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

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

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Abstract

Many European companies face the challenge of lowering CO_2 emissions from their company car fleets. A promising lever is to increase the notoriously low electric usage of Plug-in Hybrid Electric Vehicles (PHEVs). This paper examines whether home charging infrastructure can help achieve these goals. We leverage quasi-experimental variation in the delivery and installation of home chargers to quantify the impact of this technology on energy use and CO_2 emissions of PHEV company cars held by 856 employees of a large German company. Since fuel and electricity expenditures for these cars are covered by the employer, home charging mainly changes the non-monetary costs to an employee. We find that access to home charging increases electricity consumption by 317.9 ($\pm$23.3) kWh per quarter and decreases fuel consumption by 97.97 ($\pm$36.5) liters, reducing CO_2 emissions by 38%. Moreover, access to home charging increases the employee's propensity to choose a Battery Electric Vehicle (BEV) upon renewal of the lease by 28.4 ($\pm$25.6) percentage points. We use these estimates to compute the private levelized abatement costs of home chargers for a range of scenarios characterizing the diffusion of BEVs and the effect of the program on vehicle choice. With current tax-inclusive energy prices, home chargers break even for the company within eight to 16 years.

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

JEL-code: D12, L91, Q52, R42

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1 Introduction

The environmental benefit of Plug-in Hybrid Electric Vehicles (PHEVs) critically depends on user behavior. When operated with gasoline or diesel, PHEVs have no advantage over conventional cars in terms of carbon dioxide (CO_2) emissions per kilometer traveled. Only the electric use of PHEVs can drive specific emissions to zero, provided that the electricity they charge is coming from renewable sources or from an electricity sector that is subject to a binding cap on emissions.[1] To tap the abatement potential offered by electrification, PHEV drivers should maximize the electric driving share, defined as the share of kilometers traveled using electric energy in total kilometers traveled. In the real world, however, this share falls short of what is technically feasible or assumed in official test procedures (Chakraborty et al., 2020), with the result that CO_2 emissions of PHEVs are two to five times higher than on the test stand (Plötz et al., 2022; Tsanko, 2023). Encouraging more electric driving of PHEVs is thus a necessity for decarbonizing road transportation.

This issue is highly relevant for the many companies in Europe that provide employees with a company car for both personal and business-related trips. Due to generous rules for deducting ownership and fuel costs from wage taxes, company cars are regarded as an attractive fringe benefit by employees and employers alike. This has led to the emergence of large company car fleets in almost all member states of the European Union (EU).[2] Since CO_2 emitted by these cars counts towards corporate emissions,[3] companies that pursue decarbonization targets are searching for ways to reduce emissions without abolishing company cars, e.g., by increasing the electric driving share of PHEVs and promoting the adoption of Battery Electric Vehicles (BEVs).

This paper empirically investigates whether providing home charging infrastructure is a cost effective tool for decarbonizing company car fleets. We hypothesize that access to home charging stations increases electric driving because it reduces the inconvenience and time requirements of charging, which have been identified as key deterrents in the literature (Krishna, 2021), and based on survey evidence of a strong preference for charging electric vehicles (EVs) at home (e.g., Barber et al., 2024). Our paper provides the first causal evidence on the impacts of home charging stations in

[1] This is true for Europe but not necessarily in other parts of the world. Holland et al. (2016) show that electric driving tends to increase CO_2 emissions in most US counties.

[2] While exact numbers on company cars in the above-defined sense are not publicly available, Antich (2024) compiles data on the share of *company-owned cars* in new registrations of passenger cars. In 2023, this share exceeded 50% in 19 out of 27 EU member states, including the EU's largest car markets Germany and France. In Germany, roughly three out of five newly registered passenger cars with a corporate owner are estimated to be company cars (Kampermann, 2023). Across Europe, PHEVs accounted for twice as many new registrations by corporate owners than by private owners in 2023 (Antich, 2024).

[3] Depending on use (business vs. personal travel) and ownership (leasing vs. owning), those emissions count towards scope one, two or three.

the context of company cars, using data from a large German company. To promote electric driving, the company launched a program that paid for the installation of a charging station at the employee's home, with separate metering and automatic settlement of electricity expenses related to charging the company car. Qualifying employees were enrolled in the company's fuel cost compensation scheme, which covers all fuel and charging costs associated with the personal use of the company car via a fixed monthly deduction from their pre-tax salary. Participants thus did not incur any variable monetary cost for refueling or charging. The roll-out of this program was staggered because supply chain disruptions following the COVID-19 pandemic, as well as capacity constraints of the installation firm, delayed the installation of the charger by several months. We exploit quasi-experimental variation in delays across program participants to estimate the causal impacts on PHEV and BEV use, as well as on the propensity to adopt a BEV among participants who changed their company car.

Our analysis sample consists of 856 employees holding a PHEV and 407 employees holding a BEV. These employees applied for the home charging program between the start of the program in January 2021 and November 2022. Based on over 266,000 refueling and charging transactions for these vehicles, we estimate the effect of access to charging at home between January 2020 and September 2022. The data contain the amount of fuel in liters and electricity in kilowatt-hours (kWh), the time stamp, employee-reported odometer readings, and information on the vehicle's make and model. Using emission factors and energy prices for the different energy sources, we also estimate CO_2 emissions and energy expenditures.

We estimate causal effects of installing charging infrastructure at home using the Difference-in-Differences estimator by Callaway & Sant'Anna (2021). To avoid any bias from selection into the home charger adoption, we identify the average treatment effect on the treated from the difference in contemporaneous outcomes between treated employees and not-yet-treated employees who receive a home charger later in the sample period. Intensive-margin outcomes of primary interest are the amount of electricity charged, the amount of fuel used, CO_2 emissions, energy expenditures, and vehicle kilometers traveled (VKT).

We find that the availability of home charging increased electricity consumption of PHEVs by 317.9 (±23.3 for the 95% confidence interval) kWh per quarter while decreasing consumption of gasoline or diesel by 97.97 (±36.5) liters per quarter. This 38%-reduction in fuel consumption saved tailpipe emissions on the order of 237.12 (±87.5) kg of CO_2 per quarter, in spite of a 15%-rebound in VKT per quarter by 671.13 (±474.9). Among BEV holders, home chargers increased electricity consumption by 36%, corresponding to an additional 172.05 (±143.12) kWh consumed per quarter. While corporate energy costs for PHEVs decreased significantly by €102.52 (±61.6) per quarter, we do not see a similar cost decrease for BEVs due to the rebound effect and the comparatively small price difference between charging at home and at other charging stations.

Providing employees with access to home charging increases the likelihood of ordering a BEV as the next company car by 28.4 ($\pm$25.6) percentage points (pp). This extensive-margin effect boosts the overall abatement effect of home charging by shifting *all* transport-related CO_2 emissions of the company car under the regulatory cap of the European Union's Emissions Trading System, which – notwithstanding the intricacies of the Market Stability Rule – is binding on emissions and declines over time. We identify this effect in a subset of program participants who may order a new vehicle as their initial lease ends. Variation in the end-of-lease dates and in the delivery time of the home charger implies that some employees have gathered experience with the home charger when ordering a new company car, while others have not. Our preferred estimator for the extensive-margin effect compares vehicle choices after matching treated and untreated employees who ordered their home charger at a similar time.

We use our estimated treatment effects to analyze the net present value of the home charger program to the firm. We find that the home charger program is a cost-effective way to abate between four and 21 tons of CO_2 emissions over a 20-year horizon for the average employee in our sample. We quantify total abatement and energy expenditures using plausible forecasts about BEV diffusion among untreated employees and varying the strength of the program's estimated impact on BEV adoption among treated employees. In almost all scenarios, the installation of the home charger pays off for the company within eight to 16 years. Given that the lifespan of a home charger can exceed 20 years, the program can yield substantial benefits, not just in terms of emissions abatement but also financially. The only scenario where home chargers give rise to positive costs per ton of CO_2 abated is when the company also makes the adoption of a BEV mandatory upon renewal of the lease. While the BEV mandate itself reduces energy costs and CO_2 emissions, the abatement benefits arise regardless of whether BEVs are being charged at home or at a public charging station. The cost differences between those options are not large enough to justify the investment into home charging stations.

Our paper contributes to a growing economics literature on the adoption and the use of EVs. Previous research has analyzed how those outcomes respond to financial incentives and to the provision of charging infrastructure. The first strand of literature shows that people respond to prices when charging their vehicles. Electricity prices affect the time of charging (Qiu et al., 2022; Bailey et al., 2024), the choice of charging at home vs. at the workplace (Chakraborty et al., 2019), the decision to charge a PHEV at all (Chakraborty et al., 2020), and the kilometers traveled for BEVs (Nehiba, 2024). In addition, the use of PHEVs is affected by the price of fossil fuels, a close substitute for electricity. In line with this, Grigolon et al. (2024) estimate higher fuel price elasticities for PHEVs than for conventional cars. Habit formation does not seem to play a role in this context, as the estimated effects disappear when financial incentives are removed (Bailey et al., 2024; Grigolon et al., 2024). Our paper departs from this literature by empirically analyzing the impact of the non-monetary costs of charging EVs on user behavior. The fuel cost compensation scheme described above removes any marginal financial incentives when drivers refuel or charge their vehicles. The company car setting is ideal for our analysis, in the sense that it minimizes the scope for financial incentives that could easily confound estimates in non-experimental settings.

The other strand of literature focuses on EV adoption. This literature provides evidence for a positive effect of EV purchase subsidies (Beresteanu & Li, 2011; Xing et al., 2021; Muehlegger & Rapson, 2022; Springel, 2021; Remmy, 2022; He et al., 2023; Fournel, 2024), and for indirect network effects of public charging infrastructure on EV sales (Li et al., 2017; Illmann & Kluge, 2020; Ou et al., 2020; Springel, 2021; Remmy, 2022; Li, 2023). When it comes to home charging infrastructure, substantial differences in the adoption of EVs between homeowners and renters have been linked to different abilities to install charging infrastructure (Davis, 2019). Ability to charge at home has been a strong predictor of consumer interest in PHEVs since their early days (much stronger than public charging points; cf. Bailey et al., 2015). Conversely, dissatisfaction with the convenience of charging and with not having 240-volt charging at home were stated as main reasons by PHEV owners in California for choosing to discontinue electric driving (Hardman & Tal, 2021). Lee et al. (2023) present further evidence that this replacement decision correlates with the convenience of charging and access to home charging. Building on this literature, our study takes a significant step ahead by directly analyzing the effects of home charging on the intensive and extensive margins of electric vehicle use. By tracking the vehicles' energy consumption across all sources –electric and fossil– we can estimate responses of intensive-margin outcomes such as CO_2 emissions for PHEVs and BEVs. At the extensive margin, our analysis of vehicle renewal choices contributes much needed evidence on the impact of home charging stations on BEV adoption.

The remainder of this paper is structured as follows: Section 2 introduces the context of our study, the data, and the empirical strategy. Section 3 presents our empirical results. Based on those results, Section 4 simulates the effects of a home charging station on emissions and energy costs throughout its useful life to compute its benefits and costs to the company. Section 5 discusses implications of our results and concludes.

2 Research Design

2.1 Quasi-Experimental Roll-Out of Home Charging

We study the roll-out of home chargers among employees of a 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 deduction from the net salary (which is proportional to the net list price of the car), employees get a car that they can use for business-related but also for 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, including electricity charged at home.[4] Company cars are chosen by the employees from a large set of makes and models. In 2022, vehicles with an internal combustion engine (ICEVs) continued to be the most popular choice, followed by PHEVs and BEVs. Electric vehicles can be charged at public charging points and in company parking lots, at no extra cost to employees enrolled in the fuel cost compensation scheme. Even so, the electric utilization rate of PHEVs is low among employees without access to home charging. The utility factor, defined as the ratio between VKT using electricity and total VKT (Plötz et al., 2021), averages at 0.69 in type-approval ratings under the New European Driving Cycle (NEDC) test procedure (Vallée et al., 2022). In our sample, employees achieved a utility factor of only 0.29 in 2020, prior to the installation of a home charger.[5]

To encourage at-home charging by PHEV and BEV holders, the company introduced a program that subsidized the installation cost of a 22 kilo-Watt home charger and automatically reimburses expenses for the electricity consumed by it. The subsidy of up to €2,750 was sufficiently generous to cover the cost of the home charger including its installation.[6] The program was rolled out in January 2021 and was open to all employees (i) driving a PHEV or BEV company car (or having ordered one) and (ii) participating in the fuel cost compensation scheme. The program continued beyond the end of our sample period (November 2022).

Several features of the application and installation process resulted in a staggered adoption of home chargers over time. First, during the first eight months of the program, participants could order a home charger only through 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, during our sample period, supply-side frictions in the aftermath of the COVID-19 pandemic caused delays

[4]See Appendix A for more background on the German company car scheme.

[5]Plötz et al. (2020) find an even lower average utility factor of 0.18 in a sample of German company cars.

[6]For more details on the installation cost, refer to Appendix C.3.

in the delivery and installation of home chargers. Third, employees can only participate in the home charger program once they hold or have ordered a BEV or PHEV. They typically become eligible to order a company car after three years of tenure with the company (regardless of whether they need it for business travel or not). Employees must hold on to a company car for four years before they can order a new car or opt out of the company car scheme (which rarely occurs due to large tax advantages over private car ownership). 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 the above factors delayed the installation dates of the home chargers in ways that varied considerably and randomly across participants, as can be seen for PHEVs in Figure 1. Panel (a) exhibits a distinctive gap between the date of application and the date on which the home charger is first used. The cross-sectional distribution of this waiting time is depicted in panel (b); while the mean is four months, some employees had to wait more than 12 months for the installation. Panel (c) shows that the average waiting times by month of application also varied considerably over the sample period, ranging from two to more than five months.

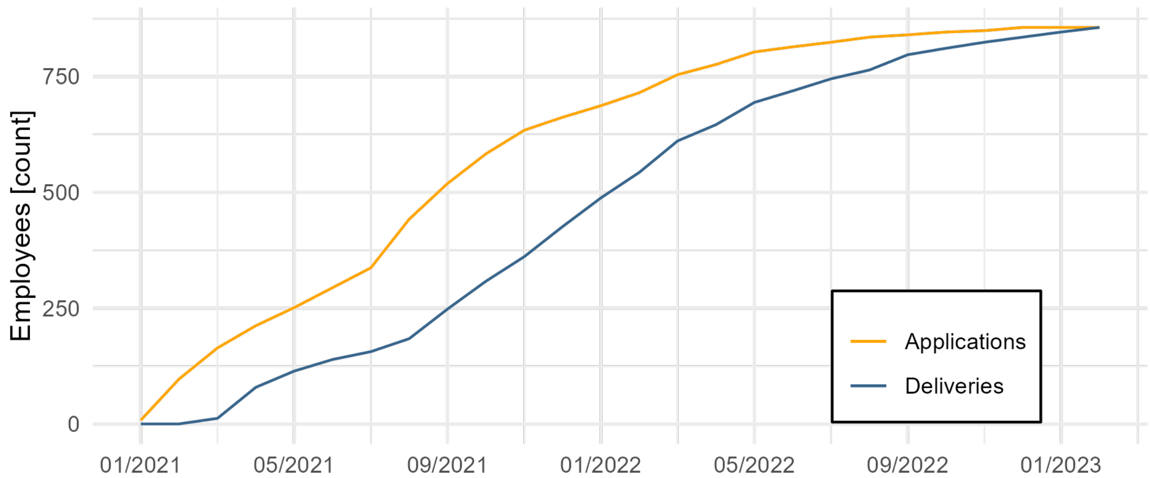
2.2 Econometric Framework

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

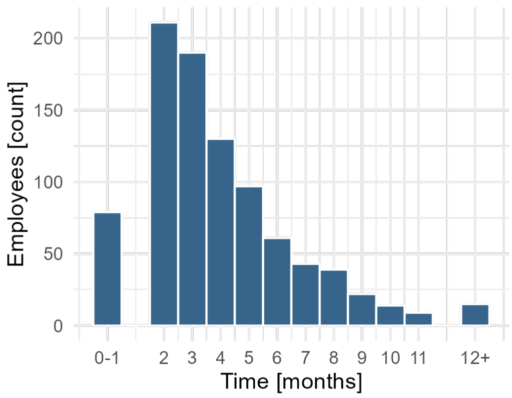
$$Y_{it} = \beta_1 \mathbb{1}(t \geq \mathrm{G}_i) + \eta_i + \mu_t + \epsilon_{it} \tag{1}$$

where the variable Y_{it} measures relevant outcome variables of employee i in quarter t, G_i denotes the quarter in which the home charger becomes available to employee i, and η_i and μ_t are employee and quarter fixed effects (and ϵ_{it} is the error term). Since this estimator may be biased under heterogenous treatment effects, we aggregate separately-estimated average treatment effects on the treated $ATT(g,t) = \mathbb{E}(Y_{it}(g) - Y_{it}(0)|G_i = g)$ where $G_i = g$ indicates that employee i belongs to the group of employees receiving treatment in period g. Adopting the dynamic potential outcome framework (Robins, 1986), $Y_{it}(g)$ denotes the potential outcome of employee i in period t if that employee receives the home charger in period g and $Y_{it}(0)$ (with a slight abuse of notation) denotes the employee's potential outcome in period t if she had not yet received the home charger in that period. To estimate group-by-quarter-specific treatment effects $\widehat{ATT}(g,t)$, we employ the doubly-robust estimator proposed by Callaway & Sant'Anna (2021) and use a control group of not-yet-treated program participants who receive

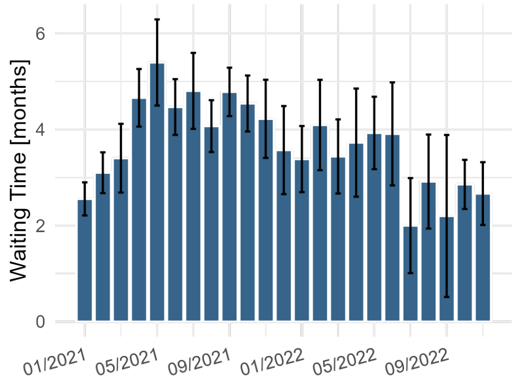
Figure 1: Home Charger Applications and Distribution of Waiting Times



(a) Applications and Deliveries over Time



(b) Distribution of Waiting Times across Employees



(c) Average Waiting Times by Month of Application

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

a home charger at a later point in time.[7] These estimates are aggregated up to the overall ATT of home charger adoption as follows:

$$\theta^O_{sel} = \sum_{g \in \mathcal{G}} P(G_i = g | G_i \leq T) \underbrace{\frac{1}{T - g + 1} \sum_{t=g}^{T} \widehat{ATT}(g, t)}_{\widehat{ATT} \text{ for employees with } G_i = g} \tag{2}$$

where T is the last period in the sample ($t = 1, \ldots, T$), and $P(G_i = g|G_i \leq T)$ is the share of employees receiving the home charger in period g as a fraction of all employees receiving the home charger by T. The estimator assigns equal weight to all employees, regardless of the number of post-treatment observations.

To estimate event-study coefficients for treatment effects as a function of the length of treatment exposure, we aggregate the group $\times$ time-specific estimates of the ATT into an estimator of the treatment effect at differential temporal exposure to the treatment (Callaway & Sant'Anna, 2021):

$$\theta_{es}(e) = \sum_{g \in \mathcal{G}} \mathbb{1}(g + e \leq T) P(G_i = g | G_i + e \leq T) \widehat{ATT}(g, g + e) \tag{3}$$

Here, $e = t - g$ is the number of periods group g is exposed to the treatment (event time), and $\theta_{es}(e)$ simply aggregates group $\times$ time-specific ATTs with the same exposure time e into a summary measure of the treatment effect after e periods of treatment. In so doing, it weights each group by the number of employees in the group relative to the total number of employees observed with exposure time e.[8] 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 times of home charger adoption, since the composition of groups observed with a given exposure time might change. We provide evidence for homogeneous treatment effects across treatment groups (in terms of the $ATT(g, g+1)$) in Appendix Figure E.4.[9]

2.3 Data

Sample Composition Our analysis considers all home charger applications between January 2021 and November 2022. For our analysis, we separate the transaction data

[7]The estimator is doubly robust in the sense that it yields consistent estimates if either the outcome evolution in the control group or the probability of treatment assignment are correctly specified.

[8]Note that later-treated groups are not observed with long treatment exposure.

[9]Panel (e) of that figure shows heterogenous treatment effects for VKT. Appendix Figure E.5 suggests that this heterogeneity arises over time rather than across treatment groups.

on refueling and electric charging events for PHEV and BEV holders.[10] Since all charging transactions are automatically recorded, the raw data needed little cleaning (cf. Appendix B).

For PHEVs, we additionally have data on odometer readings that employees are required to report each time they use the corporate fuel card to pump gas at a filling station. Since fuel efficiency and mileage outcomes rely on these data, we conduct several cleaning steps to make sure that vehicle kilometers traveled between two odometer readings are plausible. Starting with transaction data for 1,021 PHEVs held by 939 employees during our sample period (some employees renewed their lease during the sample period and got a different car, hence more cars than employees), we drop 63 cars with less than two odometer readings. To the remaining odometer readings, we apply a data cleaning algorithm that identifies infeasible mileages and imputes more plausible ones by interpolating between odometer readings that were deemed feasible (cf. Appendix B for details). In this cleaning step, we drop 26 cars with less than two feasible odometer readings that are needed to calculate VKT. We also 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 vehicle's fuel and electricity consumption was below the bottom half percent (0.005) or exceeded the top half percent (4.68).[11] We further drop all observations after September 2022, since, for many cars, we observe the second-to-last refueling event –and hence, the last vehicle mileage– before September 2022.

After cleaning, our analysis samples comprise 928 PHEVs held by 856 employees and 421 BEVs held by 407 employees, respectively. We observe 208,105 refueling and charging transactions for the PHEVs and 59,864 charging transactions for the BEVs. We aggregate these transactions to quarterly observations for two reasons. First, to meet minimum size requirements of the estimator by Callaway & Sant'Anna (2021), which cannot be met in a monthly aggregation. Second, aggregating to weekly or monthly observations would result in noisy VKT estimates since some cars are charged or filled up only every couple of weeks.

Since the main focus of this paper is on the effect of home charging on the use of PHEVs, we will focus on the PHEV sample in the remainder of this section and in most of Section 3. We defer the analysis of the program's effects on BEV use to Section 3.3, and analyze BEV adoption in Section 3.4.

[10] Some employees switched from a PHEV to a BEV in our sample period. We split such time-series into two employee-by-vehicle series.

[11] 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.

Summary Statistics Transaction data from January 2020 until September 2022 comprises the date and time of refueling or recharging, the amount of fuel in liters (electricity in kWh), the employee-reported odometer reading, 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), 2024). We estimate CO_2 emissions using the appropriate emission factors for each energy source (gasoline, diesel, and electricity) published by the German Environment Agency (Juhrich, 2022; Icha & Lauf, 2022). We calculate energy expenditures associated with charging on firm premises or at public charging stations, and for refueling the car using data on yearly average energy prices; for charging at home, we use the contractual price per kWh. Appendix Table C.1 summarizes the assumptions made on emission factors and energy prices. Appendix Table E.1 summarizes driving and charging outcomes, vehicle attributes, as well as employee characteristics in the analysis 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 but did not apply during the analysis period. Those differences might be correlated with outcomes associated with the adoption of home chargers. To guard against selection bias, our identification strategy discards non-applicants and relies on quasi-experimental variation in the installation time among participants of the home charger program. This strengthens the internal validity of our approach.

External validity hinges on how different applicants are from non-applicants. Out of more than 2,500 employees who held a PHEV during the period of analysis, 856 participated in the program. Table 1 shows the differences in mean characteristics between these groups in 2020, the year before the program was launched.[12] We observe that program applicants tend to be male; they are older and have a longer tenure with the company than non-applicants. The correlation with tenure and age points to home ownership, which increases with age and reduces legal obstacles to installing a charging station, as an underlying determinant of program participation. With a 2% higher mileage per quarter, applicants use 9% less fuel and 24% more electricity than non-applicants. Thus, their PHEV use is more climate-friendly than that of non-applicants already before adopting a home charger. Given these differences, a naïve estimate based on never-takers of the home charger would likely yield biased results.

Within the sample of program participants, selection issues could arise if early adoption correlates with unobservable determinants of PHEV use. However, exogenous waiting times between the application for and installation of the home charger, as well

[12]Since PHEV adoption grew very fast during this period, both groups were considerably smaller in 2020, yet the proportion between these groups remained relatively stable over time.

Table 1: Home Charger Applicants vs. Non-applicants (with PHEVs)

	Home Charger		No Home Charger	
Variable	Mean	Sd	Mean	Sd
Panel A: Vehicle Use in 2020				
Mileage per quarter [km]	4318.28	(2838.04)	4215.240	(2728.7)
Emissions [kgCO_2]	646.17	(550.62)	700.37	(575.97)
Tailpipe emissions [kgCO_2]	627.57	(556.94)	686.34	(582.05)
Electricity per quarter [kWh]	48.57	(82.77)	36.63	(73.09)
Fuel per quarter [l]	259.87	(231.4)	285.88	(242.78)
Fuel consumption [l/100 km]	5.78	(3.2)	6.50	(3.08)
Electricity consumption [kWh/100 km]	1.46	(2.66)	1.20	(2.5)
Utility factor [km elec./km total]	0.29	(0.38)	0.19	(0.38)
Energy expenditures [Euro]	342.75	(293.73)	374.48	(309.74)
Panel B: Vehicle Characteristics				
Fuel efficiency [l/100 km WLTP]	1.59	(0.35)	1.54	(0.36)
Electric efficiency [kWh/100 km WLTP]	17.46	(3.15)	16.65	(2.5)
Price [Euro]	32135.91	(4195.48)	30279.44	(4764.88)
Weight [kg]	1997.62	(255.93)	1895.78	(211.14)
Panel C: Employee Characteristics				
Age [years]	48.22	-	43.19	-
Tenure [years]	17.43	-	12.89	-
Female [%]	0.16	-	0.24	-

Notes: Comparison of the sample of employees selecting into the home charger program between January 2021 and December 2022 (N = 856 employees) to the group of employees not selecting into the home charger program during that period (N = 2695 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".

as pre-determined leasing cycles and their effect on program eligibility imply that employees cannot easily select into early treatment adoption. Moreover, employees who received access to home charging in 2021 are similar to those receiving access in 2022 in terms of their average fuel and electricity consumption per 100 km in the year prior to program participation, and in terms of employee and vehicle characteristics (cf. Appendix Table E.4). However, substantial differences exist in variables reflecting the total use of the vehicle, such as VKT, fuel and electricity consumption. We think that these differences in total mobility demand are caused by changes in restrictions to individual mobility due to the COVID-19 pandemic between 2020 and 2021.

Finally, it is important to note that our approach does not rely on balance in covariates between treatment and control groups, but on a parallel trends assumptions, which we assess via inspection of pre-trends in Figures 3 to 5.

Average Outcomes for Treated and Not-yet-treated Employees Figure 2 compares average outcomes between employees who have installed a company-sponsored charging station at home and those who do not yet have it, for the years 2020 to 2022.[13] Panel (a) shows that the utility factor among users of home chargers is almost three times as high as among non-users. The difference is mainly driven by charging at home, which dwarfs charging at the firm or at public stations (panel b). Panel (c) depicts specific emissions per km for those who have a home charger and those who have not yet received it, both in terms of real-driving emissions and according to the Worldwide Harmonised Light-Duty Vehicles Test Procedure (WLTP). While emissions according to WLTP are very similar across groups, real-driving emissions per kilometer drop by nearly two thirds for employees with access to home charging, closing 86% of the gap to official ratings according to WLTP. Before home charging, real-driving emissions in our sample exceed WLTP emissions by a factor of 3.3, which is similar to the gap observed for the average newly registered PHEV in the EU fleet (European Commission, 2024a). The next section investigates whether these descriptive findings hold up in a causal evaluation framework.

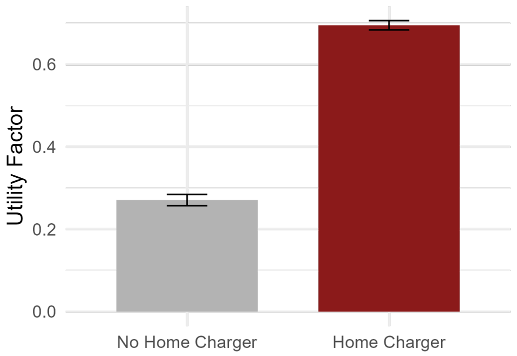
3 Treatment Effects of Home Charger Adoption

3.1 Treatment Effects by Quarter

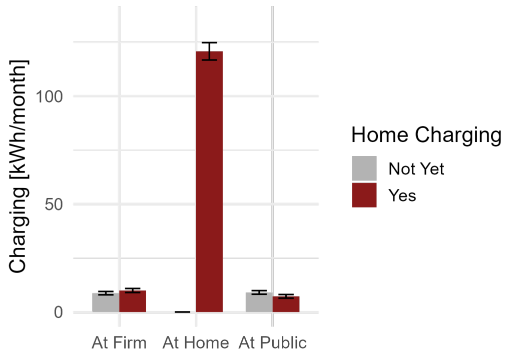
Quarterly ATTs for various PHEV outcome variables are plotted in Figures 3 to 5. Point estimates in quarter zero are lower in absolute value than those for subsequent quarters because subjects receive the home charger on different dates during that

[13] The COVID-19 pandemic may have distorted transportation behavior in 2020 and 2021. In Appendix Figure E.1 we use only data for the year 2022 which was only partially affected by the pandemic. We find very similar results.

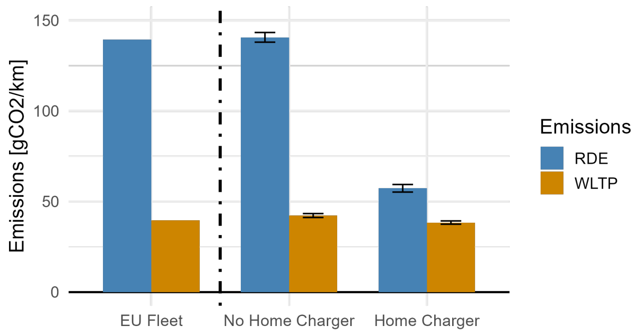
Figure 2: Average Differences in PHEV Use: Treated vs. Not-yet-treated Employees



(a) Utility Factor



(b) Charging by Source



(c) Emissions Per Kilometer

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 New European Driving Cycle (NEDC) testing procedure. For details on the calculation, see Appendix B. 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. "WLTP" are vehicle CO_2 emissions per kilometer, according to the Worldwide Harmonised Light-Duty Vehicles Test Procedure (WLTP) type approval tests. "RDE" are real-world driving emissions. "EU Fleet" are vehicle emissions for the entire fleet of vehicles in Europe which already report RDE over the air (numbers based on Commission Report COM/2024/122). 95% confidence intervals are indicated where possible.

quarter. Therefore, quarter one is the first quarter in which we observe all treated employees for the entire three-month period. Point estimates get noisier for higher-order lags because fewer not-yet-treated employees remain in the control group and because long treatment exposures are only observed for early treatment cohorts. The panel is unbalanced since a fraction of employees switch to a new car on a monthly basis.[14]

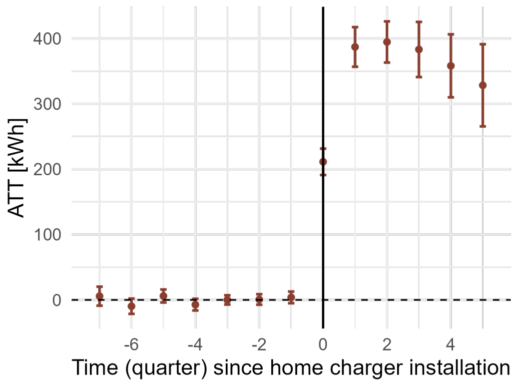
We begin the discussion of the results by considering the margin of charging vs. refueling. Panel (a) of Figure 3 shows that total electricity consumption of PHEVs increases sharply when treated employees receive their home charger. The effect size is around 400 kWh per quarter initially and begins to decrease towards 330 kWh in the fourth quarter after adoption. Panel (b) shows that treated subjects reduce charging at public stations, to an increasing extent, by up to around 50 kWh per quarter. We observe from panel (c) that point estimates for charging on company premises are negative but not statistically significant. Note that there are no significant differences between the treatment group and the control group in terms of charging behavior prior to treatment. This finding holds true also for the outcome variables analyzed below, supporting the parallel pre-trends assumption underlying the DiD estimator.

Figure 4 displays outcomes related to fuel consumption and mileage. We observe that the increase in electric charging is accompanied by a drop in fuel consumption (panel a), which is driven by reductions in both the number of refueling transactions per quarter (panel b) and the average amount of fuel per transaction (panel c). On average, treated subjects reduce their 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 decreases with the length of the event window.

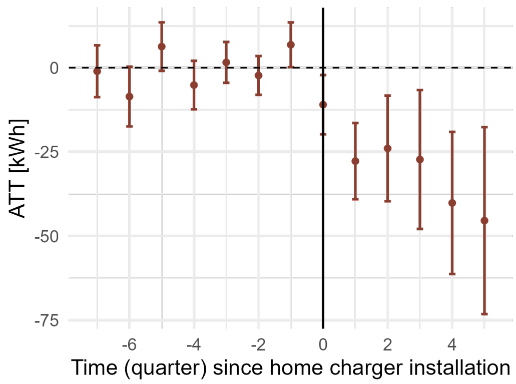
Five quarters after the installation of the home charger, the estimated fuel savings weaken whereas increased electric charging is sustained (see Figure 3a). This begs the question of whether treated employees end up driving more. Indeed, panel (d) of Figure 4 shows an increase in quarterly vehicle kilometers traveled by about 1,000, or 20% from 2020 levels. While the point estimates become statistically insignificant from quarter four onward, aggregate treatment effects presented in Table 2 below confirm that home chargers cause a rebound effect on driving. Two reasons for this effect come to mind. First, the home charger makes charging more convenient and also less time-consuming, lowering the non-monetary cost of driving. Second, environmentally conscious employees might drive their PHEV more because electric driving has a much lower environmental impact in terms of air pollution and CO_2 emissions (for a discus-

[14] A few employees received the home charger after receiving their PHEV company car (for details, see Appendix Figure E.2). Attrition is low; only 78 out of 1,442 drop out of the sample after treatment because they left the firm and returned their company car.

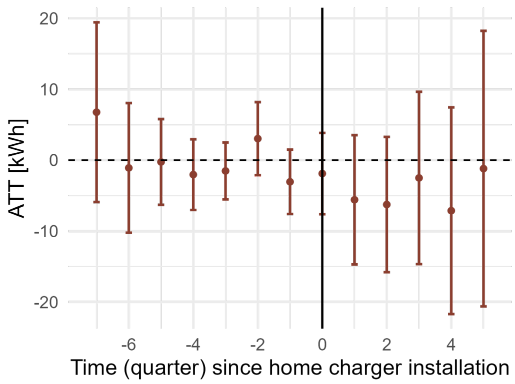
Figure 3: Treatment Effects on Electric Charging



(a) Total Charging



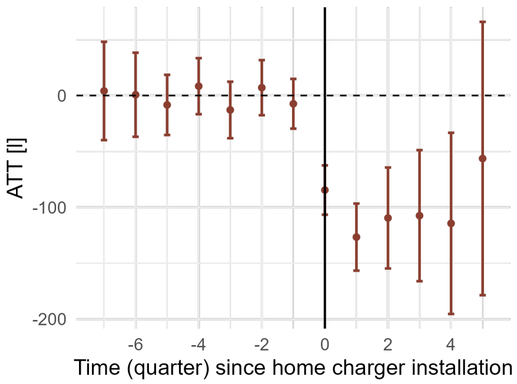
(b) At Public Station



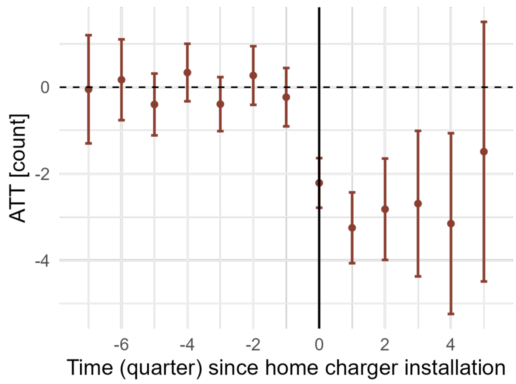
(c) At Firm

Notes: Estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021)as specified in Equation (3). "Total Charging" is the sum of all kWh charged at home, at public charging stations and at company-owned charging stations on company premises. "At Public Station" and "At Firm" correspond to the kWh charged at the corresponding sources. Event time indicated on the x-axis. Employees receive access to home charging at some point during quarter 0. The analysis is clustered at the level of the participating employee. 95% confidence intervals are based on bootstrapped standard errors (1,000 draws).

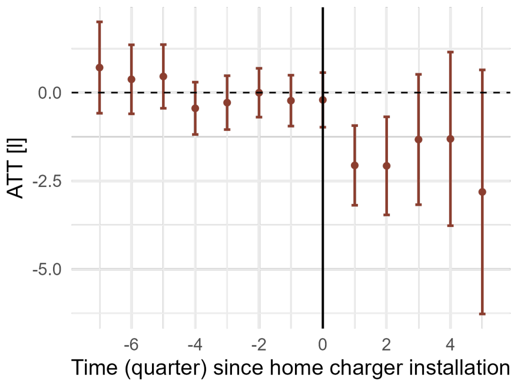
Figure 4: Treatment Effects on Fuel Consumption and Mileage



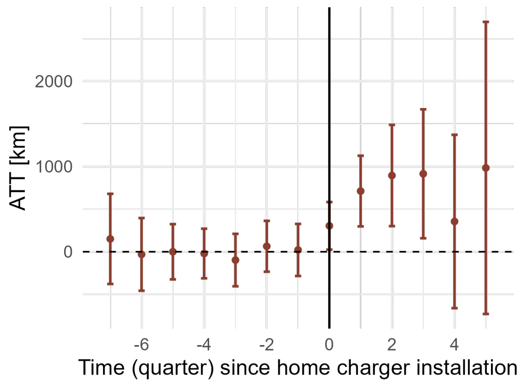
(a) Fuel in Liters



(b) Number of Refueling Transactions



(c) Liters per Refueling Transaction



(d) Kilometers Traveled

Notes: Estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021) as specified in Equation (3). "Fuel in Liters" is the amount refueled (pooled across gasoline and diesel PHEVs). "Number of Refueling Transactions" and "Liters per Refueling Transaction" are self-explanatory. "Kilometers Traveled" is the number of vehicle kilometers traveled in a given quarter. Event time indicated on the x-axis. Employees receive access to home charging at some point during quarter 0. The analysis is clustered at the level of the participating employee. 95% confidence intervals are based on bootstrapped standard errors (1,000 draws).

sion of moral licensing in an environmental context, see, e.g., Tiefenbeck et al., 2013). Both these factors make PHEV driving more attractive, generating additional trips or inducing substitution away from other means of transportation, including another car that is privately owned by the household.

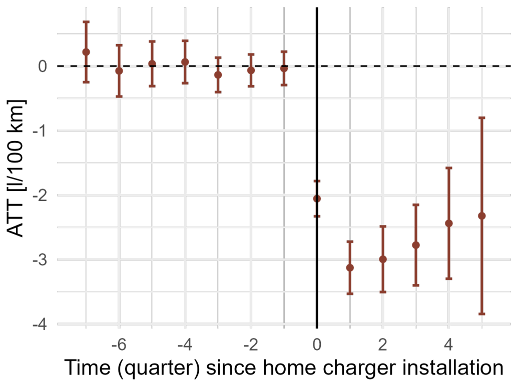
Finally, Figure 5 shows that the treatment reduced the average fuel consumption per 100 km by up to three liters (panel a) as it increased the electric driving share of PHEVs by up to 40 pp. (panel b). These effects are very large relative to pre-treatment averages in 2020 (see Table 1): the average fuel consumption per 100 km drops by more than 50% while the utility factor more than doubles. The extent to which this translates into CO_2 abatement depends on assumptions about the emissions caused by electricity generation for charging. We assume that no additional emissions are generated because fossil-based electricity generation in the EU is subject to an emissions cap set under the EU ETS. Thus, any incremental emissions from charging must be offset by reduced emissions elsewhere under the cap. As a consequence, the change in total emissions is equal to the reduction in tailpipe CO_2 emissions from fuel consumption of up to 300 kg per quarter (panel c). For comparison, panel (d) shows the effect of treatment on CO_2 emissions if the additional electricity charged were to give rise to unregulated CO_2 emissions at the prevailing average CO_2 intensity in the German electricity grid (cf. Appendix C.1). In 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.

Lastly, 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, on company premises, or at public stations. We find that home charger adoption significantly lowered energy costs of PHEV use. 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.

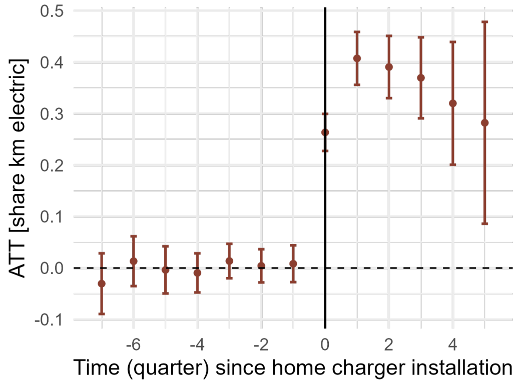
3.2 Overall Treatment Effects

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. Table 2 reports the resulting ATT estimates, all of which are statistically significant at the 5% or 1% level. Home charger adoption increased electricity consumption by 317.90 (±23.3 for the 95% confidence interval) kWh, almost a quintupling from the baseline of 65.5 kWh. At the same time, it decreased consumption of gasoline or diesel by 97.97 (±36.5) liters per quarter (38.4%).

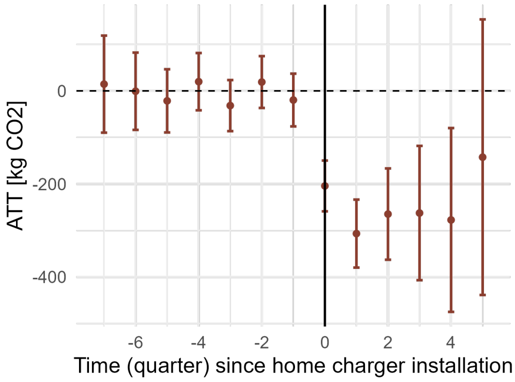
Figure 5: Treatment Effects on Fuel Efficiency, CO_2 Emissions and Energy Costs



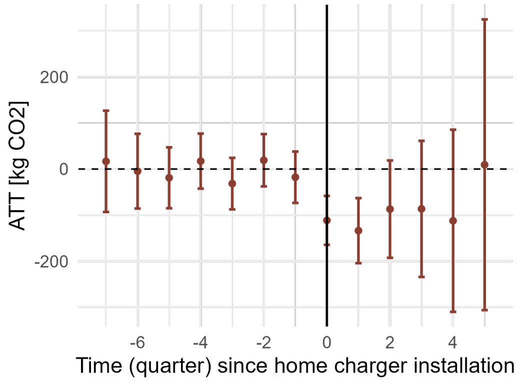
(a) Fuel Consumed per 100 km



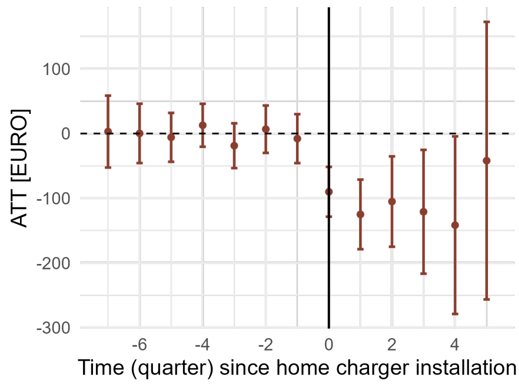
(b) Electric Driving Share



(c) CO_2 Emissions (EU ETS Cap)



(d) CO_2 Emissions (No EU ETS Cap)



(e) Company Energy Expenditures

Notes: Estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021) as specified in Equation (3). The "Electric Driving Share" is calculated as described in Appendix B. "CO_2 Emissions" in panel (c) are computed assuming that charging is not associated with any CO_2 emissions under the EU ETS cap whereas in panel (d) we impute CO_2 emissions from charging using the average CO_2 intensity of the German electricity grid (cf. Appendix C.1). "Company Energy Expenditures" summarize expenditures for all fuel and all electricity charged (cf. Appendix C.2). General notes from Figures 3 and 4 also apply here.

Table 2: Aggregate Treatment Effects on PHEV Holders

	Energy		Mileage	Emissions		Expenditures
	Electricity [kWh]	Fuel [l]	Mileage [km]	No EU ETS Cap [kg CO_2]	EU ETS Cap [kg CO_2]	Energy [Euro]
Treated	317.9***	-97.97***	671.13***	-93.04**	-237.12***	-102.52***
	(11.87)	(18.6)	(242.28)	(46.44)	(44.62)	(31.43)
Mean (pre-treatment)	65.5	255	4482	645	616	446
Employees	856	856	856	856	856	856
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: Estimator θ^O_{sel} from (Callaway & Sant'Anna, 2021) as in Equation 2. Mean (pre-treatment) is the average of the corresponding outcome variable in the last quarter before home charger adoption (619 observations). "Groups" are groups of employees receiving home charging in the same quarter. "Periods" are quarters. "No EU ETS Cap" stands for CO_2 emissions being computed under the assumption that additional electricity charged leads to CO_2 emissions at the average CO_2 intensity in the German electricity grid (cf. Appendix C.1). "EU ETS Cap" stands for CO_2 emissions being computed under the more 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). The analysis is clustered at the level of the participating employee. Standard errors in parentheses (bootstrapped, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The net effect on emissions is a reduction of 237.12 (±87.5) kg of CO_2 under the assumption of non-additionality of emissions under the EU ETS. Emissions would have fallen by 93.04 (±91.0) kg if additional charging had induced higher CO_2 emissions from electricity generation at the average emissions intensity in the German electricity grid. In addition, the adoption of home chargers caused a reduction in energy costs of €102.52 (±61.6) for the company. Finally, the average employee's mileage increased by 671.13 (±474.9) km per quarter, which can be interpreted as a 15% rebound effect in terms of VKT.

3.3 Treatment Effects for Battery Electric Vehicles

For employees with a BEV during the sample period, we estimate the effect of home charging on electricity consumption, emissions, and energy expenditures.[15] Table 3 reports the aggregate ATT estimates. We find that home charging increased total electricity consumption by 172.05 (±143.12) kWh per quarter, after netting out significant decreases in both charging on the firm premises of 52.38 (±47.35) kWh and, especially, on the public grid of 247.73 (±122.66) kWh. This result suggests that BEVs were, similar to PHEVs, driven more once a home charger was installed, pointing to

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

Table 3: Average Treatment Effects on BEV Holders

	Electricity Consumption				
	Total [kWh]	Firm [kWh]	Public [kWh]	Emissions [kg CO_2]	Expenditures [Euro]
Treated	172.05**	-52.38**	-247.73***	79.84**	23.03
	(73.02)	(24.16)	(62.58)	(32.16)	(24.84)
Mean (pre-treatment)	477	103	374	208	173
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: Estimator θ^O_{sel} from (Callaway & Sant'Anna, 2021) as in Equation 2. Mean (pre-treatment) is the average of the corresponding outcome variable in the last quarter before home charger adoption (228 observations). "Groups" are groups of employees receiving home charging in the same quarter. "Periods" are quarters. Emissions are calculated under the assumption that additional electricity charged leads to CO_2 emissions at the average CO_2 intensity in the German electricity grid (cf. Appendix C.1). In the more realistic EU ETS scenario, additional emissions are zero and are therefore not reported here. Standard errors in parentheses (bootstrapped, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

an economically significant rebound effect. Since we do not observe odometer readings for BEVs, we use the average electricity consumption of 15.61 kWh per 100 km (see Table E.2) to estimate the rebound effect at 1,100 km per quarter. As explained above for PHEVs, rebound could arise from increased convenience and lower non-monetary cost of home charging. Moral licensing cannot explain the rebound because BEVs are always driven electrically. However, due to their exclusive availability, home chargers likely reduce 'range anxiety' among BEV holders, leading them to drive more relative to the control group.

Increased charging hardly raises expenditures, however, because charging at home is cheaper than in the public charging network.[16] The ATT for charging expenditures is thus economically and statistically insignificant. The effect on total CO_2 emissions is zero due to cap-and-trade in the electricity sector. In the absence of the EU ETS cap, incremental CO_2 emissions due to home charging would amount to 79.84 ($\pm$63.03) kg per quarter.

In support of the external validity of these findings for the broader population of BEV company car holders, Appendix Table E.2 shows that electricity consumption prior to treatment is very similar between adopters of home chargers and non-adopters, and that differences in the electric efficiency, weight and price of the respective BEVs are minor. Similar to the PHEV sample, treated BEV holders tend to be male, older

[16]For a discussion of energy prices, see Appendix C.2.

than non-participants, and have longer tenure with the company.

3.4 Treatment Effects on Vehicle Choice

Employees entitled to a company car get to choose a new vehicle every four years. This provides an opportunity to investigate whether experience with convenient home charging promotes BEV adoption. We hypothesize that employees who already have access to home charging with their previous vehicle are more likely to choose a BEV. To test this hypothesis, we focus on 157 program participants with a PHEV lease ending between October 2020 and March 2023. In this group, we define treated employees as those who gained experience with home charging before the end of their PHEV lease. Treatment assignment thus depends on (i) the order date of the home charger, (ii) the waiting time until the charger is installed, and (iii) the end-of-lease date for the PHEV. Employees had no control over (ii) or (iii), but they were free to choose the order date of the home charger. This could give rise to selection into (early) treatment by employees who are determined to order a BEV as their next company car.[17] A naïve estimator comparing adoption propensities among employees with and without access to home charging might hence be biased. We resort to a matching estimator to address this issue.

Adopting the potential outcome framework by Rubin (1974), denote by Y_i an indicator for choosing a BEV upon renewal of the lease. The treatment indicator W_i (exposure) takes the value of one when the employee has access to home charging by the end of the previous lease and zero otherwise. For treated employees, we only observe $Y_i(1)$, the vehicle choice when treated. To estimate the average treatment effect on the treated, $\text{ATT} = \mathbb{E}[Y_i(1) - Y_i(0)|W_i = 1]$, we follow Abadie & Imbens (2011) and impute the non-treated outcome $Y_i(0)$ via matching of similar observations from the control group:

$$\widehat{\text{ATT}} = \frac{1}{N} \sum_{i:W_i=1} \left(Y_i(1) - \underbrace{\frac{1}{M} \sum_{j \in \mathcal{J}_M(i)} Y_j(0)}_{\hat{Y}_i(0)} + \underbrace{\hat{\mu}_0(X_i) - \frac{1}{M} \sum_{j \in \mathcal{J}_M(i)} \hat{\mu}_0(X_j)}_{\text{bias correction}} \right) \tag{4}$$

where $\mathcal{J}_M(i)$ is the set of M nearest neighbors to observation i based on covariates X_i, and the asymptotic bias in those matches is corrected for by an auxiliary regression model to predict $\hat{\mu}_w(x)$ for the conditional expectation $\mu_w(x) = \mathbb{E}[Y_i(w)|X_i = x]$. The estimator is robust to misspecification of $\hat{\mu}_w(x)$ (Abadie & Imbens, 2011). We choose

[17] In line with this, Appendix Figure E.6 shows that treated employees tended to order the home charger earlier than untreated employees. Moreover, untreated employees who ordered a BEV rather than a PHEV as their next company car tended to order the home charger earlier.

Table 4: Effect of Access to Home Charger on Propensity to Order a BEV

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample				$0 \leq$ Gap ≤ 7	
Exposure	0.326***	0.312***	0.340*	0.354	0.284**	0.283
	(0.095)	(0.101)	(0.206)	(0.245)	(0.131)	(0.227)
Charging		✓		✓		
Order Gap			✓	✓		✓
Employees	157	157	157	157	60	60
Treated Empl.	49	49	49	49	20	20

Notes: Coefficient estimates of the ATT in eq. (4) with nearest-neighbor matching with replacement (one neighbor for all treated units, including ties). All specifications match on the home charger order date. "Exposure (0/1)": Employee receives a home charger before the end of the initial PHEV lease. "Charging": Exact matching on a categorical variable for the average amount of electricity charged with the initial PHEV before home charger adoption (categories: $\leq$ median charging (7.2 kWh/month), $>$ median charging). "Order Gap": include the number of months between the order date for the charger and the end of the initial car lease in addition to the home charger order date as a matching covariate. Columns (1) to (4) include all participants in the home charger program whose PHEV lease ends between Oct. 2020 and Mar. 2023. Columns (5) and (6) restrict the sample to employees whose car lease ends at most seven months after they have ordered the charger. Heteroskedasticity-robust standard errors from Abadie & Imbens (2011). * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01.

$M = 1$ and the Mahalanobis-distance to determine $\mathcal{J}_M(i) = \arg\min_{j:W_j=0} \|X_j - X_i\|_A$.

Our choice of matching covariates X seeks to achieve covariate balance, while the small sample size dictates a parsimonious approach. In all specifications reported in Table 4, we match on the month in which the home charger is ordered, the principal source of endogeneity. Columns (2) to (4) additionally control for the amount of electricity charged with the previously held PHEV (exact match on below/above the median) and on the time expired between the order date of the home charger and the end of the initial vehicle lease, which we refer to as the order gap (match on the number of months). To the extent that these variables carry information about preferences for BEVs, this controls for selection into early treatment.[18]

We find that access to a home charger increases the probability of ordering a BEV by 31.2 to 35.4 pp. in the full sample. Matching on both charging and the order gap inflates the standard errors so that the treatment is no longer statistically significant for this specification, but the point estimates remain similar across all four specifications.

Consistency of the matching estimator relies on an unconfoundedness assumption

[18]We assess other potential confounders by inspecting the data. To examine the influence of time trends, Appendix Figure E.8(a) shows the distribution of BEV vs. PHEV choices among untreated employees in our sample. We see that the relative attractiveness remains unchanged over time. Moreover, choosing one or the other vehicle did not make a difference for the waiting time between the order and the delivery date of the home charger, as depicted in Figure E.8(b).

which is more plausible when covariates are balanced. Table E.5 and Figure E.7 in the Appendix show that we achieve good balance in terms of the order date of the home charger as well as consumption of electricity with the previous vehicle. This is not quite true for the order gap where nearest-neighbor matching is complicated by a lack of common support for order gaps of more than seven months (cf. Appendix Figures E.7(g) and (h)). Therefore, columns (5) and (6) of Table 4 report estimates from specifications that enforce common support by matching exactly on the order gap not exceeding seven months. While this considerably reduces the sample size, the estimated treatment effect remains statistically significant at 28.4 pp. At the risk of overfitting, we also report specifications that additionally match on the length of the order gap in months (column 6) to improve balance of the continuous order gap variable (cf. Appendix Figure E.7(i)). This estimate is less precise yet virtually identical in magnitude.

In sum, we interpret our results as evidence that experiencing the convenience of charging at home has convinced a sizable share of PHEV holders to go all electric and switch to a BEV. In the cost-benefit analysis below, we use 28.4 pp. as our preferred estimate. In view of the limitations set by the institutional setup, small sample size, and the remaining imbalance on the order gap, we also consider a more conservative scenario where home chargers have no effect on the adoption of BEVs.

3.5 Robustness Checks

We examine the robustness of our results to using alternative approaches concerning the relevant control group, the estimator, and the extrapolation of odometer readings to compute mileages.

To begin, we re-estimate the treatment effects on the use of PHEVs using as a control group only employees who do not select into home charger adoption. Working with a constant control group of never-treated employees rules out that changes in the composition of the control group could drive the estimation results.[19]

In addition, we estimate the event studies using the following two-way fixed-effects event-study regression:

$$Y_{it} = \sum_{e=-K}^{-2} \delta_e \, \mathbb{1}(t - \mathrm{G}_i = e) \sum_{e=0}^{L} \beta_e \, \mathbb{1}(t - \mathrm{G}_i = e) + \eta_i + \mu_t + \epsilon_{it} \qquad (5)$$

where the notation follows Section 2.2 and K and L indicate the maximum number of pre-treatment and post-treatment periods possible.

[19]We were not working with never-treated employees in our main specification because employees select into home charger adoption and Table 1 demonstrates that this selection is associated with meaningful differences in driving behavior.

Appendix Figure E.3 plots the estimated coefficients, which are very similar across the two alternative specifications. When compared to the main results in Figures 3 to 5 above, the results are robust – with a few noteworthy differences. First, the larger control group increases precision: It is no longer the case that coefficients for longer treatment exposure are more noisily estimated. Moreover, the point estimates are more stable, in particular in quarter five after treatment. This suggests that the increasing variability in the coefficients estimated on higher-order treatment lags in our main specification reflects compositional changes in a shrinking sample rather than dynamic treatment effects. We thus conclude that treatment effects are constant also for longer treatment exposures. Finally, the rebound effect on VKT is not robust to using never-treated employees as the control group.

Appendix Table E.3 reports the overall treatment effects estimated with the alternative control group. Again, all results are robust with the exemption of the rebound effect on VKT. Comparing the effect sizes for fuel and electricity consumption to those reported in Table 2, we see that the mileage rebound hinges on smaller estimated fuel savings in the main specification. Since pre-trends for both specifications (using never-treated and not-yet-treated units as the control group) are parallel, this difference must be driven by differential post-treatment trends in fuel use across control groups. Such trends are unobservable to us, but it seems plausible that outcomes for not-yet-treated program participants better represent trends in non-treated potential outcomes of treated employees. We thus prefer using not-yet-treated units as the control group, and interpret the increase in VKT observed in our main specification as a rebound effect.

To corroborate this interpretation, we perform an additional sensitivity analysis for outcomes that depend on VKT, a variable we construct from odometer readings that employees record each time they pump gas or diesel at a filling station. As explained above, we identify and drop erroneous entries and impute mileage by interpolating between correct mileages. We also use extrapolation when the first or the last odometer reading in a series is erroneous.[20] The extrapolation combines fuel and electricity consumption with their assumed or observed efficiency to impute kilometers traveled. As the treatment might change the electric driving share in ways we cannot directly observe without mileage, this could introduce error. In Appendix F, we assess the robustness of the rebound effect to different extrapolation methods. We show that our results for mileage, fuel efficiency and utility factor are robust to different assumptions about the specific energy use per kilometer, as long as we consider both fuel and electricity consumption to extrapolate erroneous mileages (as we do). We also find that extrapolating using only fuel consumption biases the estimated treatment effects on

[20] Alternatively, we would have to discard observations with implausible odometer readings at the beginning and the end of the sample period, thus diminishing our observation window.

these outcomes, particularly the one for mileage, towards zero. This is expected since (i) electricity consumption is not accounted for and (ii) the treatment substantially reduced fuel consumption (cf. Figure 4a).

4 Cost-Benefit Analysis

This section relates emissions abatement due to home charger adoption to the associated costs incurred by the company. We simulate emission trajectories into the future, assuming that home chargers have a lifespan of around 20 years. Doing so requires us to combine all of our previously estimated intensive- and extensive-margin impacts of home charger adoption. Specifically, we take into account that adopters are more likely to switch to BEVs, that BEV holders use the home charger differently than PHEV holders, and that access to a home charger has different effects on charging behavior of PHEV and BEV holders. We adapt the method by Dugoua & Gerarden (2023, Appendix D) to our potential outcome framework, using conditional expectations instead of derivatives. Formal derivations and a detailed description of the simulations are relegated to Appendix D.

The basic idea is to consider repeated vehicle choices every four years and then forward-simulate the paths of the outcome variables (emissions and energy costs) over a 20-year period starting from the period 2020 - 2023.[21] We simulate these outcomes under alternative assumptions about employees' vehicle choices, subsumed in scenarios. Each scenario is fully characterized by a matrix specifying the choice probabilities of individual i holding car type $k_{it} \in \{ICEV, PHEV, BEV\}$ in period t under treatment status $D_i \in \{0, 1\}$. The transition matrix is assumed to be constant over time and takes the form:

$$\mathbf{E}(\Theta_i^k(D_i)) = \begin{pmatrix} \mathbf{E}(\theta_i^{ICEV}(D_i)|ICEV) & \mathbf{E}(\theta_i^{ICEV}(D_i)|PHEV) & \mathbf{E}(\theta_i^{ICEV}(D_i)|BEV) \\ \mathbf{E}(\theta_i^{PHEV}(D_i)|ICEV) & \mathbf{E}(\theta_i^{PHEV}(D_i)|PHEV) & \mathbf{E}(\theta_i^{PHEV}(D_i)|BEV) \\ \mathbf{E}(\theta_i^{BEV}(D_i)|ICEV) & \mathbf{E}(\theta_i^{BEV}(D_i)|PHEV) & \mathbf{E}(\theta_i^{BEV}(D_i)|BEV) \end{pmatrix} \quad (6)$$

where θ_i^k is an indicator for whether employee i adopts vehicle type k. That is, for any vehicle type and treatment status, there is a certain probability of choosing another or the same car type. Some of these choice probabilities are given by our estimated ATTs, others are based on assumptions outlined below.

[21] Employees have to hold on to their company car at our partner company for four years, so roughly one in four chooses a new car every year. For tractability, we assume instead that all employees choose at the same time every four years.

4.1 Scenarios

Across scenarios, we rely on a set of common assumptions. First, emissions from electricity generation are non-additional due to the binding cap of the EU ETS. Second, there is no exit from vehicle ownership. Third, the initial fleet of PHEVs in the first four years is equal to the PHEV fleet observed in the data (in terms of technical characteristics). Fourth, all employees choose a new company car simultaneously in four-year increments. Fifth, treatment effects are constant over time, i.e., a home charger has the same effect on charging behavior and vehicle adoption in each period. Sixth, vehicle choice is independent of vehicle use, i.e., the average treatment effects on vehicle use and future vehicle choices are independent. Seventh, car use, emissions factors (particularly for electricity generation), and energy prices are constant over time. All cost outcomes are expressed in 2020 euros and all future cost outcomes are discounted to that year.

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

A1 BEV adoption is an absorbing state (employees do not go back to ICEVs or PHEVs once a BEV has been chosen).

A2 EV adoption is an absorbing state (employees do not go back to ICEVs once a PHEV or BEV has been chosen).

Under these two assumptions, the first column and the first row in equation (6) become irrelevant and the transition matrix for treated employees simplifies to:

$$\mathbf{E}(\Theta_i(1)) = \begin{pmatrix} 0.429 & 0 \\ 0.571 & 1 \end{pmatrix} \tag{7}$$

That is, the probability that a PHEV holder chooses a BEV upon treatment is 0.571, based on the extensive-margin effects of home chargers estimated in Section 3.4 above. Over time, this effect compounds and hence accelerates BEV adoption. We take this into account when computing the overall treatment effects (cf. eq. D.10 in the appendix). In contrast, the following scenarios abstract from this effect.

Scenario 1: No Effect on Vehicle Choice We assume that access to home charging does not change vehicle choice. The choice probabilities for different vehicle types are thus given by a simplified transition matrix that does not depend on treatment status:

$$\mathbf{E}(\Theta_i(1)) = \mathbf{E}(\Theta_i(0)) = \begin{pmatrix} 0.713 & 0 \\ 0.287 & 1 \end{pmatrix} \tag{8}$$

Since the treatment no longer affects vehicle choice, we only need to consider the intensive-margin treatment effects for the ATTs (eq. D.10, with $\mathbf{E}(\Delta\theta_{it}^{BEV}) = 0$).[22]

Scenario 2: Vehicle Choices as in Overall Company Car Population Like scenario 1, but we replace assumptions **A1** and **A2** with the assumption that the vehicle choice probabilities among employees in the home charger program are the same as in the population of all employees who have to replace their company car. 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 of the survey reported the engine type of the company car they currently had and the car they were planning to choose next. This yields the following transition matrix:

$$\mathbf{E}(\Theta_i(1)) = \mathbf{E}(\Theta_i(0)) = \begin{pmatrix} 1,779/3,038 & 105/598 & 15/300 \\ 643/3,038 & 277/598 & 8/300 \\ 661/3,038 & 216/598 & 277/300 \end{pmatrix} \tag{9}$$

based on 3,038 ICEVs, 598 PHEVs, and 300 BEVs in the survey.[23] Furthermore, we only need to consider the intensive-margin treatment effects for the period-ATTs (eq. D.10, with $\mathbf{E}(\Delta\theta_{it}^{BEV}) = 0$).

Scenario 3: PHEV Lock-In We assume that employees do not change their vehicle type over time; they are locked into their initial choice. Then the overall ATT is simply given by the net present value of the period-treatment effects on PHEV use (eq. D.10, with $\mathbf{E}(\Delta\theta_{it}^{BEV}) = 0$ and setting $\mathbf{E}(\theta_{it}^{PHEV}(1)) = 1 \quad \forall t$).

Scenario 4: Forced Transition to BEVs We assume that, from the second four-year period onward, all employees switch to a BEV. This scenario illustrates a forced transition to a zero-emission car fleet which would be consistent with corporate pledges for net-zero emissions. Recently, some companies have taken steps into this direction by adopting BEV mandates for new company car leases. The dynamic ATTs then correspond to the ATTs during the first four-year period, since the treatment has no lasting effects on emissions in this case (eq. D.10, with $\mathbf{E}(\Delta\theta_{it}^{BEV}) = 0$ and setting $\mathbf{E}(\theta_{i1}^{PHEV}(1)) = 1$ and $\mathbf{E}(\theta_{it}^{PHEV}(1)) = 0 \quad \forall t > 1$)).

This gives us all the ingredients needed to simulate the ATT on CO_2 emissions and energy costs, combining intensive- and, depending on the scenario, extensive-margin reactions. We collect the required parameters in Appendix Table D.1.

[22] Note that the indicator θ_{it}^k for whether employee i holds a vehicle of type k in period t will vary over time, even when the transition matrix $\mathbf{E}(\Theta_i(D_i))$ is constant over time.

[23] In the survey, a small fraction of employees were undecided which vehicle type they would choose for their next company car. We removed those employees to obtain the transition matrix above.

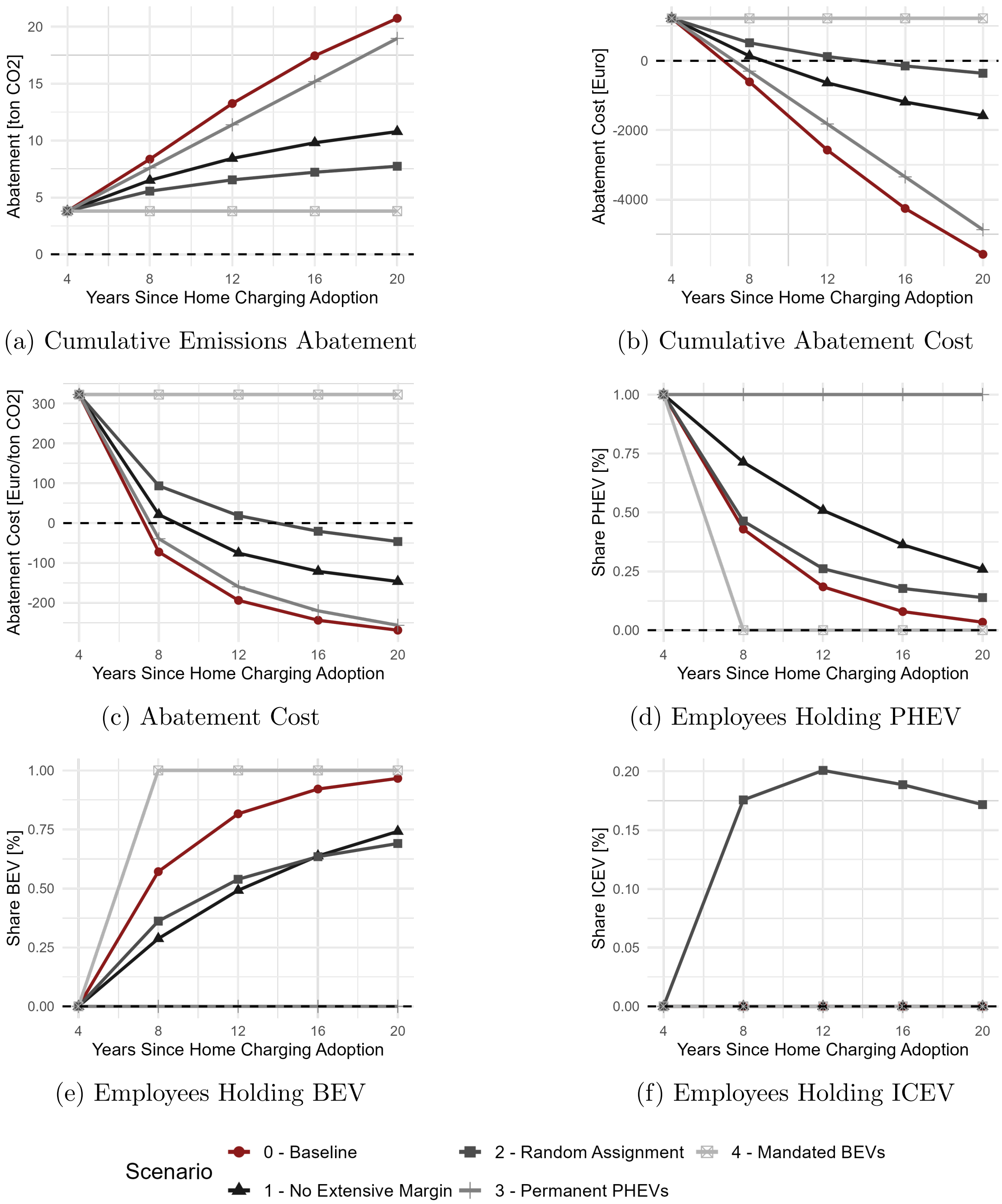
4.2 Simulation Results

Figure 6 displays the 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 fleet need to be renewed. We examine how the company car fleet develops over time when treated employees receive a home charger at the beginning of period 1, and how this impacts emissions and abatement. Panels (a)-(c) show abatement and abatement costs per employee while (d)-(f) display the shares of employees holding PHEVs, BEVs, and ICEVs, respectively.

Panel (a) depicts cumulative CO_2 emissions abatement, which starts from 3.8 tons after four years (the intensive-margin treatment effect per quarter cumulated over four years). Depending on the scenario, the cumulative abatement can reach almost 21 tons of CO_2 after 20 years, or remain as low as 3.8 tons of CO_2. The lower bound arises in scenario 4 where the forced transition to a pure BEV fleet implies that all vehicles operate at 100% electric utility factor from year five onward and hence adding chargers does not further reduce emissions thereafter. Cumulative abatement is highest in the baseline scenario because treatment boosts the adoption of BEVs relative to the counterfactual. To see the importance, note that total abatement over 20 years in the baseline scenario (20.7 tCO_2 per employee) is almost twice as high as in scenario 1 (10.8 tCO_2 per employee), which shuts off the extensive margin. The only way in which intensive-margin treatment effects alone could generate similar amounts of cumulative abatement is by shutting down the exogenous transition towards BEVs in the control group (scenario 3). Under this counterfactual assumption, access to home charging leads to constant abatement of CO_2 emissions over the useful life of the charging station. However, this scenario is associated with much higher CO_2 emissions than the baseline scenario, due to the continued combustion of fossil fuels. In scenarios 1 and 2, which allow for an exogenous transition towards BEVs but do not consider the extensive-margin effect of access to home charging on BEV adoption, emission abatement is considerably lower. This is due to an increasing share of employees adopting a BEV (or an ICEV in scenario 2), independent of access to home charging. For these employees, the home charger does not generate additional emission reductions.

Panel (b) displays the cumulative total abatement cost of 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 BEVs from the second four-year period onward, since home chargers do not result in additional emissions reductions. Abatement is lowest in the baseline scenario. Note that an abatement cost of zero implies that the home charger installation has paid off. Negative abatement costs result when the home charger program pays for itself. The cost-benefit ratio of the home charger program

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 BEV

(f) Employees Holding ICEV

Notes: Estimates for the dynamic ATT, aggregating treatment effects on PHEV and BEV use and BEV adoption under different assumptions for PHEV and BEV diffusion (cf. Appendix D).

improves (falls) when (i) more PHEVs remain in the fleet, or (ii) access to charging at home has a positive impact on BEV adoption. The break-even point is reached in less than eight years in the baseline scenario and in scenario 3 (note that we model decisions in four-year increments such that actual amortization periods can be shorter than indicated). For the remaining two scenarios, the break-even point is four to eight years later, either because the transition to BEVs due to the treatment proceeds more slowly (see panel e) or because some employees revert back to ICEVs (see panel f). Per ton of CO_2 emissions, we estimate levelized abatement costs at €323 after four years, and they eventually become negative. After 20 years, the profit per ton of CO_2 avoided ranges between €46 and €269 (see panel c).

The previous scenarios assumed that energy prices observed during the sample period 2020-2022 are representative of energy prices over the next 20 years. To gauge the impact of this assumption on our results, Appendix G presents a sensitivity analysis using projections for future electricity prices and the future development of carbon prices for the transport sector in Germany. As shown in Figure G.1, our assumptions about the future development of energy prices have little effect on our results. The reason is that the cost of driving one kilometer using fossil fuels already is substantially higher than driving the same distance using electricity. Since this cost differential remains large relative to the projected price changes for each energy type, the qualitative finding that home chargers are cost-effectiveness holds up.[24]

5 Conclusion

This paper contributes, to the best of our knowledge, the first causal evidence that access to home charging infrastructure substantially reduces the environmental footprint of plug-in hybrid electric vehicles. Exploiting quasi-experimental variation in the adoption of home chargers by German company car holders, we find that electric charging almost quintuples upon installation of the charger whereas the consumption of gasoline or diesel drops by 38%. The associated reduction in CO_2 emissions is equally large because any incremental emissions from electric charging are capped under the EU ETS. We thus conclude that the provision of home charging infrastructure can be a highly effective tool for achieving much-needed CO_2 abatement in the road transportation sector. Starting in 2027, those emissions will be subject to a carbon price set by the EU ETS 2. To produce the same short-run abatement as our intervention, that carbon price would have to increase gasoline prices by 95% and diesel prices

[24] Considering price developments for home charging stations is not necessary, since this investment is made once at the beginning of the sample period. Considering the price developments for different vehicle types (particularly the price differences between BEV and ICEV) is also not necessary in the given setting, as employees have a fixed budget for a new company car.

by 135% (based on recent elasticity estimates for German PHEV drivers by Grigolon et al., 2024). Our review of the available projections for the EU-ETS-2 price suggests that the induced increase in the fuel price will be an order of magnitude smaller. If policymakers were to double fuel prices, this would be highly unpopular (Douenne & Fabre, 2022). Hence, policies aimed at reducing the carbon footprint of PHEVs must continue to rely on instruments other than carbon pricing, such as promoting access to home chargers.

Two additional results strengthen this policy recommendation. First, we have shown that the diffusion of home chargers also accelerates the transition to driving battery electric vehicles, which generates sizable knock-on effects on CO_2 abatement by shifting on-road emissions under the EU ETS cap. Second, charging at home leads to energy cost savings that eventually offset the upfront investment when chargers are used for approximately six years and longer. In our setting, such net savings accrue to the company, which also pays for the home charger. A robust insight from analyzing those cash flows under different assumptions is that home chargers reduce corporate carbon emissions at low – if not negative – levelized costs that are competitive with international carbon offsets.

Our analysis provides evidence on a cost-effective tool for reducing CO_2 emissions from corporate passenger car fleets. This is important given the size of such fleets in markets like Germany, where 39% of all new passenger car registrations in 2022 were company cars, according to industry estimates (Kampermann, 2023).[25] As 51% of all PHEVs and 40% of BEVs were company-owned in 2023 (Kraftfahrt-Bundesamt, 2024a), our findings are immediately relevant to a substantial share of the overall stock of EVs. Since company cars are replaced every few years and enter the used-car market, they drive the diffusion of new vehicle technologies in the total stock of cars. This insight is behind recent efforts by the European Commission to leverage the potential of corporate car fleets to accelerate the decarbonization of the transport sector (European Commission, 2024b). The positive effect of home chargers on BEV adoption we find could thus lead to further emissions reductions down the road by increasing the supply of used BEVs.

There are policy implications beyond the particular context of company cars. The treatment effects we have estimated are driven exclusively by non-monetary aspects of home charging like convenience, exclusive availability, and time savings. It seems highly plausible that all these aspects work in the same direction for privately held PHEVs. The magnitude of the treatment effects may differ, however, due to financial incentives. We expect the increase in the electric driving share to be larger than in our

[25]According to administrative data from the German Federal Motor Transport Authority, company-owned cars accounted for 67% of all new passenger car registrations in Germany in 2023 (Kraftfahrt-Bundesamt, 2024b). Not all cars with a corporate owner are company cars, however. For example, car dealers often register new vehicles for resale purposes.

study because private PHEV owners internalize the energy cost savings associated with home charging. The EU ETS 2 will likely reinforce this effect by raising the costs of gasoline and diesel, thus creating a complementarity between charging infrastructure and carbon pricing.

This points to a case for government-subsidized home chargers. When designing such a subsidy, policymakers should take into account environmental externalities other than climate change, such as air pollution, as well as external costs imposed on the electricity sector (Heid et al., 2024). Measuring all external effects of driving and charging PHEVs is complex due to their high variability across locations and over time. Given the policy relevance, this is an important topic for future research.

Our findings are relevant to the process of electrifying road transportation. Electric driving shares among PHEV users in our sample before the adoption of the home charger align well with those observed for the fleet of new PHEVs in Europe (cf. Figure 2c). With PHEVs accounting for roughly 8% of new vehicle registrations in the European Union in 2023 (European Environment Agency, 2024) and as much as 18 % in China during the first half of 2024 (InsideEVs, 2024), our results identify and quantify an effective lever to reduce emissions in a significant portion of the vehicle market. To tap this potential, policymakers can reduce administrative barriers to installing a home charger and actively mandate installation rights for renters. For example, a 2020 federal law gives tenants in Germany a right to install a charging station at their rented home, which can only be denied under special circumstances. In addition, governments could improve the social returns to subsidizing the adoption of PHEVs. This is a widespread policy in Europe, in particular for company cars, which yields environmental benefits to the extent that PHEVs are driven electrically. However, the subsidy does not reward electric driving itself. Our result that having a charging station at home increases electric driving suggests that conditioning the PHEV subsidy on the availability of home charging infrastructure would raise its cost effectiveness.

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Appendix (For Online Publication)

A Company Cars

Many companies provide generous mobility options to their employees, not only for business trips but also for the commute to work and 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. In addition, a company car is often perceived as a status symbol and can make working for an employer more attractive. Therefore, companies are reluctant to remove this privilege, even though they are faced with external or internal ambitions to rapidly decrease CO_2 emissions, also from their employees' mobility.

B Data Preparation

For this project, our partner company provided us with data from different sources: i) the company car register 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) data on charging transactions on the company's premises and at public charging stations, iii) data on charging transactions at the employee's home (if the employee participated in the home charger program), and iv) data on refueling transactions 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 (total mileage up to this point).

The odometer readings sometimes give implausible vehicle mileages between two refueling transactions, either because i) the implied mileage is negative or ii) the mileage information is not consistent (too high or too low) 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 observed mileage using i) and ii) via 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 (ADAC).[26] For each PHEV model, we obtain the combined energy consumption (using both electricity and fuel) 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 fuel consumption of the vehicle in charge-sustaining mode, i.e., when the PHEV's battery is (almost) depleted and the PHEV mainly uses the internal combustion en-

[26] 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.

gine for driving (Riemersma & Plötz, 2017). In the ADAC data, only the combined fuel consumption is available (average between charge-sustaining and charge-depleting mode, i.e., the PHEV's fuel consumption when the battery is fully charged). 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):

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

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

where C^{NEDC} is the combined NEDC fuel consumption, C_1^{NEDC} is the charge-depleting NEDC fuel consumption, C_2^{NEDC} is the charge-sustaining NEDC fuel consumption, and D_e^{NEDC} is the NEDC electric driving range of the PHEV. Finally, to account for the underestimation of fuel consumption in 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 Plötz et al. (2021) and Grigolon et al. (2024):

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

where C_2^{real} is the on-road fuel consumption in charge-sustaining mode.

We further obtain the electric efficiency (according to NEDC) of the PHEV version of the model, where possible. If we only observe the WLTP electric efficiency, we divide that value by 1.2 to obtain a proxy of 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 the testing procedures; see, e.g., Plötz et al. (2021). This implies that we obtain the efficiency of purely electric driving by dividing the combined NEDC electricity consumption by 0.8.

With this information, 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 refueling dates. Based on the electric efficiency of the vehicle, we then convert the electricity consumption into kilometers, which we subtract from the mileage obtained from 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 vehicle's fuel consumption in charge-sustaining mode (C_2^{real}) by more than a factor of 3 or else if it is lower than 20 % of C_2^{real}, we flag the mileage as erroneous. We interpolate flagged mileages using an energy-weighted average of 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.

Further, we drop time series with less than two non-flagged mileage observations because we cannot calculate driving distances for these vehicles. There are three reasons why we could observe only one or two mileages: i) there are indeed very few refueling procedures, especially for vehicles bought at the end of the sample period, ii) company car drivers charge their PHEV privately, so that the observed average fuel consumption is constantly below the lower bound implied by 20 % of C_2^{real}, or iii) the employee did not take entering the odometer readings seriously, such that the sequence of recorded mileages does not reflect driving behavior. Note that the latter case should be rare since not correctly entering odometer readings violates corporate policies.

Suppose flagged mileages occur at the end of a time series for a particular car. In that case, 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 vehicle's average fuel consumption per 100 km we observe in the non-flagged transaction data (see above).[27] 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.

In contrast to the employee-recorded odometer readings, we take the amount of fuel and electricity consumed in the transaction 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 205,481 refueling procedures) and we winsorize electric charging at 130 % of the vehicle's gross battery capacity (this affects 15,497 out of 949,406 recharging and refueling procedures).[28]

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

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

where 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).

C 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 C.1.

[27] To test whether this extrapolation affects our results for the vehicle's mileage, average fuel consumption per 100 km, and utility factor, we perform a sensitivity analysis with two alternative imputation procedures in Appendix F.

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

C.1 CO_2 Emissions

PHEVs can drive using electricity and either gasoline or diesel, depending on the car. 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 used emissions factors for fossil fuels from the German Environmental Protection Agency (Juhrich, 2022).

To convert electricity consumption into CO_2 emissions under a non-EU ETS scenario, we make the simplifying assumption that the emissions intensity of electricity generation in Germany is constant over the course of a year. 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).

C.2 Energy Prices

To calculate the energy cost savings for the firm, we need to assign a monetary value to the observed energy consumption. For home charging, we directly observe the price per kWh of electricity. The average kWh charged at the employees home had cost the company €0.28. To approximate the prices paid for fuel and electricity charged in the company's premises or on the public grid, we used 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, 2023). 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).

C.3 Home Charging Installation Cost

Our partner company cooperated with a utility company to provide employees with subsidized home charging stations. The utility had a modular pricing schedule. More complex installations, e.g., in underground parking, needed to pay for an inspection prior to the installation to check whether installing a home charger would be feasible. Depending on the complexity of the installation (defined by the length of the electrical cable needed and the number of walls through which these cables needed to go), the employees were offered one of two prices for installation. The subsidy provided by the company was capped at €2,750, 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 out of their own pocket. Furthermore, the subsidy for the home charger installation was subject to a flat income tax rate of 25%.

C.4 Abatement Cost

We calculate the abatement cost assuming that the company paid the full subsidy to all employees and that this covered the full installation cost. The installation cost of the home charger is thus covered by a subsidy of €2,750. To obtain abatement cost, we use a 20-year horizon, which should correspond to the useful lifetime of the home charger, 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 lifetime of the home charger. Aggregating over the useful lifetime, 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 of the levelized abatement cost.

Table C.1: CO_2 Emission Factors and Energy Prices

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

D Derivations for Cost-Benefit Analysis

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

To build some intuition and introduce notation, we first consider a one-off decision for vehicle adoption (a four-year lease) where employee i decides on vehicle type $k \in \{ICEV, PHEV, BEV\}$ given her treatment status $D_i \in \{0,1\}$ ($D_i = 1$ for treated individuals). Treatment status D_i and vehicle type k jointly determine the outcomes CO_2 emissions $E_i^k(D_i)$ and corporate 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 $Y_i(D_i) = \sum_k \theta_i^k(D_i)Y_i^k(D_i)$, where θ_i^k is an indicator for whether employee i adopts vehicle type k. Using this notation, we can define the ATT as:

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

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

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

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

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

We assume that vehicle choice θ_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 that 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 rewrite:

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

By definition, the CO_2 emissions of ICEVs and BEVs (under the assumption of a binding cap of the EU ETS) and the energy costs of ICEVs are not affected by the treatment status. Furthermore, we did not find significant differences in the energy costs of BEVs for treated and untreated employees (see Table 3). Thus, we can simplify our notation: $Y_i^k(1) = Y_i^k(0) = Y_i^k \,\forall\, i,\, k \in \{BEV,\, ICEV\}, Y \in \{E,\, C\}$. This implies that we can rewrite the ATT as:

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

Adding a "smart zero" yields:

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

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

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

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 during the lifetime of the home charger, implying $\mathbf{E}(\Delta\theta_i^{PHEV}) + \mathbf{E}(\Delta\theta_i^{ICEV}) + \mathbf{E}(\Delta\theta_i^{BEV}) = 0$. Second, we assume that among the employees selecting into the home charger program, employees who currently hold a PHEV or a BEV will never choose an ICEV again, even without access to home charging. Together, these assumptions imply that $\mathbf{E}(\Delta\theta_i^{ICEV}) = 0$ and $\mathbf{E}(\Delta\theta_i^{PHEV}) = -\mathbf{E}(\Delta\theta_i^{BEV})$, and we can rewrite the ATT:

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

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 $\mathbf{E}(\Delta Y_i^{PHEV})$ and $\mathbf{E}(\Delta\theta_i^{BEV})$ for our sample of employees who initially hold a PHEV and select into the home charger program. We estimate $\mathbf{E}(E_i^{PHEV}(0))$, $\mathbf{E}(C_i^{PHEV}(0))$ and $\mathbf{E}(C_i^{BEV})$ using the corresponding sample averages among not-yet-treated PHEV or BEV owners. Furthermore, $E_i^{BEV} = 0$ by assumption.

D.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:

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

where t denotes the time period (e.g., $t = 1$ is the first four-year period 2020 - 2023) and γ_Y^t is a factor for the respective outcome Y in period t that simultaneously aggregates over the four-year periods considered and discounts to the year 2020, when the investment decision was made. We work with an annual discount rate of 3% 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 (we relax the latter assumption on energy prices later on). The ATT then simplifies to:

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

Estimating the ATT over time thus requires an estimate of the share of employees holding a PHEV in each period t, $\mathbf{E}(\theta_{it}^{PHEV}(1))$. The vector

$$\mathbf{E}(\theta_{it}(D_i)) = \left(\mathbf{E}(\theta_{it}^{\text{ICEV}}(D_i)), \mathbf{E}(\theta_{it}^{\text{ICEV}}(D_i)), \mathbf{E}(\theta_{it}^{\text{ICEV}}(D_i))\right)'$$

denotes the share of employees holding a certain vehicle type in period t, given treatment status D_i. We assume that it follows a Markov process starting from an initial distribution of vehicle types θ_{i0}, and evolves as $\mathbf{E}(\theta_{it}(D_i)) = \mathbf{E}(\theta_{it-1}(D_i)\Theta_{it}(D_i))$ where $\mathbf{E}(\Theta_i(D_i))$ is a transition matrix. Since the treatment was found to affect the vehicle choice probabilities, this transition matrix depends on the employees' treatment status and can be written as follows:

$$\mathbf{E}(\Theta_{it}(D_i)) = \begin{pmatrix} \mathbf{E}(\theta_{it}^{ICEV}(D_i)|ICEV) & \mathbf{E}(\theta_{it}^{ICEV}(D_i)|PHEV) & \mathbf{E}(\theta_{it}^{ICEV}(D_i)|BEV) \\ \mathbf{E}(\theta_{it}^{PHEV}(D_i)|ICEV) & \mathbf{E}(\theta_{it}^{PHEV}(D_i)|PHEV) & \mathbf{E}(\theta_{it}^{PHEV}(D_i)|BEV) \\ \mathbf{E}(\theta_{it}^{BEV}(D_i)|ICEV) & \mathbf{E}(\theta_{it}^{BEV}(D_i)|PHEV) & \mathbf{E}(\theta_{it}^{BEV}(D_i)|BEV) \end{pmatrix} \tag{D.11}$$

where, e.g., $\mathbf{E}(\theta_{it}^{ICEV}(D_i)|ICEV)$ is the probability of individual i adopting an ICEV in time period t, conditional on holding an ICEV in the previous period and under treatment status D_i. We assume that the transition matrix is constant over time. Given our interest in the ATT, we need an estimate of the transition matrix for both treated and untreated employees $\mathbf{E}(\Theta_i(D_i))$.

Note that $\mathbf{E}(\Delta\theta_{it})$ still has a time index, since it depends on the constant period-treatment effect and on the difference in the share of EVs arising from the different accumulation of EVs up to time period T:

$$\mathbf{E}(\Delta\theta_{iT}) = \left(\left(\mathbf{E}(\Theta_i(1))^{T-1} - \mathbf{E}(\Theta_i(0))^{T-1}\right)\theta_{i,0}\right)$$

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:

$$\mathbf{E}(\Theta_i(D_i)) = \begin{pmatrix} \mathbf{E}(\theta_i^{ICEV}(D_i)|ICEV) & 0 & 0 \\ \mathbf{E}(\theta_i^{PHEV}(D_i)|ICEV) & \mathbf{E}(\theta_i^{PHEV}(D_i)|PHEV) & \mathbf{E}(\theta_i^{PHEV}(D_i)|BEV) \\ \mathbf{E}(\theta_i^{BEV}(D_i)|ICEV) & \mathbf{E}(\theta_i^{BEV}(D_i)|PHEV) & \mathbf{E}(\theta_i^{BEV}(D_i)|BEV) \end{pmatrix} \tag{D.12}$$

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:

$$\mathbf{E}(\Theta_i(D_i)) = \begin{pmatrix} \mathbf{E}(\theta_i^{PHEV}(D_i)|PHEV) & \mathbf{E}(\theta_i^{PHEV}(D_i)|BEV) \\ \mathbf{E}(\theta_i^{BEV}(D_i)|PHEV) & \mathbf{E}(\theta_i^{BEV}(D_i)|BEV) \end{pmatrix} \tag{D.13}$$

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:

$$\mathbf{E}(\Theta_i(1)) = \mathbf{E}(\Theta_i(0)) + \mathbf{E}(\Delta\Theta_i) \tag{D.14}$$

Based on our estimated treatment effects on vehicle choice from Table 4, we obtain an estimate for $\mathbf{E}(\Delta\theta_i^{BEV}|PHEV) = -\mathbf{E}(\Delta\theta_i^{PHEV}|PHEV)$ 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:

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

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

Table D.1 lists all the coefficients and parameters needed for the cost-benefit analysis.

Table D.1: Coefficients and Parameters for the Cost-Benefit Analysis

Parameter	Source
Panel A: Estimated ATTs	
$\mathbf{E}(\Delta\theta_i^{BEV}) = 0.283$	Table 4
$\mathbf{E}(\Delta E_i^{PHEV}) = -237.12$ kg CO_2 per quarter	Table 2
$\mathbf{E}(\Delta C_i^{PHEV}) = -102.52$ € per quarter	Table 2
$\mathbf{E}(\Delta C_i^{BEV}) = 0$ € per quarter	Table 3
Panel B: Observed Population Averages	
$\mathbf{E}(E_i^{PHEV}(0)) = 646.17$ kg CO_2 per quarter	Table 1
$\mathbf{E}(C_i^{PHEV}(0)) = 342.75$ € per quarter	Table 1
$\mathbf{E}(C_i^{BEV}) = 63.40$ € per quarter	Table E.2
Panel C: Parameter Assumptions	
$\mathbf{E}(\theta_{i1}^{PHEV}(0), \theta_{i1}^{BEV}(0), \theta_{i1}^{ICEV}(0)) = (1, 0, 0)$	Starting from PHEV users
$\mathbf{E}(E_i^{BEV}) = 0$	Assumption given EU ETS Cap
$\gamma_C^t = \sum_{y=1}^{4}(1.03)^y$	Ad hoc
$\gamma_E^t = 4$	Ad hoc
$\mathbf{E}(\Theta_i(D_i))$	See scenarios

E Additional Graphs and Tables

Table E.1: Summary Statistics

Variable	Mean	Sd	Min	Pctl. 25	Median	Pctl. 75	Max
Panel A: Driving Behavior after Home Charger Adoption							
Mileage [km]	5092	2794	25	3023	4643	6691	18122
Emissions [gCO_2]	492	368	3.93	252	393	631	3764
Tailpipe Emissions [gCO_2]	305	377	0.257	57.1	166	412	3722
Fuel [l]	126	155	0.0951	23.8	69.2	169	1560
Charge at home [kWh]	362	307	0	119	311	519	2504
Charge at firm [kWh]	30	71	0	0	3.64	30.9	1203
Charge at public [kWh]	21.8	64.4	0	0	0	16.4	986
Fuel consumption [l/100 km]	2.37	2.21	0.00587	0.696	1.74	3.31	14
Electricity consumption [kWh/100 km]	9	6.29	0	3.97	8.09	13.2	37.3
Energy Expenditures [EURO]	351	281	2.83	170	271	450	3029
Panel B: Vehicle Characteristics							
Price [Euro]	32542	4488	0	30802	32474	35290	49631
Weight [kg]	2017	262	1480	1840	2025	2105	2655
Fuel Consumption [l/100 km WLTP]	1.58	0.341	0.8	1.4	1.4	1.7	2.9
Electricity Consumption [kWh/100 km WLTP]	17.5	3.17	13.3	15.3	16.2	18.7	24.2
Panel C: Employee Characteristics							
Age [Years]	48.2	-					
Tenure [Years]	17.4	-					
Female [%]	0.156	-					

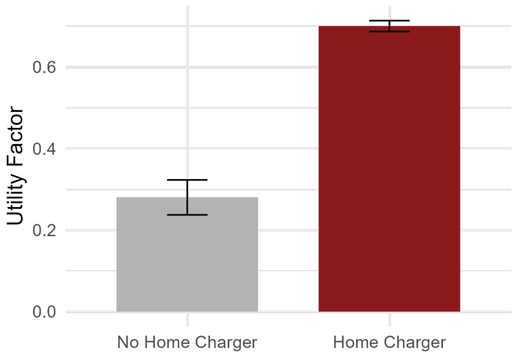
Notes: Descriptive statistics on the sample of employees and their PHEVs, respectively, in the home charger program between January 2021 and December 2022 (N = 856 employees). Panel A shows summary statistics for vehicle use after the employee has received access to home charging. This reduces the size of the sample to N = 752 employees since we exclude the last-treated group receiving acces to home charging in Q4/2022. Panel B displays vehicle characteristics obtained from the General German Automobile Club's car catalog. Panel C displays employee characteristics. Note that each employee is assigned the average characteristics of the group simultaneously adopting a home charger. WLTP stands for "Worldwide Harmonized Light Vehicles Test Procedure".

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

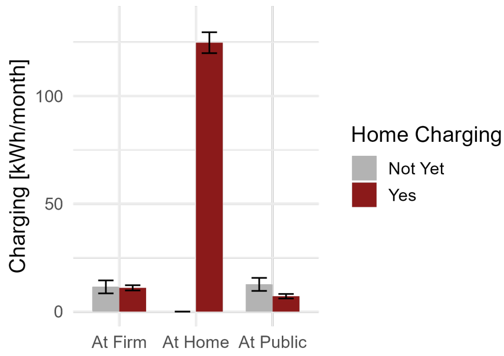
Variable	Home Charger Mean	Home Charger Sd	No Home Charger Mean	No Home Charger Sd
Panel A: Vehicle Use in 2020				
Emissions [kgCO2]	94.89	(105.5)	93.06	(99.56)
Electricity per quarter [kWh]	247.75	(275.46)	242.97	(259.96)
Energy expenditures [Euro]	63.40	(87.42)	65.30	(90.68)
Panel B: Vehicle Characteristics				
Price [Euro]	32642.92	(11468.1)	31268.43	(12404.58)
Weight [kg]	1980.91	(349.8)	1901.06	(330.25)
Electricity consumption [kWh/100 km WLTP]	15.62	(2.11)	15.43	(2.51)
Panel C: Employee Characteristics				
Age [years]	48.34	-	43.19	-
Tenure [years]	17.54	-	12.89	-
Female [%]	0.16	-	0.24	-

Notes: Comparison of the sample of employees holding BEVs and 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".

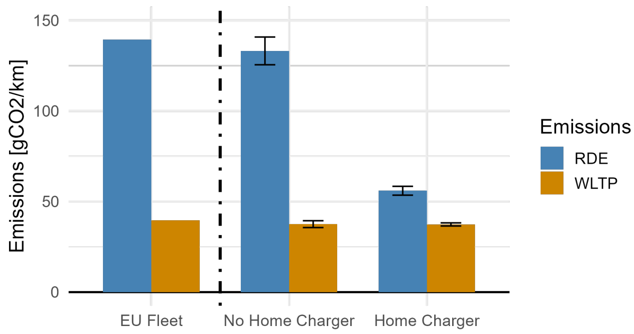
Figure E.1: Average Differences In Electric Utilization Between Treated and Not-yet-treated Employees in 2022 (Post COVID-19)



(a) Utility Factor



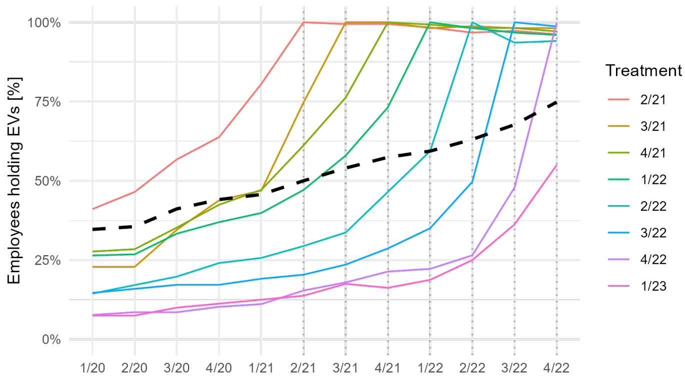
(b) Charging by Source



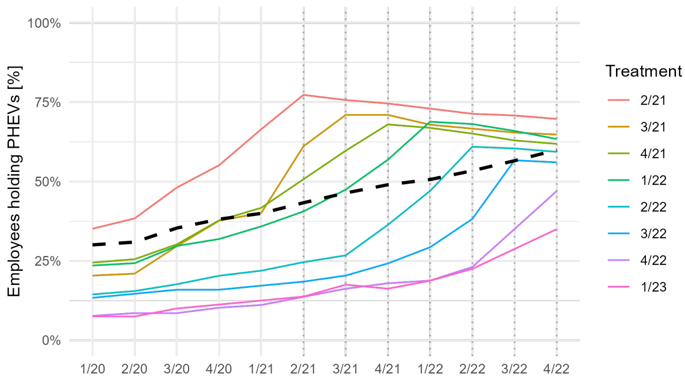
(c) Emissions Per Kilometer

Notes: Based on transaction data for the year 2022. Utility factors are calculated based on the observed on-road fuel consumption and the vehicle's fuel consumption in charge-sustaining mode in the NEDC testing procedure. For details on the calculation, see Appendix B. 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. "WLTP" are vehicle CO_2 emissions per kilometer, according to WLTP type approval tests. "RDE" are real-world driving emissions. "EU Fleet" are vehicle emissions for the entire fleet of vehicles in Europe which already report real-driving emissions over the air, numbers based on Commission Report COM (2024) 122. 95% confidence intervals are indicated, where possible.

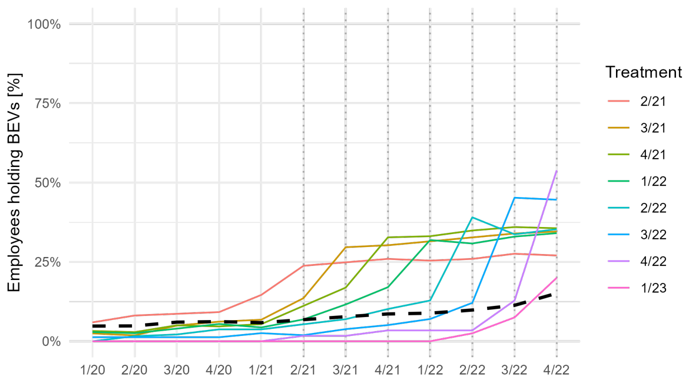
Figure E.2: Vehicle Adoption Across Treatment Groups



(a) EVs



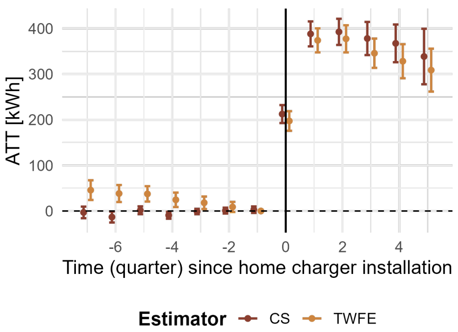
(b) PHEVs



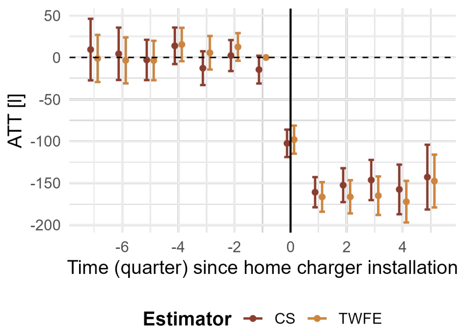
(c) BEVs

Notes: Share of employees in a treatment group holding a company car of the type indicated in the sub-caption. "Treatment" indicates groups of employees receiving access to home charging in the indicated quarter. X-axis label indicates quarter/year. EVs are BEVs plus PHEVs. In the treatment quarter, the share of employees holding EVs must be 100%. Based on 1,442 participants in the home charger program. Dashed black line indicates the share of the corresponding vehicle type among 5,498 employees holding an EV company car at some point during the sample period.

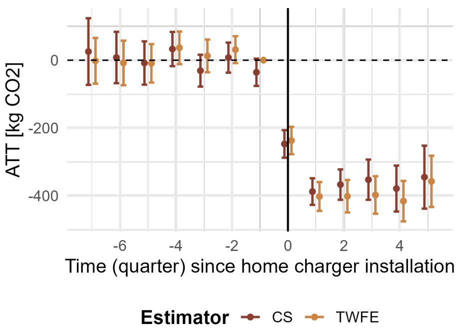
Figure E.3: Event Studies Comparing TWFE and Callaway & Sant'Anna (2021)



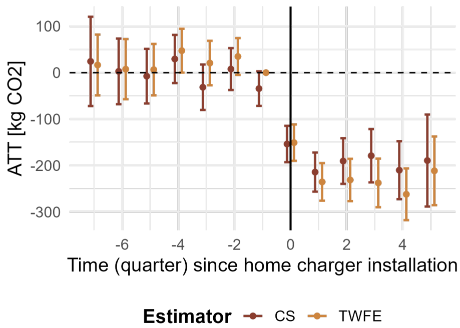
(a) Electricity in kWh



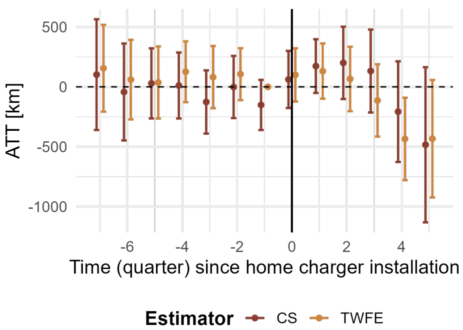
(b) Fuel in Liters



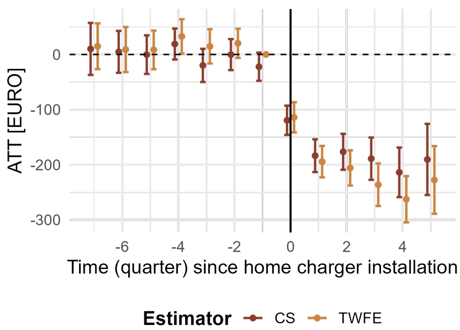
(c) CO_2 Emissions (EU ETS Cap)



(d) CO_2 Emissions (No EU ETS Cap)



(e) Kilometers Traveled



(f) Company Energy Expenditures

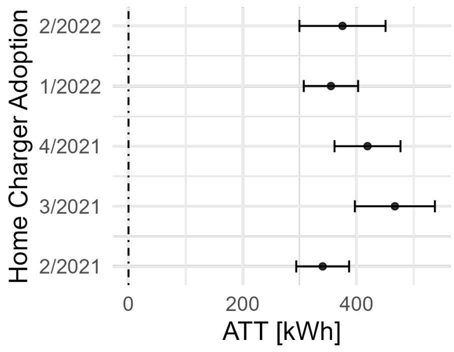
Notes: CS indicates that estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021) as specified in Equation (3) is used. TWFE indicates that the two-way fixed-effects event-study regression in Equation (5) is estimated. Never-treated employees with a PHEV are used as the control group. All outcomes are computed as described in the notes to Figures 3 - 5. The analysis is clustered at the employee level. 95% confidence intervals are indicated (for CS: bootstrapped standard errors, 1,000 draws).

Table E.3: ATT based on Never-treated Units as Controls across Different Outcomes

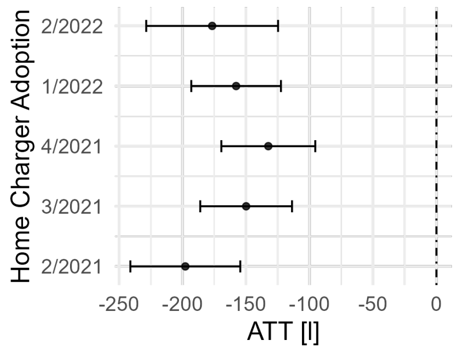
	Energy		Mileage	Emissions		Cost
	Electricity [kWh]	Fuel [l]	Mileage [km]	No EU ETS Cap [kg CO2]	EU ETS Cap [kg CO2]	Energy [Euro]
Treated	318.46***	-137.98***	35.93	-187.91***	-332.14***	-171.68***
	(10.74)	(7.69)	(103.3)	(20.24)	(21.03)	(13.17)
Employees	3551	3551	3551	3551	3551	3551
Groups	6	6	6	6	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: Estimator θ^{O}_{sel} from Callaway & Sant'Anna (2021) as in Equation 2. Never-treated employees not selecting into home charger program are used as the control group. "Groups" are groups of employees receiving home charging in the same quarter. "Periods" are quarters. "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 C.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). The analysis is clustered at the level of the participating employee. Standard errors in parentheses (bootstrapped, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

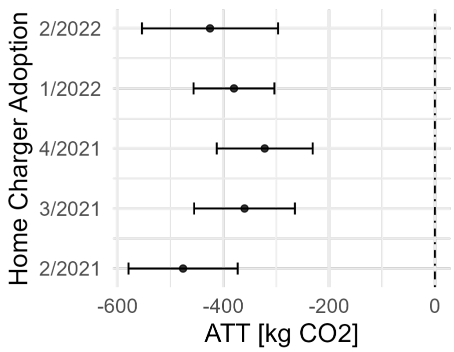
Figure E.4: Group-Specific ATT in the First Quarter After Home Charger Adoption



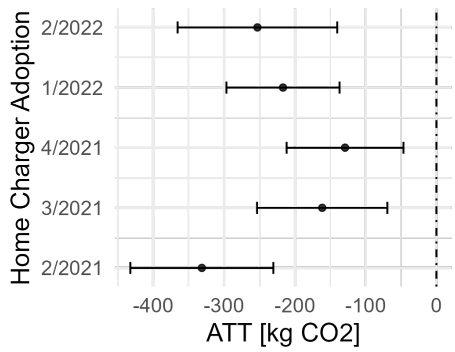
(a) Electricity in kWh



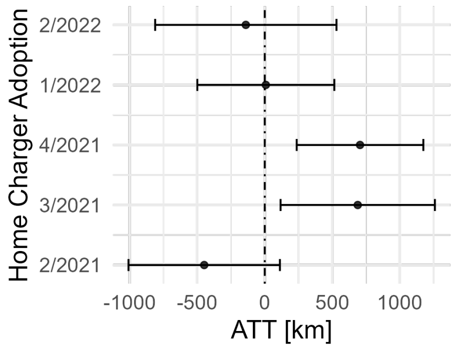
(b) Fuel in Liters



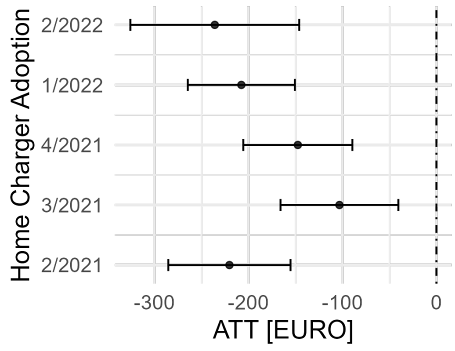
(c) CO_2 Emissions (EU ETS Cap)



(d) CO_2 Emissions (No EU ETS Cap)



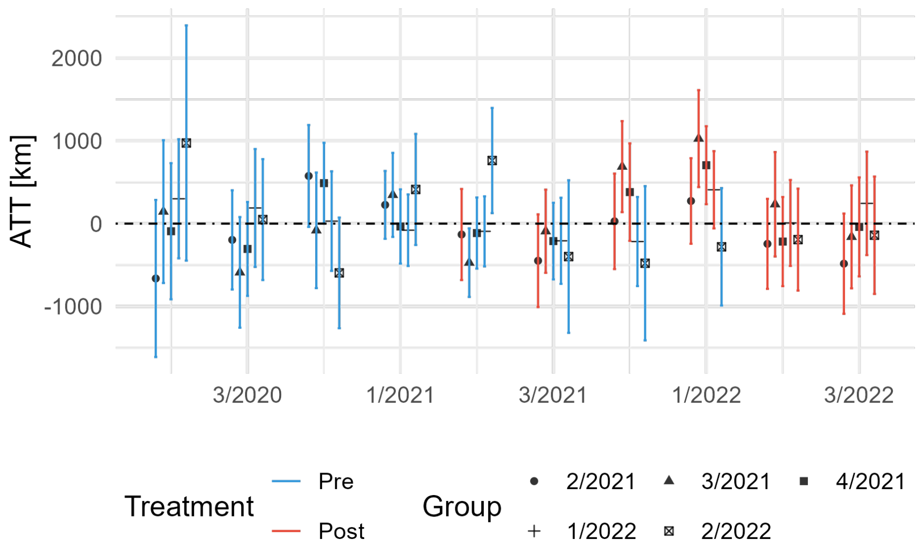
(e) Kilometers Traveled



(f) Company Energy Expenditures

Notes: Group-specific ATTs for the first quarter after the installation of the home charger using the doubly-robust estimator by Callaway & Sant'Anna (2021). "Home Charger Adoption" indicates the quarter in which the corresponding group received access to home charging. Never-treated employees with a PHEV are used as the control group. All outcomes are computed as described in the notes to Figures 3 - 5. The analysis is clustered at the employee level. 95% confidence intervals are indicated (bootstrapped standard errors, 1000 draws).

Figure E.5: Group-Specific ATT on Kilometers Traveled Over Time



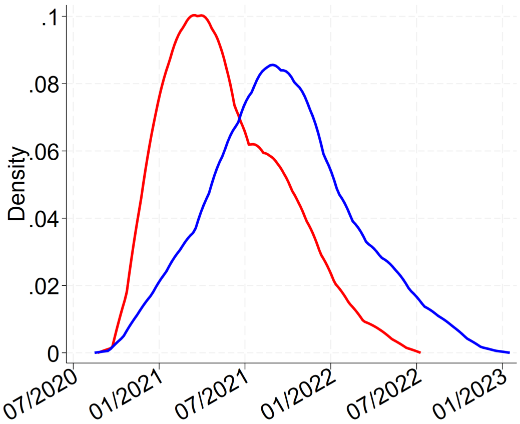
Notes: Group-specific ATTs after the installation of the home charger using the doubly-robust estimator by Callaway & Sant'Anna (2021). "Group" indicates the quarter in which the corresponding group received access to home charging. "Treatment" indicates that this group has received access to home charging. Never-treated units (employees holding a PHEV but not selecting into the home charger program) are used as the control group. All outcomes are computed as described in notes to Figures 3 - 5. The analysis is clustered at the level of the participating employee. 95% confidence intervals are indicated (bootstrapped standard errors, 1000 draws).

Table E.4: Home Charger Adoption in 2021 vs. 2022

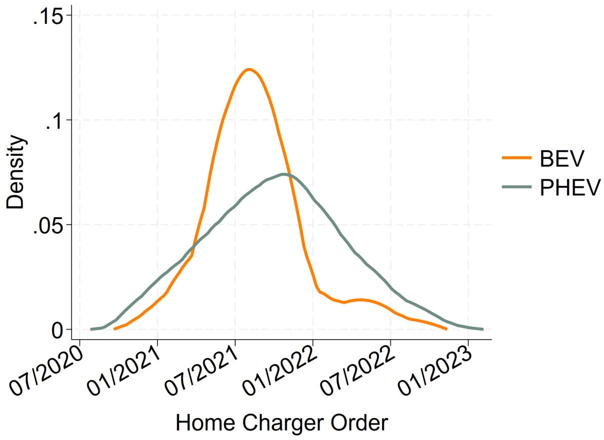
	Adoption in 2021		Adoption in 2022	
Variable	Mean	Sd	Mean	Sd
Panel A: Vehicle Use in Year before Home Charger Adoption				
Mileage per quarter [km]	3976.09	(2589.93)	4870.94	(3038.39)
Emissions [kgCO_2]	581.91	(503.46)	731.03	(582.55)
Tailpipe Emissions [kgCO_2]	562.12	(511.44)	703.28	(590.11)
Electricity per quarter [kWh]	48.29	(82.38)	63.55	(111.81)
Fuel per quarter [l]	232.39	(211.96)	291.36	(244.66)
Fuel consumption [l/100 km]	5.59	(3.15)	5.89	(2.94)
Electricity consumption [kWh/100 km]	1.62	(2.91)	1.50	(2.64)
Utility factor [km elec./km total]	0.30	(0.38)	0.25	(0.37)
Energy expenditures [Euro]	349.81	(303.56)	505.91	(411.44)
Panel B: Vehicle Characteristics				
Fuel efficiency [l/100 km WLTP]	1.60	(0.32)	1.56	(0.36)
Electric efficiency [kWh/100 km WLTP]	17.36	(3.05)	17.61	(3.26)
Price [Euro]	32590.58	(4682.52)	32494.10	(4293.65)
Weight [kg]	2005.93	(249.2)	2029.16	(275.19)
Panel C: Employee Characteristics				
Age [years]	48.24	-	48.25	-
Tenure [years]	18.07	-	16.79	-
Female [%]	0.15	-	0.16	-

Notes: Comparison of the sample of employees receiving access to home charging in 2021 (N = 426 employees) to the group of employees receiving access to home charging in 2022 (N = 430 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 before home charger adoption. This implies that employees adopting the home charger in 2021 are observed in 2020 and employees adopting the home charger in 2022 are observed in 2021. The sample sizes are reduced to N = 333 and N = 333 employees, respectively. 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 E.6: Selection Into Early Home Charger Orders Among Employees Ordering BEVs



(a) Treatment Assignment



(b) Vehicle Choice (Control Group)

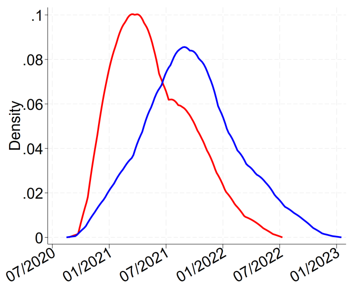
Notes: Panel (a) displays the kernel density of home charger orders over time for 157 program participants who had to order a new company car between Oct. 2020 and Mar. 2023. "Treated" indicates that the employee received the home charger before the end of their previous vehicle's lease. "Control" is the opposite case. Panel (b) displays the kernel density of home charger orders over time for the 108 participants in the control group. "BEV"/"PHEV" indicates that the employee ordered a BEV/PHEV as their next vehicle. Kernel density estimator *kdens* in Stata (Jann, 2005), using an Epanechnikov-kernel with the upper-bound optimal bandwidth by Salgado-Ugarte et al. (1996).

Table E.5: Balance Company Car Order Before vs. After Access to Home Charging

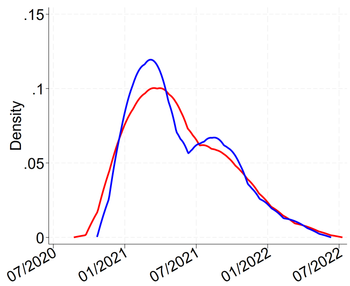
	Std. Mean Difference		Variance Ratio	
	Raw	Matched	Raw	Matched
Order Month	-.96	-.01	.66	.99
Electricity [kWh]	.096	-.03	.70	.57
Fuel [l]	-.26	.19	1.08	1.31

Notes: Balance table for the estimator in Equation (4) for the ATT of access to home charging on the propensity to order a BEV company car instead of a PHEV company car. Sample: employees selecting into the home charger program whose PHEV-lease ended between Oct. 2020 and Mar. 2023. “Std. Mean Difference” displays the standardized difference in means between treatment and control group. “Variance Ratio” displays the ratio of the corresponding variances in the treatment and the control group. Columns “Raw” correspond to the sample before matching. “Matched” corresponds to the matched control group and the original treatment group. Order month is the month (count since Jan. 2020) in which the home charger was ordered. Electricity [kWh] is the average amount of electricity charged per month before access to home charging, with a previously held PHEV company car. Fuel [l] is the corresponding amount of fuel combusted. Nearest-neighbor matching: 1 nearest neighbor for all treated units. Covariates included in the matching: order month of the home charger and categorical variable for the average amount of electricity charged with the previously held PHEV before home charger adoption (categories: not charged, $<$ 50 kWh/month, $\geq$ 50 kWh/month). Standard errors reported are the heteroskedasticity-robust standard errors from Abadie & Imbens (2011). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

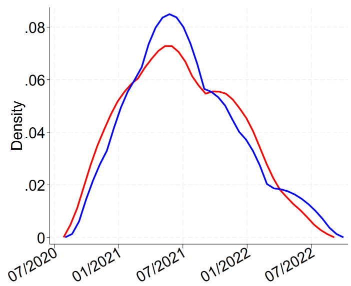
Figure E.7: Kernel Density Plots Before and After Matching



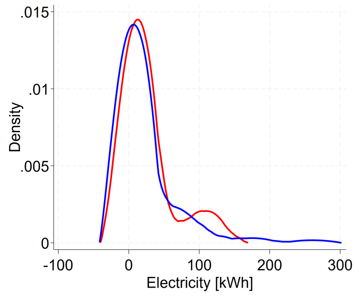
(a) Charger Order,
Before Matching



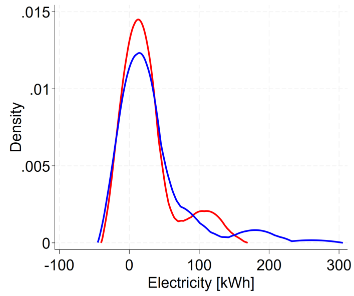
(b) Charger Order,
After Matching



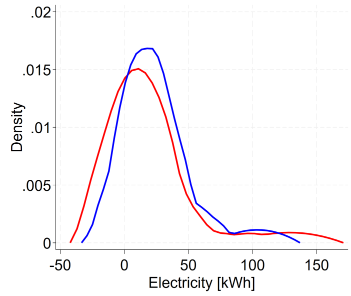
(c) Charger Order,
Order Gap $\leq$ 7 Months



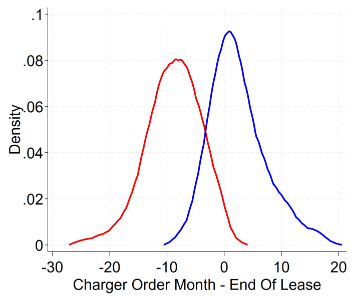
(d) Electricity Consumed,
Before Matching



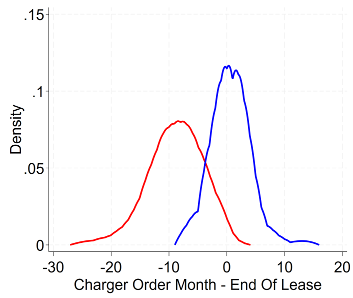
(e) Electricity Consumed,
After Matching



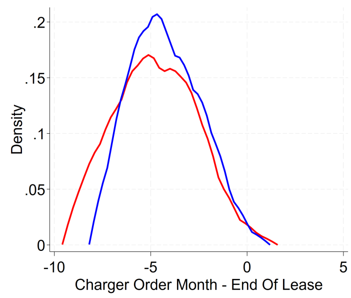
(f) Electricity Consumed,
Order Gap $\leq$ 7 Months



(g) Order Gap,
Before Match



(h) Order Gap,
After Match

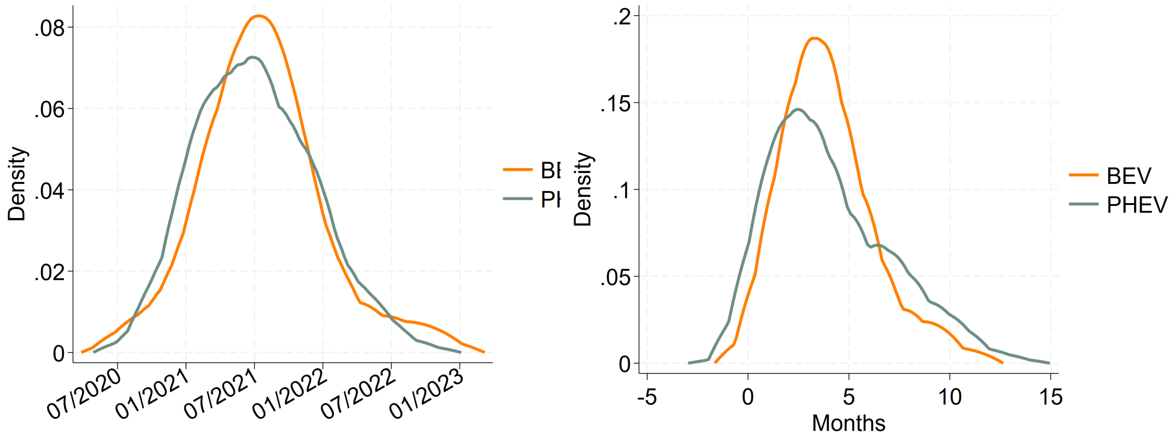


(i) Order Gap,
Order Gap $\leq$ 7 Months

Treated
Control

Notes: Before Matching: 157 program participants who had to order a new company car between Oct. 2020 and Mar. 2023. "Treated" indicates that the employee received the home charger before the end of their previous vehicle's lease. "Control" is the opposite case. After Matching: 49 treated employees and their nearest neighbors (corresponding to 49 observations after assigning equal weights summing to one to ties). Panels (a) and (b) display the kernel density of home charger orders over time. Panels (c) and (d) display the kernel density of electricity consumption with the previous vehicle in an average month. Panels (e) and (f) display the kernel density of fuel consumption with the previous vehicle in an average month. Kernel density estimator *kdens* in Stata (Jann, 2005). Kernel density estimated using an Epanechnikov-kernel and the upper-bound optimal bandwidth by Salgado-Ugarte et al. (1996).

Figure E.8: No Selection Into Order Dates and Waiting Times



(a) End of Previous Lease (b) Waiting Time for Home Charger

Notes: Sample includes 108 program participants who had to order a new company car between Oct. 2020 and Mar. 2023 and did not yet have access to home charging when ordering a new car. "BEV"/"PHEV" indicates that the type of company car ordered by the employee. Panel (a) displays the kernel density of the previous vehicle's end of lease dates for these employees. Panel (b) displays the kernel density of the waiting time between the order and the delivery date of the home charger. Kernel density estimator *kdens* in Stata (Jann, 2005). Kernel density estimated using an Epanechnikov-kernel and the upper-bound optimal bandwidth by Salgado-Ugarte et al. (1996).

F Sensitivity Analysis on Vehicle Kilometers

As mentioned in Appendix B, we performed 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 as in Appendix B, 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. Based on fuel and electricity consumption data, we show that access to home charging reduces the vehicle's fuel consumption while increasing its electricity consumption. 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 downward. In specification (ii) we use the vehicle's fuel consumption in charge-sustaining mode in the NEDC testing procedure. We know that NEDC testing procedures tend to be overly optimistic about the electric driving share of PHEVs. Adjusting the value to display consumption in charge-sustaining mode, we try to correct for this bias. Nevertheless, we trust the imputation in the baseline specification more.

Table F.1 displays the results of the sensitivity analysis. In the first panel, we see that extrapolating 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. We find that the differences are very small in the specifications accounting for electricity consumption. The weaker effect on vehicle mileage in the "Fuel Only" specification translates into a weaker reduction in average fuel consumption per 100 km and a weaker increase in the electric driving share compared to the "Baseline" specification.

The sensitivity analysis shows that even under an extrapolation scheme that imposes a negative bias on the number of kilometers traveled (column 2), the average fuel consumption per 100 km is reduced and the electric driving share is increased substantially. However, the comparison between the baseline extrapolation and the extrapolation based on the vehicle's fuel and electricity consumption from NEDC test values (column 3) 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. This is reassuring given the proven inaccuracy of the NEDC testing values we used to clean the mileage variable.

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

	Baseline	Fuel Only	Efficiencies
	Mileage [km]		
Treated	671.13***	117.08	669.72***
	(228.16)	(284.92)	(232.33)
	Fuel [l/100km]		
Treated	-2.53***	-1.83***	-2.58***
	(0.22)	(0.18)	(0.22)
	Utility Factor		
Treated	0.33***	0.24***	0.34***
	(0.03)	(0.02)	(0.03)
Employees	856	856	856
Groups	6	6	6
Periods	11	11	11
Employee FE	X	X	X
Time FE	X	X	X

Notes: Estimator θ^{O}_{sel} from (Callaway & Sant'Anna, 2021) as in Equation (2). 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 transform fuel consumption into kilometers traveled. The analysis is clustered at the level of the participating employee. Standard errors in parentheses (bootstrapped, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G Sensitivity Analysis on Future Energy Prices

The treatment effects reported in Section 3.2 are estimated during the sample period from January 2020 until September 2022. Extrapolating into the future to obtain estimates of the abatement cost of the home charger over its useful life relies on the assumption that the energy prices observed during that period are representative of the next 20 years. In this section, we provide a sensitivity analysis to show that working with changing energy prices for electricity and fossil fuels does not change our results much. To this end we combine estimated treatment effects on energy cost for fuel and electricity -shown in Table G.1, along with quantity outcomes reproduced from the main results in Table 2- with alternative assumptions about future developments in energy and carbon prices. We maintain all other assumptions as in the baseline scenario and consider the following three energy price scenarios.

Scenario A1: Changes in the Relative Price of Fuel and Electricity We assume that the relative prices of fuel and electricity change over time, due to carbon prices levied on electricity and fuel as well as due to a growing share of renewable energy sources in German electricity generation. We calibrate electricity price changes relative to 2020-23 using a projection for future wholesale electricity prices in Germany (Kreidelmeier & Wuensch, 2023). To be precise, we linearly interpolate between three nodes provided in the projection to obtain average electricity prices in the four-year periods 2024-27, 2028-31, 2032-35, and 2036-39: Electricity prices in 2024 (€128/mWh), 2030 (€76/mWh) and 2050 (€59/mWh). For 2020-23, we obtain annual electricity prices on the spot market from Schwenke & Troost (2024). Dividing the four-year averages (and interpolated averages) by the average price during 2020-23, we obtain a growth factor for electricity prices, which we use to extrapolate our treatment effect into future periods.

This extrapolation relies on the assumption that household and industry electricity prices as well as electricity prices at public charging stations are driven by the underlying wholesale electricity price. The relative prices across the three charging options (at home, at public stations, and in the firm's premises) are assumed to be constant over time. We also assume that the electricity prices observed during our sample period are representative of the period 2020-23 (i.e., the first period in our simulations).

We apply a similar procedure to extrapolate fuel prices, assuming that future increases in fuel prices in Germany are driven only by an increase in carbon prices under the European Emission Trading System 2 (EU ETS 2) and not by the relatively volatile oil prices on the world market.[29] Data on the current level of the national carbon price in these sectors are obtained from Bundesministerium der Justiz (2019) and Emissionshaendler.com (nd). For a projection of future prices under the EU ETS 2, we rely on the baseline scenario of Graichen & Ludig (2024). In this scenario, the EU ETS 2 price will increase to €84 in 2030. We use this projection and the mandated carbon price in Germany for 2025 (€55) to linearly extrapolate carbon prices for the years 2025-39. This series, combined with the observed carbon prices up to 2025, is used to obtain average prices over the four-year periods used in our simulation.

To compute a fuel price path relative to the 2020-23 average, we first obtain the average fuel price without carbon pricing during that period and then add projected

[29] The EU ETS 2 will replace a national carbon price in Germany that covers sectors not covered under the EU ETS 1, such as buildings and road transport.

carbon prices. Next, we divide by the average price during the period 2020-23 to calculate fuel price growth factors. We use these growth factors to extrapolate the treatment effect on fuel costs to future periods.

Adding up the estimates for future treatment effects on fuel and electricity expenditures estimates, we obtain a time-series of treatment effects on the total energy cost given our assumptions on the relative price development of fuel and electricity.

Scenario A2: Lower Future Fuel and Electricity Prices Our sample period coincides with a period of extraordinarily high energy prices in Europe, as a consequence of the Russian invasion of Ukraine in February 2022 and the resulting embargoes on Russian oil and gas. Given the approach outlined in scenario A1, we consider that fuel and electricity prices in the sample period are higher than the average prices in the period 2020-23. To take this into account, we rescale our price paths in scenario A1 as follows: Instead of considering prices relative to the average of the four-year period 2020-23, we now consider prices relative to their 2022 levels. We do so because the average fuel price obtained by dividing the effects of the treatment on fuel expenditures by the effect on fuel consumption in Table G.1 implies a fuel price of €1.97, which is closest to the prices of 2022.

Scenario A3: Lower Future Fuel Prices Unlike fuel prices, electricity prices are relatively rigid. Household electricity prices in Germany are often fixed by long-term contracts, implying that the shock to wholesale electricity prices does not immediately translate into shocks for retail prices paid by consumers. Similarly, large industrial electricity consumers can sign long-term purchasing power agreements, which would stabilize electricity prices. This is not true for fuel prices, which tend to respond immediately to changes in the oil price. To take this into account, we consider in this scenario electricity price changes relative to the period 2020-23 and fuel prices relative to their 2022 levels.

Table G.2 summarizes the relative price paths for all three scenarios and Figure G.1 plots how they affect abatement costs. Since the emission profiles are exactly the same as in the baseline scenario, only the abatement cost is reported. One can see that changes in the relative price of electricity and gasoline do not change our results much. This is driven by a pre-existing price differential between gasoline and electricity that largely outweighs changes in future prices for both energy sources. To see this, one can calculate the average price per kWh (€0.28) and liter of fuel (€1.97) implied by the treatment effects in Table G.1. From Table 1, we see that the average employee with access to home charging consumes 5.8 liters of fuel per 100 km. If she drove in electric mode, her vehicle would consume 17.5 kWh per 100 km. These numbers imply a price difference of 133%, which is large compared to any price change over time in all scenarios.

Table G.1: ATT on Energy Consumption and Expenditures By Source

	Energy	Electricity		Fuel	
	Energy [Euro]	Electricity [kWh]	Electricity [Euro]	Fuel [l]	Fuel [Euro]
Treated	-102.52***	317.9***	90.03***	-97.97***	-192.55***
	(31.43)	(11.87)	(3.88)	(18.6)	(32.01)
Employees	856	856	856	856	856
Groups	6	6	6	6	6
Periods	11	11	11	11	11
Employee FE	X	X	X	X	X
Time FE	X	X	X	X	X

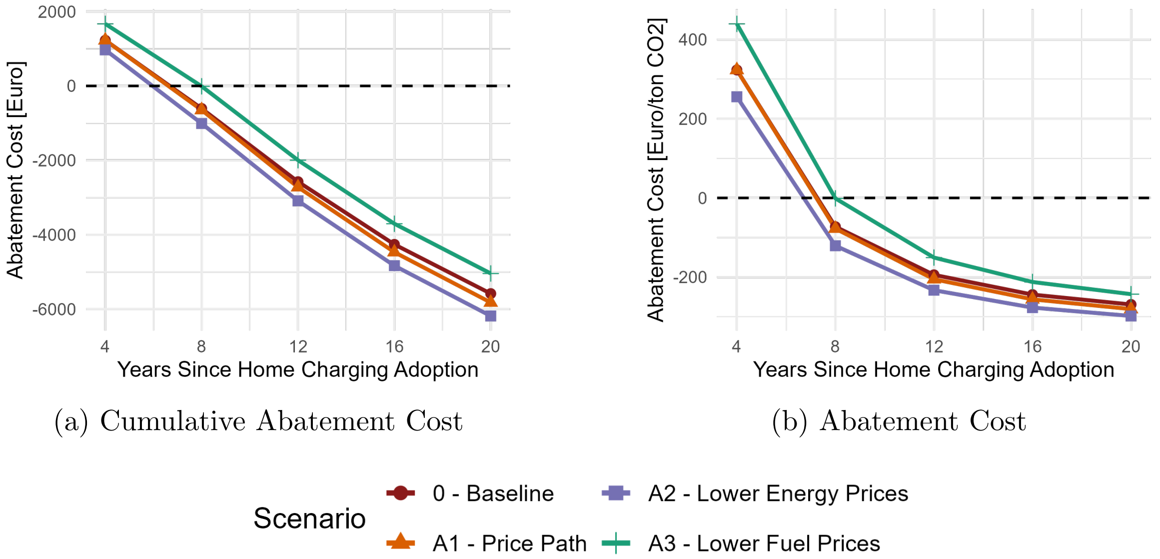
Notes: Estimator θ^{O}_{sel} from (Callaway & Sant'Anna, 2021) as in Equation 2. "Energy" corresponds to electricity, diesel and gasoline. "Fuel" corresponds to both diesel and gasoline. "Groups" are groups of employees receiving home charging in the same quarter. "Periods" are quarters. The analysis is clustered at the level of the participating employee. Standard errors in parentheses (bootstrapped, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table G.2: Period-ATTs Relative to Estimated ATTs [%]

	Baseline		Scenario A1		Scenario A2		Scenario A3	
Period	**Fuel**	**Electr.**	**Fuel**	**Electr.**	**Fuel**	**Electr.**	**Fuel**	**Electr.**
2020 - 2023	100	100	100	100	84.6	47.8	84.6	100
2024 - 2027	100	100	103.5	100.5	87.5	48	87.5	100.5
2028 - 2031	100	100	107.2	72	90.6	34.4	90.6	72
2032 - 2035	100	100	110.3	63.8	93.3	30.4	93.3	63.8
2036 - 2039	100	100	113.6	60.8	96.1	29.1	96.1	60.8

Notes: Price path relative to reference period, as described in scenarios Baseline and A1 - A3. Electricity price path is obtained by dividing the projection for the average wholesale electricity price in the period by the reference point corresponding to the scenario. Fuel price path is obtained by adding the predicted carbon price to the average gasoline price in Germany in the period 2020 - 2023, before the carbon tax. Percentages are obtained by dividing that price by the average carbon tax-inclusive gasoline price during the reference period of the corresponding scenario.

Figure G.1: Simulation of Cumulative Treatment Effects over Time, Incorporating Changes in Energy Prices



(a) Cumulative Abatement Cost

(b) Abatement Cost

Notes: Estimates for the dynamic ATT, aggregating treatment effects on PHEV and BEV use and BEV adoption under different assumptions for PHEV and BEV diffusion (cf. Appendix D). Scenario 0 is the baseline scenario. In scenario A1, projections for the future development of electricity prices and carbon prices for gasoline are considered. In scenario A2, we assume our estimates were affected by high energy prices during 2022. We adjust by scaling the estimated treatment effects on fuel and electricity using the ratio between i) the fuel price implied by the treatment effects in Table G.1 and ii) the wholesale electricity price in 2022 and the corresponding prices over the period 2020 - 2023, based on the sources indicated in Table C.1. In scenario A3, we adjust only the fuel price in that way.

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