligned} ATT(Y_{it}) = &\sum_{t=1}^{5} \gamma^t \mathbf{E}(\delta_{it}^{PHEV}(1))\mathbf{E}(\Delta Y_i^{PHEV}) \\ &+ \sum_{t=1}^{5} \gamma^t \mathbf{E}(\Delta\delta_{it}^{EV})\mathbf{E}(Y_i^{EV} - Y_i^{PHEV}(0)) \end{aligned} \tag{E.10}$$

Note that $\mathbf{E}(\Delta\delta_{it}^{EV})$ still has a time index, since it depends on the constant period treatment effect $\mathbf{E}(\Delta\delta_i^{EV})$, and on the difference in the share of EVs arising from the different accumulation of EVs due to the changed transition matrix

$$\mathbf{E}(\Delta\delta_{iT}^{EV}) = \mathbf{E}(\Delta\delta_i^{EV}) + \sum_{t=1}^{T-1} \left(\mathbf{E}(\delta_{it}(1)|k_{it})^t - \mathbf{E}(\delta_{it}(0)|k_{it})^t \right)$$

Estimating the ATT over time thus requires an estimate of the share of employees holding a PHEV in each period t, $\mathbf{E}(\delta_{it}^{PHEV}(1))$. To obtain this share for each period, we need to make an assumption on the initial distribution of vehicle types in the sample of employees receiving access to company-financed home charging. In addition, we need to specify the transition matrix for vehicle choices among employees holding different vehicle types. Since the treatment was found to affect the vehicle choice probabilities, this transition matrix depends on the employees' treatment status and an be written as follows:

$$\begin{aligned} &\mathbf{E}(\delta_{it}(D_{it})|k_{it}) = \\ &\mathbf{E}\begin{pmatrix} \mathbf{E}(\delta_{it}^{ICEV}(D_{it})|ICEV) & \mathbf{E}(\delta_{it}^{ICEV}(D_{it})|PHEV) & \mathbf{E}(\delta_{it}^{ICEV}(D_{it})|EV) \\ \mathbf{E}(\delta_{it}^{PHEV}(D_{it})|ICEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_{it})|PHEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_{it})|EV) \\ \mathbf{E}(\delta_{it}^{EV}(D_{it})|ICEV) & \mathbf{E}(\delta_{it}^{EV}(D_{it})|PHEV) & \mathbf{E}(\delta_{it}^{EV}(D_{it})|EV) \end{pmatrix} \end{aligned} \tag{E.11}$$

where $\mathbf{E}(\delta_{it}^{ICEV}|ICEV)$ is the probability of adopting an ICEV, conditional on currently holding an ICEV. We assume that this transition matrix is constant over time. Given our interest in the ATT, we need an estimate of the transition matrix for treated employees $\mathbf{E}(\delta_i(1)|k_{it})$. In line with the previous section, we assume that employees selecting into the home charging program and currently holding either a PHEV or a BEV will never revert to an ICEV company car:

$$\mathbf{E}(\delta_{it}(D_{it})|k_{it}) = \\ \mathbf{E}\begin{pmatrix} \mathbf{E}(\delta_{it}^{ICEV}(D_{it})|ICEV) & 0 & 0 \\ \mathbf{E}(\delta_{it}^{PHEV}(D_{it})|ICEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_{it})|PHEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_{it})|EV) \\ \mathbf{E}(\delta_{it}^{EV}(D_{it})|ICEV) & \mathbf{E}(\delta_{it}^{EV}(D_{it})|PHEV) & \mathbf{E}(\delta_{it}^{EV}(D_{it})|EV) \end{pmatrix} \tag{E.12}$$

Starting from a population of employees holding BEVs or PHEVs (this was an admission criterion for the program), we can thus consider a reduced transition matrix since no employee in our sample will ever hold an ICEV again:

$$\mathbf{E}(\delta_{it}(D_{it})|k_{it}) = \\ \mathbf{E}\begin{pmatrix} \mathbf{E}(\delta_{it}^{PHEV}(D_{it})|PHEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_{it})|EV) \\ \mathbf{E}(\delta_{it}^{EV}(D_{it})|PHEV) & \mathbf{E}(\delta_{it}^{EV}(D_{it})|EV) \end{pmatrix} \tag{E.13}$$

We can rewrite this transition matrix as the sum of the transition matrix in the control group and the matrix of treatment effects on vehicle choice previously estimated:

$$\mathbf{E}(\delta_{it}(1)|k_{it}) = \mathbf{E}(\delta_{it}(0)|k_{it}) + \mathbf{E}(\Delta\delta_i|k_{it}) \tag{E.14}$$

Based on our estimated treatment effects on vehicle choice from Table 3, we obtain an estimate for $\mathbf{E}(\Delta\delta_i^{EV}|PHEV) = -\mathbf{E}(\Delta\delta_i^{PHEV}|PHEV)$ given the no-exit assumption on company car ownership. Additionally, we assume that BEV adoption is an absorbing state for employees selecting into the home charging program. Together, these assumptions imply:

$$\mathbf{E}(\delta_i(1)|k_{it}) = \mathbf{E}(\delta_i(0)|k_{it}) + \mathbf{E}(\Delta\delta_i|k_{it}) = \\ \begin{pmatrix} (1 - \mathbf{E}(\delta_i^{EV}(0)|k_{it} = PHEV)) & 0 \\ \mathbf{E}(\delta_i^{EV}(0)|k_{it} = PHEV) & 1 \end{pmatrix} + \begin{pmatrix} -\mathbf{E}(\Delta\delta_i^{EV}|k_{it} = PHEV) & 0 \\ \mathbf{E}(\Delta\delta_i^{EV}|k_{it} = PHEV) & 0 \end{pmatrix} \tag{E.15}$$

We can observe the probability of choosing a BEV among PHEV owners in the control group.

F Sensitivity Analysis on Vehicle Kilometers

As mentioned at the end of Appendix C, we run a sensitivity analysis on the imputation procedure for implausible mileages at the beginning or the end of a vehicle time series. In the baseline specification, we extrapolated these values based on a vehicle's observed on-road fuel consumption on kilometers traveled without electricity and the vehicle's NEDC electricity consumption per 100 km (dividing the testing value by 0.8 to translate the electricity consumption under an 80 % utility factor into a hypothetical 100 % electric driving electricity consumption). As alternative specifications, we use i) the vehicle's average fuel consumption on all vehicle kilometers and impute using only fuel consumption or ii) the vehicle's electricity consumption as in the baseline specification and the vehicle's NEDC fuel consumption in charge-sustaining mode, i.e. when the vehicle's battery is not charged. Note that specification i) is certainly going to bias our results on the effect on mileage since we ignore the vehicle's electricity consumption for the mileage imputation at the end or the beginning of a series. We show that access to home charging reduces the vehicle's fuel consumption while increasing its electricity consumption, based on fuel and electricity consumption data. Since access to home charging is an absorbing state in our study, we will thus impute lower mileages for treated households at the end of the sample period, which will bias the effect on mileage downwards. In specification ii) we use the vehicle's fuel consumption in charge-sustaining mode in the NEDC testing procedure. We know that the NEDC testing procedures tend to be overly optimistic regarding the electric driving share of PHEVs. Adjusting the value to display consumption in charge-sustaining mode, we try to adjust for this bias. Nevertheless, we trust the imputation in the baseline specification more.

The results of the sensitivity analysis are displayed in Table F.1. In the first panel, we see that the extrapolation at the end of a series can cause meaningful differences in the estimated effect on vehicle mileage. Especially if the vehicle's electricity consumption is ignored, we find that the rebound effect in terms of vehicle miles is reduced by 70 % and is no longer significant. In the specifications accounting for electricity consumption, we find that the differences are very small. The weaker effect on vehicle mileage translates into a weaker reduction in the average fuel consumption per 100 km and into a weaker increase in the electric driving share by 25 %. The sensitivity analysis shows, that even under an extrapolation scheme that is imposing a negative bias on the number of kilometers traveled in the treated sample, the average fuel consumption per 100 km is reduced and the electric driving share is increased substantially. On the other hand, the comparison between the baseline extrapolation and the extrapolation based on the vehicle's fuel and electricity consumption from NEDC test values shows that as long as electricity consumption is reasonably taken into account, changing the average fuel consumption per 100 km used to impute vehicle mileages does not change the results much. Given the proven inaccuracy of the NEDC testing values we used to clean the mileage variable, this is reassuring.

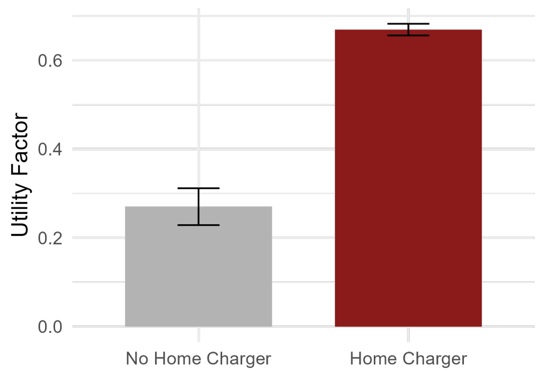
Table F.1: ATT on Outcomes Depending on Vehicle Kilometers

	Baseline	Fuel Only	Efficiencies
	Mileage [km]		
Treated	606.65**	182.03	614.65***
	(248.24)	(267.83)	(236.64)
	Fuel [l/100km]		
Treated	-2.52***	-1.95***	-2.57***
	(0.2)	(0.2)	(0.21)
	Utility Factor [%]		
Treated	0.33***	0.26***	0.34***
	(0.03)	(0.03)	(0.03)
Obs	836	836	836
Groups	6	6	6
Periods	11	11	11
Car FE	X	X	X
Time FE	X	X	X

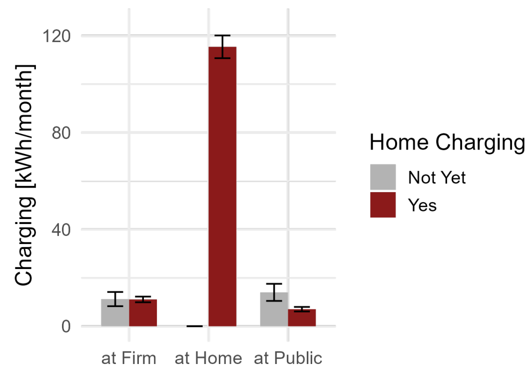
Notes: Doubly-robust ATT estimator (Callaway & Sant'Anna, 2021). Baseline: extrapolation of implausible mileages at the end of a vehicle time series as in the main analysis. Fuel Only: extrapolation based on fuel consumption only, ignoring electricity consumption. Efficiencies: extrapolation based on both fuel and electricity consumption, but using NEDC fuel consumption in charge sustaining mode to translate fuel consumption into kilometers traveled. *, **, *** means that the corresponding estimated parameter is different from zero at the 10 %, 5 %, and 1 % significance level, respectively.

F.1 Additional Graphs and Tables

Figure F.1: Average Differences In Electric Utilization Between Treated and Untreated Employees in 2022 (Post Covid-19)



(a) Utility Factor



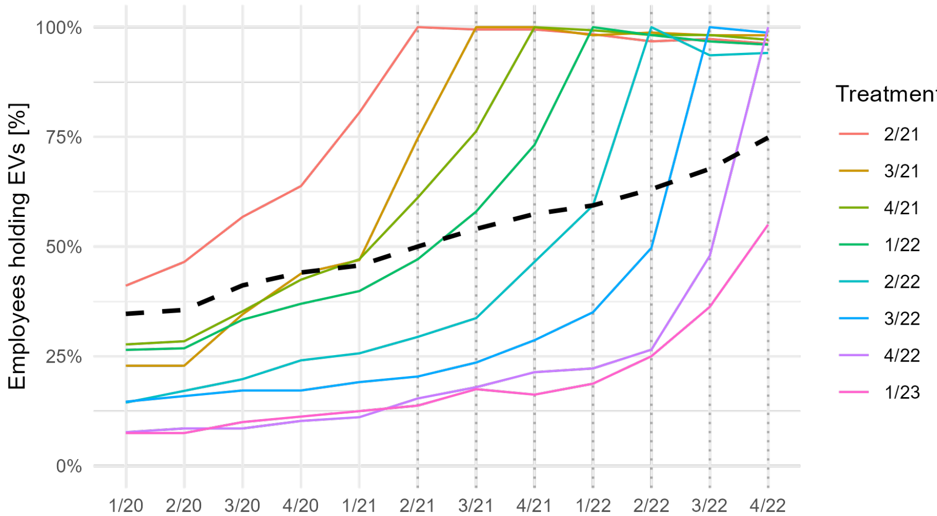
(b) Charging by Source

Table F.2: ATT based on never-treated units as controls across different outcomes

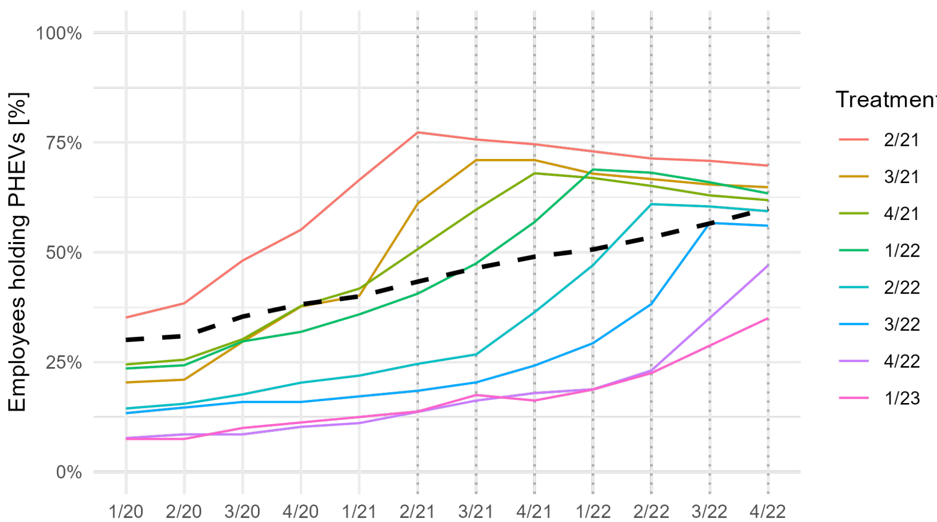
	Energy		Mileage	Emissions		Cost
	Electricity [kWh]	Fuel [l]	Mileage [km]	No EU ETS Cap [kg CO2]	EU ETS Cap [kg CO2]	Energy [Euro]
Treated	302.7***	-135.99***	63.07	-190.35***	-327.41***	-173.17***
	(10.68)	(9.22)	(119.07)	(20.29)	(23.13)	(14.37)
Employees	3519	3519	3519	3519	3519	3519
Groups	6	6	6	6	6	6
Periods	11	11	11	11	11	11
Employee FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X

Notes: Doubly-robust ATT estimator (Callaway & Sant'Anna, 2021). "Periods" are quarters. "Groups" are groups of employees receiving at home charging in the same quarter. "No EU ETS Cap" stands for CO_2 emissions being computed under the (counterfactual) assumption that additional electricity charged by the treated group leads to unregulated CO_2 emissions at the average CO_2 intensity in the German electricity grid (cf. Appendix D.1). "EU ETS Cap" stands for CO_2 emissions being computed under the realistic assumption that charging is not associated with any CO_2 emissions under the cap implied by the EU's emissions trading scheme (EU ETS). *, **, *** means that the corresponding estimated parameter is different from zero at the 10 %, 5 %, and 1 % significance level, respectively. *, **, *** means that the corresponding estimated parameter is different from zero at the 10 %, 5 %, and 1 % significance level, respectively.

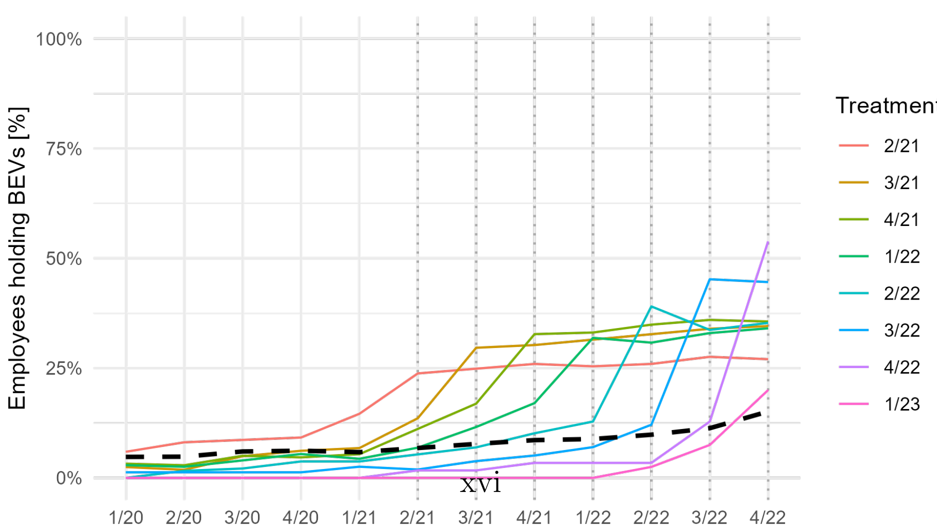
Figure F.2: Vehicle Adoption Across Treatment Groups



(a) EVs

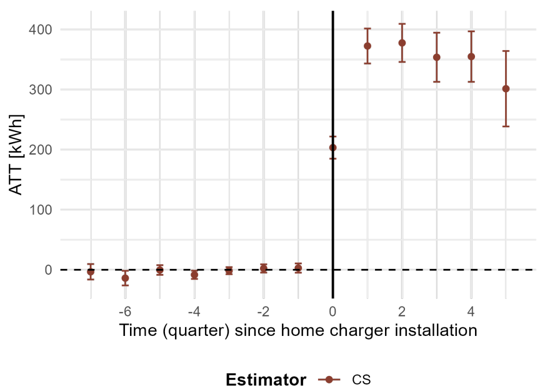


(b) PHEVs

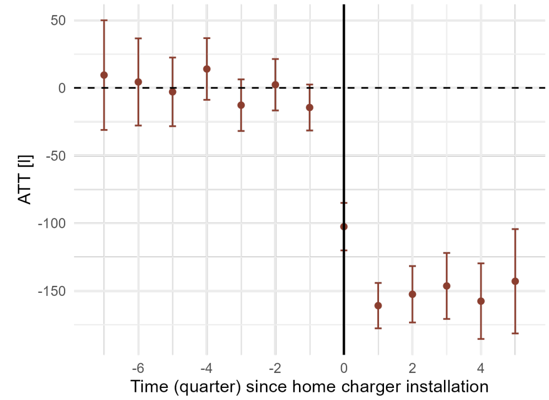


(c) BEVs

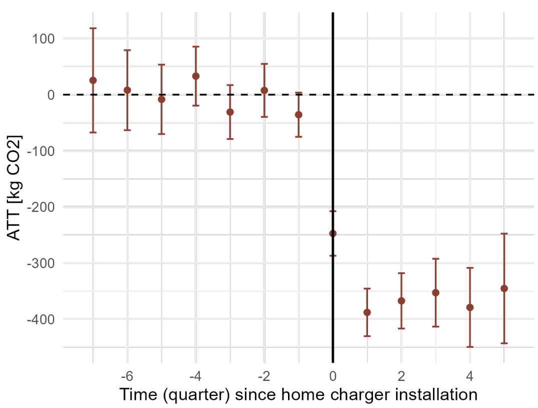
Figure F.3: Event Studies Using Never-Treated Units as Control



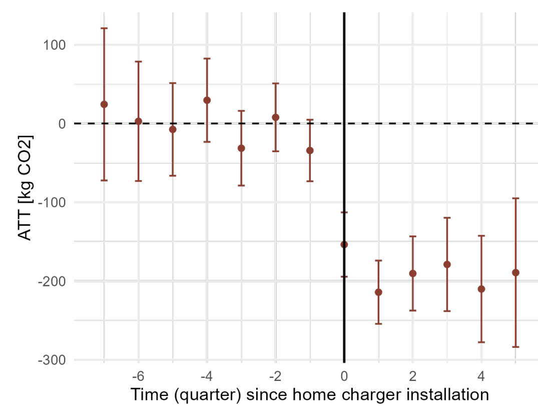
(a) Electricity in kWh



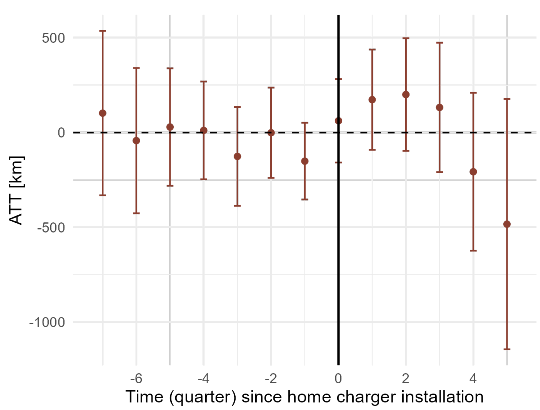
(b) Fuel in Liters



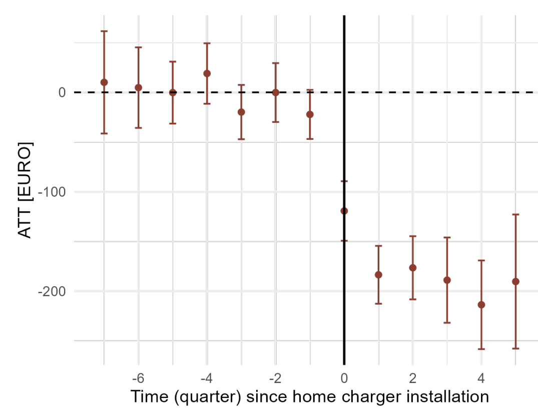
(c) Tailpipe Emissions in kg CO_2



(d) Emissions (No EU ETS) in kg CO_2

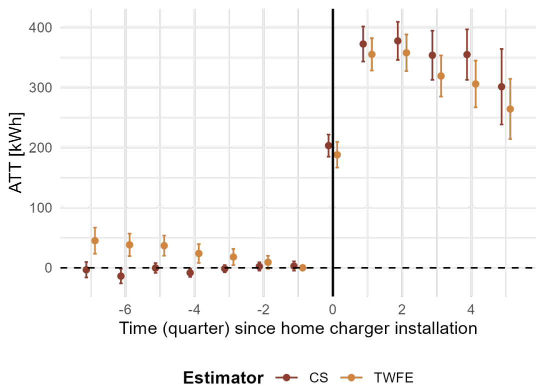


(e) Kilometers Traveled

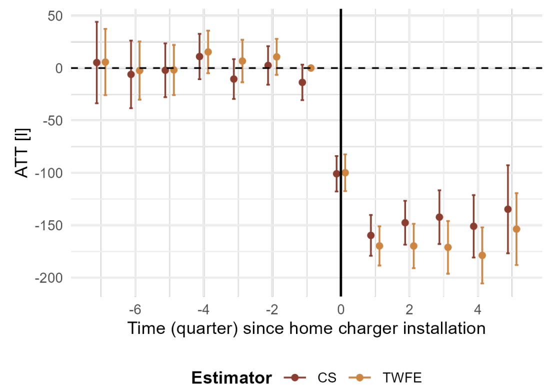


(f) Energy Expenditures in Euro

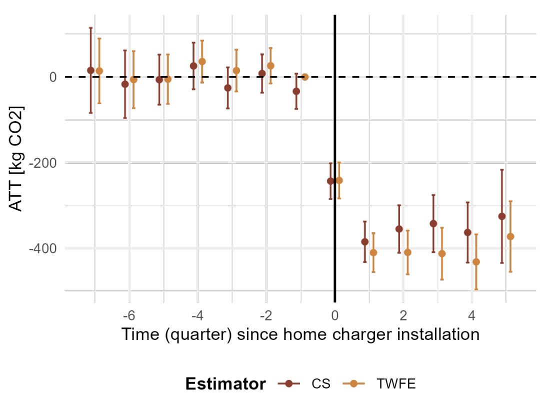
Figure F.4: Event Studies Comparing TWFE and Callaway & Sant'Anna (2021)



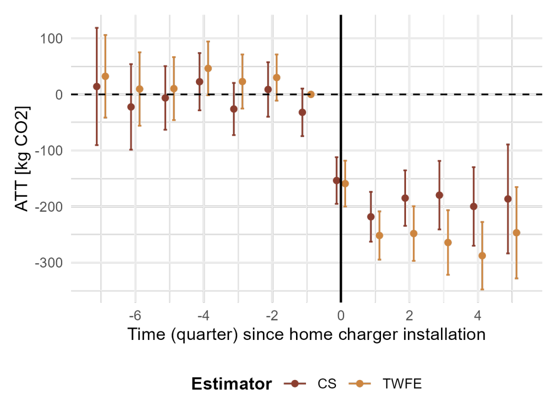
(a) Electricity in kWh



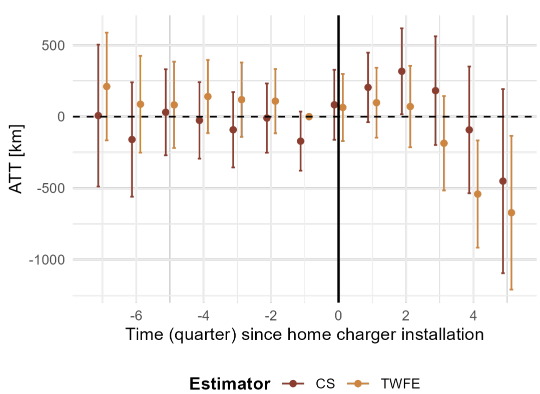
(b) Fuel in Liters



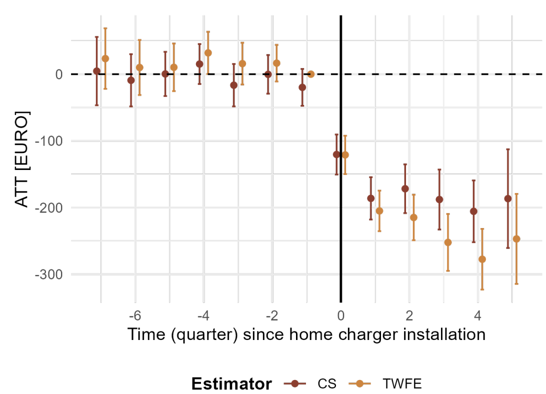
(c) Tailpipe Emissions in kg CO_2



(d) Emissions (No EU ETS) in kg CO_2



(e) Kilometers Traveled



(f) Energy Expenditures in Euro