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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 almost quintuples electricity consumption: Total charging increases by 318 kWh per quarter while fuel consumption falls by 98 liters, reducing tailpipe CO_2 emissions by 38%. Moreover, access to home charging doubles the employee's propensity to choose a Battery Electric Vehicle (BEV) upon renewal of the lease. Based on these estimates we compute the private levelized abatement costs of home chargers for a range of scenarios characterizing the diffusion of BEVs and the evolution of tax-inclusive energy prices over a 20-year horizon. Home chargers break even within twelve years, saving on average 13 tons of CO_2 over a 20-year lifetime at negative levelized cost.

Keywords: charging infrastructure, plug-in hybrid and battery electric vehicles, electric driving share, technology adoption, company cars, marginal emissions

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 a PHEV can drive its specific emissions to zero, provided that the vehicle is charged with electricity from renewable sources or from fossil power plants that are 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). Thus, encouraging more electric driving of PHEVs is 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 because there is a strong stated pref-

[1] This is true for Europe but not necessarily in other parts of the world. Holland et al. (2016) show that electric driving tended to reduce CO_2 emissions in most US counties (using marginal emissions). Holland et al. (2022) demonstrate that, in spite of falling average CO_2 emissions in the US electricity sector, marginal emissions increased between 2010 and 2019, making electric vehicles less attractive as an abatement option.

[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.

erence 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 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. Thus, participants 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 350 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 more than 260,000 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 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 access to home charging infrastructure dramatically increased total charging. Quarterly electricity consumption of treated PHEVs increased by 318 kWh—almost quintupling from a baseline of 66 kWh—while consumption of gasoline or diesel dropped by 98 liters. This 38%-reduction in fuel consumption saved tailpipe emissions on the order of 237 kg of CO_2 per quarter, in spite of a 15%-increase in VKT per quarter (a potential rebound effect which, however, is not robust but vanishes in various specifications). This decrease in tailpipe emissions corresponds to a 1:1 decrease in total emissions under the regulatory cap of the European Union's Emissions Trading System (EU ETS). The cap is important yet not critical for overall emissions abatement. We quantify incremental electricity-sector emissions due to increased charging using econometrically estimated hourly marginal emissions factors in the German electricity grid. If such incremental emissions were not offset by reductions elsewhere under the EU ETS cap, the decrease in total emissions still amounted to one-third of the reduction in tailpipe emissions. Among BEV holders, home chargers increased quarterly electricity consumption by 35% (183 kWh). Corporate energy costs for PHEVs decreased significantly by €103 per quarter as electricity was cheaper than fossil fuel. Energy costs for BEVs did not change because increases in charging volume were offset by inframarginal cost savings from substituting cheap electricity at home for expensive electricity at public charging points.

Providing employees with access to home charging increased the likelihood of ordering a BEV as the next company car by 28 percentage points. 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 EU ETS, which—notwithstanding the intricacies of the Market Stability Rule (cf. Borghesi et al., 2023)—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 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.

With these estimated treatment effects at hand, we analyze the net present value of the home charger program for the firm. We find that the program is a cost-effective way to abate between six and 16 tons of CO_2 emissions over a 20-year horizon for the average employee in our sample, depending on the scenario. We quantify total abatement and energy expenditures using plausible assumptions about BEV diffusion among untreated employees and varying the strength of the program's estimated impact on BEV adoption among treated employees. In scenarios that allow for the program's effect on vehicle choice, installation of the home charger pays off for the company within twelve years. For lifespans longer than this, home chargers deliver substantial financial benefits on top of emissions abatement. In scenarios that abstract from the program's effect on vehicle choice, the levelized cost per ton of CO_2 abated remains negative as long as a sufficient fraction of employees keeps driving a PHEV company car.

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 former 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. (2026) 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., 2026). Our paper builds on 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 at the driver level that could easily confound estimates in non-experimental settings.

The other strand of literature related to this paper focuses on EV adoption. It provides strong evidence for a positive effect of EV purchase subsidies (Beresteanu & Li, 2011; Xing et al., 2021; Springel, 2021; Muehlegger & Rapson, 2022; He et al., 2023; Fournel, 2024; Remmy, 2025), 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; Li, 2023; Remmy, 2025). 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). The ability to charge at home has been a strong predictor of consumer interest in PHEVs since their early days, in some studies 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. Interestingly, Burlig et al. (2021) find that even EVs with access to home charging are driven surprisingly little, which suggests that there are other barriers to electric driving. These barriers could be exacerbated by a lack of access to convenient 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 the external validity of our results, and Section 6 concludes with policy implications of our results.

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. They can be used for business-related but also for private trips, while both purchase and operating costs for the car, including expenditure on fuel, are often covered by the employer.

All employees in our sample participate in such a fuel cost compensation scheme and are allowed to use their company cars privately. To the employee, all monetary costs of holding a company car are comprised in a fixed monthly deduction from their salary. This deduction is a function of the price of the car, government and company subsidies for different vehicle types, dealer discounts, and the distance between the home and the workplace of the employee. Its principal components are income taxes on the non-cash benefit received and a payment to the employer. Importantly, the cost of holding a company car is not affected by the employee's driving behavior.[4] Employees must choose a company car with a gross price that fits the budget associated with their career level. Higher subsidies and favorable tax rules for EV company cars imply that, for a given budget, employees end up paying less for a BEV or PHEV company car than for a company car with an internal combustion engine (ICEV), and less for a BEV than for a PHEV.

Eligible employees at our partner firm can choose a company car from a large set of makes and models. Despite monetary incentives for the adoption of EVs, ICEVs continued to be the most popular choice in 2022, followed by PHEVs and BEVs. EVs can be charged at public charging points and in company parking lots, at no extra cost to employees. 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

[4]See Appendix A for additional details on the monetary cost of holding a company car and for more background on the German company car scheme.

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 home charging by PHEV and BEV holders, the company introduced a program that subsidizes the installation cost of a home charger with a standard capacity of 11 kW (up to 22 kW could be installed) and automatically reimburses expenses for the electricity consumed by it. The program was rolled out in January 2021 and continued beyond the end of our sample period in November 2022. It is open to all employees who (i) drive a PHEV or BEV company car (or have ordered one) and (ii) participate in the company's fuel cost compensation scheme, which already included charging at public charging stations and on the company's premises.[6] Therefore, the program participants do not face any change in the monetary incentives for electric charging. Nevertheless, program participation creates monetary benefits and costs for the employee. The company fully reimburses installation costs up to €2,750, which is sufficiently generous to cover the cost of purchasing and installing a home charger in a standard configuration.[7] This constitutes a financial benefit as the employee owns the company-financed home charger. On the cost side, the installation subsidy is subject to income taxation,[8] and employees need to pay any costs in excess of the maximum subsidy out of their own pocket. Important for our study design is that these monetary consequences are independent of the employees' vehicle choice and driving behavior.

Several features of the application and installation process resulted in the 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 the applications and forwarded them in batches to the company that installed the home chargers. Second, during our sample period, supply-side frictions in the aftermath of the COVID-19 pandemic caused delays 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

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

[6] As of 2021, the company had installed at least 1 charging station per 10 EV company cars in Germany on its premises.

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

[8] The reimbursement of electricity costs is tax-free, since fuel and electricity cost compensation for company cars is already covered by income taxes paid for the company car. See Appendix A for details on the taxation of company cars.

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

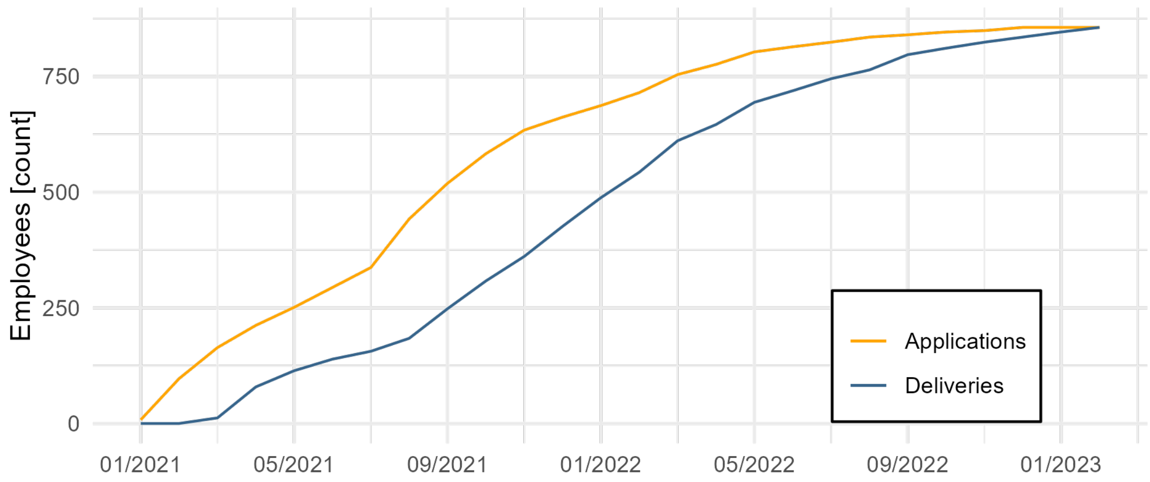
The setting described above suggests employing a generalized Difference-in-Differences (DiD) estimator to study the effects of installing home chargers. The traditional approach would implement a two-way fixed-effects estimator based on the equation

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

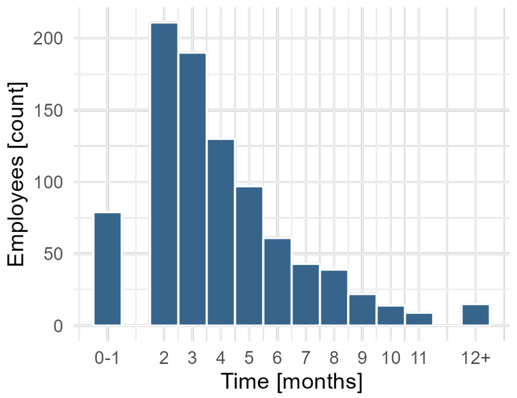
where the variable Y_{it} measures relevant outcome variables of employee i in period (quarter) t, G_i denotes the quarter in which the home charger becomes available to employee i, and η_i and μ_t are employee and quarter fixed effects (and ϵ_{it} is the error term). Since this estimator may be biased under heterogeneous 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 estimator proposed by Callaway & Sant'Anna (2021) and use a control group of not-yet-treated program participants who receive a home charger at a later point in time.[9] These estimates are aggregated up to the overall ATT of home charger adoption, θ^O_{sel} (as in the notation of Callaway

[9]Since we rely on an unconditional parallel-trends assumption, that is, the potential outcomes are assumed to evolve in parallel even before conditioning on pre-treatment covariates, the three estimators (outcome-regression, inverse probability weighting and doubly-robust) proposed by Callaway & Sant'Anna (2021) collapse to the same unconditional Difference-in-Differences estimator.

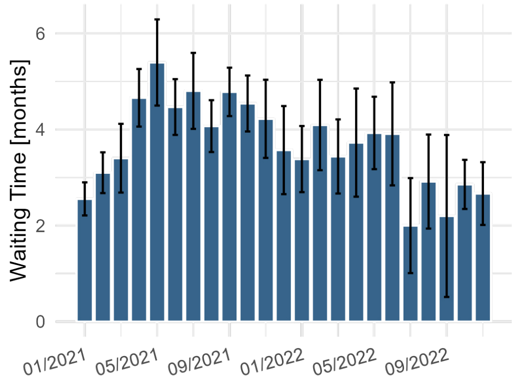
Figure 1: Home Charger Applications and Distribution of Waiting Times



(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.

& Sant'Anna, 2021), 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 ($t = 1, \dots, T$), 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, $\theta_{es}(e)$, 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.[10] 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 (except for VKT) across treatment groups (in terms of the $ATT(g, g+1)$) in Appendix Figure E.6.[11]

2.3 Sample and Data

Sample Composition Our analysis considers all home charger applications between January 2021 and November 2022. We separate the transaction data on refueling and electric charging events for PHEV and BEV holders.[12] Since all charging and refueling transactions are automatically recorded, the raw data needed little cleaning (cf. Appendix B).

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

[11] Appendix Figure E.7 suggests that the heterogeneity for VKT (panel (e), Appendix Figure E.6) arises over time rather than across treatment groups.

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

For PHEVs, we also 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 VKT between two odometer readings are plausible. We start with transaction data for 1,011 PHEVs held by 922 employees in the period January 2020 to September 2022 (some employees renewed their lease during the sample period and got a different car, hence more cars than employees). We 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. From this sample, we drop 43 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 (7,010 out of 30,819 mileage observations had to be corrected, cf. Appendix B for details). In this cleaning step, we drop 32 cars with less than two feasible odometer readings that are needed to calculate VKT. We also drop two cars without a single day with non-zero energy consumption (fossil fuels and electricity, these can occur due to erroneous transactions that were corrected within the day) and three 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 0.5th percentile or exceeded the 99.5th percentile. The last step removes three additional vehicles for which all mileage outcomes were deemed implausible.

After cleaning, our analysis samples comprise 928 PHEVs held by 856 employees and 362 BEVs held by 350 employees, respectively. We observe 223,595 refueling and charging transactions for the PHEVs and 38,973 charging transactions for the BEVs. We aggregate these transactions to quarterly observations for two reasons. First, the estimator we use performs well only when treatment cohorts are sufficiently large (Callaway & Sant'Anna, 2021; Callaway & Sant'Anna, 2025), which is no longer given for a monthly aggregation of the BEV-sample.[13] Second, aggregating to weekly or monthly observations would result in noisy VKT estimates since many PHEVs are refueled 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 analyze the program's effects on the use and adoption of BEVs in Sections 3.3 and 3.4, respectively.

[13]For information on the distribution of cohort sizes in the sample of BEV-drivers in a monthly vs. a quarterly aggregation, see Appendix Table E.5.

Data Transaction data from January 2020 (one year before the start of the program) to September 2022 include the date and time of refueling or recharging, the amount of energy (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). To calculate energy expenditures, we use the annual national average prices for gasoline, diesel, and electricity charged on firm premises or at public charging stations. For charging at home, we observe the contractual price per kWh.

We estimate CO_2 emissions based on the observed energy consumption using different approaches. For fossil fuels combusted on the road (gasoline and diesel), we use time-constant emission factors published by the German Environment Agency (Juhrich, 2022; Icha & Lauf, 2022). Appendix Table C.2 summarizes the assumptions made on emission factors and energy prices. For electricity, we must consider the CO_2 emissions caused by one additional kWh demanded in the German electricity grid at the time of charging. We consider two scenarios for this. In the first scenario, a reduction in tailpipe emissions is equal to the reduction in total emissions. This is justified to the extent that the EU ETS puts a binding cap on electricity-sector emissions. In the second scenario, we use the emissions of the marginal power plant at the time of charging. The emissions intensity of this marginal plant varies substantially across hours of the day, mainly due to variation in demand and availability of renewable energy. Not accounting for such variation could bias our estimates because charging at home occurs mostly later in the day, when employees return home, whereas charging at the firm's premises often occurs in the morning (see Appendix Figure E.2). To account for temporal variation in the emissions intensity of electricity generation, we estimate marginal emission factors (MEFs) for electricity using a modified version of the approach taken in Borenstein & Bushnell (2022).[14] We allow emission factors to vary by hour-of-day, weekend-vs-weekday and by season (winter vs. summer) to account for systematic differences in which power plant is marginal at a given point in time.[15] Furthermore, the approach by Borenstein & Bushnell (2022) allows us to estimate MEFs for the electricity consumed (instead of the electricity generated) in Germany, taking into account electricity imports and controlling for exports. Doing so is important because electricity imports accounted for 14% of residual load in Germany in the analysis period (Bundesnetzagentur, 2023).

Table 1 summarizes driving and charging outcomes, vehicle attributes, as well as

[14]Details on the estimation of MEFs for the German electricity grid can be found in Appendix C.1.

[15]These differences matter. We find that, e.g., natural gas-fired power plants tend to be marginal in peak-load hours in summer, while coal-fired power plants can be marginal during off-peak hours in winter, implying different MEFs.

employee characteristics in the PHEV analysis sample (discussed below), in the last quarter prior to the adoption of a home charger. For additional summary statistics on our sample, we refer the interested reader to Appendix Tables E.2 and E.3.

Selection into Treatment Employees who applied for the home charger program differ systematically from those who drove a PHEV but did not apply during the analysis period (cf. Appendix Table E.1). Of more than 2,500 employees who held a PHEV during that period, 856 participated in the program. Even before adopting a home charger, program applicants have 2% higher mileage per quarter, use 9% less fuel and 24% more electricity than non-applicants. Given these differences, a naïve estimate based on never-takers of the home charger might yield biased results.

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. We shall discuss the external validity of our results in Section 5 below.

Among program participants, further 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 as pre-determined leasing cycles and their effect on program eligibility imply that employees cannot easily select into early treatment.[16] Comparing the driving behavior of early vs. late adopters in Table 1, we find that 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 quarter prior to program participation, and in terms of employee and vehicle characteristics. However, significant differences exist in terms of their total energy expenditures. We believe that this is caused by changes in energy prices and in individual mobility demand over time, in particular 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 assumption, which we assess via inspection of pre-trends in Figures 3–5 below.

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.[17]

[16]Employees can, however, select into deferring the order of their home charger. A robustness test presented in Section 3.5 shows that controlling for this selection channel does not change our main results, but it does result in noisier estimates. We thus work with the population of not-yet-treated program participants as the control group in our main specification.

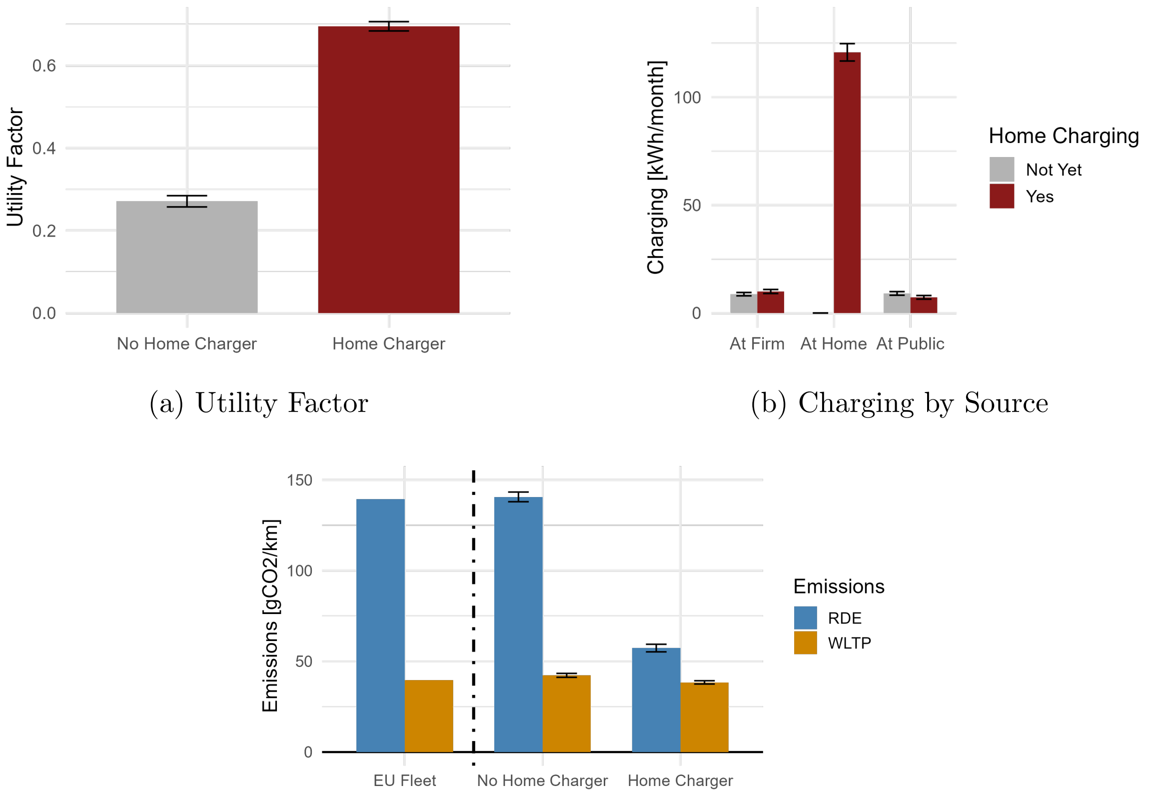
[17]The COVID-19 pandemic may have distorted transportation behavior in 2020 and 2021. In Appendix Figure E.1 we only use data for the year 2022 which was only partially affected by the pandemic. We find very similar results.

Table 1: Home Charger Adoption in 2021 vs. 2022

Variable	Adoption in 2021 Mean	Sd	Adoption in 2022 Mean	Sd	p-value
Panel A: Vehicle Use in Year before Home Charger Adoption					
Mileage per quarter [km]	4331.97	(2681.04)	4636.29	(2989.98)	0.13
Emissions [kg CO_2]	620.46	(516.14)	678.68	(556.51)	0.13
Tailpipe Emissions [kg CO_2]	592.78	(527.44)	640.66	(566.46)	0.21
Electricity per quarter [kWh]	57.33	(97.1)	73.86	(125.37)	0.06
Fuel per quarter [l]	245.11	(217.42)	265.56	(234.77)	0.20
Fuel consumption [l/100 km]	5.48	(2.88)	5.62	(3.02)	0.56
Electricity consumption [kWh/100 km]	1.69	(3.13)	1.94	(3.2)	0.34
Utility factor [km elec. /km total]	0.31	(0.35)	0.28	(0.39)	0.28
Energy expenditures [Euro]	400.56	(331.96)	492.36	(422.36)	0.00
Panel B: Vehicle Characteristics					
Fuel efficiency [l/100 km WLTP]	1.60	(0.32)	1.56	(0.36)	0.16
Electric efficiency [kWh/100 km WLTP]	17.36	(3.05)	17.61	(3.26)	0.35
Price [Euro]	32590.58	(4682.52)	32494.10	(4293.65)	0.98
Weight [kg]	2005.93	(249.2)	2029.16	(275.19)	0.07
Panel C: Employee Characteristics					
Age [years]	48.24	-	48.25	-	-
Tenure [years]	18.07	-	16.79	-	-
Female [share]	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 last quarter before home charger adoption, comparing employees at different points in time. The sample sizes are reduced to N = 315 and N = 304 employees, respectively. A contemporaneous comparison would only be possible in 2020, however only a selected sample of late-treated employees would already drive a PHEV at that time. Panel B displays vehicle characteristics obtained from the General German Automobile Club's car catalog (Allgemeiner Deutscher Automobil-Club e.V. (ADAC), 2024). Panel C displays employee characteristics, which are only available in terms of group averages. WLTP stands for "Worldwide Harmonized Light-Duty Vehicles Test Procedure". P-value is the p-value of a two-sample t-test for equality of means.

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, defined as the ratio between VKT using electricity and total VKT (Plötz et al., 2021), 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 average amount charged at each source. Both measures compare employees who have already received home chargers ("Home Charger") with employees who selected into the program but have not yet received home chargers ("No Home Charger"). Thus, some employees switch between the two samples as time proceeds. "WLTP" are vehicle CO_2 emissions per kilometer, according to the Worldwide Harmonized Light-Duty Vehicles Test Procedure (WLTP) type-approval tests. "RDE" are real 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.

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 (RDE) and according to the Worldwide Harmonized Light-Duty Vehicles Test Procedure (WLTP). While emissions according to WLTP are very similar across groups, RDE per kilometer drop by about 60% for employees with access to home charging, closing 86% of the gap to official ratings according to WLTP. Before adoption, RDE 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

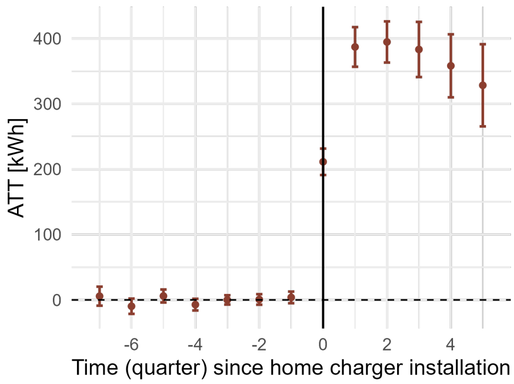
3.1 Treatment Effects by Quarter

Quarterly ATTs for various PHEV outcome variables are plotted in Figures 3–5. 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 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 each month.[18]

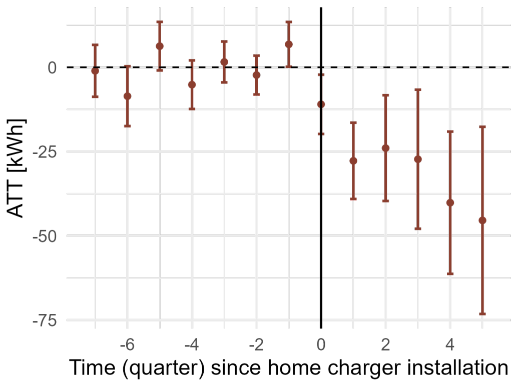
We begin the discussion of the results by considering the margin of charging vs. refueling. Panel (a) of Figure 3 shows that total electricity consumption of PHEVs sharply increased when treated employees received their home charger. The effect size is around 400 kWh per quarter initially and decreases towards 330 kWh in the fourth quarter after adoption. Panel (b) shows that treated subjects reduced 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,

[18]A few employees received the home charger after receiving their PHEV company car (for details, see Appendix Figure E.3). Attrition is low; only 78 out of 1,442 participants in the home charger program drop out of the sample after treatment because they left the firm and returned their company car.

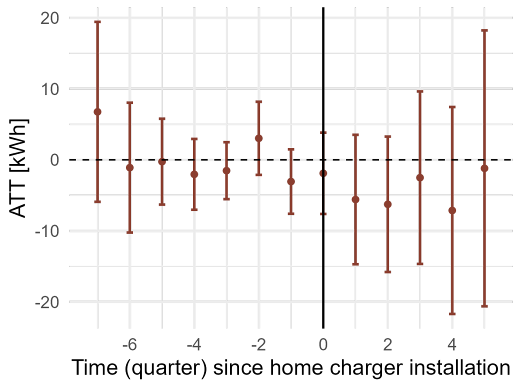
Figure 3: Treatment Effects on Electric Charging



(a) Total Charging



(b) At Public Station



(c) At Firm

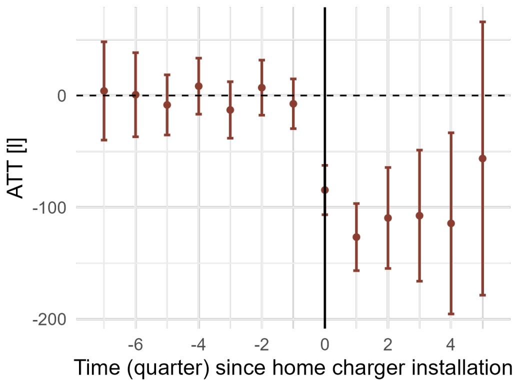
Notes: Estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021) as specified in eq. (3). "Total Charging" is the sum of all kWh charged at home, at public charging stations and at company-owned charging stations on company premises. "At Public Station" and "At Firm" correspond to the kWh charged at 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).

supporting the parallel pre-trends assumption underlying the DiD estimator.

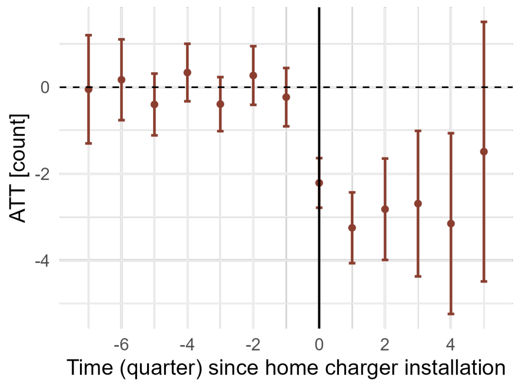
Figure 4 displays outcomes related to fuel consumption and mileage. We observe that the increase in electric charging is accompanied by a drop in fuel consumption (panel a), which is driven by reductions in both the number of refueling transactions per quarter (panel b) and the average amount of fuel 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 between electricity and 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 the increase in electric charging is sustained (see Figure 3a). This

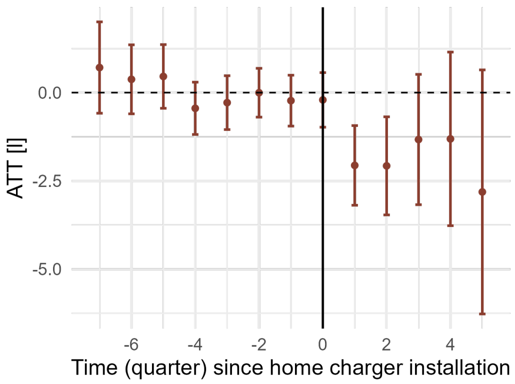
Figure 4: Treatment Effects on Fuel Consumption and Mileage



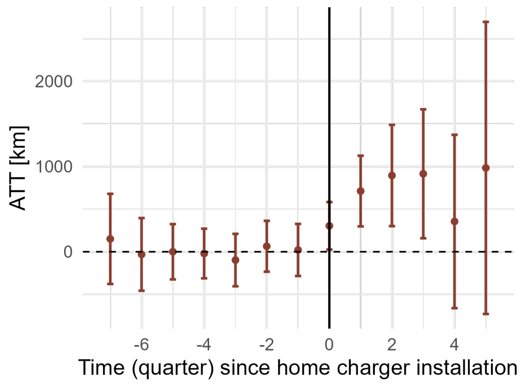
(a) Fuel in Liters



(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 eq. (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).

begs the question of whether treated employees end up driving more. Indeed, panel (d) of Figure 4 shows an increase in quarterly VKT by about 1,000 km, or 20% from 2020 levels.

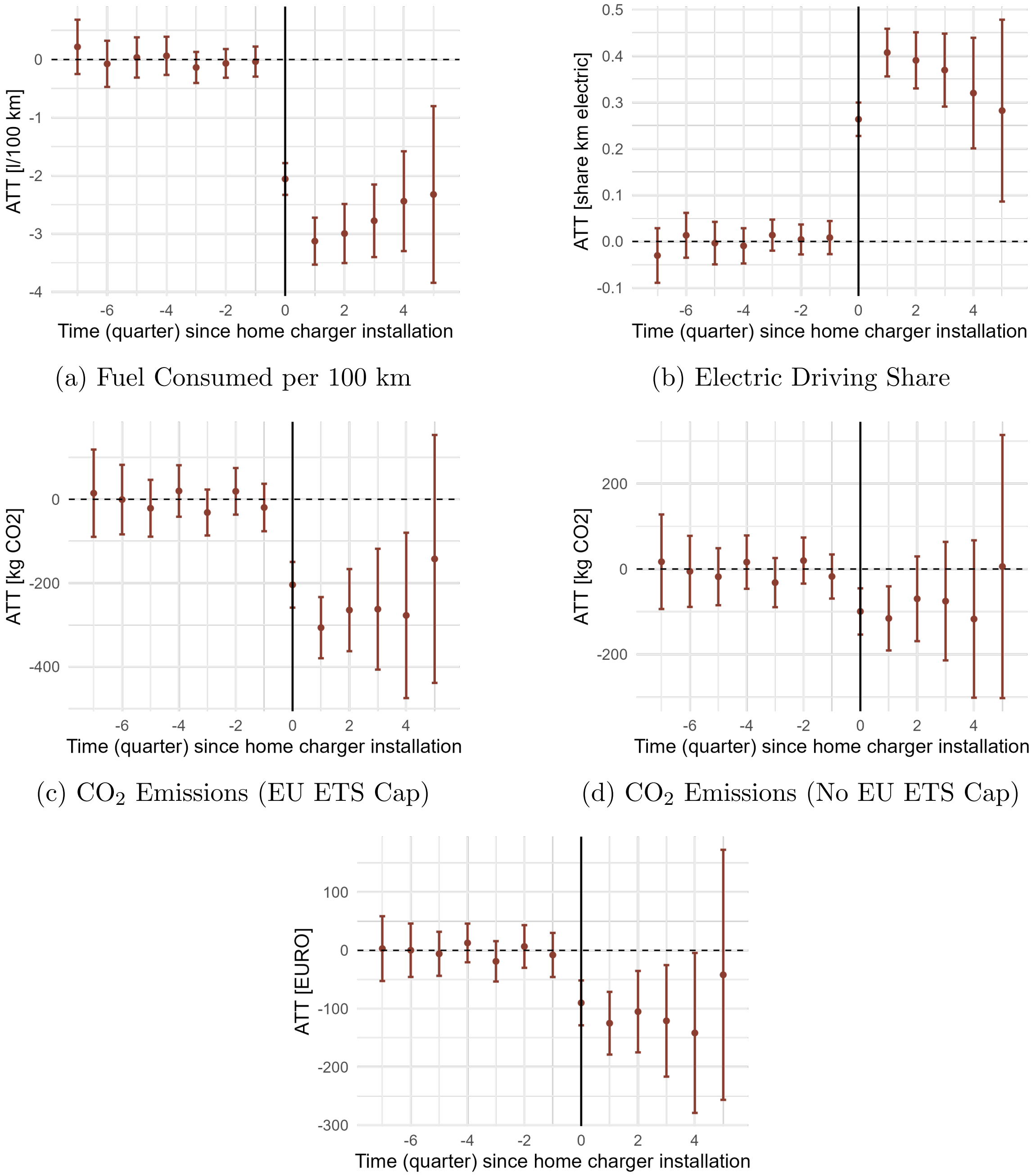
Finally, Figure 5 shows that the treatment reduced the average fuel consumption per 100 km by up to three liters (panel a) as it increased the electric driving share of PHEVs by up to 40 percentage points (pp) (panel b). These effects are very large relative to pre-treatment averages in 2020 (see Table E.1): the average fuel consumption per 100 km drops by more than 50% while the utility factor more than doubles. Given the EU ETS' binding cap on emissions from sectors including electricity generation, 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 short-term marginal CO_2 intensity of electricity consumed in Germany (cf. Appendix C.1). In this scenario, emissions abatement drops to one-third to one-half of the abatement in the other scenario, and is no longer statistically significant in later treatment periods.

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 lowers 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 318 (±23 for the 95% confidence interval) kWh, almost a quintupling from the baseline of 66 kWh. At the same time, it decreased consumption of gasoline or diesel by 98 (±37) liters per quarter (38%). The net effect on emissions is a reduction of 237 (±88) kg of CO_2 under the assumption of non-additional emissions under the EU ETS. Emissions would have fallen by 84 (±83) kg if additional charging had induced higher CO_2 emissions from electricity generation at the marginal short-term emissions intensity of electricity consumed in Germany (cf. Appendix C.1). The adoption of home chargers caused a reduction in energy costs of €103 (±62) for the company, despite an average mileage increase by 671 (±475) km per quarter, which corresponds to 15% of baseline VKT. The increase in VKT is

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 eq. (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 marginal 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***	-83.75**	-237.12***	-102.52***
	(11.87)	(18.6)	(242.28)	(42.09)	(44.62)	(31.43)
Mean (pre-treatment)	66	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

Notes: Estimator θ_{sel}^{O} from Callaway & Sant'Anna (2021) as in eq. (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 marginal CO_2 intensity of the German electricity grid (cf. Appendix C.1). "EU ETS Cap" stands for CO_2 emissions being computed under the assumption that emissions from electricity generation are non-additional given the binding 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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

reminiscent of rebound effects that arise when fuel efficient vehicles are driven more due to lower per-km expenses for fuel (Gillingham et al., 2016).[19] However, since the rebound effect on VKT proves not robust to the bulk of our sensitivity analyses (presented in Section 3.5 below), we caution against a strong interpretation of this result.

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.[20] Table 3 reports the aggregate ATT estimates. We find that home charging increased total electricity consumption by 183 (±158) kWh per quarter, after netting out substantial reductions in charging on the public grid of 249 (±138) kWh and on the firm premises

[19]Since fuel costs are out of the picture, two other channels could rationalize a rebound effect in our setting: First, the home charger lowers the non-monetary cost of driving as it increases convenience and saves time. 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 discussion of moral licensing in an environmental context, see, e.g., Tiefenbeck et al., 2013). Both of 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. If the rebound effect reflects substitution away from other, unobserved modes of transport rather than induced mobility, our estimates can be interpreted as a lower bound on the program's true effect on environmental and financial outcomes.

[20]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 June 2022 (Q2 2022). In Q2 2022, the control group still comprised 23 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	182.7**	-56.24*	-248.58***	90.91**	25.34
	(80.71)	(28.87)	(70.46)	(40.95)	(29.3)
Mean (pre-treatment)	523	112	412	262	190
Employees	350	350	350	350	350
Groups	5	5	5	5	5
Periods	10	10	10	10	10

Notes: Estimator θ^{O}_{sel} from Callaway & Sant'Anna (2021) as in eq. (2). Mean (pre-treatment) is the average of the corresponding outcome variable in the last quarter before home charger adoption (200 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 marginal CO_2 intensity of 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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

by 56 (±57, significant at 10%) kWh. This result suggests that BEVs were driven more once a home charger was installed. Since we do not observe odometer readings for BEVs, we use the average electricity consumption of 15.4 kWh per 100 km (see Table E.4) to estimate the resulting mileage increase at 1,186 km per quarter. Such a rebound effect 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 might also reduce 'range anxiety' among BEV holders, leading them to drive more relative to the control group.

Increased charging hardly raises expenditures because charging at home is cheaper than in the public charging network:[21] The ATT for charging expenditures is statistically insignificant. The effect on total CO_2 emissions is zero under the assumption of 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 91 (±80) kg per quarter.

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

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

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.[22] A naïve estimator comparing adoption propensities among employees with and without access to home charging might hence be biased. We employ 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, 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 N is the number of treated employees and $\mathcal{J}_M(i)$ 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 $M = 1$ 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 being parsimonious on account of the small sample size. 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)–(4) additionally control for the amount of electricity

[22] In line with this, Appendix Figure E.8 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

	Full Sample				$0 \leq$ Gap ≤ 7	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.326***	0.312***	0.340*	0.354	0.284**	0.283
	(0.0946)	(0.101)	(0.206)	(0.245)	(0.131)	(0.227)
Charging	✓		✓			
Order Gap			✓	✓		✓
Employees	157	157	157	157	60	60
Treated Employees	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: ≤ 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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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.[23]

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 (columns 1–4). 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. This effect is large: among employees who had to choose a new vehicle before gathering experience with charging at home, only 29% ordered a BEV, with the remainder choosing a PHEV again.

Consistency of the matching estimator relies on an unconfoundedness assumption which is more plausible when covariates are balanced. Table E.11 and Figure E.9 in the Appendix show that we achieve good balance in terms of the order date of the

[23] We assess other potential confounders by inspecting the data. To examine the influence of time trends, Appendix Figure E.10(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.10(b).

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.9(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.9(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, the small sample size, and the remaining imbalance on the order gap, we also consider a more conservative scenario in which home chargers have no effect on the adoption of BEVs.

3.5 Robustness Checks

We examine the robustness of our results to choosing different control groups, using alternative extrapolation rules when computing mileage from odometer readings, and to using a traditional fixed-effects estimator.

We start with a discussion of using the not-yet-treated employees as a control group. Doing so strengthens the identification argument because employees cannot bring forward the moment they become eligible for ordering a home charger and hence cannot select into treatment. However, once employees are eligible, they do have the ability to select into a later-treated cohort by sufficiently delaying the order of the charger. Appendix Table E.6 shows that such delays are frequent and change the treatment cohort for roughly 46% of participants. While the median employee orders the home charger within six weeks of receiving an EV company car, some employees delay the order substantially (the maximum delay we observe is 93 weeks). Appendix Table E.7 shows that the fraction of eligible employees who decided to enroll in the program remained below 26% throughout the sample period.

To control for potential selection effects, we re-estimate eq. (2) while conditioning on the order cohort. In so doing, we compare only employees who ordered the charger at the same time but experienced wait times until delivery.[24] This leaves us with 580

[24] We ensure overlap between treated and not-yet-treated employees within order cohorts by dropping post-order periods for which fewer than 20 control units remain within the order cohort. In addition, we drop order cohorts for which fewer than 20 units get treated during the reduced sample

employees who ordered their home charger between Q1 2021 and Q4 2021. In contrast to our main specification, we now apply an inverse probability weighting on the home charger order date when estimating the group-by-time specific $ATT(g, t)$.[25] Appendix Table E.8 reports the results of regressions on the reduced sample. We find that all of our main results are robust to this alternative specification except for the effect on mileage. Re-estimating treatment effects within each cohort in isolation confirms the sign of the results obtained in our main specification in Table 2,[26] although many coefficients are estimated imprecisely due to the much smaller sample size.

Another potential concern about using not-yet-treated employees as controls is that the composition of the control group changes for each cohort. To assess whether this could drive our results, we re-estimate the treatment effects using a constant control group of never-treated employees who do not adopt a home charger.[27] As shown by Appendix Table E.9, the overall treatment effects are robust to this, except that there is no increase in VKT. Comparing the effect sizes for fuel and electricity consumption to those reported in Table 2, we see that the VKT rebound leads to smaller estimated fuel savings in the main specification. As an additional robustness test, we remove employees with exceptionally large quarterly VKT (at least one observation exceeding the 97.5th percentile of 11,678 km) and re-estimate our main specification on the reduced sample. The results in Table E.10 display a familiar pattern: all results are robust except for the VKT rebound.

Unlike outcome variables that are readily available from machine-recorded transaction data, we construct VKT from odometer readings that employees self-report each time they pump gas or diesel at a filling station. Since human error might affect this variable more than others, 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.[28] 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 therefore assess the robustness of the rebound effect to different extrapolation

period after applying the previous restriction.

[25]This ensures that we assign positive weight only to those employees in the control group who ordered their home charger at the same point in time as at least one of the treated employees.

[26]The effect on VKT is again the only result that is not robust in the sense that the sign of the effect changes between treatment cohorts. Appendix Figure E.7 shows that this heterogeneity seems to be caused by changes in the effect on VKT over time rather than differences across treatment cohorts.

[27]This is not our choice for the main specification because employees select into home charger adoption and Table E.1 demonstrates that this selection is associated with meaningful differences in driving behavior.

[28]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.

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 both fuel and electricity consumption are used to extrapolate erroneous mileages. We also find that mileage extrapolation based only on fuel consumption leads to attenuation bias in estimated treatment effects on these outcomes, particularly the one for mileage. This is expected since (i) electricity consumption is not accounted for and (ii) the treatment substantially reduced fuel consumption (cf. Figure 4a).

Finally, we assess the robustness of our event studies regarding the choice of estimator. First, we re-estimate our main specification using a universal base period for the pre-treatment event-study coefficients.[29] Appendix Figure E.4 plots the resulting estimates side-by-side. We find that pre-trends are parallel for either choice of base period, supporting internal validity of our empirical strategy. Second, we re-estimate the event studies using never-treated employees as the control group, and compare the estimator by Callaway & Sant'Anna (2021) to the following two-way fixed-effects event-study regression:

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

where the notation follows Section 2.2 and K and L indicate the maximum number of pre-treatment and post-treatment periods possible. Appendix Figure E.5 plots the estimated coefficients, which are, again, very similar across the two alternative specifications. When compared to the main results in Figures 3–5 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 over longer treatment exposures.

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,

[29] Using the estimator by Callaway & Sant'Anna (2021), the researcher can decide whether she wants to compare pre-treatment coefficients to the last period before treatment (the "universal" base period) or to the coefficient one period earlier (the "varying" base period). For a discussion on the choice of base period, see Callaway (2025).

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 approach by Dugoua & Gerarden (2025, 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.[30] We simulate these outcomes under alternative assumptions about employees' vehicle choices, subsumed in scenarios. Each scenario is fully characterized by two outcome vectors and a matrix specifying the choice probabilities of individual i holding car type $k_{it} \in \{ICEV, PHEV, BEV, OO\}$ in period t under treatment status $D_i \in \{0, 1\}$. We abbreviate vehicle fuel types as before, and additionally introduce the outside option OO, which will correspond to leaving the company.[31] The transition matrix is assumed to be constant over time and across individuals and takes the form:

$$\Theta(D_i) = \begin{pmatrix} \theta_{ICEV,ICEV}(D_i) & \theta_{PHEV,ICEV}(D_i) & \theta_{BEV,ICEV}(D_i) & \theta_{OO,ICEV}(D_i) \\ \theta_{ICEV,PHEV}(D_i) & \theta_{PHEV,PHEV}(D_i) & \theta_{BEV,PHEV}(D_i) & \theta_{OO,PHEV}(D_i) \\ \theta_{ICEV,BEV}(D_i) & \theta_{PHEV,BEV}(D_i) & \theta_{BEV,BEV}(D_i) & \theta_{OO,BEV}(D_i) \\ \theta_{ICEV,OO}(D_i) & \theta_{PHEV,OO}(D_i) & \theta_{BEV,OO}(D_i) & \theta_{OO,OO}(D_i) \end{pmatrix} \quad (6)$$

where $\theta_{k,k'}(D_i)$ is again the probability that an employee who currently holds vehicle k will choose k' in the next period under treatment status D_i. 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.

4.1 Scenarios

We break down our analysis into scenarios that consider partial deviations from the following set of maintained assumptions: (1) A fraction of employees will leave the

[30] 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.

[31] Since owning a company car will, under most circumstances, be an extremely attractive option for eligible employees, we assume throughout that employees do not opt out of the company car offer.

company each period, e.g., to retire or work for another employer. Beyond that, there is no exit from holding a company car. (2) All employees choose a new company car (or leave the company) simultaneously in four-year increments. (3) In the absence of home charging, the transition probabilities between vehicle types are summarized in matrix $\Theta(D_i)$.[32] (4) Vehicle choice depends only on the type of company car currently held, and not on the history of previous company cars (i.e., vehicle choice is a Markov-process). (5) Experience with charging at home only affects the propensity with which PHEV-drivers choose a BEV instead of a new PHEV, leaving all other entries in $\Theta(D_i)$ unaffected. (6) Treatment effects are constant over time, i.e., a home charger has the same effect on charging behavior and vehicle adoption in each period. (7) Driving patterns in the absence of access to home charging are reflected in pre-treatment driving behavior, and are constant over time. Vehicle kilometers traveled with ICEVs are assumed to be the same as for PHEVs; the corresponding fuel consumption, CO_2 emissions and fuel expenditures are estimated using the average on-road fuel consumption of all ICEVs newly registered in the EU in 2021 (European Commission, 2024a). (8) Emissions factors are constant over time; energy prices evolve according to a deterministic price path. (9) Due to the binding cap of the EU ETS, increased charging does not generate incremental emissions in the electricity sector. All cost outcomes are expressed in 2020 euros, with future costs being discounted to that year.

We bundle our scenarios into two groups. In the first set of scenarios, we assess whether the program cost-effectively reduces corporate CO_2 emissions, and study the robustness of our conclusion regarding alternative assumptions. In the second set of scenarios, we assume that the program had no effect on vehicle choice and illustrate how the pace of an exogenous transition away from PHEVs affects levelized abatement costs.

Scenario 0: Baseline The baseline scenario maintains all of the above assumptions. Experience with charging at home affects both the use and the adoption probabilities of EVs (BEVs and PHEVs). The overall effect of the home charger program accumulates over 20 years according to the following formula:

$$ATT(Y_{it}) = \sum_{t=1}^{5} \delta_Y^t \left[\gamma_0\, \Theta(1)^{t-1}\, \mathbf{E}(\Delta Y_{it}) + \gamma_0\big(\Theta(1)^{t-1} - \Theta(0)^{t-1}\big)\mathbf{E}(Y_{it}(0))\right] \quad (7)$$

[32] We estimate the transition matrix based on a 2023 survey among 3,981 company car drivers at our partner company who had to choose a new company car within the next two years. The job retention rate is calibrated to be 95% per annum, which is close to the average job retention rate at the company during the years 2020–2024 according to its annual reports.

where t denotes the four-year time period (e.g., $t = 1$ corresponds to years 2020–2023) and the outcome-specific discount factor δ_Y^t relates monetary outcomes to the year 2020 when the investment decision was made. The vector γ_0 contains the shares of employees holding each vehicle type in the starting period. By assumption, we assign 100% of employees in our program to a PHEV company car in the first period. $\Theta(D_i)$ is the transition matrix under treatment status D_i, $\mathbf{E}(\Delta Y_{it})$ are the average effects of the program on vehicle use, and $\mathbf{E}(Y_{it}(0))$ corresponds to the average vehicle use in the absence of home charging access. Both elements are 4×1-vectors, mapping outcomes for each of the four vehicle ownership states. All parameters in eq. (7) are calibrated as detailed in Appendix Table D.1.

Scenario 1: No Extensive-Margin Effect We assume that access to home charging does not change the choice probabilities for different vehicle types given by transition matrix $\Theta(0)$. Thus, we only need to consider the intensive-margin treatment effects for the ATTs and the second term in eq. (7) drops out.[33]

Scenario 2: No EU ETS The baseline scenario models a binding cap on electricity sector emissions under the EU ETS by treating emissions from electric charging and emissions from fossil fuel combustion on the road differently. While the former are nil, the latter are not. In scenario 2, we deviate by assuming that electric charging generates incremental emissions from electricity generation. Following the approach by Borenstein & Bushnell (2022), we estimate season $\times$ weekend/weekday $\times$ hour-of-day specific emission factors for electricity consumption in Germany (see Appendix C.1 for details). We use the estimated marginal emission factors to assign CO_2 emissions from electricity consumption at baseline $\mathbf{E}(Y_i(0))$ as well as to the corresponding treatment effect $\mathbf{E}(\Delta Y_i)$. We then incorporate these alternative emission outcomes in eq. (7).

Scenario 3: No ICEVs This scenario deviates from the baseline by assuming that PHEV-drivers do not go back to driving an ICEV, and BEV-drivers do not go back to a PHEV or ICEV (effectively, we assume that EV adoption is an absorbing state). We make this assumption to examine the robustness of our results to possible selection (discussed in Section 2.3) into the home charger program. While the baseline scenario considers the polar case where selection does not matter at all, scenario 3 considers the opposite extreme where only employees with a very strong preference for electric driving (those who no longer consider choosing an ICEV) select into the program. Under this assumption, we can estimate the vehicle transition matrix $\Theta(0)$ based on revealed preferences of program participants in our analysis sample (rather

[33] Note that the distribution of vehicle types will still vary over time, for reasons unrelated to the home charger program.

than survey responses). Among PHEV holders in our sample who chose a new vehicle *before* obtaining access to home charging, 71% chose to order another PHEV, while the remainder opted for a BEV.

To shed light on the importance of the extensive-margin effect on EV adoption for the cost-benefit analysis of the home charging program, we further consider a set of scenarios in which the program does *not* affect vehicle choice.

Scenario T.0: New Baseline Identical to scenario 0, but there is no effect of the program on vehicle choice.

Scenario T.1: No ICEVs Based on scenario 3, but with the additional assumption that there is no effect of the program on vehicle choice.

Scenario T.2: PHEV Lock-In Employees do not change their vehicle type over time, but are locked into their initial choice (i.e., $\Theta(0)$ is an identity matrix). The overall ATT simplifies to the net present value of the period-treatment effects on PHEV-use ($\mathbf{E}(\Delta Y_{it}^{PHEV})$).

Scenario T.3: Mandated BEVs We assume that all employees switch to a BEV in the second four-year period. 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.

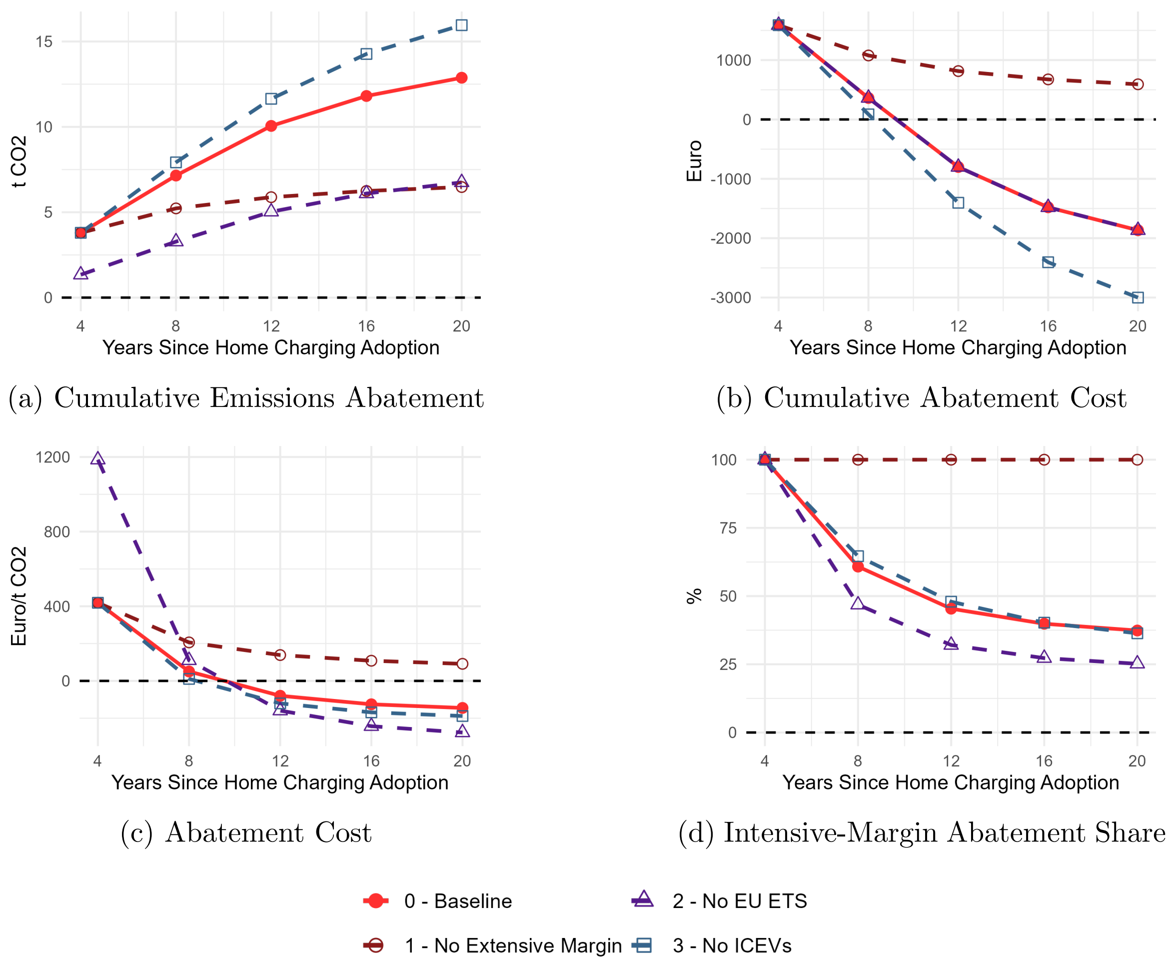
This gives us all the ingredients needed to simulate the ATT on CO_2 emissions and energy costs, with an eye to assessing the relative importance of intensive-margin and extensive-margin adjustments.

4.2 Simulation Results

Figure 6 displays the cumulative treatment effects of home charging adoption over time in the first set of scenarios. We start from the end of year four, when the leases for the initial PHEV fleet need to be renewed. The composition and evolution of the company car fleet over time change when treated employees receive a home charger at the beginning of the first period. We examine how this impacts emissions and abatement.

Panel (a) depicts cumulative CO_2 emissions abatement for the average participant. Over the lifetime of the home charger, the program achieves substantial emission re-

Figure 6: Simulation of Cumulative Treatment Effects over Time



(a) Cumulative Emissions Abatement

(b) Cumulative Abatement Cost

(c) Abatement Cost

(d) Intensive-Margin Abatement Share

Notes: Estimates for the dynamic ATT based on eq. (7), aggregating treatment effects on PHEV and BEV use and BEV adoption under different assumptions for PHEV and BEV diffusion, and emissions from electricity generation. Scenarios as described in Section 4.1.

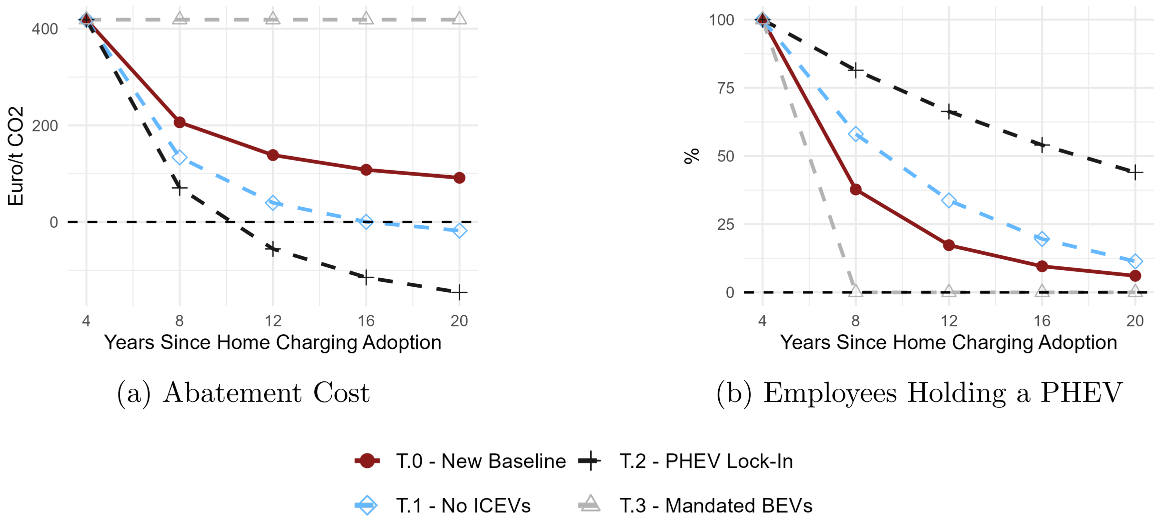
ductions ranging from 6 to 16 tons of CO_2, depending on the scenario. Estimates for scenarios 1 and 2 are at the lower end because they either do not account for effects of the program on vehicle choice or consider emissions from electricity generation as additional (as they would be without the binding cap of the EU ETS). In the most optimistic scenario 3, the average annual abatement of a home charger would offset almost half of the average per-capita emissions attributed to the German transportation sector in 2023 (Our World in Data, 2026).

Panel (b) displays the total cumulative abatement cost, computed as installation costs minus properly discounted cost savings resulting from the substitution from fuel (gasoline or diesel) to electricity. Panel (c) relates these to abatement by displaying the levelized abatement cost per ton of CO_2. Note that zero abatement cost implies that the home charger installation has paid off. Negative abatement costs result when the home charger program pays for itself. From the company's perspective, the program breaks even financially within 12 years, as long as we account for its effects on vehicle choice. If there were no extensive-margin effects, the program would not break even financially but deliver CO_2 abatement at a levelized cost of €91 per ton. This cost is close to recent prices for European Emission Allowances (EUA).[34] The importance of the extensive-margin effect of the program is highlighted again in panel (d), which displays the share of emissions abated due to intensive-margin changes in vehicle use. Over the lifetime of the charger, this share is less than 40% for all scenarios allowing for an extensive-margin response. Inducing employees to adopt a BEV has substantial effects on emissions, since these employees do not cause any driving-related CO_2 emissions over the next four years. In addition, they are less likely to revert to driving a (polluting) PHEV or an ICEV than employees driving a PHEV.

Having established the importance of extensive-margin effects, we provide additional scenario analyses in Figure 7 to shed light on the role of PHEVs for the intensive-margin effects of the program. Panel (a) displays levelized abatement cost over time, and panel (b) displays the share of PHEVs remaining in the sample. On comparison, we see that levelized abatement costs are inversely related to the share of PHEVs. This is because the benefits of the program-induced substitution between electric charging and fossil fuel accrue only among employees currently holding a PHEV. If the share of PHEV-drivers drops for exogenous reasons—such as the ban on non-BEV company cars considered in scenario T.3—there is less scope for the program to induce electric driving. Therefore, scenarios with a lower share of PHEV company cars may be associated with lower abatement (due to the home charger program) and lower total CO_2 emissions. If all employees keep driving a PHEV for as long as they work for our partner company, the program will again break even within 12 years.

[34]EUA prices reached €92 on January 15, 2026 (Trading Economics, 2026). An EUA allows to emit one ton of CO_2 under the EU ETS.

Figure 7: Cumulative Treatment Effects without the Extensive-Margin Response



Notes: Estimates for the dynamic ATT based on eq. (7), aggregating treatment effects on PHEV and BEV use and BEV adoption under different assumptions for PHEV and BEV diffusion. All scenarios assume that the program does not affect vehicle choice. Scenarios as described in Section 4.1.

The previous scenarios assumed that energy prices over the next 20 years develop according to a deterministic price path, which is calibrated to current forecasts by the IEA and industry organizations (for details, see Appendix G). To gauge the impact of this assumption on our results, Appendix G presents a sensitivity analysis using alternative price paths for future electricity and fuel prices and the future development of carbon prices for the transport sector in Germany. As shown in Appendix Figure G.1, those assumptions can change levelized abatement cost substantially, especially if we assume future price developments that make fossil fuels cheaper and electricity more expensive. However, even these pessimistic scenarios do not alter the conclusion that the program pays for itself during the lifetime of the charger. The reason is that the cost of driving one kilometer using fossil fuels is substantially higher than driving the same distance using electricity. This cost differential remains large relative to the projected price changes for each energy type.[35]

5 Discussion

We have derived our results from a particular sample of EV drivers facing a particular set of incentives. Any generalization of those findings to the broader population of EV drivers in Germany should be predicated on a thorough assessment of (i) how

[35] 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.

representative our sample is of the German population along observable characteristics, (ii) whether the incentives and constraints that affect home charging in our study are comparable to those faced by EV drivers in a broader population that also includes privately-owned cars. The subsequent discussion of these issues draws on additional data from a large-scale German travel survey covering the years 2023 and 2024 (infas et al., 2025).[36] Furthermore, we assess how alternative regimes for regulating CO_2 emissions would affect our conclusions.

Representativeness The average quarterly mileage of PHEVs in our data (4,318 km) lies in-between that of privately-owned PHEVs in Germany (3,308 km) and company-car PHEVs (5,799 km). The high mileage of company cars in Germany is driven by employees whose jobs require frequent business travel (e.g., sales force, field service), and who tend to be overrepresented among company car holders. In contrast to this, eligibility for a company car at our partner company is not conditional on such roles but is granted to most employees. This explains why the mileage observed in our sample is closer to the arithmetic mean of mileage driven with privately-held and company-car PHEVs in Germany (4,553 km), rather than to any one of them.

The average electric driving share in our sample (0.28) points to limited electric utilization. This is consistent with evidence of low electric driving shares among PHEVs in Europe (between 0.22 and 0.42 according to Plötz & Gnann, 2025).

When it comes to socioeconomic characteristics, EV drivers analyzed in our sample resemble those observed in the EV driver population in Germany. PHEV drivers in our sample are, on average, slightly older than the German working-age population (48 vs. 44 years; reference year 2017; Statistisches Bundesamt, 2018) and predominantly hold white-collar positions with above-average pay. In the German population, households with access to at least one EV have, on average, 48% higher monthly incomes than the German average (€ 6,022 vs. € 4,071). The share of female PHEV holders is low, both in our sample (0.16) and in the German population (0.28, as of December 31, 2023; Creutzburg et al., 2025), although holding a car does not necessarily imply being the main user.

Constraints and incentives for home charging Key features of our study design relate to the feasibility of adopting a home charger and the incentives for using it.

First, all PHEV drivers in our sample have the opportunity to install a home charger. This cannot be taken for granted when considering the broader population of PHEV drivers. For example, differences in home ownership can matter for adoption. Renters may be less inclined to invest in the installation of charging equipment than owners. Landlords may shy away from making the investment or refuse to give their

[36] Unless noted otherwise, figures are based on this dataset.

consent for necessary technical modifications. To remove such barriers to adoption, a law passed in 2020 grants tenants in Germany a statutory right to conduct reasonable modifications to install charging infrastructure at their rented home (subject to case-by-case approval, potential reinstatement obligations and typically with the tenant bearing the costs; see NOW GmbH, 2025). As the effects of this reform have yet to be evaluated, whether or not our findings hold up in a sample of renters remains a topic for future research. In contrast, home owners face lower barriers to installing a home charger, which makes them more similar to the employees we study. In Germany, 65% of households with regular access to at least one car and 66% of households with at least one PHEV are homeowners.[37] Moreover, there remains scope for further adoption as less than half (46%) of German households with at least one PHEV report having access to a home charger (74% among households with a BEV). To leverage this potential, the German government recently introduced subsidies for charging stations at apartment buildings (Bundesministerium für Verkehr, 2026).

Second, do the effects of the non-monetary incentives for home charging emphasized in this study carry over to PHEV holders who in addition face a monetary trade-off between refueling and recharging? Using German micro-data, Grigolon et al. (2026) estimate that operating a PHEV in electric mode is about €2.90 per 100 km cheaper than operating it in combustion mode. The employees we study are not exposed to this monetary incentive, but they appear to value the convenience of home charging. We expect fuel-cost savings to complement—rather than offset—the convenience channel through which home charging increases electric utilization in our study. Given the overwhelming evidence that low electric utilization rates of PHEVs prevail despite these monetary incentives, more convenient access to charging could be a catalyst for electric driving in the broader population.

Third, company cars may be replaced more frequently (e.g., on four-year lease cycles, as in our setting) than privately-owned vehicles. In our context, employees can choose a new vehicle (PHEV or BEV) at the end of the lease term. This comparatively low-friction replacement process likely contributed to the large treatment effect we estimated for the uptake of BEVs upon lease renewal. In the general population, vehicle turnover is slower and involves personal financial risk. Private car owners may not switch as quickly due to concerns about resale values or upfront costs. Consequently, the treatment effect on BEV adoption outside of the company-car context might be smaller or delayed. Our cost-benefit analysis approximates this possibility in scenarios without an extensive-margin effect.

[37]For comparison, in 2022, 44% of all households in Germany lived in owner-occupied homes (see Bundesministerium für Wohnen, Stadtentwicklung und Bauwesen (BMWSB), nd).

Carbon-market regulation One might ask whether our results hold under alternative regulatory regimes. For example, in most countries outside the EU, emissions from electricity generation are not subject to a cap. Section 4 has considered this case explicitly in a scenario with uncapped electricity-sector emissions. Using empirically-estimated, marginal emission factors for electricity demand in Germany, we found that home charging still yields sizable CO_2 abatement, albeit lower than those achieved when total emissions are capped, as is the case with the EU ETS.

In addition to the EU ETS, the EU has decided to cap emissions from road transport under a future EU ETS2, scheduled to become operational in 2028. If the cap is binding, increased charging would no longer reduce aggregate emissions at the EU level. However, price containment tools will increase allowance supply in the EU ETS2 if allowance prices exceed €45. In either case, our results pertaining to the profitability of the private investment in a home charger would continue to apply, also when taking projected allowance prices under the EU ETS2 into account.

In sum, we believe that our results are generalizable to broader populations of PHEV drivers in Germany and beyond, subject to the caveats and specifications discussed in this section.

6 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 more than one-third. 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.

In the near future, those emissions will be subject to a carbon price set by the "EU ETS2". To produce the same short-run abatement as our intervention, this price would have to increase gasoline prices by 95% and diesel prices by 135%, based on recent elasticity estimates for German PHEV drivers (Grigolon et al., 2026). Because policies aimed at increasing fuel prices are highly unpopular (Douenne & Fabre, 2022), policymakers will prefer politically more palatable instruments to reduce emissions. Given our results, promoting access to home chargers qualifies as such.

Two additional results strengthen this policy recommendation. First, we have shown that the diffusion of home chargers also accelerates the transition to BEVs.

This generates sizable knock-on effects on CO_2 abatement by locking drivers into a technology that shifts all their on-road emissions under the EU ETS cap. Second, charging at home leads to energy cost savings that offset the upfront investment for the average program participant after 12 years, if not earlier. While the exact levelized abatement costs of home chargers depend on their lifespan and other assumptions, even conservative estimates are competitive with buying EU ETS permits or international carbon offsets which represent companies' next best alternatives to reducing emissions from their car fleets.

In contrast, the widespread purchase subsidies for PHEVs have proven a very expensive instrument for emissions abatement. A recent study estimates the implicit abatement costs of PHEV subsidies in Germany at €2,470 per ton of CO_2 (Haan et al., 2025). A likely reason is that PHEV purchase subsidies do not affect two margins of abatement that our study has identified as critical: they do not lower charging costs (intensive margin) and—being targeted at PHEVs—they fail to encourage BEV adoption (extensive margin).

A central result of our analysis is that PHEVs and access to home chargers are strong complements when it comes to abating on-road emissions. One policy implication is that conditioning PHEV subsidies on the availability of home charging infrastructure might greatly improve the economic rationale of such subsidies. Iterating on this line of reasoning, policymakers might want to grant vehicle purchase subsidies only for BEVs, and additionally subsidize home chargers. This would promote electric driving at the intensive and extensive margins while avoiding the risk of "fossil" usage that comes with PHEV subsidies.

Such policies provide a powerful lever to curb road emissions because they would affect a substantial share of the overall stock of EVs and passenger cars more broadly: At the end of our study period, 39% of all new car registrations in Germany were company cars (Kampermann, 2023) whilst 51% of all PHEVs and 40% of BEVs were company-owned (Kraftfahrt-Bundesamt, 2024). The most recent data available puts the share of PHEVs among new vehicle registrations at 9% in the European Union (International Council on Clean Transportation, 2026) and 20% in China (Opletal, 2025). Furthermore, since company cars are replaced every few years and enter the used-car market, policies that target company car fleets can help to accelerate the diffusion of new vehicle technologies in the total stock of cars (European Commission, 2024b). Specifically, the positive effect of home chargers on BEV adoption we find reduces emissions in the medium term by increasing the supply of used BEVs.

We close by noting two caveats to the case for subsidizing home chargers. First, an optimally designed subsidy must account for environmental externalities other than climate change, such as air pollution, as well as additional generation and congestion costs imposed on the electricity sector (Heid et al., 2024). Second, the distributional effects of subsidizing home chargers might well be regressive if high-income households face lower barriers to adoption—a common issue in the context of mitigating the climate impact of buildings and transportation. To measure and correct such undesirable consequences are promising topics for future research.

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Appendix (For Online Publication)

A Company Cars – Institutional Context

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.

In Germany, allowing employees to use a company car for private transportation comes at a monetary cost to the employee. Private use is considered a non-cash benefit ("Entnahme von betrieblichem Vermögen"), which is subject to income taxation. In addition, companies that allow the private use of company cars can require employees to pay a share of the costs. These payments are then deducted from the value of the tax-relevant non-cash benefit. In the remainder of this section, we will first provide a summary of the taxation of private company car use in Germany. For a more thorough description of company car taxation in Germany, the interested reader is referred to the study by Diekmann et al. (2011, in German). Secondly, we characterize the structure of payments from employees to our partner company for the private use of company cars.

The private use of company cars constitutes a non-cash benefit to the employee, whose value is subject to income taxation. There are two methods to determine the value of the non-cash benefit. In our sample, all employees use the second method. For completeness, we also briefly describe the first method. Under the first method, the employee must document the use of the company car for both private and business-related trips. The tax authority can then use this documentation to determine the value of the non-cash benefit. The second method determines the value of the non-cash benefit independently from vehicle use, assuming that the value is proportional to the gross manufacturer-suggested retail price (list price) of the car. During our sample period, the use of an ICEV is valued at 1% of the gross list price per month, while the use of PHEVs is valued at 0.5%, and for BEVs at 0.25% of the gross list price of the car. This tax schedule is meant to promote the adoption of EV company cars. Employees need to pay income taxes on the value of the non-cash benefit, according to their income tax rate. In addition to taxation on the private use of the car, employees also need to pay income taxes on the use of the company car for their commute. This is quantified as 0.03% of the gross list price of the car times the kilometers between their primary residence and their location of work, per month. Although this payment may be correlated with vehicle use, it does not impose a monetary cost on vehicle use.

At our partner company, employees holding a company car pay a deduction from their net monthly salary to cover part of the cost. This deduction is also a function of the list price of the car. The company determines the monthly co-payment as a (small) fraction of the list price (net of taxes), the manufacturer share of a government subsidy for both PHEVs and BEVs in Germany (Umweltbonus; see BAFA, 2020), potential dealer discounts, and several company bonuses for the adoption of cleaner cars. Government and company subsidies imply that, in general, the co-payments will be highest for ICEV company cars, followed by PHEVs and BEVs, given that the gross price of these cars would be equal to the employee's budget for ordering a new company car. Another factor determining the co-payments is whether employees want their employer to pay for electricity and fuel expenditures. All employees in our sample take part in fuel cost compensation, which implies that they face no variable cost of driving their cars. Participation in fuel cost compensation comes at the cost of a higher co-payment, i.e., employees in the fuel cost compensation scheme pay a higher share of the net vehicle price as a monthly deduction from their salary. Employees opting out of fuel cost compensation are not eligible for the home charging program. In contrast to their peers, they pay for fuel expenditures themselves, but also pay a lower fraction of the net vehicle price of the car as a monthly deduction. Both the lump-sum payment and fuel expenditures can be deducted from the tax-relevant non-cash benefit, and thus reduce the income taxes paid by employees. Since employees need to pay only a fraction of the non-cash benefit as income taxes, a higher co-payment always implies a higher total monthly payment for the employee.

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, the date on which the employee ordered a home charger (if applicable), 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 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). For charging at home and at the firm, we also observe the exact starting time of charging (plugin-time). Note that all of the following cleaning steps are applied to the entire corporate sample and not only to the experimental sample we used for the analysis.

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 (Allgemeiner Deutscher Automobil-Club e.V. (ADAC), 2024). 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 Harmonized 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 engine 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 an upper-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):

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

$$\implies C_2^{NEDC} = C^{NEDC} \frac{D_e^{NEDC} + 25}{25} - C_1^{NEDC} \frac{D_e^{NEDC}}{25} \leq \frac{(25 + D_e^{NEDC}) C^{NEDC}}{25} \tag{B.2}$$

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. (2026):

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

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.

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 (among program participants, this affects 7,010 out of 30,819 mileage observations). We interpolate flagged mileages using an energy-weighted average of the last and the next correct observed odometer reading, i.e. we assign the total mileage between two correct odometer readings to the refueling procedures between them based on the energy consumption (both fuel and electricity) implied by each transaction. 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.

To conduct the mileage cleaning, we had to remove some vehicles from our data. Starting from a sample of 1,011 PHEVs observed during the period January 2020 until September 2022[38], we drop time series with less than two non-flagged mileage observations because we cannot calculate driving distances for these vehicles (we remove 43 PHEVs with less than two odometer readings and an additional 32 PHEVs with less than two plausible odometer readings). 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 two cases should be rare since home charging before the program implied a monetary cost for households while free options were available, and not correctly entering odometer readings violates corporate policies.

Suppose flagged mileages occur at the beginning or the end of a time series for a particular car (of the flagged mileages, 1850, equivalent to 6% of all mileage observations, appear at the beginning or the end of a time series). In that case, we extrapolate based on the last (first) correct odometer reading and the fuel and electricity use of the vehicle after (before) that. For each refueling procedure after (before) the last (first) 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). 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. 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.

After this cleaning procedure for vehicle mileages, some implausible mileage observations remained (2% of cleaned mileages were still deemed implausible by our own metric, note that this is a huge improvement over the initial rate of 23%). We removed the following observations after aggregating the transaction data to an employee-by-quarter panel. We drop two PHEVs with either zero energy consumption during the sample period or zero mileage but non-zero energy consumption and three PHEVs that had more than 30% of their quarterly mileages above the 99.9th percentile of quarterly mileages (value 18,724 km), and we additionally drop all quarterly observations where (i) the mileage exceeded the 99.9th percentile of quarterly mileages (value 18,724 km) 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 0.5th percentile (value 0.5) or exceeded the 99.5th percentile (value 4.5). The last step removes three additional vehicles for which all mileage outcomes were deemed implausible.

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

[38] We drop observations in the last quarter of 2022, since, for many cars, we observe the second-to-last refueling event—and hence, the last vehicle mileage—before September 2022.

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 none of the 30,478 refueling procedures for our final sample) and we winsorize electric charging at 130% of the vehicle's gross battery capacity (this affects 2,382 out of 232,090 recharging procedures for our final sample, including BEVs and PHEVs).[39]

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. (2026):

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

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 we make when computing CO_2 emissions and energy costs on the basis of energy consumption observed in terms of electricity and fossil fuels (either diesel or gasoline). Table C.2 summarizes these assumptions.

C.1 CO_2 Emissions

PHEVs have both an electric engine and an internal combustion engine powered by gasoline or diesel. We observe the amount of energy consumed in kWh of electricity and liters of fuel, respectively. Converting fuel consumption into CO_2 emissions is straightforward since the amount of CO_2 emitted is proportional to the amount of fuel burned. To quantify that relationship, we use emissions factors for fossil fuels from the German Environmental Protection Agency (Juhrich, 2022).

To convert additional electricity consumption into CO_2 emissions in a counterfactual scenario in which emissions from electricity generation are not subject to a binding cap under the EU ETS, we need to estimate marginal emission factors (MEFs) for the German electricity grid. Our estimation strategy builds on Borenstein & Bushnell (2022) but extends their approach in two important aspects. First, we allow MEFs to vary by hour-of-day, season, and weekends vs. weekdays. Capturing variation in MEFs over time is important in our setting because access to home charging not only changes the frequency but also the timing of electric charging. Second, we adjust the approach to reflect the comparatively deeper integration of the European electricity market. In contrast to the US electricity grid, the European market is segmented into bidding zones (which often correspond to national borders), all of which are interconnected either directly or indirectly through other zones. This implies that the number of interconnected bidding zones between which electricity trade is possible is much larger. In practice, transmission capacity constraints imply that additional electric-

[39] 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.

ity demand in Germany is very likely to cause additional generation in some bidding zones, but unlikely to affect others.

To address this more complex market structure, we aggregate bidding zones in Europe into three different "regions": Germany-Luxembourg, bidding zones with a direct interconnection to Germany-Luxembourg (neighbors), and other European bidding zones (others). We make the simplifying assumption that load in Germany can cause additional generation (and, with that, emissions) in Germany-Luxembourg and in neighboring, but not in other bidding zones. This assumption probably over-simplifies the European electricity market, especially when neighboring bidding zones are small. However, the alternative assumption that additional load in Germany can cause generation anywhere in Europe completely abstracts from capacity constraints, and would introduce excessive noise into our estimation (for a discussion of the issues that can arise in this setting, see Holland et al., 2024). We then estimate the effect of aggregate load in these two regions on aggregate emissions across the two regions in the following stacked regression:

$$\Delta E_{rt} = \sum_{l\in L}\sum_{s\in S}\sum_{D}\sum_{h\in H} \beta_{r,r',h,D,s}\, \Delta RL_{r',t}\, \mathbb{1}(l = r')\, \mathbb{1}(\text{day}(t) \in D) \times \mathbb{1}(\text{season}(t) = s)\, \mathbb{1}(\text{hour}(t) = h) \tag{C.1}$$

where $E_{r,t}$ are total emissions in region r in hour t, $RL_{r',t}$ is residual load, i.e., total load net of renewable generation in region r' in the same hour t, and Δ corresponds to one-week-differences in the corresponding variable, where we difference each observation with the observation 168 hours earlier (the same hour-of-day, one week before). This one-week-differencing should partial out structural time-constant components in the outcome variables and the regressor. Furthermore, L is the set of regions, including Germany-Luxembourg and its neighbors, S are seasons, winter and summer, D is a set of days, either including all weekdays or the weekend, and H is the set of hours in a day (1–24).

To obtain MEFs for the electricity mix in Germany-Luxembourg, we add up the estimated β-coefficients that correspond to the effect of load in Germany on emissions in Germany ($\beta_{DE,DE,h,D,s}$) and on emissions in neighboring bidding zones ($\beta_{NE,DE,h,D,s}$) for all $h \in H, D \in \{\text{Weekend, Weekday}\}, s \in S$.

Turning to the data requirements for estimating eq. (C.1), we rely on data from ENTSO-E, the transparency platform maintained by the European Network of Transmission System Operators for Electricity (2025), to measure total load and renewable generation within a region. To construct the dependent variable, we additionally need to know the quantity and carbon intensity of fossil fuel burnt at each power plant in those regions. ENTSO-E publishes data on hourly electricity generation for all generating units larger than 100 MW capacity (data set ActualGenerationOutputPerGenerationUnit_16.1.A_r3). To estimate the fuel burned at those units, we translate electricity generated into required energy inputs using data on electrical efficiency available from Hilgado Gonzalez et al. (2019). Generation at units smaller than 100 MW capacity is aggregated up into fuel-type specific residual plants in each bidding zone. We measure generation of the residual plant as the residual between hourly type-level generation from ENTSO-E (data set AggregatedGenerationPerType_16.1.B_C_r3) and the aggregate unit-by-hour-by-type generation based on the unit-level generation data. We approximate the efficiency of the residual plant using the following procedure: for

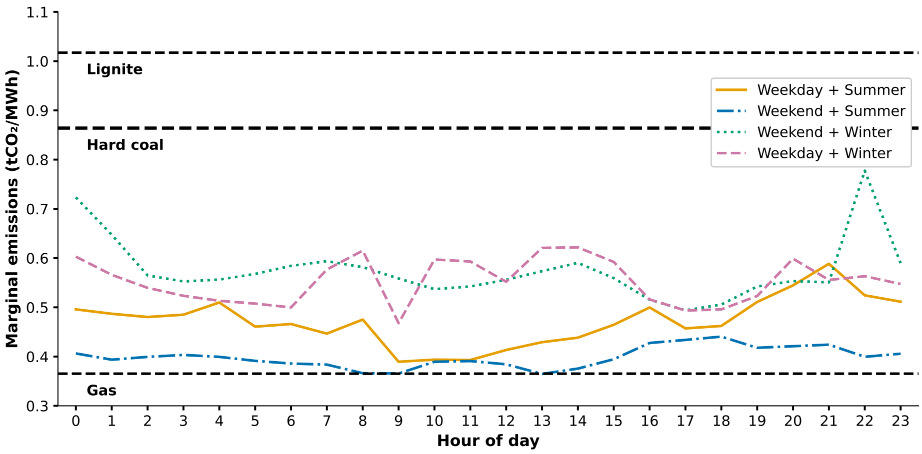


Figure C.1: Emission Factors for Residual Load in Germany, 2020-2022
Notes: Marginal emission factors (MEF) calculated using eq. (C.1), following Borenstein & Bushnell (2022). Horizontal lines indicate average technology-specific CO_2 emissions per unit of energy output based on CO_2 emission factors for fossil fuel combustion in Germany (Juhrich, 2022), assuming the following efficiencies, following Schlömer et al. (2014): coal (lignite and hard coal) - 0.39, gas - 0.55. They are included solely as a reference point to assess the estimated MEFs.

Germany, we take the average efficiency rate of all generating units smaller than 100 MW from Arnold et al. (2024). For the other European bidding zones, we adjust the average efficiency rate of all generating units larger than 100 MW for a given fuel type by the ratio between the average efficiency of large vs. small plants (< 100 MW) in Germany, to account for the fact that smaller units may be less efficient. With these efficiency estimates at hand, we compute the energy inputs required for the observed generation at each residual plant. Finally, we estimate CO_2 emissions for electricity generation based on (estimated) energy inputs, using fuel-type specific emission factors provided by the German Environmental Protection Agency (Juhrich, 2022) for Germany (including hard coal, lignite, gas, coal-derived gas, oil, and an emission factor for waste incineration from the 2006 IPCC guidelines) and following the 2006 IPCC guidelines in the neighboring regions (Gómez et al., 2006) (including gas, coal-derived gas, hard coal, lignite, oil, oil shale, peat, and waste).

The results of this exercise are reported in Table C.1 and plotted in Figure C.1. Our estimated grid-level MEFs lie in between the average MEF for hard-coal fired and natural-gas fired power generating units, respectively. The grid-level MEF varies considerably by hour of day, weekend and season. It ranges from 370 grams of CO_2 per kWh at dawn on summer weekend days to 760 grams of CO_2 per kWh at midnight on a winter weekend. Compared to other estimates for the German electricity sector, the MEFs we estimate are similar to the time-constant MEF implied by the baseline scenario in Heid et al. (2024) and to the hour-by-day specific MEFs for Germany estimated by Beltrami et al. (2025). In contrast to our approach, neither Heid et al. (2024) nor Beltrami et al. (2025) account for emissions from generation outside of Germany. Moreover, Heid et al. (2024) estimate marginal emissions employing an engineering (merit-order) model instead of a regression-based approach.

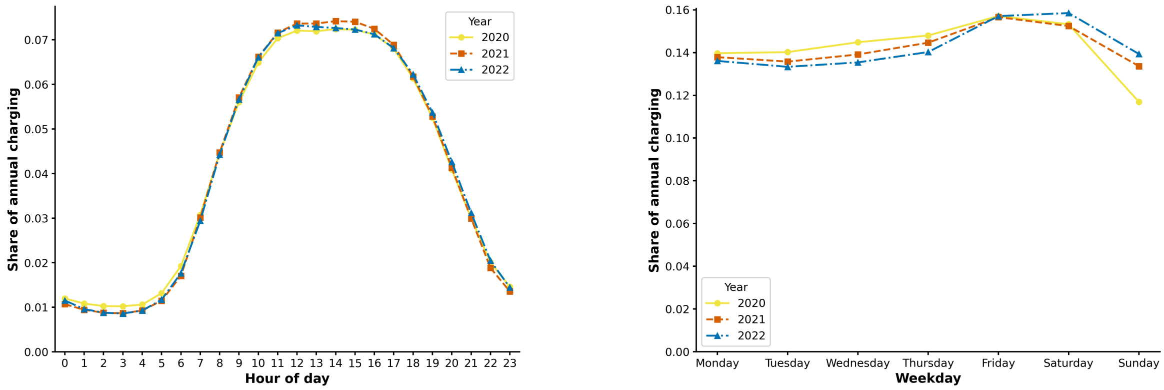
To estimate CO_2 emissions from increased electric charging, we multiply hourly electricity consumption with the corresponding MEF estimate. We can map electricity consumption across time thanks to the timestamp in our transaction data which provides us with both date and time for electricity consumption at home and at the firm's premises. Since we only get the date (but not the time) for charging events at

Table C.1: Marginal Emission Factors for Residual Load in Germany, 2020-2022

hour	Winter-Weekday	Summer-Weekday	Winter-Weekend	Summer-Weekend
0	0.603	0.496	0.723	0.406
1	0.566	0.487	0.647	0.394
2	0.540	0.480	0.565	0.399
3	0.523	0.485	0.553	0.403
4	0.513	0.510	0.556	0.399
5	0.508	0.461	0.568	0.391
6	0.500	0.466	0.584	0.386
7	0.577	0.447	0.594	0.384
8	0.615	0.475	0.582	0.366
9	0.468	0.389	0.559	0.366
10	0.597	0.394	0.537	0.389
11	0.593	0.393	0.542	0.391
12	0.552	0.413	0.556	0.384
13	0.621	0.429	0.573	0.365
14	0.622	0.438	0.590	0.376
15	0.592	0.465	0.559	0.395
16	0.516	0.500	0.516	0.428
17	0.493	0.457	0.494	0.434
18	0.496	0.462	0.506	0.440
19	0.523	0.511	0.542	0.418
20	0.599	0.545	0.553	0.421
21	0.556	0.588	0.551	0.424
22	0.563	0.524	0.778	0.400
23	0.547	0.511	0.590	0.406

Notes: Marginal emission factors (MEFs) in tCO_2/MWh. Calculated adding up the coefficients reflecting the effect of additional load in Germany-Luxembourg on emissions there and in neighboring bidding zones from eq. (C.1), following Borenstein & Bushnell (2022). Regression diagnostics: Observations: 52,272, R-squared: 0.835, Adj. R-squared: 0.834, F-statistic: 111.9 (Df = 384). Standard errors clustered by day-of-observation.

Figure C.2: Distribution of Total kWh Charged at Public Stations in Germany



Notes: Empirical distributions generated by aggregating all charging (in kWh) at public stations during a year. Based on Data from NOW GmbH, Nationale Leitstelle Ladeinfrastruktur (2025) for the years 2020–2022.

public charging stations, we assume that charging times follow the empirical distribution observed for those stations and assign the corresponding MEFs in proportion. Figure C.2 plots this distribution using data on all charging transactions at public charging stations in Germany that received government subsidies (NOW GmbH, Nationale Leitstelle Ladeinfrastruktur, 2025). Given the small share of public charging ex-ante (see Figure 2b), this approximation should not impact our results.

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 at the company's premises or on the public grid, we use 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 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 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 the 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%. Importantly, any such monetary costs borne by the employee do not vary with either driving behavior or vehicle choice. This is why we interpret access to home charging in our setting as the removal of a non-monetary barrier to electric charging.

We have no information about the exact amount the firm ended up paying per installation, and cannot reveal the exact pricing structure given our non-disclosure agreement. However, we can provide the interested reader with three scenarios for how payments are split between company and employee (abstracting from the employee's income tax liability on the subsidy mentioned above). First, the installation of a home charger for an above-ground parking (garage or outdoor) in close proximity to the house would be more than fully covered by the maximum company subsidy of €2,750, with no additional payment required from the employee. Second, the maximum subsidy would almost fully cover a standard installation in underground parking, with the employee paying a small amount of money on top of the €2,750 paid by the company. Third, a complex installation requiring more than two wall breaches, more than 15 meters of additional electrical cables, or any of the above combined with underground parking would substantially exceed the maximum company subsidy, but the copayment by the employee would not exceed €800. Given this payment structure, and personal communication with our partner company, we treat the maximum company subsidy of €2,750 as a realistic estimate for the average cost of a home charger installation.

The skeptical reader can adjust our cost-benefit analysis by adding hypothetical additional installation costs to the cumulative abatement costs in all our scenarios. To change the qualitative conclusion that the home charger program breaks even financially, it would take an additional investment cost of at least €1,800, which we deem highly unrealistic.

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. 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 follows a deterministic scenario for future energy prices (which we use to scale our estimated period-1 ATTs on energy costs, for details see Appendix C.2), and calculate the total cost per employee as the net present value of the initial investment (the subsidy) minus 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.2: 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	own calculation, see Table C.1	Borenstein & Bushnell (2022)
		Data: ENTSO-E
Panel B: Prices		
Diesel	1.124 Euro/l (2020)	Bittkau et al. (2022)
	1.399 Euro/l (2021)	Bittkau et al. (2022)
	1.960 Euro/l (2022)	Bittkau et al. (2022)
Gasoline	1.293 Euro/l (2020)	Bittkau et al. (2022)
	1.579 Euro/l (2021)	Bittkau et al. (2022)
	1.962 Euro/l (2022)	Bittkau et al. (2022)
Electricity Firm	0.100 Euro/kWh (2020)	DESTATIS (2023)
	0.150 Euro/kWh (2021)	DESTATIS (2023)
	0.246 Euro/kWh (2022)	DESTATIS (2023)
Electricity Public	0.38 Euro/kWh (2020)	Kampwirth (2020)
	0.39 Euro/kWh (2021)	Kampwirth (2021)
	0.43 Euro/kWh (2022)	Kampwirth (2021, 2023)
Cost of Home Charger	2750 Euro	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 to hold a company car V_i of vehicle type $k \in \{ICEV, PHEV, BEV, OO\}$ given her treatment status $D_i \in \{0, 1\}$. Vehicle types are abbreviated as before, and OO corresponds to the outside option of no longer holding a company car. Treatment status D_i and vehicle choice V_i jointly determine the outcomes CO_2 emissions $E_i(D_i, V_i)$ and corporate energy costs $C_i(D_i, V_i)$ for employee i. We adopt the notation $Y_i(D_i, V_i) \in \{E_i(D_i, V_i), C_i(D_i, V_i)\}$. Employee i's outcomes can then be written as $Y_i(D_i) = \sum_k \mathbb{1}(V_i = k|D_i)Y_i(D_i, V_i = k)$, where $\mathbb{1}(V_i = k|D_i)$ 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:

$$\mathbf{E}(Y_i(D_i)) = \mathbf{E}\left(\sum_k \mathbb{1}(V_i = k|D_i)Y_i(D_i, V_i = k)\right) \tag{D.3}$$

We assume that vehicle choice V_i is independent of vehicle use $Y_i(D_i, V_i = k)$. We provide a discussion of this assumption in Appendix D.3. Under the independence assumption, we can rewrite:

$$\mathbf{E}(Y_i(D_i)) = \sum_k \mathbf{E}\left(\mathbb{1}(V_i = k|D_i)\right)\mathbf{E}\left(Y_i(D_i, V_i = k)\right) \tag{D.4}$$

By definition, energy costs and CO_2 emissions will be affected by access to home charging in some states, but not in others. CO_2 emissions and energy costs of ICEVs, for example, will not be affected. This implies that we can rewrite the ATT as:

$$\begin{aligned} ATT(Y_i) = &\sum_{k\in\{\text{Affected}\}} \mathbf{E}(\mathbb{1}(V_i = k|1))\mathbf{E}(Y_i^k(1)) - \mathbf{E}(\mathbb{1}(V_i = k|0))\mathbf{E}(Y_i^k(0)) \\ &+ \sum_{k'\in\{\text{Unaffected}\}} \mathbf{E}(\mathbb{1}(V_i = k|1) - \mathbb{1}(V_i = k|0))\mathbf{E}(Y_i^{k'}(0)) \end{aligned} \tag{D.5}$$

Adding a "smart zero" yields:

$$\begin{aligned} ATT(Y_i) = &\sum_{k\in\{\text{Affected}\}} \mathbf{E}(\mathbb{1}(V_i = k|1))\mathbf{E}(Y_i^k(1)) - \mathbf{E}(\mathbb{1}(V_i = k|0))\mathbf{E}(Y_i^k(0)) \\ &+ \sum_{k\in\{\text{Affected}\}} \mathbf{E}(\mathbb{1}(V_i = k|1))\mathbf{E}(Y_i^k(0)) - \mathbf{E}(\mathbb{1}(V_i = k|1))\mathbf{E}(Y_i^k(0)) \\ &+ \sum_{k'\in\{\text{Unaffected}\}} \mathbf{E}(\mathbb{1}(V_i = k|1) - \mathbb{1}(V_i = k|0))\mathbf{E}(Y_i^{k'}(0)) \end{aligned} \tag{D.6}$$

We adopt the notation $\mathbf{E}(\mathbb{1}(V_i = k|1) - \mathbb{1}(V_i = k|0)) = \Delta\theta_k$ and $Y_i^k(1) - Y_i^k(0) = \Delta Y_i^k$ and rearrange terms:

$$\begin{aligned} ATT(Y_i) = &\sum_{k\in\{\text{Affected}\}} \Delta\theta_k\mathbf{E}(Y_i^k(0)) + \mathbf{E}((\mathbb{1}(V_i = k|1))\mathbf{E}(\Delta Y_i^k) \\ &+ \sum_{k'\in\{\text{Unaffected}\}} \Delta\theta_k'\mathbf{E}(Y_i^{k'}(0)) \end{aligned} \tag{D.7}$$

To obtain an estimate of the ATT, we need to make three additional assumptions: First, we assume that the observed pre-treatment driving behavior among employees selecting into the home charger program is representative of vehicle driving behavior without access to charging at home ($\mathbf{E}(Y_i^k(0))$). Second, experience with home charging changes only the propensity to order a BEV instead of a PHEV. Effectively, we assume that the treatment does not affect the propensity that employees will order an ICEV or select out of having a company car, which we deem plausible. The assumption implies that $\Delta\theta_{PHEV} = -\Delta\theta_{BEV}$ and $\Delta\theta_k = 0$ for all other vehicle choices k. Third, we note that access to charging at home can affect only the driving behavior of BEVs and PHEVs. Assuming that emissions from electricity generation are non-

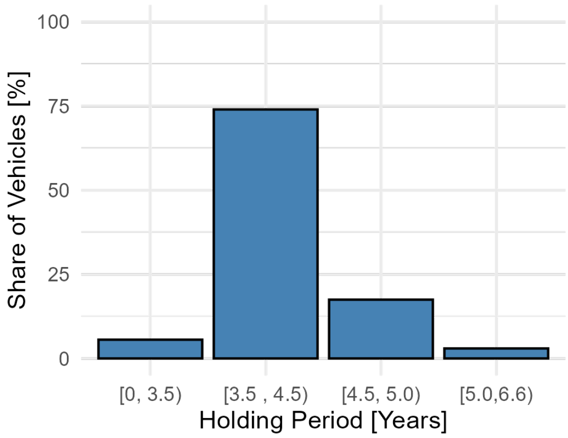


Figure D.1: Period Between Two Subsequent Vehicle Orders
Notes: Based on 269 employees whose lease of a PHEV company car ends between January 2020 and December 2021, and who order an EV company car again thereafter. Including both program participants and non-participants.

additive under the binding cap of the EU-ETS ($\mathbf{E}(E_i^{BEV}(0)) = \mathbf{E}(E_i^{BEV}(1)) = 0$), and finding that our treatment did not affect the quarterly energy costs caused by a BEV ($\mathbf{E}(\Delta C_i^{BEV}) = 0$), we can rewrite the ATT:

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

The first term in this expression is the intensive-margin effect: employees purchasing a PHEV will change their driving behavior. The second term is the extensive-margin effect: some employees choose a BEV instead of a PHEV as their next company car. Note that we have already estimated $\mathbf{E}(\Delta Y_i^{PHEV})$ and $\Delta\theta_{BEV}$ 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 $\mathbf{E}(C_i^{BEV}(0))$ using the corresponding sample averages among not-yet-treated PHEV or BEV owners (see Table C.2).

D.2 Approximating the ATT with Repeated Vehicle Choices

In our setting, employees have to decide on a new company car every four years (at our partner company, 90% of employees hold their cars for between 3.4 and 4.8 years, see Figure D.1 for the distribution of vehicle-holding periods). To simulate the effect of the program over the lifetime of a home charger, we need to track changes in the choice of company car, and the implied energy consumption for a treated and a not-treated process over time.

We simulate changes in the distribution of vehicle types under the assumption that vehicle choice follows a Markov-process, where choice probabilities will depend only on the vehicle previously owned, and not on the entire history of vehicles owned. Under this assumption, we can characterize the diffusion of different vehicle types with an initial state vector γ_0 of vehicle choices, giving the share of vehicle choices in the initial period, and by a transition matrix $\Theta(D_i)$ reflecting the choice probabilities for different vehicle types given the treatment status of the employee and his current vehicle choice. We assume that the transition matrix is constant over time, and common for all employees:

$\Theta(D_i) =$

$$\begin{pmatrix} \theta_{ICEV,ICEV}(D_i) & \theta_{PHEV,ICEV}(D_i) & \theta_{BEV,ICEV}(D_i) & \theta_{OO,ICEV}(D_i) \\ \theta_{ICEV,PHEV}(D_i) & \theta_{PHEV,PHEV}(D_i) & \theta_{BEV,PHEV}(D_i) & \theta_{OO,PHEV}(D_i) \\ \theta_{ICEV,BEV}(D_i) & \theta_{PHEV,BEV}(D_i) & \theta_{BEV,BEV}(D_i) & \theta_{OO,BEV}(D_i) \\ \theta_{ICEV,OO}(D_i) & \theta_{PHEV,OO}(D_i) & \theta_{BEV,OO}(D_i) & \theta_{OO,OO}(D_i) \end{pmatrix} \tag{D.9}$$

where $\theta_{k,k'}(D_i)$ is the probability that an employee who currently holds vehicle k will choose k' in the next period under treatment status D_i. That is, for any vehicle type and treatment status, there is a certain probability of choosing another or the same car type. These choice probabilities are estimated combining our estimated ATTs with survey data on employees' vehicle choices, making some assumptions outlined below. Furthermore, we assume that $\gamma_0 = (0, 1, 0, 0)$, i.e., initially, all participants hold a PHEV company car. The distribution of states in any future period t can then be characterized as $\gamma_t = \gamma_0 \Theta(D_i)^t$.

We assume that (i) these decisions occur simultaneously for all employees, (ii) 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 (iii) car usage, emissions factors, and treatment effects are constant over time and energy prices follow a deterministic price path (we assess the sensitivity of our results to alternative price paths in Appendix G). We thus obtain a new equation to extrapolate the ATT over the subsequent 20 years:

$$ATT(Y_{it}) = \sum_{t=1}^{5} \delta_Y^t \left[\gamma_0\, \Theta(1)^{t-1}\, \mathbf{E}(\Delta Y_{it}) + \gamma_0(\Theta(1)^{t-1} - \Theta(0)^{t-1})\mathbf{E}(Y_{it}(0))\right] \tag{D.10}$$

where t denotes the time period (e.g., $t = 1$ is the first four-year period 2020–2023) and δ_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. The transition matrix in the treated process corresponds to the transition matrix in the not-treated process plus a matrix of treatment effects ($\Theta(1) = \Theta(0) + \Delta\Theta$). As before, we assume that experience with charging at home changes vehicle choice only for drivers of PHEVs,[40] inducing them to more frequently adopt a BEV instead of a PHEV, while leaving all other choice probabilities unchanged. We thus calibrate $\Delta\Theta$ using only the ATT on BEV-choice. $\Theta(0)$ is calibrated based on a survey we ran with 3,981 employees at our partner company who had to choose a new company car within the next two years,[41] and with 5% of employees leaving the company per year (equivalent to a

[40] This assumption is plausible, since drivers of ICEV company cars and employees who left the company are no longer eligible for the program, and for BEV-drivers, the treatment should not reduce the propensity to adopt a BEV again. This propensity is already close to 1 at baseline (see eq. (D.11)), leaving almost no scope for additional treatment effects.

[41] Exact question in the survey: Please indicate what type of car your next *[name of company]* company car is going to be: *[Car with internal combustion engine (gasoline-/diesel-powered), Pure battery electric vehicle, Plug-in hybrid electric vehicle, I am undecided]*. The question was answered by 5,279 employees, but we drop 1,298 employees who were undecided at the time of the survey. 50% of respondents received a treatment message informing them about company sustainability goals.

job retention rate of $P = 0.95^4$ over four years).[42] Both matrices are calibrated as shown below. Calibrating the transition matrix in the not-treated process this way, we implicitly assume that vehicle choice probabilities in our sample are the same as in the population of company car drivers at our partner company.

$$\Theta(0) = \left(\begin{array}{c|cccc} & ICEV & PHEV & BEV & OO \\ \hline ICEV & P \times 1,799/3,083 & P \times 105/598 & P \times 15/300 & 0 \\ PHEV & P \times 643/3,083 & P \times 277/598 & P \times 8/300 & 0 \\ BEV & P \times 661/3,083 & P \times 216/598 & P \times 277/300 & 0 \\ OO & 1-P & 1-P & 1-P & 1 \end{array} \right) \tag{D.11}$$

$$\Delta\Theta = \left(\begin{array}{c|cccc} & ICEV & PHEV & BEV & OO \\ \hline ICEV & 0 & 0 & 0 & 0 \\ PHEV & 0 & -P \times \Delta\theta_{PHEV,BEV} & 0 & 0 \\ BEV & 0 & P \times \Delta\theta_{PHEV,BEV} & 0 & 0 \\ OO & 0 & 0 & 0 & 0 \end{array} \right) \tag{D.12}$$

As in the single-period exercise, the overall effect of the program will depend on intensive- and extensive-margin treatment effects, as well as baseline behavior. Along the intensive margin, the program can only have effects on PHEV and BEV driving behavior, which we have estimated in Tables 2 and 3. The transition matrix implies that over time, employees will also drive ICEVs or leave the company. To calibrate baseline outcomes for these states (in addition to the EV-driving behavior, which we observe pre-treatment), we assume that the behavior of employees leaving the company no longer concerns the emissions and financial accounting of the company ($\mathbf{E}(Y_{it}^{OO}(0)) = 0$). To obtain an estimate for ICEV driving behavior, we assume that the quarterly VKT with an ICEV are similar to the pre-treatment VKT of PHEVs, and calculate an estimate for quarterly CO_2 emissions and energy costs (based on an average national fuel price of €1.76 for Germany in the period 2021–2022) assuming that an ICEV consumes on average 7.44 liters per 100 km. The specific fuel consumption per 100 km reflects the average on-road fuel consumption of new ICEVs registered in Europe in 2021, according to a report by the European Commission (2024a). In contrast to the single-period exercise, the overall effect of the program will also depend on the transition matrix, the initial state vector and the discount rate. In our scenarios outlined in the main text, we study the sensitivity of our result to variations in the transition matrix and in $\mathbf{E}(Y_{it}(0))$ and $\mathbf{E}(\Delta Y_{it})$, but leave the initial state vector and the discount rate unchanged. This choice is motivated by the importance of an exogenous transition towards BEVs in the given context.

Table D.1 lists all the coefficients and parameters needed for the cost-benefit analysis. Note that we aggregate quarterly estimates to annual estimates by multiplying them by 4 where necessary.

Since this treatment did not significantly alter the indicated vehicle choices, we pool treatment and control group to estimate the transition matrix.

[42] This number is calibrated to the employee retention rate at our partner company in the years 2020–2024.

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

Parameter	Source
Panel A: Estimated ATTs	
$\mathbf{E}(\Delta\theta_i^{BEV}) = 0.284 \times 4$	Table 4
$\mathbf{E}(\Delta E_i^{PHEV}) = -237.12 \times 4$ kg CO_2 per year	Table 2
$\mathbf{E}(\Delta C_i^{PHEV}) = -102.52 \times 4$ Euro per year	Table 2
$\mathbf{E}(\Delta C_i^{BEV}) = 0 \times 4$ Euro per year	Table 3
Panel B: Observed Population Averages per Year	
$\mathbf{E}(E_i^{PHEV}(0)) = 616.46 \times 4$ kg CO_2	Table E.2
$\mathbf{E}(C_i^{PHEV}(0)) = 445.95 \times 4$ Euro	Table E.2
$\mathbf{E}(C_i^{BEV}) = 190.43 \times 4$ Euro	Table E.4
$\mathbf{E}(E_i^{ICEV}(0)) = 4482.44 \times 4$ km $\times$ 180.3 g CO_2/km	Table E.2
$\mathbf{E}(C_i^{ICEV}(0)) = 4482.44 \times 4$ km/100$\times$ 7.44 l per 100 km $\times$1.716 Euro per liter	Table E.2
$\Theta(0)$ (see eq. (D.11))	employee survey
Panel C: Future Developments	
$E_{i,t}$ is constant	Ad hoc
Deterministic price path for $C_{i,t}$	Appendix G
Panel D: Parameter Assumptions	
$\gamma_0 = (0, 1, 0, 0)$	Starting from 100% PHEV users
$\mathbf{E}(E_i^{BEV}) = 0$	Assumption given EU ETS Cap
$\mathbf{E}(Y_i^{OO}) = 0$	Outcomes outside the firm
$\delta_C^t = \sum_{y=1}^{4}(1.03)^y$	Ad hoc
$\delta_E^t = 4$	Ad hoc

D.3 Discussion: Independence of Vehicle Choice and Vehicle Use

The derivations in Appendices D.1 and D.2 rely on the assumption that vehicle choice is independent of vehicle use. We justify this assumption by the following argument: suppose that a company offers to install home charging infrastructure for employees initially holding PHEVs. The employees participating in this program have similar characteristics and preferences ex ante. Changes in vehicle choice will thus be driven by i.i.d. shocks to employee preferences for sustainable transportation.

The independence assumption would be untenable if we saw evidence of selection into BEV-adoption among program participants. To examine this, we focus on employees who have to choose a new vehicle during our sample period[43] and compare the driving behavior of those ordering a BEV to those ordering a PHEV as their next vehicle. The results of an OLS regression are displayed in Table D.2. Panels A and B show that there are no significant differences in energy consumption and total VKT between these two groups among participants of the home charger program. This lends support to the independence assumption. Panel C reports results from the same re-

[43] That is, employees whose lease for a PHEV company car ends between October 2020 and March 2023. We exclude employees who change cars early in 2020, since these employees might not yet know that the home charger program will be introduced in 2021 and thus choose follow-up cars differently.

gressions performed in the group of PHEV drivers who did not participate in the home charging program (and are thus not included in our analysis sample). In line with prior literature (Xing et al., 2021), we find evidence for selection into BEV-adoption in this group. This does not challenge the validity of our assumption, but it suggests there may be limits to generalizing the results to a context with non-voluntary participation in home charger adoption.

Table D.2: Use of Previous PHEV

	Mileage [km]	Fuel [l]	Charging [kWh]	On-Road [l/100 km]
Model:	(1)	(2)	(3)	(4)
Panel A: Program Participants Choosing Before Treatment				
Constant	4,838.99***	404.80***	10.28***	8.53***
	(571.03)	(48.80)	(3.22)	(0.34)
Next Car: BEV	-247.51	-53.72	5.95	0.77
	(1,308.90)	(95.62)	(13.81)	(0.97)
Fit statistics				
Employees	58	58	58	58
R^2	0.00	0.00	0.01	0.01
Adjusted R^2	-0.02	-0.01	-0.01	-0.00
Panel B: Program Participants Choosing After Treatment				
Constant	4,136.20***	160.98***	178.43***	4.00***
	(455.78)	(30.10)	(31.86)	(0.69)
Next Car: BEV	-553.46	-9.40	-37.48	0.45
	(818.40)	(47.30)	(51.34)	(0.96)
Fit statistics				
Employees	40	40	40	40
R^2	0.01	0.00	0.01	0.01
Adjusted R^2	-0.02	-0.03	-0.01	-0.02
Panel C: Employees Not Participating in the Program				
Constant	4,300.48***	336.29***	14.57***	7.80***
	(190.02)	(17.71)	(2.35)	(0.19)
Next Car: BEV	-736.79	-114.68***	5.23	-1.34***
	(510.60)	(34.12)	(6.18)	(0.51)
Fit statistics				
Employees	250	250	250	250
R^2	0.01	0.02	0.00	0.03
Adjusted R^2	0.00	0.02	-0.00	0.02

Notes: Samples of employees whose PHEV-lease ends between October 2020 and March 2023. All panels describe driving behavior in the last three months before the end of their current company car lease, i.e. before switching company cars. Data aggregated to employee totals (for one quarter). Panel A describes program participants who need to decide for a new car before obtaining access to home charging. Panel B describes participants choosing a company car at least 3 months after obtaining home charging. Panel C describes employees not participating in the home charger program. Ordinary Least Squares Regression of the variables indicated above on an indicator whether the employee ordered a BEV as their next company car. Heteroskedasticity-robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

By providing suggestive evidence that the independence assumption holds among program participants, but not among the population of company car drivers, Table 3 creates a tension between the independence assumption and the assumptions made for baseline vehicle choice in eq. (D.11). There, we assume that vehicle choice probabilities in our sample (in the absence of treatment) are the same as vehicle choice probabilities in the population of company car drivers. We believe this assumption is conservative, since program participants holding a PHEV are more inclined to choose an EV company car than the average employee (compare the PHEV-holder column of the transition matrix for scenarios 0 and 3 in Section 4). In scenario 3, we estimate the transition matrix $\Theta(0)$ based on vehicle choices of program participants to account for selection into the program also in the baseline transition matrix. If anything, this strengthens our results.

E Additional Graphs and Tables

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

	Home Charger		No Home Charger		
Variable	Mean	Sd	Mean	Sd	p-value
Panel A: Vehicle Use in 2020					
Mileage per quarter [km]	4318.28	(2838.04)	4215.24	(2728.70)	0.89
Emissions [kg CO_2]	652.52	(548.73)	705.04	(574.10)	0.00
Tailpipe Emissions [kg CO_2]	627.57	(556.94)	686.34	(582.05)	0.00
Electricity per quarter [kWh]	48.57	(82.77)	36.63	(73.09)	0.00
Fuel per quarter [l]	259.87	(231.40)	285.88	(242.78)	0.00
Fuel consumption [l/100 km]	5.78	(3.20)	6.50	(3.08)	0.00
Electricity consumption [kWh/100 km]	1.46	(2.66)	1.20	(2.50)	0.03
Utility factor [km elec./km total]	0.29	(0.38)	0.19	(0.38)	0.00
Energy expenditures [Euro]	342.75	(293.73)	374.48	(309.74)	0.00
Electricity expenditures [Euro]	10.65	(24.34)	7.31	(18.56)	0.00
Fuel expenditures [Euro]	332.09	(297.50)	367.17	(313.09)	0.00
Panel B: Vehicle Characteristics					
Fuel efficiency [l/100 km WLTP]	1.59	(0.35)	1.54	(0.36)	0.00
Electric efficiency [kWh/100 km WLTP]	17.46	(3.15)	16.65	(2.50)	0.00
Price [Euro]	32135.91	(4195.48)	30279.44	(4764.88)	0.00
Weight [kg]	1997.62	(255.93)	1895.78	(211.14)	0.00
Panel C: Employee Characteristics					
Age [years]	48.22	-	43.19	-	-
Tenure [years]	17.43	-	12.89	-	-
Female [share]	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 = 1535 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 Harmonized Light-Duty Vehicles Test Procedure". P-value is the p-value of a two-sample t-test testing for equal means.

Table E.2: PHEV-Driving Participants Before Home Charger Adoption

Variable	Mean	Sd	Min	Pctl. 25	Median	Pctl. 75	Max
Panel A: Driving Behavior before Home Charger Adoption							
Mileage [km]	4482.44	2839.83	40.87	2403.13	3940	6142.99	18326.40
Emissions [kg CO_2]	649.25	536.84	4.00	256.69	491.98	895.56	3637.53
Tailpipe Emissions [kg CO_2]	616.46	547.17	4.00	207.46	445.68	888.36	3612.33
Fuel [l]	255.22	226.22	1.67	86.94	185.16	370.23	1513.78
Charge [kWh]	65.50	112.19	0	0	20.20	78.28	996.34
Charge at firm [kWh]	27.72	75.48	0	0	0	22.98	996.34
Charge public [kWh]	37.70	79.47	0	0	0.34	33.94	506.87
Fuel consumption [l/100 km]	5.55	2.95	0.17	3.17	5.47	7.85	14.33
Electricity consumption [kWh/100 km]	1.81	3.16	0	0	0.50	1.91	22.03
Energy expenditures [Euro]	445.95	381.83	3.23	169.43	326.02	631.36	2938.25
Charging expenditures [Euro]	20.54	36.65	0	0	5.12	23.52	245.30
Fuel expenditures [Euro]	425.41	387.74	3.23	139.71	303.15	622.43	2915.54
Panel B: Vehicle Characteristics							
Price [Euro]	32127	4117	0	30545	32242	34842	44022
Weight [kg]	2006	263	1480	1820	1985	2075	2655
Fuel consumption [l/100 km WLTP]	1.58	0.34	0.8	1.4	1.4	1.7	2.9
Electricity consumption [kWh/100 km WLTP]	17.5	3.18	13.3	15.3	16.2	18.9	24.2
Panel C: Employee Characteristics							
Age [years]	48.2	-					
Tenure [years]	17.4	-					
Female [share]	0.16	-					

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 in the last quarter before the employee received access to home charging. This reduces the size of the sample to N = 619 employees since some employees receive the charger and a PHEV company car simultaneously. Panel B displays vehicle characteristics obtained from the General German Automobile Club's car catalog (Allgemeiner Deutscher Automobil-Club e.V. (ADAC), 2024). Panel C displays employee characteristics, which are only available in terms of group averages. WLTP stands for "Worldwide Harmonized Light-Duty Vehicles Test Procedure".

Table E.3: BEV-Driving Participants Before Home Charger Adoption

Variable	Mean	Sd	Min	Pctl. 25	Median	Pctl. 75	Max
Panel A: Driving Behavior before Home Charger Adoption							
Emissions [kg CO_2]	261.50	296.80	0.41	63.03	156.18	366.41	2084.66
Charge [kWh]	523.35	599.21	1.04	137.81	319.80	716.40	4591.15
Charge at firm [kWh]	111.67	239.95	0	0	36.83	112.99	2269.20
Charge public [kWh]	411.68	496.75	0	77.20	251.87	618.37	3683.88
Energy expenditures [Euro]	190.43	214.31	0.16	35.92	114.55	283.74	1438.38
Panel B: Vehicle Characteristics							
Price [Euro]	31173	11160	6350	21867	31783	39083	88538
Weight [kg]	1936	376	1095	1615	2044	2125	3500
Electricity consumption [kWh/100 km WLTP]	15.5	2.26	13.4	13.4	13.4	17.6	20.6
Panel C: Employee Characteristics							
Age [Years]	48.3	-	-	-	-	-	-
Tenure [Years]	17.6	-	-	-	-	-	-
Female [share]	0.16	-	-	-	-	-	-

Notes: Descriptive statistics on the sample of employees and their BEVs, respectively, in the home charger program between January 2021 and December 2022 (N = 350 employees). Panel A shows summary statistics for vehicle use in the last quarter before the employee received access to home charging. This reduces the size of the sample to N = 200 employees since some employees receive the charger and a BEV simultaneously. Panel B displays vehicle characteristics obtained from the General German Automobile Club's car catalog (Allgemeiner Deutscher Automobil-Club e.V. (ADAC), 2024). Panel C displays employee characteristics, which are only available in terms of group averages. WLTP stands for "Worldwide Harmonized Light-Duty Vehicles Test Procedure".

Table E.4: Home Charger Sample with BEVs vs. Population of BEVs

Variable	Home Charger Mean	Home Charger Sd	No Home Charger Mean	No Home Charger Sd	p-value
Panel A: Vehicle Use in 2020					
Emissions [kg CO_2]	124.75	(140.25)	122.66	(132.94)	0.69
Electricity per quarter [kWh]	247.75	(275.46)	242.16	(259.48)	0.71
Energy expenditures [Euro]	63.40	(87.42)	64.99	(90.52)	0.67
Panel B: Vehicle Characteristics					
Electric efficiency [kWh/100 km WLTP]	15.35	(2.19)	15.40	(2.74)	0.94
Price [Euro]	31146.03	(11223.62)	28199.31	(11632.25)	0.00
Weight [kg]	1936.53	(379.62)	1818.07	(347.43)	0.00
Panel C: Employee Characteristics					
Age [years]	48.26	-	43.19	-	-
Tenure [years]	17.60	-	12.89	-	-
Female [share]	0.16	-	0.24	-	-

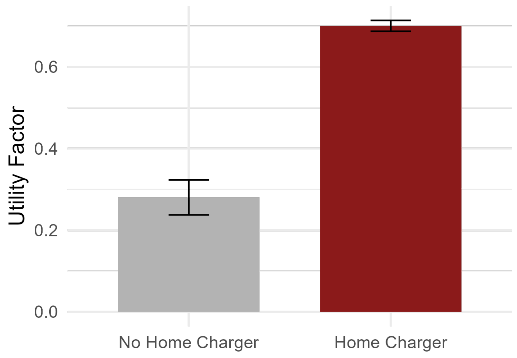
Notes: Comparison of the sample of employees holding BEVs and selecting into the home charger program between January 2021 and December 2022 (N = 350 employees) to the group of employees not selecting into the home charger program during that period (N = 465 employees). Both samples are restricted to 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 = 222 cars in the no-home charger sample. Panel B displays vehicle characteristics obtained from the General German Automobile Club's car catalog (Allgemeiner Deutscher Automobil-Club e.V. (ADAC), 2024). Panel C displays employee characteristics, which are only available in terms of group averages. WLTP stands for "Worldwide Harmonized Light-Duty Vehicles Test Procedure". P-value is the p-value of a two-sample t-test testing for equal means.

Table E.5: Cohort Size for the BEV-Sample, by Level of Aggregation

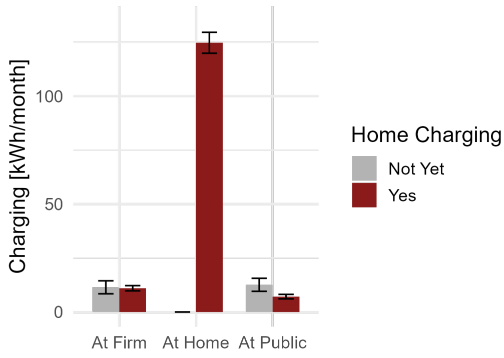
Aggregation	Cohorts	Mean Size	Min Size	Max Size	$n < 15$	$n < 20$
Monthly	15	22.6	7	36	3	6
Quarterly	5	67.8	47	97	0	0

Notes: Cohorts reflect the count of units per treatment cohort. Treatment cohorts are defined by the month or quarter of first home charger installation. Units first treated after quarter 2, 2022 (end of observation window) are coded as never-treated and excluded from cohort-size calculations.

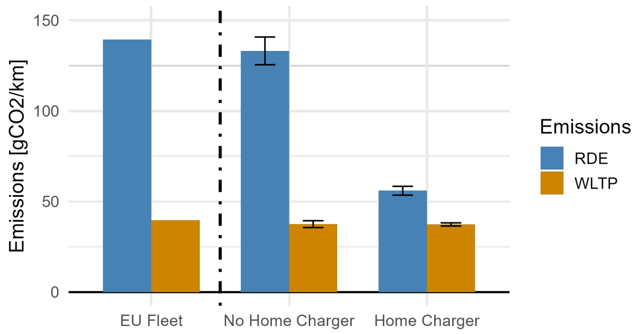
Figure E.1: Average Differences in Electric Utilization Between Treated and Not-yet-treated Employees in 2022 (Post COVID-19)



(a) Utility Factor



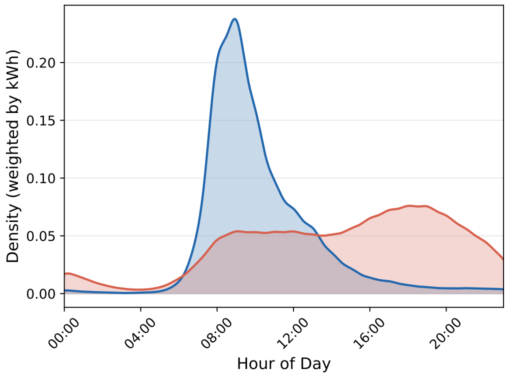
(b) Charging by Source



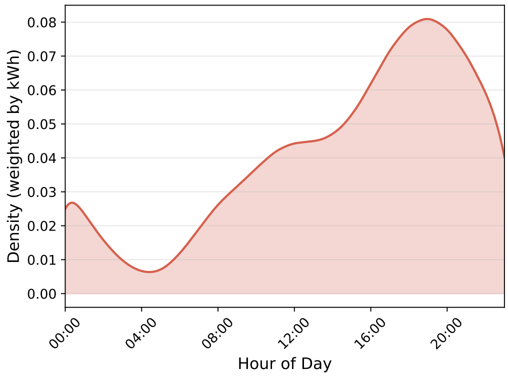
(c) Emissions Per Kilometer

Notes: Based on transaction data for the year 2022. Utility factors, defined as the ratio between VKT using electricity and total VKT (Plötz et al., 2021), are calculated based on the observed on-road fuel consumption and the vehicle's fuel consumption in 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 ("Home Charger") with employees who selected into the program but have not yet received home chargers ("No Home Charger"). Thus, some employees switch between the two samples as time proceeds. "WLTP" are vehicle CO_2 emissions per kilometer, according to the Worldwide Harmonized Light-Duty Vehicles Test Procedure (WLTP) type-approval tests. "RDE" are real 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.

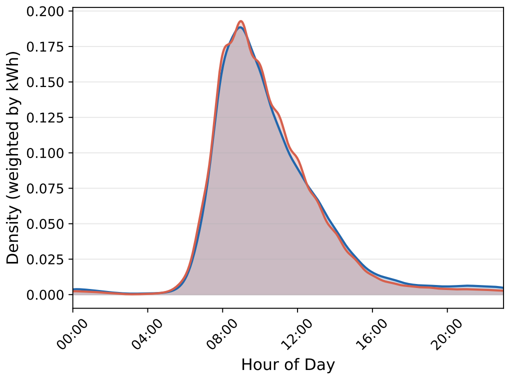
Figure E.2: Distribution of Charging over Time



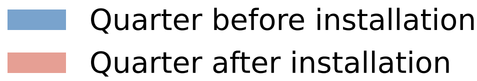
(a) At Firm + Home



(b) At Home

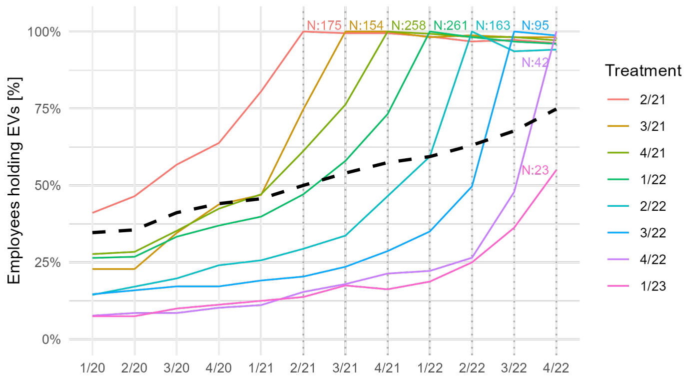


(c) At Firm

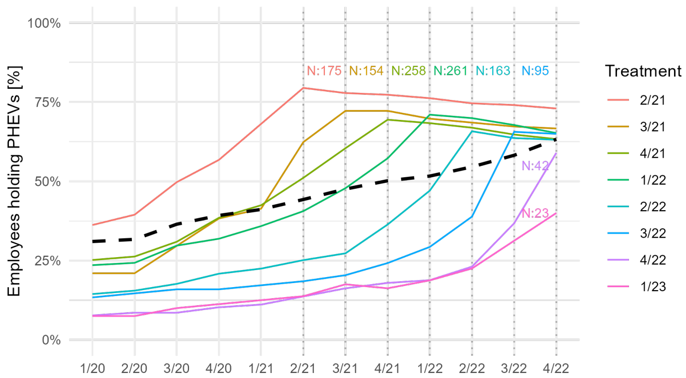


Notes: Kernel density estimates weighted by kWh charged. The sample covers the 91-day window around each employee's individual home charger installation date. Public charging is excluded due to missing plug-in timestamps. Charging hours are allocated proportionally assuming a constant charging rate of 11 kW per hour. Bandwidth selected by Silverman's rule (Silverman, 1986).

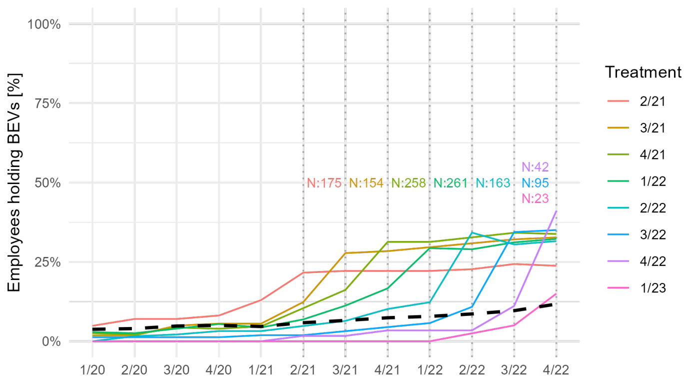
Figure E.3: Vehicle Adoption Across Treatment Groups



(a) EVs



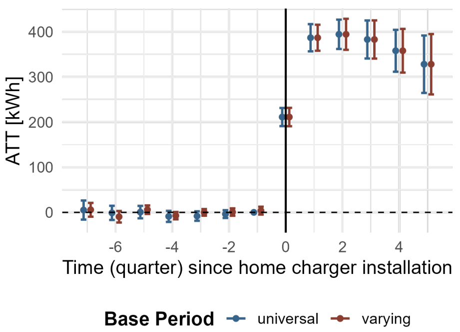
(b) PHEVs



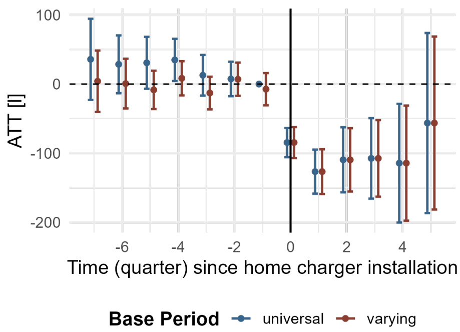
(c) BEVs

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 1,171 participants in the home charger program (35 employees are first observed with a PHEV, and a BEV later). Numbers indicate the number of employees holding an EV company car (BEV and PHEV) per treatment cohort in the period of home charger delivery. 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.

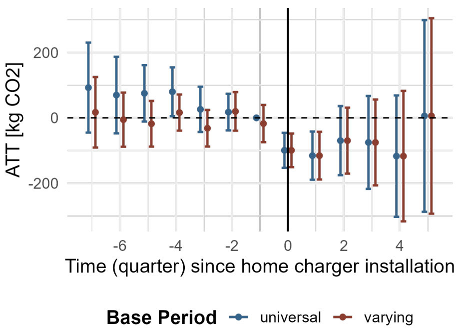
Figure E.4: Event Studies Comparing Universal and Varying Base Periods



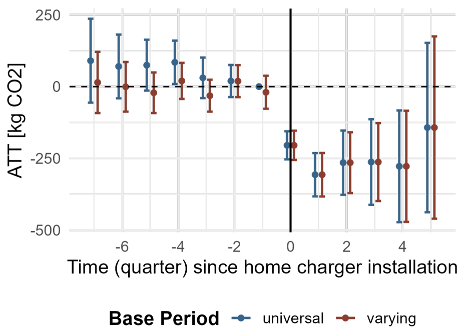
(a) Electricity in kWh



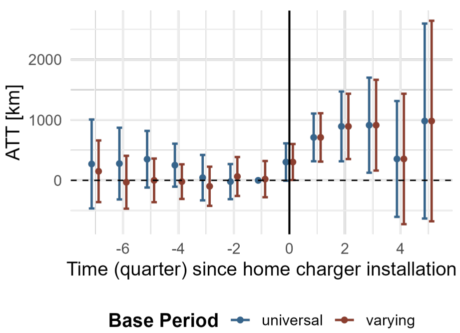
(b) Fuel in Liters



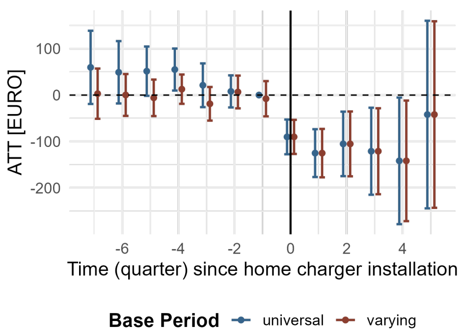
(c) CO_2 Emissions (EU ETS Cap)



(d) CO_2 Emissions (No EU ETS Cap)



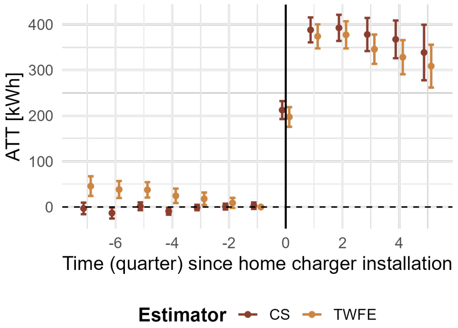
(e) Kilometers Traveled



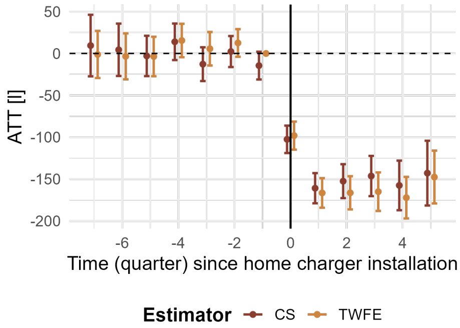
(f) Company Energy Expenditures

Notes: All event-study estimates based on estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021) as specified in eq. (3). Base period universal indicates that for pre-treatment periods, effects are relative to period $g-1$. Base period varying indicates that pre-treatment effects in period t are always relative to the effect in $t-1$. Not-yet-treated employees with a PHEV are used as the control group. As in all previous plots, the maximum lag before treatment displayed is e = -7. 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, 1,000 draws).

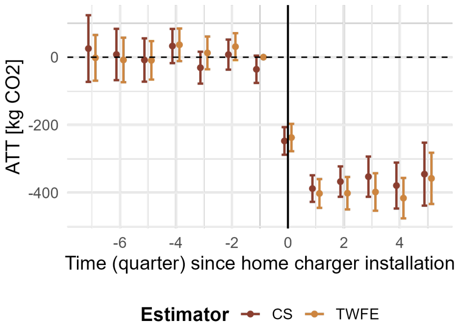
Figure E.5: Event Studies Comparing TWFE and Callaway & Sant'Anna (2021)



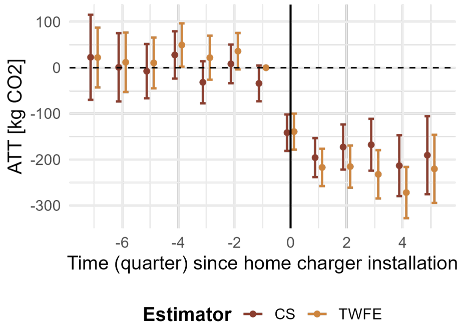
(a) Electricity in kWh



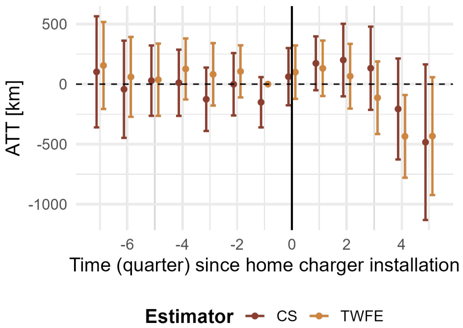
(b) Fuel in Liters



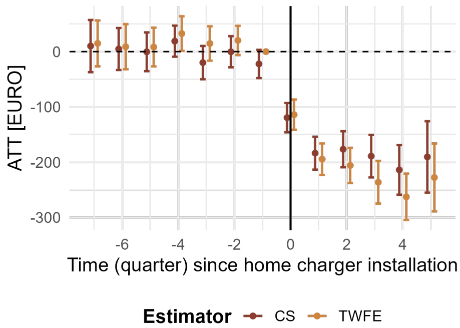
(c) CO_2 Emissions (EU ETS Cap)



(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 eq. (3) is used. TWFE indicates that the two-way fixed-effects event-study regression in eq. (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.6: Employee Eligibility and Home Charger Orders

Weeks Waited					Eligible Q1/2021,	Ordering	Employees
[min]	[q25]	[q50]	[q75]	[max]	Ordered Later [%]	Immediately [%]	
0	0	6.1	30.2	93	38.5	54.4	1160

Notes: Based on 1,160 program participants (incl. PHEV and BEV drivers) for which we observe an order date. "Weeks Waited" indicates the difference between the delivery of the employee's EV company car (eligibility for the program is conditioned on having ordered an EV company car) and the date the employee orders a home charger. "Eligible Q1/2021, Ordered Later [%]" indicates the percentage of employees who would have been eligible for the program from the outset but ordered their home charger in a later quarter. "Ordering Immediately [%]" indicates the percentage of employees ordering the home charger in the same quarter they become eligible for the program. "Employees" is the number of employees.

Table E.7: Home Charger Orders

Order Quarter	Employees	Adopters/Eligible [%]
Q1/2021	222	8.6
Q2/2021	184	13.9
Q3/2021	320	22.2
Q4/2021	195	25.4
Q1/2022	108	25.7
Q2/2022	54	24.6
Q3/2022	13	22.4

Notes: Based on 1,096 program participants (incl. PHEV and BEV drivers) for which we observe an order date and who order a home charger before Q3/2022. "Order Quarter" indicates the home charger order. "Employees" indicates the number of employees ordering a charger. "Adopters/Eligible [%]" indicates the fraction of eligible employees ordering a home charger (cumulative, since the start of the program). Program eligibility hinges on driving an EV company car.

Table E.8: Estimating ATTs Within Groups Ordering the Home Charger Simultaneously

	Energy		Mileage	Emissions [kg CO_2]		Cost
	Electricity [kWh]	Fuel [l]	Mileage [km]	No EU ETS Cap	EU ETS Cap	Energy [Euro]
Panel A: Matched Sample With Order Date Between Q1 2021 and Q4 2021						
Treated	308.82***	-132.83***	299.31	-323.97***	-161.18**	-150.31***
	(39.94)	(27.92)	(374.23)	(64.51)	(66.1)	(48.45)
Employees	580	580	580	580	580	580
Periods	9	9	9	9	9	9
Panel B: Order Date Q1 2021						
Treated	262.84***	-149.08***	-196.44	-362.93***	-248.16***	-163.42***
	(27.46)	(29.55)	(420.23)	(65.82)	(64.24)	(44.21)
Employees	145	145	145	145	145	145
Periods	6	6	6	6	6	6
Panel C: Order Date Q2 2021						
Treated	119.23***	-32.26	407.73	-76.85	-23.32	-17.71
	(21.53)	(35.59)	(544.24)	(82.06)	(84.95)	(53.68)
Employees	123	123	123	123	123	123
Periods	7	7	7	7	7	7
Panel D: Order Date Q3 2021						
Treated	248.61***	-127.18***	-326.67	-304.6***	-167.2**	-133.72**
	(25.15)	(33.09)	(454.51)	(71.27)	(71.6)	(52.96)
Employees	197	197	197	197	197	197
Periods	8	8	8	8	8	8
Panel E: Order Date Q4 2021						
Treated	237.17***	-83.27	232.91	-201.93*	-70.16	-117.84
	(39.42)	(50.98)	(558.05)	(115.18)	(118.28)	(73.33)
Employees	115	115	115	115	115	115
Periods	9	9	9	9	9	9

Notes: Trimmed sample: only group × periods with at least 20 control units, only groups with at least 20 treated units. Panel A estimates a specification with Inverse Probability Weighting (IPW) on the order quarter of the home charger. Panels B–E estimate a specification without IPW, limiting the sample to one order cohort at a time. Estimator θ^O_{sel} from (Callaway & Sant'Anna, 2021) as in eq. (2), modified to include IPW in Panel A. "Periods" are quarters. "Groups" are groups of employees receiving home charging in the same quarter. "No EU ETS Cap" stands for CO_2 emissions being computed under the assumption that additional electricity charged leads to CO_2 emissions at the marginal CO_2 intensity of the German electricity grid (cf. Appendix C.1). "EU ETS Cap" stands for CO_2 emissions being computed under the assumption that emissions from electricity generation are non-additional given the binding 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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.9: 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 CO_2]	EU ETS Cap [kg CO_2]	Energy [Euro]
Treated	318.46***	-137.98***	35.93	-177.95***	-332.14***	-171.68***
	(10.74)	(7.69)	(103.3)	(19.21)	(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

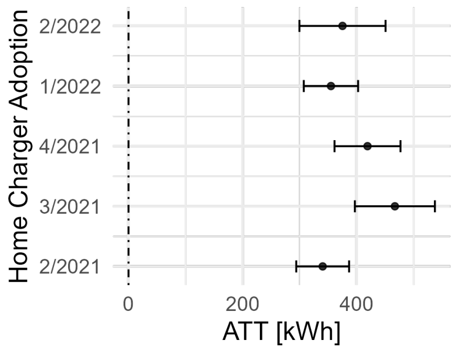
Notes: Estimator θ^O_{sel} from Callaway & Sant'Anna (2021) as in eq. (2). Never-treated employees not selecting into home charger program are used as the control group. "Groups" are groups of employees receiving home charging in the same quarter. "Periods" are quarters. "No EU ETS Cap" stands for CO_2 emissions being computed under the (counterfactual) assumption that additional electricity charged by the treated group leads to unregulated CO_2 emissions at the marginal CO_2 intensity of the German electricity grid (cf. Appendix C.1). "EU ETS Cap" stands for CO_2 emissions being computed under the assumption that emissions from electricity generation are non-additional given the binding 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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.10: ATT After Removing Employees With Exceptionally High Mileages

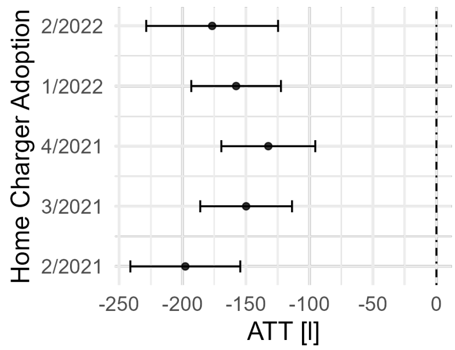
	Energy		Mileage	Emissions [kg CO_2]		Cost
	Electricity [kWh]	Fuel [l]	Mileage [km]	EU ETS Cap [kg CO_2]	No EU ETS Cap [kg CO_2]	Energy [Euro]
Treated	313.21***	-111.50***	362.18	-268.04***	-116.97***	-125.09***
	(12.66)	(15.70)	(222.93)	(41.72)	(39.32)	(27.98)
Obs	790	790	790	790	790	790
Groups	6	6	6	6	6	6
Periods	11	11	11	11	11	11

Notes: Reduced sample: removing 66 employees with at least one quarterly mileage above the 97.5th percentile (11,678 km per quarter). Estimator θ^O_{sel} from Callaway & Sant'Anna (2021) as in eq. (2). Mean (pre-treatment) is the average of the corresponding outcome variable in the last quarter before home charger adoption (619 observations). "Periods" are quarters. "Groups" are groups of employees receiving home charging in the same quarter. "No EU ETS Cap" stands for CO_2 emissions being computed under the assumption that additional electricity charged leads to CO_2 emissions at the marginal CO_2 intensity of the German electricity grid (cf. Appendix C.1). "EU ETS Cap" stands for CO_2 emissions being computed under the assumption that emissions from electricity generation are non-additional given the binding 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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

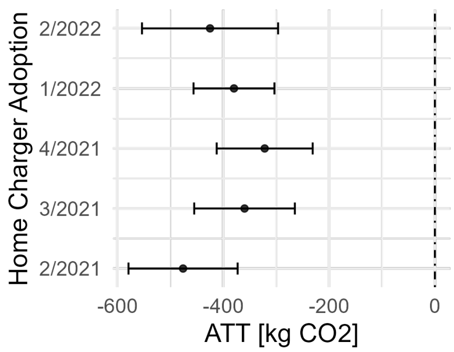
Figure E.6: Group-Specific ATT in the First Quarter After Home Charger Adoption



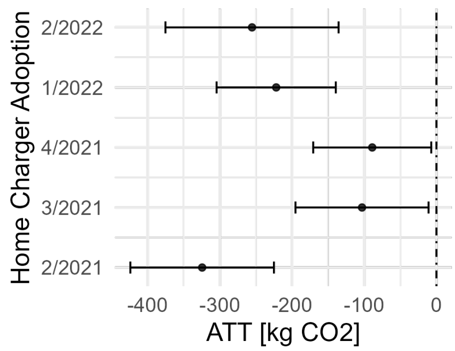
(a) Electricity in kWh



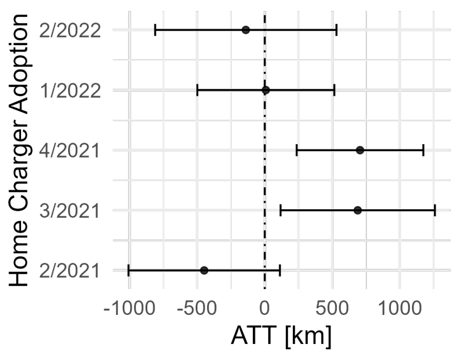
(b) Fuel in Liters



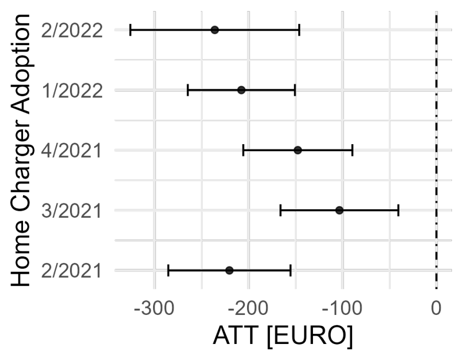
(c) CO_2 Emissions (EU ETS Cap)



(d) CO_2 Emissions (No EU ETS Cap)



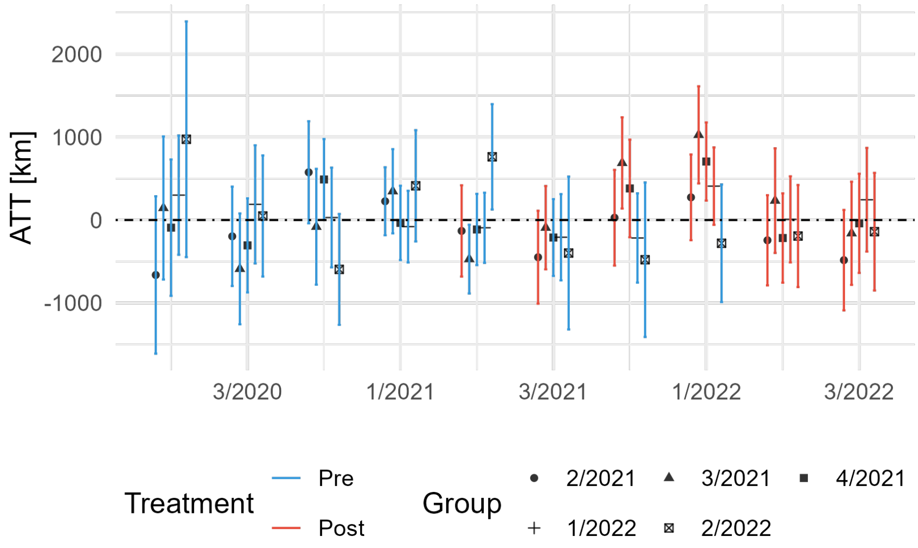
(e) Kilometers Traveled



(f) Company Energy Expenditures

Notes: Group-specific ATTs for the first quarter after the installation of the home charger using the 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.7: Group-Specific ATT on Kilometers Traveled Over Time



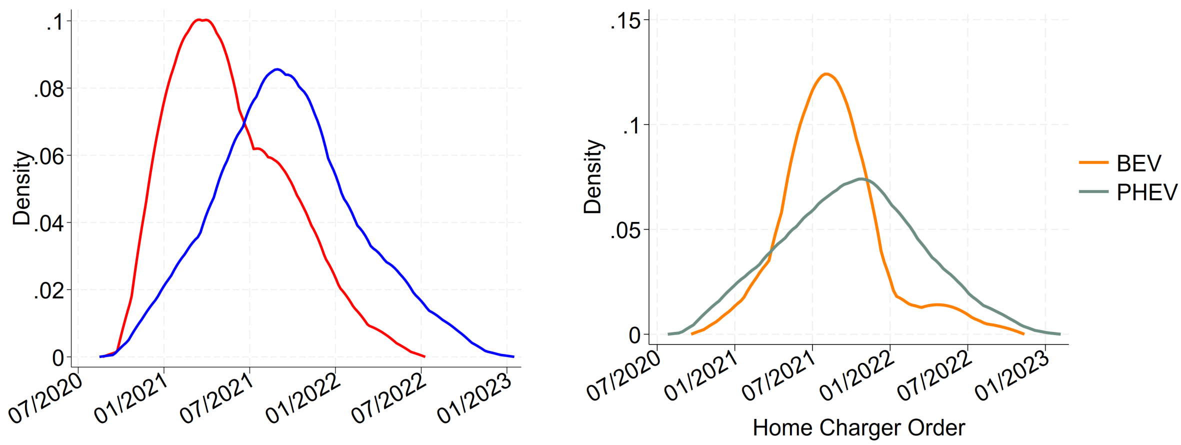
Notes: Group-specific ATTs after the installation of the home charger using the estimator by Callaway & Sant'Anna (2021). "Group" indicates the quarter in which the corresponding group received access to home charging. "Treatment" indicates that this group has received access to home charging. Never-treated 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.11: 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 eq. (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: 157 employees selecting into the home charger program whose PHEV-lease ended between October 2020 and March 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 January 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: $\leq$ median charging (7.2 kWh/month), $>$ median charging).

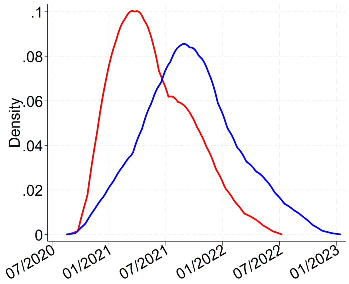
Figure E.8: Selection Into Early Home Charger Orders Among Employees Ordering BEVs



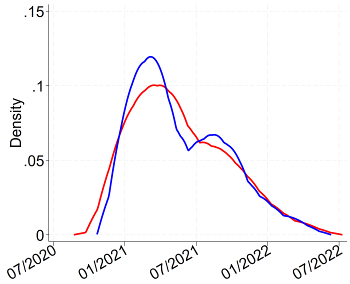
(a) Treatment Assignment　　(b) Vehicle Choice (Control Group)

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 October 2020 and March 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).

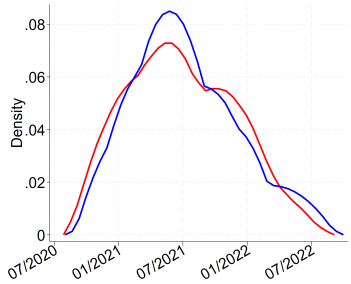
Figure E.9: Kernel Density Plots Before and After Matching



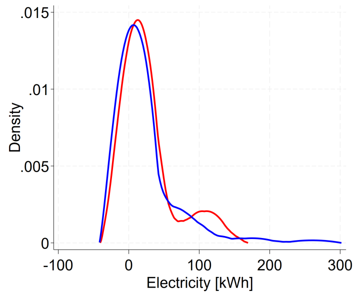
(a) Charger Order,
Before Matching



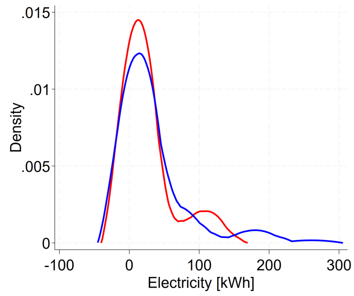
(b) Charger Order,
After Matching



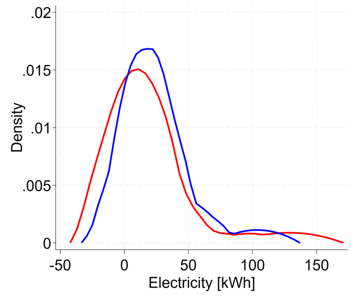
(c) Charger Order,
Order Gap ≤ 7 Months



(d) Electricity Consumed,
Before Matching

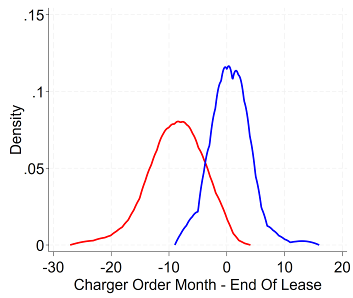


(e) Electricity Consumed,
After Matching

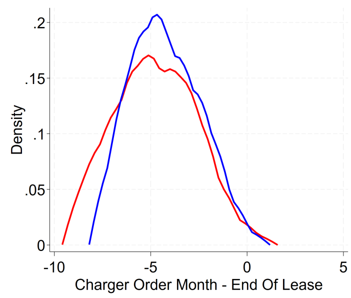


(f) Electricity Consumed,
Order Gap ≤ 7 Months

(g) Order Gap,
Before Match



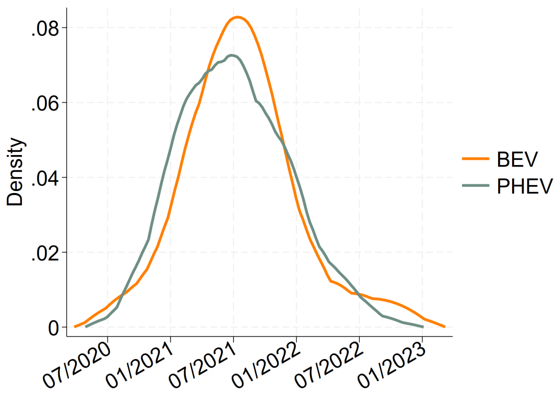
(h) Order Gap,
After Match



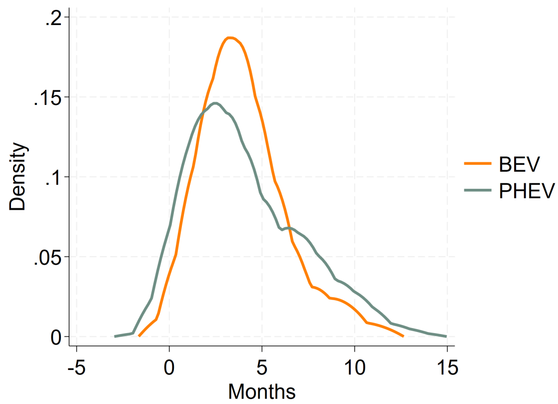
(i) Order Gap,
Order Gap ≤ 7 Months

Notes: Before Matching: 157 program participants who had to order a new company car between October 2020 and March 2023. After Matching: 49 treated employees and their nearest neighbors (corresponding to 49 observations after assigning equal weights summing to one to ties). Order Gap ≤ 7 Months: 20 treated employees and their nearest neighbors, matched after restricting the time between home charger order and vehicle order 7 months. "Treated" indicates that the employee received the home charger before the end of their previous vehicle's lease. "Control" is the opposite case. Panels (a), (b) and (c) display the kernel density of home charger orders over time. Panels (d), (e) and (f) display the kernel density of electricity consumption with the previous vehicle in an average month. Panels (g), (h) 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.10: 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 October 2020 and March 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%). 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 beginning or end 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 most.

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. For vehicle mileage, 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.

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

Notes: Estimator θ_{sel}^{O} from Callaway & Sant'Anna (2021) as in eq. (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 fuel consumption in charge-sustaining mode (according to NEDC type-approval tests) 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. To estimate the abatement cost of the home charger over its useful life, we extrapolate energy prices into the future assuming deterministic growth paths. Specifically, we calibrate growth factors for prices of electricity and fossil fuels to scale the estimated effects of the program on energy expenditures.

In this section, we provide a sensitivity analysis to show that working with alternative price paths for electricity and fossil fuels does not change our results much. To this end, we combine estimated treatment effects on the cost of fuel and electricity with alternative assumptions about future developments in energy and carbon prices. For reference, Table G.1 collects estimated treatment effects on energy quantity and cost in the baseline specification. We consider three alternative energy price scenarios, maintaining all other assumptions as in the baseline scenario. Each scenario will deviate from the baseline in at most one or two aspects.

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

Notes: Estimator θ^{O}_{sel} from Callaway & Sant'Anna (2021) as in eq. (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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Scenario 0: Baseline Our baseline scenario reflects the assumptions made in the main analysis regarding the future growth in energy prices (it is exactly the same baseline scenario as in the main analysis in Section 4). We model future prices for fossil fuels and electricity separately. We calibrate price changes relative to 2022, since our fuel-specific treatment effects for energy expenditures in Table G.1 suggest average fuel expenditures per liter that are close to average prices in Germany in that year.

We calibrate electricity price changes to match projections for future wholesale electricity prices in Germany by Kreidelmeier & Wuensch (2023). To be precise, we linearly interpolate between three projected electricity prices provided as part of a medium-price scenario and compute the implied electricity prices, averaged over each four-year period 2024–27, 2028–31, 2032–35, and 2036–39. Projected electricity prices are €128/MWh in 2024, €76/MWh in 2030, €59/MWh in 2050. We are aware that spot market prices for electricity in Germany in 2024 were much lower than the projection (€78/MWh), according to the Bundesnetzagentur, Germany's federal authority in charge of infrastructure regulation. We work with the projected price nonetheless, for two main reasons. First, a firm deciding to invest in home charging equipment would need to rely on a projection for future energy prices, too. Second, the higher-than-realistic electricity price assumptions work against us in the sense that they make the home charger program less financially attractive. For the initial period 2020–23, we use the annual average electricity prices on the spot market (Schwenke & Troost, 2024). We convert wholesale to retail prices by multiplying the four-year averages (and interpolated averages) by the ratio between average wholesale prices and average household electricity prices in the period 2020–2023 (prices based on Schwenke & Troost, 2024). We divide retail price projections obtained in this way by the average household electricity price in 2022 (Schwenke & Troost, 2024) to obtain the growth factors needed to extrapolate our treatment effect into future periods.

For diesel and gasoline, we assume that future prices will be driven by future carbon prices in Germany and the future world market price of crude oil.[44] For the period 2021 - 2025, we use Germany's mandated carbon prices for sectors not covered by the EU ETS, (2021:€25, 2022:€30, 2023:€30, 2024:€45, 2025:€55, cf. Bundesministerium der Justiz, 2019). In 2028, Germany's national carbon price will be replaced by the permit price of the new EU ETS2. According to the baseline scenario by Graichen & Ludig (2024), the EU ETS2 permit price will increase to €84 in 2030. We use this projection to linearly extrapolate the price from €55 in 2025 for years 2026–39. We calculate the implied carbon cost per liter of fuel (gasoline, for simplicity) based on the corresponding 2020 CO_2 emission factor by Juhrich (2022). For the oil price, we rely on projections by the International Energy Agency (2024) that the price per barrel of crude oil will fall from $82 in 2023 to just above $77 in 2039 (based on IEA's STEPS scenario for the global energy sector which takes into account current climate and energy policies). We linearly interpolate between the support points of this scenario to obtain average prices for all four-year periods in our simulation. To convert this into per-liter prices of fuel at the pump in Germany (in Euro, net of carbon pricing) we multiply the crude oil price (in US dollars) by a factor of 0.022, which corresponds to the ratio of the average fuel price in Germany (€1.85, average price for a liter of gasoline net of carbon pricing) and the crude oil price ($82 per barrel), evaluated in 2022. We combine the implied average fuel prices without carbon pricing with the carbon price series developed before to obtain an average tax-inclusive fuel price for each four-year simulation period. We then translate that price series into a growth factor by dividing each price by the 2022 tax-inclusive gasoline price of €1.92.

Scenario A1: Constant Prices While the baseline scenario corresponds to our best estimate for the program's abatement cost, we also consider a simpler scenario assuming that the energy prices underlying our estimated ATTs are representative of energy prices for the full 20-year lifetime of the charger. This scenario corresponds to a decision maker who has no access to energy price projections (or does not trust these projections) and forms expectations relying on the heuristic that future energy prices will, on average, be equal to current energy prices.

Scenario A2: Expensive Electricity The cost advantage of electric driving depends on electricity being relatively cheap, compared to fossil fuels. To assess whether

[44] For the electricity price path, there is no need to separately model future carbon prices, since the EU ETS prices are accounted for in the prognosis for future wholesale electricity prices by Kreidelmeier & Wuensch (2023).

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	86.3	97.7	100	100	86.3	97.7	86.2	97.7
2024–2027	99.2	98.3	100	100	99.2	188.7	96.2	188.7
2028–2031	100.2	70.4	100	100	100.2	96.7	92.7	96.7
2032–2035	102.0	62.4	100	100	102.0	74.8	90.9	74.8
2036–2039	103.9	59.5	100	100	103.9	70.6	89.6	70.6

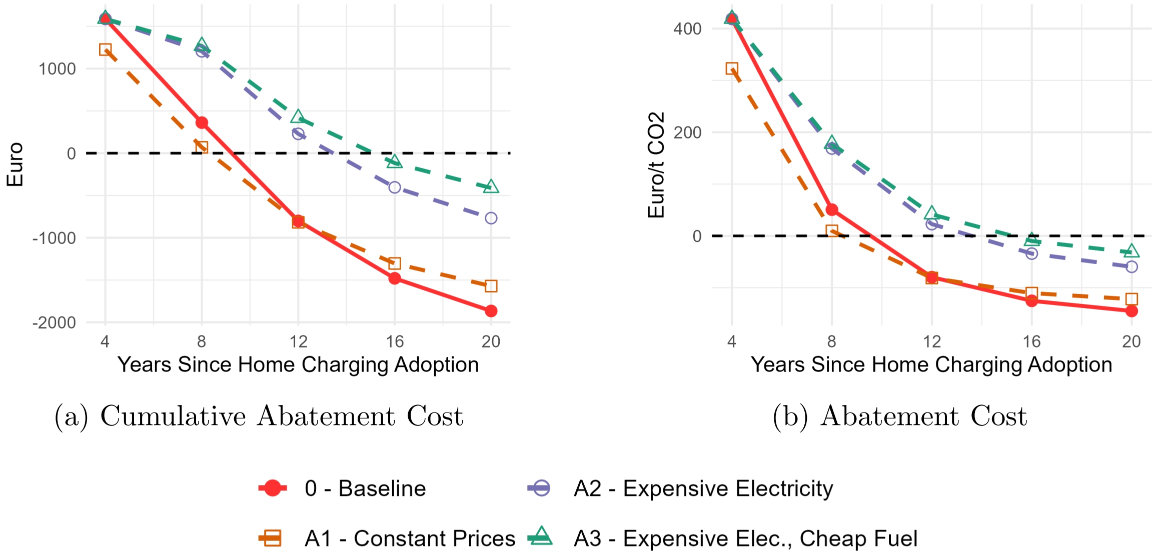
Notes: Price path relative to reference period, as described in scenarios Baseline and A1–A3. The electricity price path is obtained by dividing the projection for the average wholesale electricity price (Kreidelmeier & Wuensch, 2023) in the period by the price in 2022. The fuel price path is obtained by combining a carbon price projection under the national German carbon price, and later the EU ETS2 to a projection of future gasoline prices relying on scenarios for the price of crude oil by the International Energy Agency (2024). Percentages are obtained by dividing that price by the average carbon tax-inclusive gasoline price in Germany in 2022.

the cost-effectiveness of the home charger program is robust to more pessimistic energy price scenarios, we compute the program's effect under high electricity prices. We do so by calibrating the electricity price growth factor using the high-price scenario from Kreidelmeier & Wuensch (2023) instead of their medium-price used in the baseline scenario. This scenario assumes wholesale electricity prices in Germany of €264/MWh in 2024 which gradually decline to €80/MWh in 2039 (instead of €128/MWh and €70/MWh, respectively, in the medium-price scenario). In hindsight, the 2024 price seems extraordinarily high, but due to the war in Ukraine, electricity spot market prices had already reached an annual average of €235/MWh in 2022. A repetition of such a high-price period was considered possible in case there were further disruptions in the supply of natural gas for electricity generation.

Scenario A3: Expensive Electricity and Cheap Fuel To test the robustness of our results to even more pessimistic energy price scenarios, this scenario assumes low future prices for gasoline and diesel in addition to expensive electricity from the previous scenario. To implement a low-price scenario for fossil fuels, we calibrate fuel prices to projections in the IEA's Announced Pledges Scenario (APS) (International Energy Agency, 2024), which assumes that the price of crude oil will fall to $63 per barrel by 2039 (in contrast to $77 under the STEPS scenario). The IEA arrives at this price path by assuming that more ambitious global climate policy lowers the demand for fossil fuels relative to the previously used STEPS scenario. Despite this, we keep the carbon price for the transport sector in Germany on its baseline trajectory.

Table G.2 summarizes the relative price paths for all three scenarios. Figure G.1 shows 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

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 based on eq. (7), aggregating treatment effects on PHEV and BEV use and BEV adoption under different assumptions for future electricity and fuel prices. Scenarios as described in Appendix C.2.

the treatment effects in Table G.1. From Table E.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 larger than any price change that occurs over time in any of the scenarios.