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

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Abstract

Many European companies operating company car fleets face the challenge of lowering CO_2 emissions from their fleets. A particularly large lever in this regard exists for Plug-in Hybrid Electric Vehicles (PHEVs), as those can be run on fuel or electricity and often exhibit low electric driving shares. This paper examines the effects of a large German company installing charging stations at their employees' homes. Leveraging quasi-experimental variation in the delivery and installation of home chargers, we quantify the impact of this technology on energy use and CO_2 emissions of 856 PHEV company cars. As fuel and electricity expenditures for these cars are covered by the employer, home charging mainly changes the non-monetary costs to an employee. We find that access to home charging increases electricity consumption by 317.9 ($\pm$23.3) kWh per quarter and decreases fuel consumption by 97.97 ($\pm$36.5) liters, reducing CO_2 emissions by 38 %. Moreover, access to home charging increases the employee's propensity to choose a Battery Electric Vehicle (BEV) upon renewal of the lease by 30 %-points. We use these estimates to compute private levelized abatement costs of home chargers for a range of scenarios characterizing the diffusion of BEVs. With current tax-inclusive energy prices, home chargers break even for the company within eight to 16 years.

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

JEL-code: D12, L91, Q52, R42

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1 Introduction

The environmental impact of many potentially energy-saving technologies depends on consumer behavior. Plug-in Hybrid Electric Vehicles (PHEVs), which can run on either electricity or petroleum-based fuels, are an important case in point. Carbon dioxide (CO_2) emissions per vehicle kilometer traveled can vary substantially for this technology, depending on the share of kilometers traveled using electricity. A number of studies show that the real-world electric driving shares of PHEVs are systematically lower than what is technically feasible (Chakraborty et al., 2020; Plötz et al., 2022; Tsanko, 2023). In Europe, where CO_2 emissions for electricity generation can be considered non-additional under a binding emissions cap of the European Emission Trading Scheme (EU ETS), this increases driving-related CO_2 emissions.[1] One explanation for low electric driving shares is the additional time and effort needed to recharge the car (Krishna, 2021). The provision of charging infrastructure in convenient locations could lower that time cost and thus increase electric utilization, yet this hypothesis has not been tested empirically.

For companies maintaining fleets of company cars including a large share of PHEVs, inefficient user behavior can impose a substantial burden in the form of additional corporate CO_2 emissions. In Europe, company cars are often provided to employees as a fringe benefit. These benefits are mainly meant to increase a company's reputation among current and potential future employees. However, CO_2 emissions related to the use of company cars - be it from business trips or private trips - count towards the CO_2 emissions of the company. Companies striving to lower their greenhouse gas emissions thus need to decarbonize their fleets. The provision of charging infrastructure may provide a large lever, as it could steer the use of PHEVs towards a higher share of electric driving or even encourage the adoption of pure Battery Electric Vehicles (BEVs).

This paper investigates how employer-subsidized home chargers can impact the electric utilization rates of PHEV company cars and the adoption of BEVs. It does so by leveraging quasi-experimental variation in the adoption of company-financed electric charging at the employee's home. To support the shift toward greater electrification within their fleet, our partner company implemented a program to incentivize home charging among employees with BEV or PHEV company cars. The program provided (i) subsidies for home charger installation and (ii) automatic reimbursement for electricity expenses related to

[1] In jurisdictions without a regulatory cap on carbon emissions from electricity generation, the effect of electric driving on CO_2 emissions depends on the energy sources used for electricity generation. Holland et al. (2016) show that electric driving has a positive impact on CO_2 emissions in most US counties. Unlike Holland et al. (2016), we do not consider air pollutants other than CO_2 in this paper, since our study focuses on corporations with a greenhouse gas emission reduction target.

home charging. To participate, employees were required to hold a BEV or PHEV (or to have ordered one) and enroll in the company's fuel cost compensation scheme, where fuel and charging costs for company cars — including private usage — were covered by a fixed monthly salary deduction. Notably, this implies that participants incurred no variable monetary cost for refueling or recharging. Applications for home chargers in our sample period spanned January 2021 to December 2022, with a staggered roll-out due to, e.g., supply chain disruptions following the COVID-19 pandemic. As a result, employees experienced varied waiting times for charger installation, allowing us to analyze the effects of home charger availability on PHEV usage patterns and BEV adoption.

Our sample consists of 856 employees holding a PHEV company car. Our partner company provided us with data on almost 45,000 refueling and electric charging transactions between January 2020 and December 2022 for these vehicles. Besides the date and time of the transaction, the data contains the amount of fuel in liters (electricity in kilowatt-hours), employee-reported odometer readings, and information on the vehicle's make and model. Using emission factors for the different energy sources (Juhrich, 2022; Icha & Lauf, 2022), we also estimate CO_2 emissions. This setting allows us to study the effect of installing charging infrastructure at home using a Difference-in-Differences (DiD) estimator. As two-way fixed effects estimators can suffer from severe biases under staggered treatment adoption, we employ the estimator developed by Callaway & Sant'Anna (2021). To address concerns about selection into home-charger adoption, we use not-yet-treated PHEV users, who receive a home charger at a later point in time, as the control group. The difference in contemporaneous outcomes between treated and not-yet-treated employees identifies the average treatment effect on the treated. Outcomes of primary interest are the amount of electricity charged, the amount of fuel used, the implied CO_2 emissions and the vehicle kilometers traveled.

We find that the availability of home charging increased electricity consumption by 317.9 ($\pm$23.3) kilowatt-hours (kWh) per quarter while decreasing consumption of gasoline or diesel by 97.97 ($\pm$36.5) liters per quarter. This translates into a 38 % reduction in tailpipe emissions, corresponding to 237.12 ($\pm$87.5) kg of CO_2. The average employee's mileage increased by 671.13 ($\pm$474.9) km per quarter, which can be interpreted as a 16 % rebound effect in terms of vehicle kilometers traveled.

In addition to intensive-margin effects, we also find an extensive-margin effect on the adoption of BEVs following the installation of home chargers. In particular, for employees with a PHEV who receive access to home charging at least three months before replacing their company car, the likelihood of choosing a BEV is 30 %-points higher. This choice reduces the transport-related CO_2 emissions of this employee to zero, given the company's policy that employees need to hold on to their company car for four years.

In a cost-benefit analysis using different assumptions about the diffusion of BEVs, we find that access to home charging abates between four to 20 tons of CO_2 emissions for the average employee in our sample. This abatement is cost-free: in almost all scenarios, the installation of the home charger pays off for the company after eight to sixteen years. Given that the lifespan of a home charger can exceed 20 years, the program can be said to yield substantial benefits in terms of emissions abatement but also financially. The only scenario where we find a substantial cost per ton of CO_2 abated is when the company combines subsidized home charging with a mandate for BEV company cars after four years. While the reduction of energy costs and carbon emissions no longer justifies the investment in this scenario, there might be substantial benefits in terms of employee satisfaction. These benefits are beyond the scope of this paper.

The remainder of this paper is structured as follows: Section 2 relates our study to the existing literature. Section 3 introduces the context of our study, the data and the empirical strategy used. Section 4 shows our empirical results. Section 5 combines empirical results to extrapolate the effect of home charging across the useful life of the charging station in terms of benefits and costs to the company. Section concludes.

2 Literature

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

Concerning the former literature, a number of studies show that the charging of electric vehicles responds to financial incentives. These studies show electricity prices have an effect on the timing of charging (Qiu et al., 2022; Bailey et al., 2023), the choice of charging station (at home vs. at the place of work) (Chakraborty et al., 2019), the extensive margin of whether or not a PHEV is charged (Chakraborty et al., 2020), and on the vehicle kilometers traveled for BEVs (Nehiba, 2024). The use of PHEVs is additionally affected by the price of fossil fuels (Grigolon et al., 2024), with higher price elasticities for PHEVs than for fossil-fuel cars suggesting that consumers substitute fossil fuels by electricity. There is some evidence that financial incentives in this context do not lead to habit formation, as the observed effects on vehicle use vanish after the financial incentives are removed (Bailey et al., 2023; Grigolon et al., 2024). In our setting, there are no differences in monetary costs for PHEV users between refueling or charging their vehicle. We can thus focus on the effect of non-monetary costs associated with electric charging of PHEVs, such as the additional time needed in comparison to refuelling the car.

The second strand of literature focuses on the decision to adopt a BEV or PHEV. This literature has studied the role of monetary incentives and the availability of (mostly public) charging infrastructure in that decision. He et al. (2023) show that for the US, PHEV sales increased by an average of 2.7 % following a $2,000 tax credit incentive and that sales remained stable after the incentive's termination. A number of studies compare the effectiveness of financial incentives on EV adoption with the effect of public charging infrastructure. Springel (2021) shows for Norway that subsidies on public charging stations resulted in more than twice as many electric vehicle purchases than the same amount spent on subsidies on purchase prices. By contrast, Remmy (2022) finds that German purchase subsidies generated more electric vehicle sales than charging station subsidies. Illmann & Kluge (2020) also find a positive but small effect of charging infrastructure on monthly electric vehicle registrations for Germany. Ou et al. (2020) show in a simulation study that public charging infrastructure is more effective at promoting PHEV sales in emerging markets than in mature markets. Li et al. (2017) find that a 10 % increase in the number of public charging stations would increase PHEV sales by about 8 %. Li (2023) shows that unifying three incompatible charging standards would induce car manufacturers to build more charging stations and sell more electric vehicles. A few studies provide evidence on the effect of home charging access. Bailey et al. (2015) show that awareness of public chargers is not a strong predictor of PHEV interest and that the availability of charging at home is more important. Hardman & Tal (2021) study the purchase decisions of PHEV owners and find that PHEV discontinuance in California is related to dissatisfaction with the convenience of charging and not having 240-volt charging at home. Lee et al. (2023) show that PHEV adopters' replacement choices when deciding between a conventional car, a BEV, or (again) a PHEV correlate with charging convenience and home charging access.

In our study, we can track an employee's charging behavior across multiple energy sources using data on refueling and charging transactions for company cars. Leveraging the link between this data and information on the employee's adoption of a company-provided home charging station, our paper is the first to causally estimate the impact of access to home charging on charging behavior and the CO_2 emissions of PHEVs.

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

3 Research Design

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

3.1 Quasi-Experimental Roll-Out of Home Charging

We study the roll-out of home chargers among employees of a German firm that operates a large fleet of company cars. In Germany and other EU countries, company cars are commonly offered as a fringe benefit to employees. In exchange for a fixed monthly deduction from the net salary (which is proportional to the net list price of the car), employees get a car that they can use for business-related but also for private trips. For an additional lump-sum deduction, employees can enroll in a fuel cost compensation scheme that covers the costs of all fuel and electricity consumed by the vehicle.[2]

Employees of our partner company can choose a car from a large set of makes and models. Vehicles with an internal combustion engine (ICEVs) are (as of 2022) the most popular choice, but PHEVs have been on the rise and some employees have switched to fully electric BEVs. For PHEVs, the electric utilization rate is typically measured by the so-called utility factor (Plötz et al., 2021), which is defined as the ratio between vehicle kilometers traveled using electricity and total vehicle kilometers traveled. Since we can only observe the total number of kilometers traveled, we need to impute the utility factor based on the rated fuel consumption per 100 km of the vehicle according to official test procedures. The imputation is taken from Plötz et al. (2022), and described in more detail in Appendix B. Although electric vehicles can be charged at no extra cost to the holder

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

under the above scheme at public charging points and in company parking lots, the utility factor for employees without access to home charging is low. Employees receiving a home charger in 2021 and 2022 exhibited an average utility factor of 0.29 in 2020. This is much lower than the average utility factor of 0.69 assumed in type-approval ratings under the New European Driving Cycle (NEDC) test procedure (Vallée et al., 2022) but higher than the average utility factor of 0.18 found for German PHEV company cars (Plötz et al., 2020).

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

Several features of the application and installation process caused the roll-out of home chargers to be staggered over time. First, during the first eight months of the program, participants could order a home charger only via the employer and not directly from the provider. The employer collected applications and forwarded them in batches to the company installing the home chargers. Second, throughout the first two years of the program, supply-side 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 being employed with the company, regardless of whether they need a company car for business-related or private travel. Employees who order a company car must hold on to it for four years before they can order a new one or opt out of the program (which rarely happens due to large tax privileges as compared to private car ownership). This implies that each month, a new group of employees can decide to order an electric company car and, potentially, participate in the home charger program.

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

Figure E.2 in the appendix shows adoption of PHEVs and BEVs prior to treatment for different treatment cohorts (one cohort per quarter). We observe from panels (a) - (c) that many employees have adopted their respective vehicle that is eligible to participate in the home charger program well before the installation of the home charger, i.e., we observe almost all treated subjects for at least one full quarter before the home charger becomes available. Furthermore, as can be seen from panel (a), there is almost no attrition, with only a few employees (78 out of 1442) dropping out of the sample after treatment because they left the firm and thus needed to return their vehicle.

3.2 Econometric Framework

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

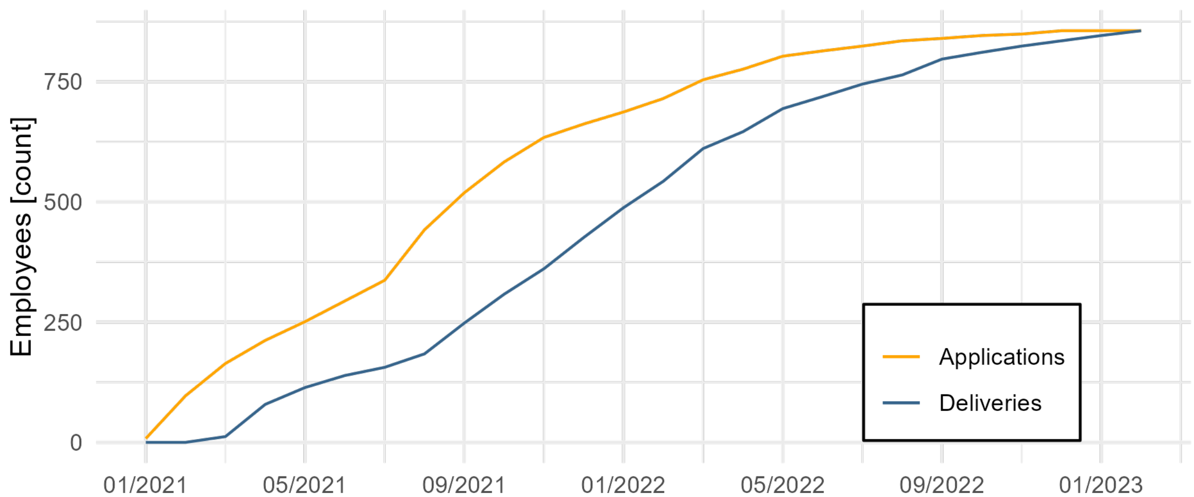
$$Y_{it} = \beta_1 \, \mathbb{1}(t \geq \mathrm{G}_i) + \eta_i + \mu_t + \epsilon_{it} \tag{1}$$

where the variable Y_{it} measures relevant outcome variables of employee i in time period t, in our case a calendar quarter, G_i denotes the quarter in which the home charger becomes available for use for employee i, and η_i and μ_t are employee and quarter fixed effects.

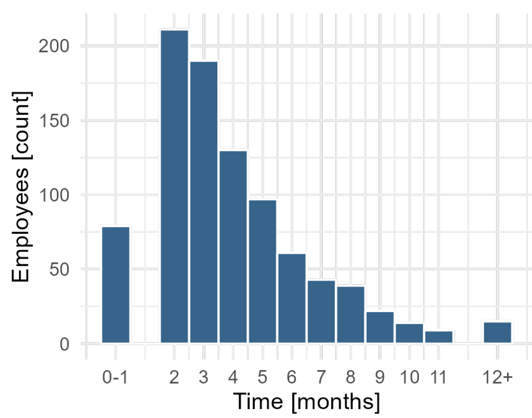
Since this two-way fixed effects estimator can suffer from severe biases under staggered treatment adoption, as is the case in our setting, we employ the alternative estimator developed by Callaway & Sant'Anna (2021). This estimator aggregates separately estimated treatment group and time-specific average 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 the treatment in period g. This notation uses the dynamic potential outcome framework developed by Robins (1986), where $Y_{it}(g)$ 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. We estimate these group and period-specific ATTs using the doubly-robust estimator proposed by Callaway & Sant'Anna (2021) and use, unless otherwise indicated, not-yet-treated PHEV users as the control group, i.e., users who receive a home charger at a later point in time.[3]

[3]While the estimator proposed by Callaway & Sant'Anna (2021) relying on outcome regression re-

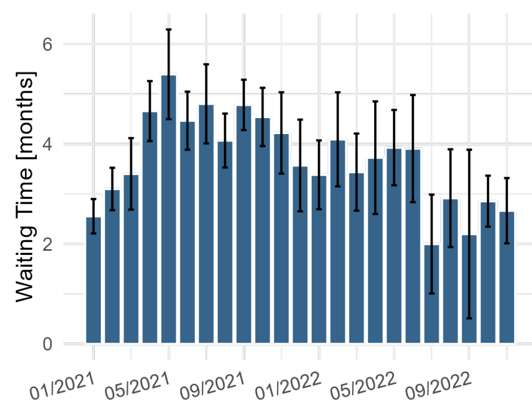
Figure 1: Home Charger Applications and Distribution of Waiting Times



(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.

We use the estimator θ^O_{sel} from Callaway & Sant'Anna (2021) to aggregate the estimated group $\times$ time-specific $\widehat{ATT}(g, t)$ into one summary measure for the overall ATT of home charger adoption:

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

The notation used here is consistent with the notation introduced above. Additionally, T is the last period in the sample ($t = 1, \ldots, T$), and $P(G_i = g|G_i \leq T)$ is the share of employees receiving the home charger in period g as a fraction of all employees receiving the home charger before the end of the sample period. This estimator assigns equal weight to all employees, independent 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 use the estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021) to aggregate the group $\times$ time-specific estimates of the ATT into an estimator of the treatment effect at differential temporal exposure to the treatment:

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

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.[4] As Callaway & Sant'Anna (2021) point out, interpreting differences in the estimator $\theta_{es}(e)$ as dynamic effects hinges on the assumption of homogeneous effects of treatment exposure across groups with different timing of home charger adoption since the composition of groups observed with a given exposure time might change.

Our primary interest is with the outcome variables amount of electricity charged, amount of fuel used, total amount of energy used, mileage, and the implied changes in CO_2 emissions and energy expenditures. The next section describes how we measure those

quires that the researcher correctly specifies the outcome evolution in the control group and the estimator based on inverse propensity score weighting requires that the researcher correctly specifies the treatment group assignment probability, the doubly-robust estimator correctly estimates the group $\times$ time-specific ATTs under *either* assumption.

[4]Note that later-treated groups are not observed with long exposure times using a constant time frame.

outcomes at the employee level.

3.3 Data

Sample Composition. Our analysis considers all home charger applications between January 2021 and December 2022. Fuel efficiency and mileage outcomes are computed based on automatically collected transaction data on charging and refueling, but also on employee-reported odometer readings. Employees report their vehicles' odometer readings only when refueling their cars. Starting with transaction data for 1,021 PHEVs held by 939 employees during our sample period (i.e., some employees renewed their lease during the sample period and got a different car), we drop 63 cars with less than two odometer readings. To the remaining odometer readings, we apply a data cleaning algorithm that identifies implausible (infeasible) mileages and interpolates between odometer readings that were deemed feasible to impute a plausible measure of mileage. We explain the details of this imputation in Appendix B. As part of the cleaning procedure, we drop 26 cars for which we do not observe at least two feasible odometer readings.[5] We drop two cars that had more than 30 % of their quarterly mileages above the 99.9th percentile of quarterly mileages, and we additionally drop all quarterly observations where i) the mileage exceeded the 99.9th percentile of quarterly mileages or ii) the ratio between the observed mileage and an approximation of the mileage based on the vehicle's fuel and electricity consumption was below 0.005 (the 0.5th percentile of the ratio) or exceeded 4.68 (the 99.5th percentile of the ratio).[6] Finally, we drop all observations after September 2022, since for many cars, we observe the second to last refueling event and thus odometer reading before September 2022. The final analysis sample thus comprises 928 PHEVs held by 856 employees and 421 BEVs held by 407 employees.

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

[5]We need at least two feasible odometer readings to calculate vehicle kilometers traveled.

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

Summary Statistics. Transaction data on fuel and electricity consumption between January 2020 and December 2022 contains automatically registered information on the date and time of refueling or recharging, the amount of fuel in liters (electricity in kWh), the employee-reported odometer readings, and administrative information on the vehicle model, which we merged with vehicle efficiency data published by the General German Automobile Club (Allgemeiner Deutscher Automobil-Club e.V. (ADAC), nd).Overall, we observe 44,322 refueling and recharging transactions for the 856 employees holding a PHEV company car in our sample. We estimate CO_2 emissions using appropriate emission factors for each energy source (gasoline, diesel, and electricity) published by the German Environment Agency (Umweltbundesamt) (Juhrich, 2022; Icha & Lauf, 2022). Table E.1 in Appendix E provides comprehensive summary statistics on driving and charging behavior, vehicle attributes, and employee characteristics for this sample, following the adoption of a home charger.

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

During the analysis period, 856 employees holding a PHEV company car participated in the program, while 2,695 employees also holding a PHEV company car did not. Table 1 shows the differences in means of all the key variables for these groups in 2020, i.e., the year before the launch of the program.[7] We observe that home charger applicants are more frequently male, they are older and have longer tenure with the company than non-applicants. That applicants are, on average, older than non-applicants seems plausible, as it is easier to have a home charger installed when an employee owns a home than when she rents a home, and home ownership increases with age. With a two % higher mileage per quarter, applicants use nine % less fuel and 24 % more electricity than non-applicants. Thus, they drive their PHEVs already more climate-friendly than non-applicants even before adopting a home charger. Given those differences, a naïve estimate based on

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

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

	Home Charger		No Home Charger	
Variable	Mean	Sd	Mean	Sd
Panel A: Vehicle Use in 2020				
Mileage per quarter [km]	4318.283	(2838.04)	4215.239	(2728.7)
Emissions [kg CO_2]	646.167	(550.62)	700.368	(575.97)
Tailpipe emissions [kg CO_2]	627.566	(556.94)	686.339	(582.05)
Electricity per quarter [kWh]	48.566	(82.77)	36.630	(73.09)
Fuel per quarter [l]	259.871	(231.4)	285.879	(242.78)
Fuel consumption [l/100 km]	5.778	(3.2)	6.504	(3.08)
Electricity consumption [kWh/100 km]	1.463	(2.66)	1.196	(2.5)
Utility factor [km elec./km total]	0.289	(0.38)	0.192	(0.38)
Energy expenditures [Euro]	342.745	(293.73)	374.480	(309.74)
Panel B: Vehicle Characteristics				
Fuel efficiency [l/100 km WLTP]	1.585	(0.35)	1.537	(0.36)
Electric efficiency [kWh/100 km WLTP]	17.456	(3.15)	16.647	(2.5)
Price [Euro]	32135.907	(4195.48)	30279.441	(4764.88)
Weight [kg]	1997.623	(255.93)	1895.784	(211.14)
Panel C: Employee Characteristics				
Age [years]	48.218	-	43.188	-
Tenure [years]	17.431	-	12.888	-
Female [%]	0.156	-	0.235	-

Notes: Comparison of the sample of employees selecting into the home charger program between January 2021 and December 2022 (N = 856 employees) to the group of employees not selecting into the home charger program during that period (N = 2695 employees). Both samples are restricted to the employees holding at least one PHEV during the sample period and opting into the fuel cost compensation scheme of the company. Panel A shows summary statistics for vehicle use in the year 2020 in which none of the employees in the home charger sample has received a home charger yet. The sample sizes are reduced to N = 388 employees that are using their PHEV during that period for the home charger sample and N = 1533 employees in the no home charger sample. Panel B displays vehicle characteristics obtained from the General German Automobile Club's car catalog. Panel C displays employee characteristics, which are only available in terms of group averages. WLTP stands for "Worldwide Harmonised Light Vehicle Testing Protocol".

never-takers of the home charger would likely induce bias in the results.[8]

Average Outcomes for Treated and Not-yet-treated Subjects. For the group of employees eventually receiving a home charger, Figure 2 compares average outcomes between employees who have a company-sponsored home charger and those who do not yet have it, for the years 2020 to 2022. Panel (a) shows that home charging users exhibited a utility factor that is almost three times as high as for non-users, despite similar overall mileage. This difference is mainly driven by charging at home, which dwarfs charging at the firm or at public places (panel b). Panel (c) depicts emissions per km for those who have a home charger and those who have not yet received it, and it also compares these emissions with the general population of PHEV drivers in the EU, both in terms of real-driving emissions and according to official test procedures (WLTP, which stands for Worldwide Harmonised Light-Duty Vehicles Test Procedure). We observe that emissions according to WLTP are very similar across groups, and real-driving emissions of those who have not received the home chargers yet are very similar to the EU average. For home charger adopters, emissions drop to nearly a third of the emissions of those who have not received the home charger yet. The next section investigates whether these findings continue to hold in the causal evaluation framework introduced earlier.

4 Treatment Effects of Home Charger Adoption

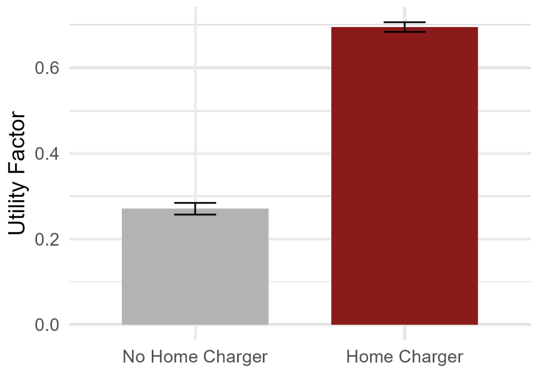
In this section, we first consider the effects of access to home charging on several outcome variables in event studies. In the second part of this section, we aggregate these quarterly treatment effects into one ATT over the full sample period, using a weighted average of the DiD estimates, as described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

4.1 Treatment Effects by Quarter

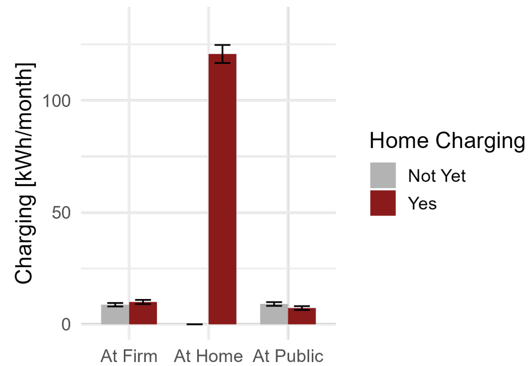
We begin our discussion of the results by considering the margin of charging vs. refueling. Figure 3 displays the ATTs per quarter, whereby quarter 0 refers to the quarter in which the home charger was installed, quarter 1 is the first quarter after the adoption quarter, and so on. Two general comments apply. First, the point estimates in quarter zero are

[8]Nevertheless, we also run robustness checks using never-treated employees as control group; see Section 4.5.

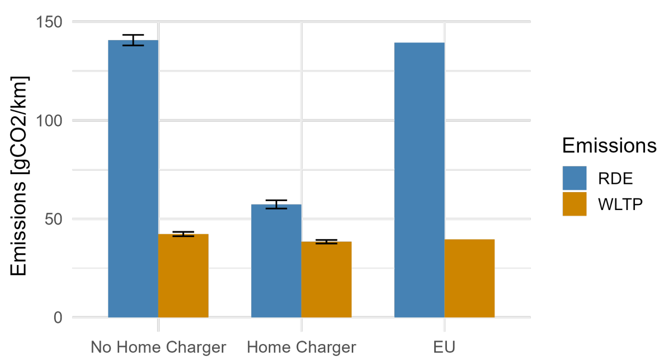
Figure 2: Average Differences in Electric Utilization Between Treated and Not-yet-treated Employees



(a) Utility Factor



(b) Charging by Source



(c) Emissions Per Kilometer

Notes: Based on transaction data for the period 2020 - 2022. Utility factors are calculated based on the observed on-road fuel consumption and the vehicle's fuel consumption in the charge-sustaining mode in the New European Driving Cycle (NEDC) testing procedure. For details on the calculation, see Appendix B. Charging by source is calculated based on the observed amount charged at each source. Both measures compare employees who have already received home chargers with employees who selected into the program but have not yet received home chargers. Thus, some employees switch between the two samples as time proceeds. "WLTP" are vehicle CO_2 emissions per kilometer, according to the Worldwide Harmonised Light-Duty Vehicles Test Procedure (WLTP) type approval tests. "RDE" are real-world driving emissions. "EU" 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.

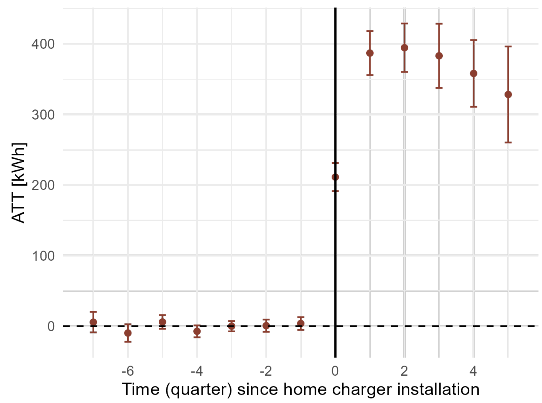
lower in absolute value than those for subsequent quarters because subjects receive the home charger on different dates during that quarter (some in week one, others in the last week of that quarter). Therefore, quarter 1 is the first quarter in which we observe all treated employees for a full quarter. Second, point estimates get noisier for higher treatment lags because the size of the control group of not-yet-treated employees falls over time.

Panel (a) of Figure 3 shows that the total electricity consumption of the PHEVs held by employees receiving a home charger increases sharply at the time of adoption by between 300 and 400 kWh per quarter. The effect is relatively stable over time, with a slight decrease in total charging beginning in quarter three after adoption. Panel (b) shows that treated subjects reduce charging at public stations, to an increasing extent, by up to around 50 kWh per quarter. We observe from Panel (c) that there is no significant impact on charging at the firm, though this estimate points in the expected direction of less charging at the firm's premises.

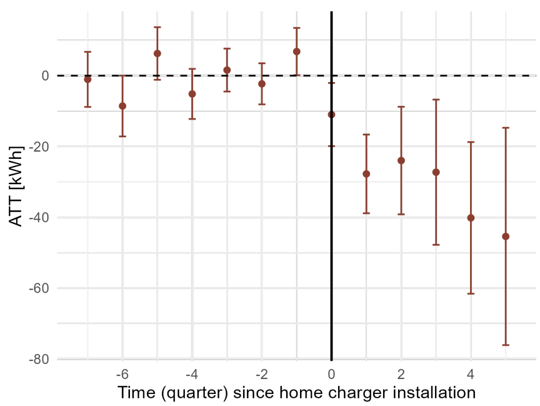
Figure 4 displays various outcomes concerning fuel consumption and mileage. We observe that the increase in electric charging is accompanied by a drop in fuel consumption (panel a), which is driven by reductions in both the number of refueling transactions per quarter (panel b) and the average quantity of fuel per transaction (panel c). On average, treated subjects reduce quarterly fuel consumption by slightly more than 100 liters in the first few quarters after adoption. These results indicate a high substitutability of electricity for gasoline among treated subjects. As before, the precision of these estimates is declining with the length of the event window.

Five quarters after the installation date for the home charger, the treatment effect on fuel consumption appears to vanish whereas the increase in electric charging is sustained (see Figure 3a). This begs the question of whether treated employees end up driving more. The estimated treatment effects on total kilometers driven per quarter are plotted in Figure 4(d). While a positive effect on the vehicle kilometers traveled is observed in the first three quarters after the adoption of home charging (mileage increases by up to 1000 km per quarter), this effect seems to become somewhat smaller in quarter four after adoption and it becomes statistically insignificant from that quarter onward. The observed increase in mileage in the first quarters after adoption is equivalent to an increase of roughly 20 % as compared to 2020 levels. This rebound effect might have several reasons. First, as charging becomes more convenient with a home charger and potentially also less time-consuming for treated subjects, this lowers the non-monetary cost of driving the PHEV, leading to higher mileage. Second, treated subjects might feel morally licensed to use their PHEV more often, as charging is associated with lower CO_2

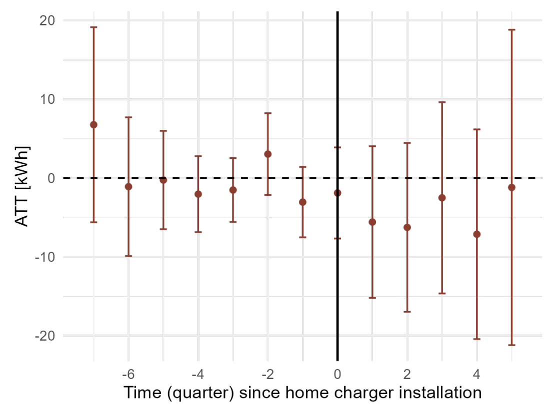
Figure 3: Treatment Effects on Electric Charging



(a) Total Charging



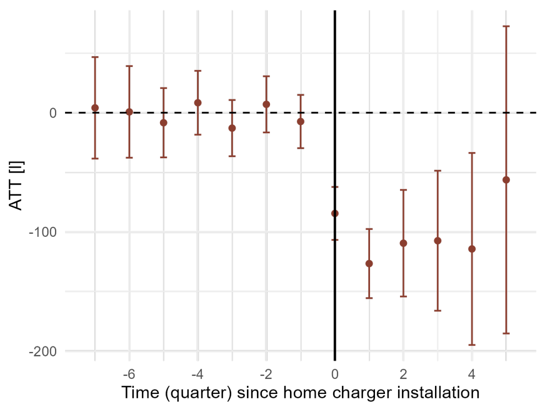
(b) At Public Station



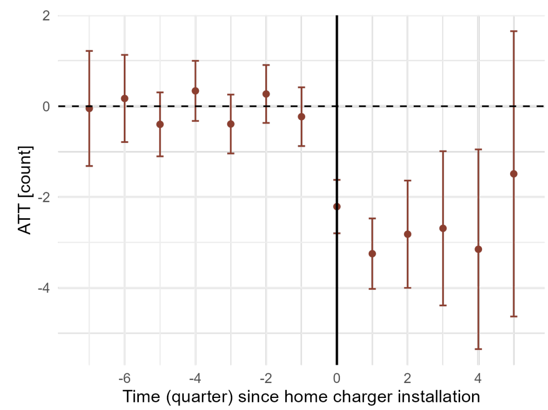
(c) At Firm

Notes: Estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021)as specified in Equation 3. "Total Charging" is the sum of all kWh charged at home, at public charging stations and at company-owned charging stations at the firm's 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. We allow for an unbalanced panel, which is necessary, since each month some employees could potentially order a new car. 95 % confidence intervals are indicated (bootstrapped standard errors, 1000 draws).

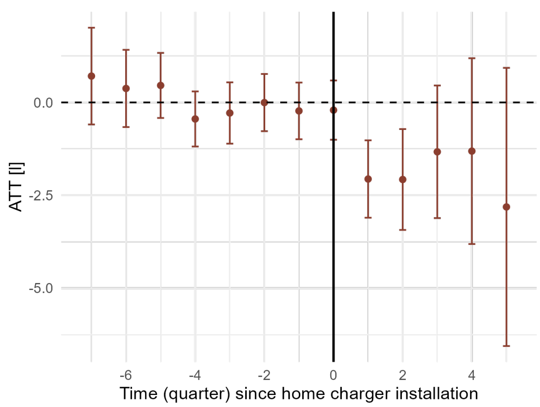
Figure 4: Treatment Effects on Fuel Consumption and Mileage



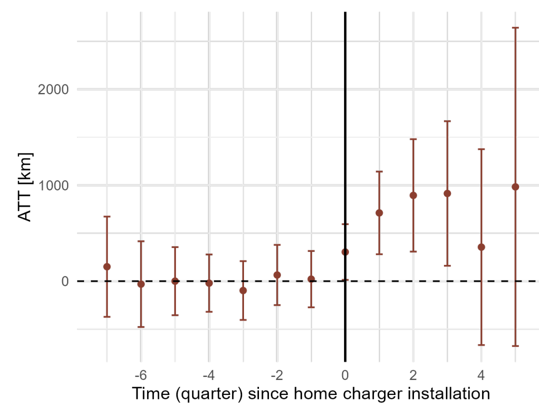
(a) Fuel in Liters



(b) Number of Refueling Transactions



(c) Liters per Refueling Transaction



(d) Kilometers Traveled

Notes: Estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021) as specified in Equation 3. "Fuel in Liters" is the amount refueled (pooled across gasoline and diesel PHEVs). "Number of Refueling Transactions" and "Liters per Refueling Transaction" are self-explanatory. "Kilometers Traveled" is the number of vehicle kilometers traveled in a given quarter. Event time indicated on the x-axis. Employees receive access to home charging at some point during quarter 0. The analysis is clustered at the level of the participating employee. We allow for an unbalanced panel, which is necessary, since each month some employees could potentially order a new car. 95 % confidence intervals are indicated (bootstrapped standard errors, 1000 draws).

emissions than refueling. In other words, they might have less of a bad conscience when driving the car electrically (for moral licensing in the environmental domain, see, e.g., Tiefenbeck et al., 2013). As a consequence, using the PHEV becomes more attractive relative to using another car that may be available in the household, or to using other modes of transport.

Finally, Figure 5 shows that the treatment reduced average fuel consumption per 100 km by up to three liters (panel a) as it increased the electric driving share of PHEVs by up to 40 percentage points (panel b). These effects indicate a drastic change in user behavior: as compared to within-sample behavior in 2020, i.e. before the adoption of the home charger, the average fuel consumption per 100 km drops by more than 50 % while the utility factor more than doubles.

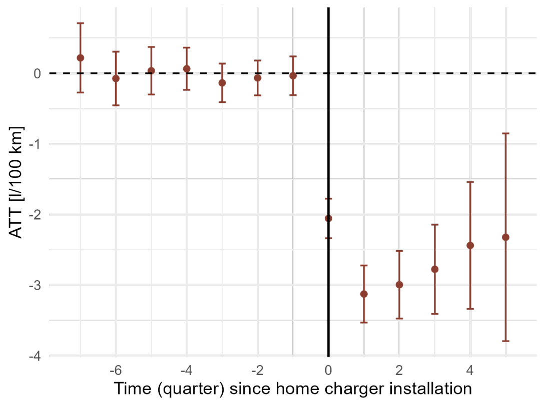
How these effects translate into CO_2 emissions abatement depends on the assumptions about the emissions caused by electricity generation for charging. We argue that the most reasonable assumption about these emissions is that no additional emissions are generated. The reason for this is that any emissions from charging are regulated under the emissions cap implied by the EU's Emissions Trading System (EU ETS). Hence, any additional emissions from charging must be reduced elsewhere under the cap. Under this realistic scenario, the reduction in fuel consumption translates into reduced CO_2 emissions of up to 300 kg per quarter (panel c). For comparison, panel (d) shows the treatment effect on CO_2 emissions if the additional electricity charged were to give rise to unregulated CO_2 emissions at the prevailing average CO_2 intensity in the German electricity grid (cf. Appendix C.1). Under this scenario, emissions abatement is still about half of the abatement under the other scenario, though the corresponding coefficient becomes statistically insignificant already shortly after the adoption of home charging infrastructure.

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

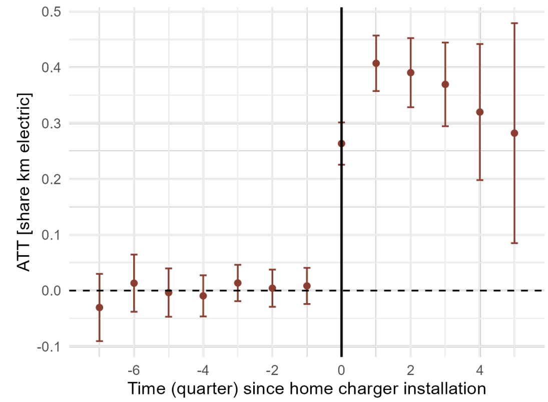
4.2 Overall Treatment Effects

Following Callaway & Sant'Anna (2021), we compute the ATT as a weighted average of the DiD estimates obtained for different cohorts and time horizons, assigning equal weight

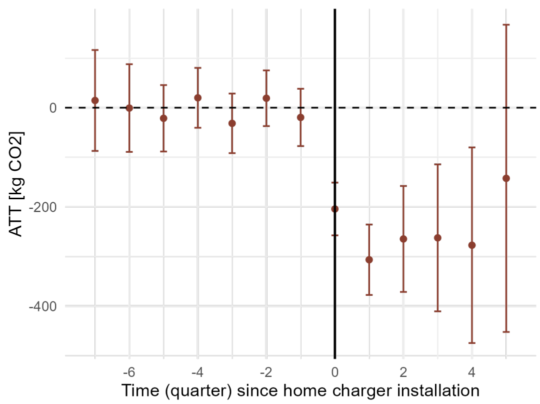
Figure 5: Treatment Effects on Fuel Efficiency, CO_2 Emissions and Energy Costs



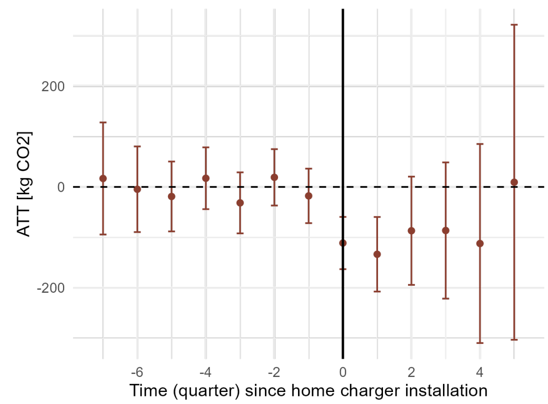
(a) Fuel Consumed per 100 km



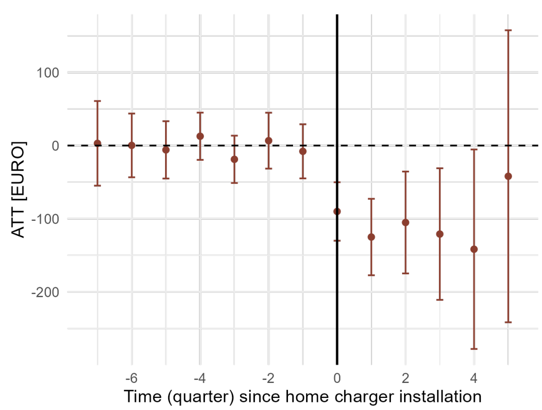
(b) Electric Driving Share



(c) CO_2 Emissions (EU ETS Cap)



(d) CO_2 Emissions (No EU ETS Cap)



(e) Company Energy Expenditures

Notes: Estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021) as specified in Equation 3. "Fuel Consumed per 100 km" is self-explanatory. "Electric Driving Share" 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 cap implied by the EU's emissions trading scheme (EU ETS), while in panel (d), they are computed assuming that electricity charged leads to CO_2 emissions at the average CO_2 intensity in 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 table notes from Figures 3 and 4 also apply here. 95 % confidence intervals are indicated (bootstrapped standard errors, 1000 draws).

to each employee in our sample. Table 2 reports the resulting ATT estimates, all of which are statistically significant at the 5 % or 1 % level. Home charger adoption increased electricity consumption by 317.9 (±23.3) kWh and decreased consumption of gasoline or diesel by 98.0 (±36.5) liters per quarter. The net effect on emissions is a reduction of 237.1 (±87.5) kg of CO_2 under the assumption of non-additionality of emissions under the EU ETS. Emissions would drop by 93.0 (±91.0) kg if additional charging were to induce higher CO_2 emissions from electricity generation at the average emissions intensity in the German electricity grid. Home charger adoption caused a reduction in energy costs of 102.5 (±61.6) euros for the company. Finally, the average employee's mileage increased by 671.1 (±474.9) km per quarter, which can be interpreted as a 16 % rebound effect in terms of vehicle kilometers traveled.

4.3 Treatment Effects for Battery Electric Vehicles

For employees obtaining a BEV during the sample period, we estimate the effect of home charging on electricity consumption and expenditures.[9] Table 3 reports aggregate ATT estimates. We find that home charging increases total electricity consumption by 172.05 (±143.12) kWh per quarter, after netting out significant decreases in both charging at the firm's premises of 52.38 (±47.35) kWh and, especially, on the public grid of 247.73 (±122.66) kWh. This result suggests that BEVs are, similar to PHEVs, driven more once a home charger is installed, pointing to an economically significant rebound effect equal to approximately 1,100 km per quarter. Since public charging is more expensive than charging at home,[10] the resulting increase in charging expenditures is economically and statistically insignificant. If there were no cap on electricity sector emissions via the EU ETS, the increase in charging would lead to incremental CO_2 emissions of 79.84 (±63.03) kg per quarter.

These effects are unlikely to be driven by systematic differences between adopters of home chargers and non-adopters. As shown in Table E.2 in the appendix, quarterly electricity consumption prior to treatment is very similar across the two groups, and differences in the electric efficiency, weight, and price of the respective BEVs are minor. As in the larger sample of BEV holders, treated BEV holders tend to be more frequently male, older than non-participants, and have longer tenure with the company.

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

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

Table 2: Aggregate Treatment Effects on PHEV Holders

	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	317.9***	-97.97***	671.13***	-93.04**	-237.12***	-102.52***
	(11.87)	(18.6)	(242.28)	(46.44)	(44.62)	(31.43)
Employees	856	856	856	856	856	856
Groups	6	6	6	6	6	6
Periods	11	11	11	11	11	11
Employee FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X

Notes: Estimator θ^{O}_{sel} from (Callaway & Sant'Anna, 2021) as in Equation 2. "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 average CO_2 intensity in the German electricity grid (cf. Appendix C.1). "EU ETS Cap" stands for CO_2 emissions being computed under the more realistic assumption that charging is not associated with any CO_2 emissions under the cap implied by the EU's emissions trading scheme (EU ETS). The analysis is clustered at the level of the participating employee. We allow for an unbalanced panel, which is necessary, since each month, some employees could potentially order a new car. 95 % confidence intervals are indicated (bootstrapped standard errors, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Average Treatment EFfects on BEV Holders

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

Notes: Estimator θ^{O}_{sel} from (Callaway & Sant'Anna, 2021) as in Equation 2. "Periods" are quarters. "Groups" are groups of employees receiving home charging in the same quarter. Emissions are calculated under the assumption that additional electricity charged leads to CO_2 emissions at the average CO_2 intensity in the German electricity grid (cf. Appendix C.1). In the more realistic EU ETS scenario, additional emissions are zero and are therefore not reported here. We allow for an unbalanced panel, which is necessary, since each month, some employees could potentially order a new car. 95 % confidence intervals are indicated (bootstrapped standard errors, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Treatment Effects on Vehicle Choice

Employees entitled to a company car get to choose a new vehicle every four years. This allows us to investigate whether the availability of convenient home charging makes it more likely that employees choose a BEV. To identify this treatment effect, we exploit quasi-experimental variation in exposure to home charging infrastructure among PHEV holders.

The estimation sample for this analysis contains all PHEV holders whose renewal decisions were scheduled between July 2021 and June 2022. These employees could have adopted a home charger at least two quarters before the renewal of their lease, and some of them did. The identifying assumption is the exogenous timing of the renewal date of the company car lease relative to the adoption of the home charger. All employees in this group eventually get a home charger, but some employees have the option to obtain a home charger *before* their previous lease ends (and they have to choose their next company car), while others have this option only *after* their previous lease ends. We thus compare PHEV holders with access to home charging for at least one full quarter before obtaining a new company car to PHEV holders who obtained access to home charging only after ordering a new company car. This identifies the treatment effect of home chargers on the choice probabilities for BEV and PHEV company cars, respectively.[11] Note that selection

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

into the home-charging program does not affect these choice probabilities, since both groups select into the program eventually.

Table 4: Access to Home Charger and BEV Adoption

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

Notes: Probit regressions. Average marginal effects reported. Bootstrapped standard errors (1000 draws). In model (2), the following covariates were included: A dummy for working at the headquarters and energy consumption with previously held PHEV (fuel in liters and electricity by source in kWh). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We hypothesize that employees who already had access to home charging with their previous vehicle are more likely to choose a BEV.[12] We test this by regressing an indicator for BEV adoption on a treatment indicator, as defined above. This is a cross-sectional regression since we observe at most one vehicle choice per employee.

Our preferred specification controls for location-specific effects (in particular the availability of charging stations at the employee's location of work and the density of the public charging network) using a headquarter dummy, and for employee-specific mobility preferences by including the total amount of energy consumed with the previously held PHEV company car.[13] Table 4 reports the estimated treatment effects on choice probabilities. Access to a home charger increases the probability of ordering a BEV by 29.8 %-points in the preferred specification. This suggests that home charger adoption induces some PHEV holders to go all-electric and switch to a BEV, thus eliminating the option of refueling in the future.

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

[13] Note that all PHEV company cars were held for approximately four years. Thus, the total fuel and electricity consumed can be interpreted as reflecting driving behavior over four years.

4.5 Robustness Tests

As a robustness test, we re-estimate the treatment effects on the use of PHEVs in Table 2 and Figures 3 - 5 using never-treated employees, i.e. employees who do not select into home charger adoption, as a control group. This exercise allows us to work with a control group that is constant over time, thus eliminating concerns that changes in the composition of the control group could drive the observed results.[14] In addition, we estimate the event studies using the following two-way fixed effects event study regression:

$$Y_{it} = \sum_{e=-K}^{-2} \delta_e \, \mathbb{1}(t - \mathrm{G}_i = e) \sum_{e=0}^{L} \beta_e \, \mathbb{1}(t - \mathrm{G}_i = e) + \eta_i + \mu_t + \epsilon_{it} \tag{4}$$

The notation is as introduced in Section 3.2, except for $-K$ and L, which indicate the maximum number of pre-treatment and post-treatment periods possible.

Appendix Figure E.3 shows that the event study results are robust to the alternative specifications for almost all outcomes. Two differences are worth pointing out: First, due to the constant and larger control group, the pattern of treatment effects becoming more noisy with longer treatment exposure is no longer visible. In particular, no treatment effect becomes insignificant in quarter five after treatment. We are thus confident that the effect we estimate can be assumed to be constant with longer treatment exposure. Second, we no longer find evidence for a rebound effect on vehicle kilometers traveled.

Mirroring the event study results, the overall ATTs reported in Table E.3 in the appendix show that almost all treatment effects are robust to the alternative control group specification. The only exemption is again the rebound effect on vehicle kilometers traveled. Comparing effect sizes for fuel and electricity consumption between Tables E.3 and Table 2, one can see that the rebound effect on vehicle kilometers in the main analysis seems to be driven by a smaller reduction in fuel use, but an equally sized increase in electricity consumption. We think that this difference in effects could be driven by selection into treatment in the specification used in the robustness test. The observed differences are consistent with pre-sample differences in fuel and electricity consumption between employees adopting a home charger and those not selecting into the program.

We conduct an additional sensitivity analysis for outcomes depending on vehicle kilometers traveled. Our mileage variable is constructed from odometer readings recorded by employees only when refueling their vehicle. While we interpolate between correct mileages to rectify erroneous entries in the interior of the time series, we have to extrap-

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

olate in case the first or the last odometer reading in a series is erroneous.[15] In Appendix F, we assess whether the extrapolation we implemented drives our results. We show that all results depending on vehicle mileage are robust as long as we consider both fuel and electricity consumption to extrapolate erroneous mileages. Only the rebound effect on vehicle mileage is not robust when extrapolating using only fuel consumption (the effect on fuel consumption per 100 km and the electric driving share are qualitatively robust). This result was expected, since the treatment reduces fuel consumption substantially (cf. Figure 4a).

5 Cost-Benefit Analysis

Building on the estimated treatment effects at the intensive and extensive margins, we conduct a cost-benefit analysis of home charger adoption, which relates total emissions abatement to the associated costs from the company's point of view. To this end, we simulate emission trajectories 20 years into the future, since home chargers should have a lifespan of around 20 years. This requires us to combine intensive- and extensive-margin impacts of home charger adoption because adopters are more likely to switch to BEVs and BEV holders use the home charger differently than PHEV holders. We address this issue by adapting the method by Dugoua & Gerarden (2023, Appendix H) to our potential outcome framework (using conditional expectations instead of derivatives). The basic idea is to first consider a one-off vehicle choice and then forward-simulate the paths of the outcome variables (emissions and energy costs) over a 20-year period starting from the period 2020 - 2023, with repeated vehicle choices every four years.[16] We simulate these outcomes under alternative assumptions about employees' vehicle choices, subsumed in scenarios. Formal derivations and a detailed description of the simulations are relegated to Appendix D.

The vehicle choices in our scenarios are governed by the following "transition matrix", i.e., the matrix that specifies the probabilities which car type individual i holding a certain car type $k_{it} \in \{ICEV, PHEV, BEV\}$ chooses in period t upon renewal of the lease under treatment status $D_i \in \{0, 1\}$ ($D_i = 1$ for treated individuals). This transition matrix is,

[15] Alternatively, we would have to discard a large number of observations at the end of the sample period, thus diminishing our observation window.

[16] Employees have to hold on to their company car at our partner company for four years. In reality, roughly a quarter of employees choose a new company car every year. We slightly abstract from that by assuming that all employees choose at the same time every four years.

in principle, given by:

$$\mathbf{E}(\delta^{it(D_i)|k_{it})=}$$

$$\mathbf{E}\begin{pmatrix} \mathbf{E}(\delta_{it}^{ICEV}(D_i)|ICEV) & \mathbf{E}(\delta_{it}^{ICEV}(D_i)|PHEV) & \mathbf{E}(\delta_{it}^{ICEV}(D_i)|BEV) \\ \mathbf{E}(\delta_{it}^{PHEV}(D_i)|ICEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_i)|PHEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_i)|BEV) \\ \mathbf{E}(\delta_{it}^{BEV}(D_i)|ICEV) & \mathbf{E}(\delta_{it}^{BEV}(D_i)|PHEV) & \mathbf{E}(\delta_{it}^{BEV}(D_i)|BEV) \end{pmatrix} \tag{5}$$

where δ_{it}^{k} is an indicator for whether employee i adopts vehicle type k in period t. That is, for any vehicle type and treatment status at any given time period, there is a certain probability of choosing another or the same car type. These probabilities are partly given by our estimated ATTs, partly we need to make additional assumptions as outlined below.

5.1 Scenarios

Across scenarios, we rely on a set of common assumptions. First, emissions from electricity generation are non-additional due to a binding cap of the EU ETS. Second, there is no exit from vehicle ownership (and from being employed at this specific company). Third, the initial fleet of PHEVs in the first four years is equal to the fleet observed in the data (in terms of technical characteristics). Fourth, all employees choose a new company car simultaneously in four-year increments. Fifth, treatment effects are constant over time, i.e., a home charger has the same effect period by period on charging behavior and vehicle adoption. Sixth, car use, emissions factors (particularly for electricity generation), and energy prices are constant over time. Finally, note that all cost outcomes are expressed in period-0 euros, and all future costs are discounted to period 0, i.e. the year 2020.

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

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

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

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

In this scenario, we take the extensive-margin effects of home chargers into account (as estimated in our previous analysis), while in the following scenarios we do not.

Scenario 1: Treatment does not affect vehicle choice We do not take extensive-margin effects into account and assume that access to home charging does not change vehicle choice. The choice probabilities for different vehicle types are thus given by the following, simplified transition matrix, which is the same independent of treatment status:

$$\mathbf{E}(\delta_i(1)|k_{it}) = \mathbf{E}(\delta_i(0)|k_{it}) = \begin{pmatrix} (1 - \mathbf{E}(\delta_i^{BEV}(0)|PHEV)) & 0 \\ \mathbf{E}(\delta_i^{BEV}(0)|PHEV) & 1 \end{pmatrix} \tag{6}$$

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

$$ATT(Y_{it}) = \sum_{t=1}^{5} \gamma^t \mathbf{E}(\delta_{it}^{PHEV}(1))\mathbf{E}(\Delta Y_i^{PHEV}) \tag{7}$$

Scenario 2: Vehicle choices as in overall company car population Like scenario 1, but replacing assumptions **A1** and **A2** with the assumption that the vehicle choice probabilities among employees in the home charger program are the same as in the population of all employees having to replace their company car within the next two years. We elicited these choice probabilities in a company-wide survey in February 2023. Employees who were going to choose a new company car within two years from the survey reported the engine types of the company car they currently had and the car they were planning to choose next. Assuming that the choice probabilities of employees who were still undecided at the time of the survey would follow the same distribution as the sample we observe, we obtain the following transition matrix:

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

where we have 3038 ICEVs, 598 PHEVs, and 300 BEVs in the survey. Furthermore, we only need to consider the intensive-margin treatment effects for the period-ATTs:

$$ATT(Y_{it}) = \sum_{t=1}^{5} \gamma^t \mathbf{E}(\delta_{it}^{PHEV}(1))\mathbf{E}(\Delta Y_i^{PHEV}) \tag{9}$$

Scenario 3: Permanent PHEV ownership We do not take extensive-margin effects into account and assume that access to home charging does not change vehicle choice.

Additionally, we make the simplifying assumption that employees do not change their vehicle type over time after their initial choice in period 1. Under these assumptions, the ATTs are simply given by the net present value of the period-treatment effects on PHEV use:

$$ATT(Y_{it}) = \sum_{t=1}^{5} \gamma^t \mathbf{E}(\Delta Y_i^{PHEV}) \tag{10}$$

Scenario 4: Forced Transition to BEVs We assume that the company only allows BEV company cars from the second four-year period onward. This scenario reflects the development that some employers have introduced mandates that new company cars have to be BEVs. 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:

$$ATT(Y_{it}) = \gamma \mathbf{E}(\Delta Y_i^{PHEV}) \tag{11}$$

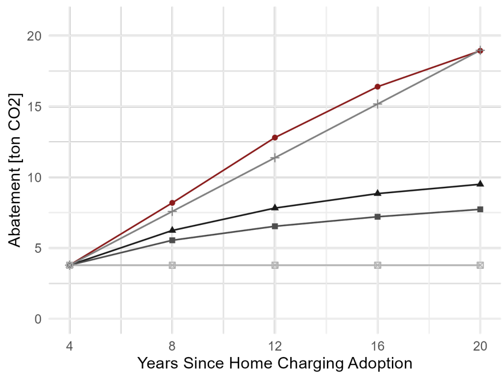
This gives us all the ingredients needed to approximate the ATT on CO_2 emissions and energy costs, combining intensive- and, depending on the scenario, extensive-margin reactions. We collect the required parameters in Table D.1 in Appendix D.

5.2 Simulation Results

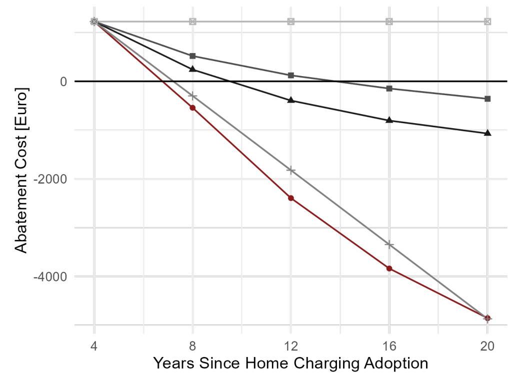
Figure 6 displays cumulative treatment effects of home charging adoption over time for various outcomes, starting from the end of year four when the leases for the initial PHEV fleet need to be renewed. We examine how the company car fleet develops over time when individuals get treated at the beginning of period 0, i.e., when they receive a home charger, and how this impacts emissions and abatement, respectively. Note that panels (a)-(c) show abatement and abatement costs per employee, while (d)-(f) display the shares of employees holding PHEVs, BEVs, and ICEVs, respectively.

Panel (a) depicts cumulative CO_2 emissions abatement, which starts from 3.8 tons after four years (the treatment effect per quarter cumulated over four years). Depending on the scenario, cumulative abatement reaches almost 19 tons of CO_2 after 20 years. Cumulative abatement remains at 3.8 tons of CO_2 in scenario 4, since the forced transition to a pure BEV fleet implies that all vehicles run at 100 % electric utility factor from period 5 onward, and hence adding chargers has no impact on emissions after year 4. In all other scenarios, the home charger program does generate emissions reductions through effects endogenous to the treatment. Cumulative abatement is highest in the baseline scenario,

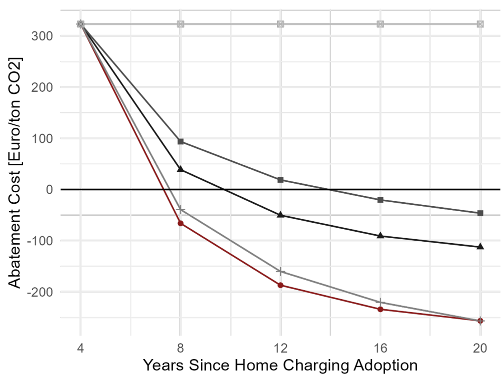
Figure 6: Simulation of Cumulative Treatment Effects over Time



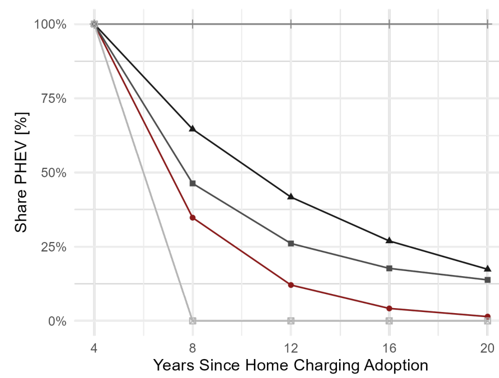
(a) Cumulative Emissions Abatement



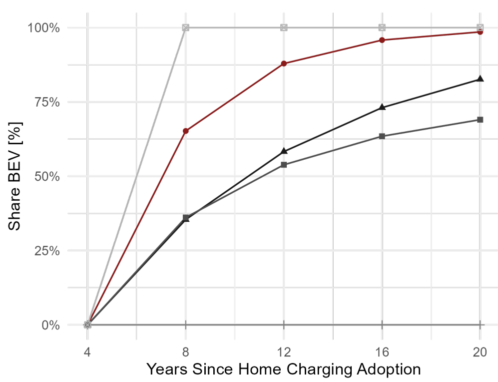
(b) Cumulative Abatement Cost



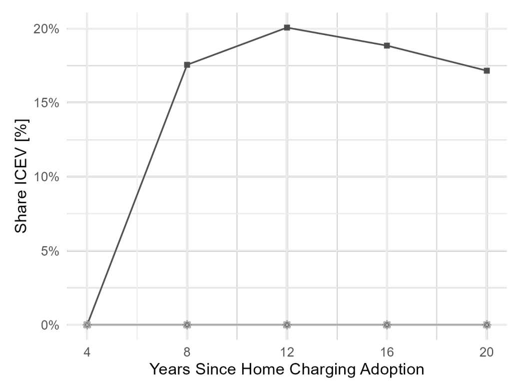
(c) Abatement Cost



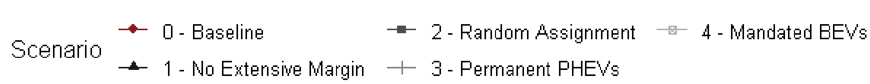
(d) Employees Holding PHEV



(e) Employees Holding BEV



(f) Employees Holding ICEV



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

which considers both intensive and extensive margin treatment effects. To obtain an understanding for the importance of the home chargers effect on BEV adoption for the overall emission abatement, we can compare the total abatement over 20 years in the baseline scenario (18.5 t CO_2 per employee) to the total abatement in scenario 1 (9.5 t CO_2 per employee). The only scenario in which intensive margin treatment effects can fully compensate this large extensive margin effect is scenario 3. This scenario shuts downs the exogenous transition towards BEVs in the control group. Under this counterfactual assumption, access to home charging leads to constant abatement of CO_2 emissions over the useful life of the charging station. However, notice that this scenario is associated with much higher CO_2 emissions than the baseline scenario, due to the continued combustion of fossil fuels. In scenarios 1 and 2, which allow for an exogenous transition towards BEVs but do not consider the extensive margin effect of access to home charging on BEV adoption, emissions abatement is considerably lower. This is due to an increasing share of employees adopting a BEV company car (or an ICEV company car in scenario 2) independent from access to home charging. For these employees, the home charger does not produce additional emissions reductions.

Panel (b) displays the cumulative total abatement cost from adopting home chargers, i.e., installation costs minus cost savings resulting from the substitution from fuel (gasoline or diesel) to electricity. We observe that the abatement cost per employee is highest if the company mandates BEV company cars from the second four-year period onward since home chargers do not result in additional emissions reductions, and it is lowest in the baseline scenario and scenario 3. Note that an abatement cost of zero implies that the home charger installation has paid off and that negative abatement cost results when there is more to be gained from the home charger program. This is the case when (i) more PHEVs remain in the fleet, as in scenario 3 or (ii) access to charging at home has a positive impact on BEV adoption, as in the baseline scenario. The break-even point is reached in less than eight years in the baseline scenario and in scenario 3 (note that we model decisions in four-year increments such that actual amortization periods can be shorter than indicated). For the remaining two scenarios, the break-even point is four to eight years later, either because the transition to BEVs due to the treatment is proceeding more slowly (see panel e), or because some employees even revert back to ICEVs (see panel f). Per ton of CO_2 emissions, we estimate levelized abatement costs of 323 euros after four years, but these decrease to between -46 and -256 euros after 20 years (see panel c).

The previous scenarios assumed that energy prices observed during the sample period 2020 - 2022 are representative of energy prices over the next 20 years. To test whether this assumption drives our results, we conduct a sensitivity analysis working with projections for future electricity prices and the future development of carbon prices for the transport sector in Germany in Appendix G. Appendix Figure G.1 shows that the assumptions made for the future development of energy prices do not drive our results. This is due to a large price differential between driving one kilometer using fossil fuels and driving the same distance using electricity, which remains large relative to all projected price changes within either category.[17]

6 Conclusion

This paper contributes, to the best of our knowledge, the first causal evidence on the effects of home charger adoption on the use of PHEVs. We find that CO_2 emissions from PHEVs fall by 38 % when the vehicle holder obtains access to home charging infrastructure, under the assumption that electric charging does not cause additional emissions under the EU's Emissions Trading System. Home charging predominantly replaces refueling with gasoline or diesel rather than other charging options, and hence reduces CO_2 emissions. This reduction is in spite of a 16 % rebound effect in terms of increased vehicle kilometers traveled. To achieve an equivalent short-run reduction in fuel consumption, prices for gasoline and diesel would need to increase by between 95 % and 131 %, based on (short-run) price elasticities estimated by Grigolon et al. (2024). This is an order of magnitude larger than the price increase between 2020 and 2040 implied by projections for the carbon price under the EU ETS 2.[18] Even under a more pessimistic assumption that electric charging leads to emissions proportional to the average emissions intensity of the German electricity mix, installing a home charger significantly reduces total CO_2 emissions.

In a cost-benefit analysis, we find that in most scenarios the installation of the home charger pays off (for the company) within eight to 16 years. The longer the time that the home charger lasts, the larger are the net benefits from installing it, with considerably negative levelized abatement costs after 20 years. Per employee, total abatement from adopting a home charger ranges from four to 19 tons of CO_2 emissions over 20 years. Given that annual average CO_2 emissions from transport (in 2018) amounted to 1.85 tons per capita in Germany (Statista, 2023), this is a sizable reduction.

In addition, our research demonstrates that installing home chargers can motivate individuals to switch to BEVs. Home charger adoption leads to a 30 %-points higher

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

[18] For details on the effect of future carbon prices on prices for fossil fuels, see Appendix G.

likelihood of choosing a battery electric company car under the periodical renewal of the employee's lease. This is likely because home chargers greatly enhance convenience and reduce both the time costs and uncertainties associated with charging. For companies aiming to fully electrify their fleets, securing employee acceptance of electric mobility is crucial. Based on our findings, subsidizing the installation of home chargers could contribute to smoothing the transition to electric mobility.

Two specifics of the context of our analysis are worth pointing out. First, we work with a sample of employees who selected into installing a charging station at home. It stands to reason that these employees are more likely to benefit from access to charging at home than the average PHEV-user, e.g., because their mobility patterns allow them to frequently charge their car at home. While this suggests that the treatment effects we estimate might exaggerate the effect for the broader population, descriptive evidence on differences in the charging behavior between applicants and non-applicants suggest that the scope for emission reductions might be even larger for non-adopters, since they use public charging stations and charging stations at the firms premises less. The convenience of charging at home should also incentivize members of this group to increase the electric driving share of their PHEVs. We leave the exploration of this trade-off for future research.

Second, our study uses on data from a subsidy program implemented within a company car fleet. In this setting, there are no financial incentives to charge the PHEV electrically. Nevertheless, we believe that our results are informative for government interventions, as the use patterns of PHEVs in our sample (before the adoption of a home charger) are well-aligned with use-patterns observed for the fleet of new PHEVs in Europe (cf. Figure 2c). With PHEVs accounting for roughly 8 % of new vehicle registrations in the European Union in 2023 (European Environment Agency, 2024) and as much as 18 % in China during the first half of 2024 (InsideEVs, 2024), our findings hold substantial policy relevance. Our results identify and quantify an effective lever for reducing emissions across a significant portion of the vehicle market. Governments should condition support for the adoption of PHEVs on the availability of access to electric charging at home. Governments aiming to reduce the emissions from existing PHEV-fleets should considersubsidizing the installation of home charging infrastructure for households holding PHEVs. In addition to subsidies, governments should enable the wide-spread adoption of home charging by reducing the administrative burden to install a home charger, and by mandating installation rights for tenants. As an example for such policies, Germany implemented a law in 2020, giving tenants the right to install a charging station at their rented home, which can only be denied under special circumstances.

Looking ahead, factors such as declining equipment costs, increased equipment durability, rising carbon taxes on fossil fuels, and the decarbonization of electricity grids will likely accelerate the adoption of home charging solutions, amplifying the environmental and financial benefits of electric mobility even further.

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Appendix (For Online Publication)

A Company Cars

Many companies provide generous mobility options to their employees, not only for business trips but also for the commute to work and leisure trips. The most prominent example are company cars, which typically can also be used privately. The use of company cars is heavily subsidized in many countries, particularly in Europe (Copenhagen Economics, 2010). Furthermore, companies often reimburse up to 100 % of the car's fuel cost. These two factors make a company car much cheaper for an employee than if the same car were purchased privately. Additionally, providing a company car is often perceived as a status symbol and can make working for an employer more attractive. Therefore, companies are reluctant to take away this privilege, even though they are confronted with external or internal ambitions to rapidly decrease CO_2 emissions, also from their employees' mobility.

As an alternative to a company car, some companies have started to offer a so-called mobility budget to their employees. A mobility budget is a predefined individual budget that can be used flexibly by employees during a certain period, e.g., a year, to choose any transport mode that is available on the market or allowed to be used. In the European Union, around 30 % of the companies with at least one company car already offer this option or are considering doing so in the future; see Kantar/Arval Mobility Observatory, 2020. For an analysis of sustainability incentives within a mobility budget, see Gessner et al. (2024).

B Data Preparation

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

The odometer readings sometimes give implausible vehicle mileages between two refueling transactions either because i) the implied mileage is negative or ii) the mileage information is not consistent (too high or too low) with the fuel and electricity consumption of the car and the car's efficiency. To clean the mileage variable, we assess the plausibility of the mileage observed using i) and ii). To do so, we apply the following procedure. We manually match the vehicle model descriptions in the company car register to vehicle models as listed in the model catalog of the General German Automobile

Club (ADAC).[19] For each PHEV model, we obtain the combined energy consumption (using both electricity and fuel) per 100 km according to type-approval tests using the New European Driving Cycle (NEDC). The NEDC was the European Union's testing procedure for type-approval before 2017, and NEDC testing values had to be provided for all model years in Europe until 2019. For all but 63 vehicles in our sample, a NEDC fuel consumption is available. If the efficiency is only available for the newer Worldwide Harmonised Light-Duty Vehicles Test Procedure (WLTP), we use that value divided by 1.2 as an NEDC-equivalent value. To clean the data, we used the vehicle's fuel consumption 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 a lower-bound estimate for the fuel consumption in charge-sustaining mode using the formula for the combined consumption under the NEDC procedure (as found in Riemersma & Plötz, 2017)

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

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

where C^{NEDC} is the combined NEDC fuel consumption, C_1^{NEDC} is the charge-depleting NEDC fuel consumption, and D_e^{NEDC} is the NEDC electric driving range of the PHEV, and C_2^{NEDC} is the NEDC fuel consumption in charge-sustaining mode. Finally, to account for the underestimation of fuel consumption under the NEDC testing procedure, particularly for PHEVs (Plötz et al., 2020), we multiply the NEDC consumption in charge-sustaining mode by 1.5 to obtain an estimate for the on-road fuel consumption of the vehicle, following Plötz et al. (2021) and Grigolon et al. (2024).

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

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

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

With this information, we proceed to clean the mileage variable as follows: Based on

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

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

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

If flagged mileages occur at the end of a time series for a particular car, we extrapolate based on the last correct odometer reading and the fuel and electricity use of the vehicle after that. For each refueling procedure after the last correct odometer reading, we impute the mileage based on the vehicle's electricity and fuel consumption, translating energy consumption into kilometers traveled using the vehicle's NEDC electricity consumption per 100 km in all-electric mode (see above) and the vehicle's average fuel consumption per 100 km we observe in the non-flagged transactions data (see above). To test whether this extrapolation affects our results for the vehicle's mileage, average fuel consumption per 100 km, and utility factor, we run a sensitivity analysis with two alternative imputation procedures in Appendix F. We truncate all vehicle time series after the vehicle's last (correct or incorrect) mileage observation, i.e. after the second-to-last observed refueling procedure since we would be unable to obtain a mileage after the last refueling procedure (odometer readings are only recorded after refueling the vehicle).

In contrast to the employee-recorded odometer readings, we take the amount of fuel and electricity consumed in the transactions data almost at face value. The only correction we apply is that we winsorize refueling at 100 liters per transaction since most vehicles have a tank capacity of less than 100 liters (this affects 8 out of 205,481 refueling procedures) and we winsorize electric charging at 130 % of the vehicle's gross battery capacity (this affects 15,497 out of 949,406 recharging and refueling procedures).[20]

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

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

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

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

C CO_2 Emissions, Energy Prices and Abatement Cost

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

C.1 CO_2 Emissions

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

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

C.2 Energy Prices

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

C.3 Home Charging Installation Cost

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

C.4 Abatement Cost

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

Table C.1: Energy Prices and CO_2 Emission Factors

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

D Derivations for Cost-Benefit Analysis

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

For simplicity, we first consider a one-off decision for vehicle adoption (a four-year lease) where employee i decides on vehicle type k given her treatment status $D_i \in \{0,1\}$ ($D_i = 1$ for treated individuals) . Treatment status D_i and vehicle type k jointly determine the outcomes CO_2 emissions $E_i^k(D_i)$ and energy costs $C_i^k(D_i)$ for employee i. We adopt the notation $Y_i^k(D_i) \in \{E_i^k(D_i), C_i^k(D_i)\}$. Employee i's outcomes can then be written as $Y_i(D_i) = \sum_k \delta_i^k(D_i)Y_i^k(D_i)$, where δ_i^k is an indicator for whether employee i adopts vehicle type $k \in \{ICEV, PHEV, BEV\}$.

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

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

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

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

By definition, the CO_2 emissions of ICEVs and BEVs (under the assumption of a binding cap of the EU ETS) and the energy costs of ICEVs are not affected by the treatment status. Additionally, we found no significant differences in energy costs of BEVs for treated and untreated employees (see Table 3). Thus, we can simplify our notation: $Y_i^k(1) = Y_i^k(0) = Y_i^k \; \forall \, i, \; k \in \{BEV, \; ICEV\}, Y \in \{E, \; C\}$. This implies that we can rewrite the ATT as:

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

Adding a "smart zero" yields:

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

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

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

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

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

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

D.2 Approximating the ATT with Repeated Vehicle Choices

In our setting, employees have to decide on a new company car every four years. Assuming that these decisions occur simultaneously for all employees, we obtain a new equation to extrapolate the ATT over the subsequent 20 years:

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

where t denotes the time period (e.g., $t = 1$ is the first four-year period 2020 - 2023) and γ^t denotes the discount factor for the respective outcome in period t. We work with an annual discount rate of 3 % for energy costs and do not discount CO_2 emissions abatement. We additionally assume that (i) treatment effects are constant over time, i.e., a home charger has the same effect on vehicle adoption and charging behavior regardless of how long the employee has had access, and (ii) car usage, emissions factors, and energy prices are constant over time. The ATT simplifies to:

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

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

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

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

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

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

$$\mathbf{E}(\delta_{it}^{k}(D_i)|k_{it}) = \\ \mathbf{E}\begin{pmatrix} \mathbf{E}(\delta_{it}^{ICEV}(D_i)|ICEV) & 0 & 0 \\ \mathbf{E}(\delta_{it}^{PHEV}(D_i)|ICEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_i)|PHEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_i)|BEV) \\ \mathbf{E}(\delta_{it}^{k\,BEV}(D_i)|ICEV) & \mathbf{E}(\delta_{it}^{BEV}(D_i)|PHEV) & \mathbf{E}(\delta_{it}^{BEV}(D_i)|BEV) \end{pmatrix} \tag{D.12}$$

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

$$\mathbf{E}(\delta_{it}^{k}(D_i)|k_{it}) = \\ \mathbf{E}\begin{pmatrix} \mathbf{E}(\delta_{it}^{PHEV}(D_i)|PHEV) & \mathbf{E}(\delta_{it}^{PHEV}(D_i)|BEV) \\ \mathbf{E}(\delta_{it}^{BEV}(D_i)|PHEV) & \mathbf{E}(\delta_{it}^{BEV}(D_i)|BEV) \end{pmatrix} \tag{D.13}$$

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

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

Based on our estimated treatment effects on vehicle choice from Table 4, we obtain an estimate for $\mathbf{E}(\Delta\delta_{i}^{BEV}|PHEV) = -\mathbf{E}(\Delta\delta_{i}^{PHEV}|PHEV)$ given the no-exit assumption on company car ownership. Additionally, we assume that BEV adoption is an absorbing state for employees selecting into the home charging program. Together, these assumptions imply:

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

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

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

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

Parameter	Source
Panel A: Estimated ATTs	
$\mathbf{E}(\Delta\delta_i^{BEV}) = 0.298$	Table 4
$\mathbf{E}(\Delta E_i^{PHEV}) = -237.12$ kg CO_2 per quarter	Table 2
$\mathbf{E}(\Delta C_i^{PHEV}) = -102.52$ € per quarter	Table 2
$\mathbf{E}(\Delta C_i^{BEV}) = 0$ € per quarter	Table 3
Panel B: Observed population averages	
$\mathbf{E}(E_i^{PHEV}(0)) = 646.17$ kg CO_2 per quarter	Table 1
$\mathbf{E}(C_i^{PHEV}(0)) = 342.75$ € per quarter	Table 1
$\mathbf{E}(C_i^{BEV}) = 63.40$ € per quarter	Table E.2
Panel C: Parameter assumptions	
$\mathbf{E}(\delta_{it}^{PHEV}(0), \delta_{it}^{BEV}(0), \delta_{it}^{ICEV}(0)) = (1, 0, 0)$	Starting from PHEV users
$\mathbf{E}(E_i^{BEV}) = 0$	Assumption given EU ETS Cap
$\gamma = \sum_{y=1}^{4}(1.03)^y$ for abatement cost	Ad hoc
$\gamma = 4$ for emissions	Ad hoc
$\mathbf{E}(\delta_i(1) \vert k_{it})$	See scenarios

E Additional Graphs and Tables

Table E.1: Summary Statistics

Variable	Mean	Sd	Min	Pctl. 25	Median	Pctl. 75	Max
Panel A: Driving Behavior							
Mileage [km]	5092	2794	25	3023	4643	6691	18122
Emissions [g CO_2]	492	368	3.93	252	393	631	3764
Tailpipe Emissions [g CO_2]	305	377	0.257	57.1	166	412	3722
Fuel [l]	126	155	0.0951	23.8	69.2	169	1560
Charge at home [kWh]	362	307	0	119	311	519	2504
Charge at firm [kWh]	30	71	0	0	3.64	30.9	1203
Charge public [kWh]	21.8	64.4	0	0	0	16.4	986
Fuel consumption [l/100 km]	2.37	2.21	0.00587	0.696	1.74	3.31	14
Electricity consumption [kWh/100 km]	9	6.29	0	3.97	8.09	13.2	37.3
Panel B: Vehicle Characteristics							
Price [Euro]	32542	4488	0	30802	32474	35290	49631
Weight [kg]	2017	262	1480	1840	2025	2105	2655
Fuel Consumption [l/100 km WLTP]	1.58	0.341	0.8	1.4	1.4	1.7	2.9
Electricity Consumption [kWh/100 km WLTP]	17.5	3.17	13.3	15.3	16.2	18.7	24.2
Panel C: Employee Characteristics							
Age [Years]	48.2						
Tenure [Years]	17.4						
Female [%]	0.156						

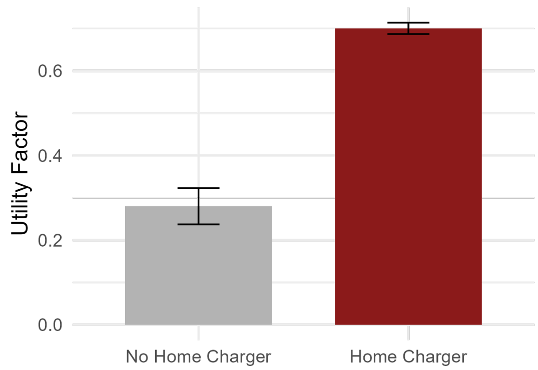
Notes: Descriptive statistics on the sample of employees and their PHEVs, respectively, in the home charger program between January 2021 and December 2022 (N = 856 employees). Panel A shows summary statistics for vehicle use after the employee has received access to home charging. This reduces the size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

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

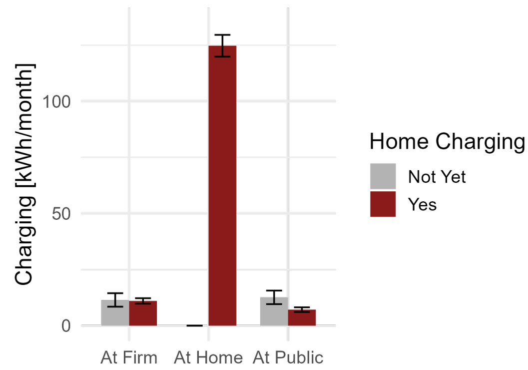
	Home Charger		No Home Charger	
Variable	Mean	Sd	Mean	Sd
Panel A: Vehicle Use				
Emissions [kg CO2]	94.889	(105.5)	93.058	(99.56)
Electricity per quarter [kWh]	247.753	(275.46)	242.972	(259.96)
Energy expendiutres [Euro]	63.398	(87.42)	65.303	(90.68)
Panel B: Vehicle Characteristics				
Electric efficiency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

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

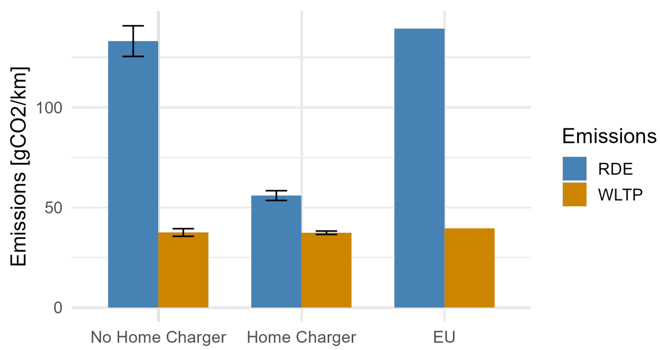
Figure E.1: Average Differences In Electric Utilization Between Treated and Untreated Employees in 2022 (Post COVID-19)



(a) Utility Factor



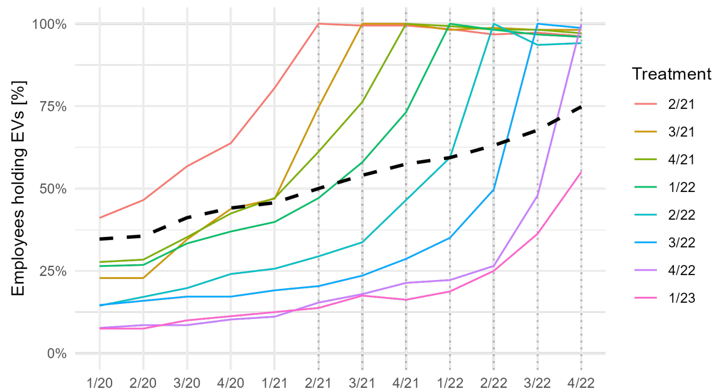
(b) Charging by Source



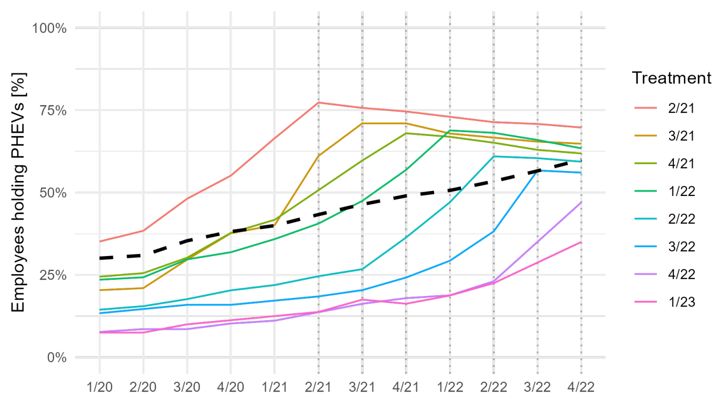
(c) Emissions Per Kilometer

Notes: Based on transaction data for the year 2022. Utility factors are calculated based on the observed on-road fuel consumption and the vehicle's fuel consumption in the charge-sustaining mode in the NEDC testing procedure. For details on the calculation, see Appendix B. Charging by source is calculated based on the observed amount charged at each source. Both measures compare employees who have already received home chargers with employees who selected into the program but have not yet received home chargers. Thus, some employees switch between the two samples as time proceeds. “WLTP” are vehicle CO_2 emissions per kilometer, according to WLTP type approval tests. “RDE” are real-world driving emissions. “EU” 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.

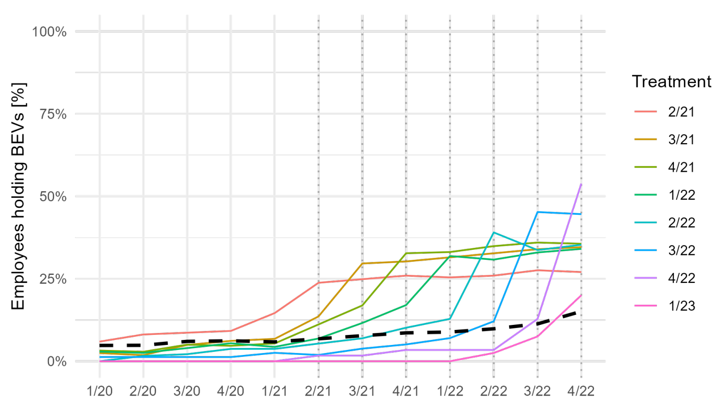
Figure E.2: Vehicle Adoption Across Treatment Groups



(a) EVs



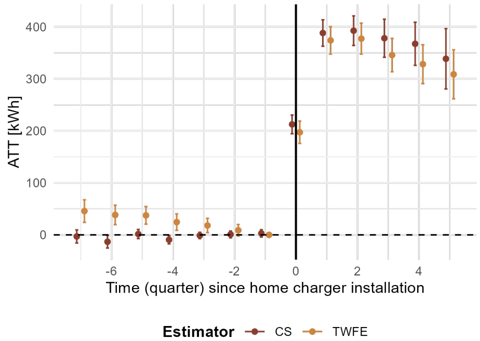
(b) PHEVs



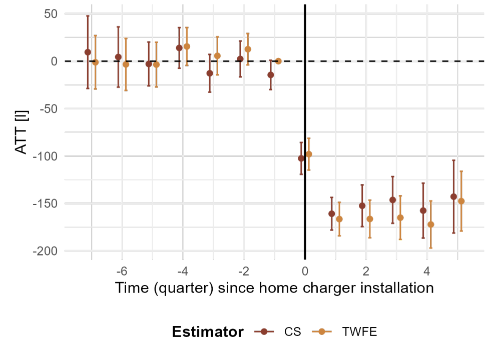
(c) BEVs

Notes: Share of employees in a treatment group holding a company car of the type indicated in the sub-caption. "Treatment" indicates groups of employees receiving access to home charging in the indicated quarter. X-axis label indicates quarter/year. EVs are BEVs plus PHEVs. In the treatment quarter, the share of employees holding EVs must be 100 %. Based on 1442 employees eventually participating the home charger program. Dashed black line indicates the share of the corresponding vehicle type among 5498 employees holding an EV company car at some point during the sample period.

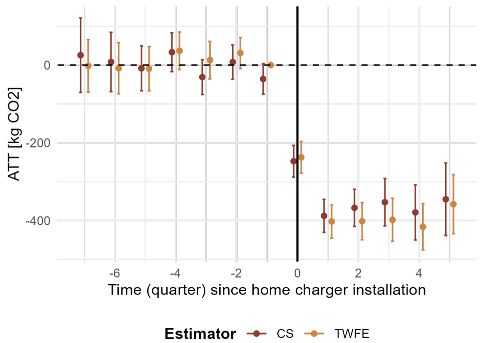
Figure E.3: Event Studies Comparing TWFE and Callaway & Sant'Anna (2021)



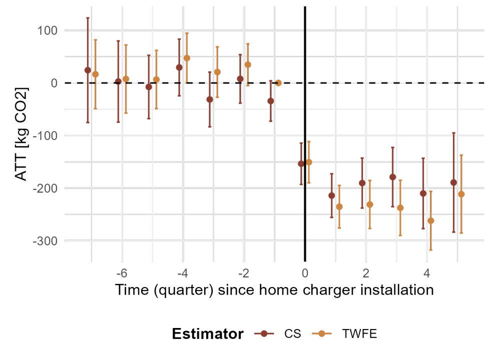
(a) Electricity in kWh



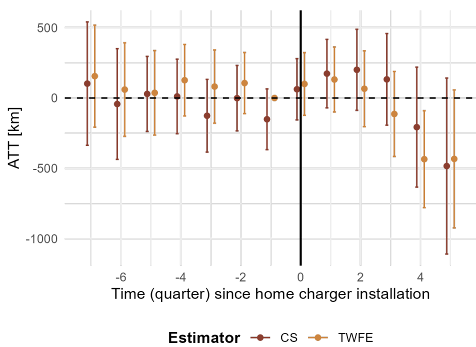
(b) Fuel in Liters



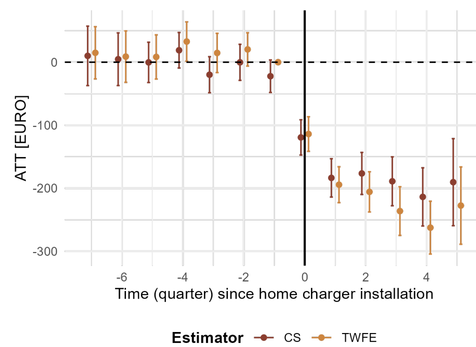
(c) CO_2 Emissions (EU ETS Cap)



(d) CO_2 Emissions (No EU ETS Cap)



(e) Kilometers Traveled



(f) Company Energy Expenditures

Notes: CS indicates that estimator $\theta_{es}(e)$ from Callaway & Sant'Anna (2021) as specified in Equation 3 is used. TWFE indicates that the two-way fixed effects event-study regression in Equation 4 is estimated. Never-treated units (employees holding a PHEV company car but not selecting into the home charger program) are used as the control group. All outcomes are computed as described in table notes of Figures 3 - 5. The analysis is clustered at the level of the participating employee. We allow for an unbalanced panel, which is necessary, since each month some employees could potentially order a new car. 95 % confidence intervals are indicated (for CS: bootstrapped standard errors, 1000 draws).

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

	Energy		Mileage	Emissions		Cost
	Electricity [kWh]	Fuel [l]	Mileage [km]	No EU ETS Cap [kg CO2]	EU ETS Cap [kg CO2]	Energy [Euro]
Treated	318.46***	-137.98***	35.93	-187.91***	-332.14***	-171.68***
	(10.74)	(7.69)	(103.3)	(20.24)	(21.03)	(13.17)
Employees	3551	3551	3551	3551	3551	3551
Groups	6	6	6	6	6	6
Periods	11	11	11	11	11	11
Employee FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X

Notes: Estimator θ^{O}_{sel} from (Callaway & Sant'Anna, 2021) as in Equation 2. Never-treated employees not selecting into home charger program are used as the control group. "Periods" are quarters. "Groups" are groups of employees receiving at home charging in the same quarter. "No EU ETS Cap" stands for CO_2 emissions being computed under the (counterfactual) assumption that additional electricity charged by the treated group leads to unregulated CO_2 emissions at the average CO_2 intensity in the German electricity grid (cf. Appendix C.1). "EU ETS Cap" stands for CO_2 emissions being computed under the realistic assumption that charging is not associated with any CO_2 emissions under the cap implied by the EU's emissions trading scheme (EU ETS). The analysis is clustered at the level of the participating employee. We allow for an unbalanced panel, which is necessary, since each month, some employees could potentially order a new car. 95 % confidence intervals are indicated (bootstrapped standard errors, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$..

F Sensitivity Analysis on Vehicle Kilometers

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

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

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

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

Notes: Estimator θ^{O}_{sel} from (Callaway & Sant'Anna, 2021) as in Equation 2. Baseline: extrapolation of implausible mileages at the end of a vehicle time series as in the main analysis. Fuel Only: extrapolation based on fuel consumption only, ignoring electricity consumption. Efficiencies: extrapolation based on both fuel and electricity consumption, but using NEDC fuel consumption in charge-sustaining mode to translate fuel consumption into kilometers traveled. The analysis is clustered at the level of the participating employee. We allow for an unbalanced panel, which is necessary, since each month, some employees could potentially order a new car. 95 % confidence intervals are indicated (bootstrapped standard errors, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G Sensitivity Analysis on Future Energy Prices

The treatment effects reported in Section 4.2 are estimated during the sample period January 2020 - September 2022. Extrapolating into the future to obtain estimates of the abatement cost of the home charger over its lifespan relies on the assumption that the energy prices observed during that period are representative of the next 20 years. In this section, we provide a sensitivity analysis to show that working with changing energy prices for electricity and fossil fuels does not change our results much.

To this end, we calculate abatement cost using three scenarios, in which we vary the development of energy and carbon prices over time, while maintaining all other assumptions made in the baseline scenario.

Scenario A1: Changes in the Relative Price of Fuel and Electricity In this scenario, we assume that the relative prices of fuel and electricity change over time and are driven by carbon prices levied on electricity and fuel and by the increasing share of renewable energy sources in German electricity generation. We model price changes for electricity and fuel by re-scaling our treatment effect on expenditures for both energy sources (electricity and fuel) with the respective predicted price changes for the two sources.

We calibrate electricity price changes relative to 2020 - 2023 using a projection for future wholesale electricity prices in Germany (Kreidelmeier & Wuensch, 2023). To be precise, we linearly interpolate between three nodes provided in the projection to obtain average electricity prices in the four-year periods 2024 - 2027, 2028 - 2031, 2032 - 2035, and 2036 - 2039: Electricity prices in 2024 (€128/mWh), 2030 (€76/mWh) and 2050 (€59/mWh). For 2020 - 2024, we obtain annual spot market electricity prices from Schwenke & Troost (2024). Dividing the four-year averages (and interpolated averages) by the average price during 2020 - 2023, we obtain a growth rate for electricity prices, which we use to extrapolate our treatment effect into future periods.

This extrapolation relies on the assumption that household and industry electricity prices as well as electricity prices at public charging stations are driven by the underlying wholesale electricity price. The relative prices across the three charging options (at home, at public stations, and at the firm's premises) are assumed to be constant over time. We additionally assume that the electricity prices observed during our sample period are representative of the period 2020-2023 (i.e. the first period in our simulations).

We apply a similar procedure to extrapolate fuel prices. In addition, we assume that future increases in fuel prices in Germany are driven only by an increase in carbon prices under the European Emission Trading System 2 (EU ETS 2) and not by the relatively volatile oil prices on the world market.[21] Data on the current level of the national carbon price in these sectors is obtained from Bundesministerium der Justiz (2019) and Emissionshaendler.com (nd). For a projection of future prices under the EU ETS 2, we rely on the baseline scenario of Graichen & Ludig (2024). In this scenario, the EU ETS 2 price will grow to €84 in 2030. We use this projection and the mandated

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

carbon price in Germany for 2025 (€ 55) to linearly extrapolate carbon prices for the years 2025 - 2039. This series, combined with the observed carbon prices up to 2025 is used to obtain average prices over the four-year periods used in our simulation.

To compute a fuel price path relative to the 2020 - 2023 average, we first obtain the average fuel price without carbon pricing during that period and then add projected carbon prices. Next, we divide by the average price during the period 2020 - 2023 to calculate fuel price growth rates. We use these growth rates to extrapolate the treatment effect on fuel costs estimated in Table G.2 into future periods.

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

Scenario A2: Exaggerated energy prices in the sample period Our sample period coincides with a period of extraordinarily high energy prices in Europe, as a consequence of the Russian invasion of Ukraine in February 2022 and the resulting embargoes on Russian oil and gas. Given the approach outlined in scenario A1, we consider that fuel and electricity prices in the sample period are higher than the average prices in the period 2020 - 2023. To take this into account, we re-scale our price paths in scenario A1 as follows: Instead of considering prices relative to the average of the four-year period 2020 - 2023, we now consider prices relative to their 2022 levels. We do so because the average fuel price obtained from dividing the treatment effects on fuel expenditures by the effect on fuel consumption in Table G.2 implies a fuel price of € 1.97, which is closest to the 2022 prices.

Scenario A3: Exaggerated fuel prices in the sample period In contrast to fuel prices, electricity prices are relatively rigid. Household electricity prices in Germany are often fixed by long-term contracts, implying that the shock to wholesale electricity prices does not immediately translate into shocks for retail prices paid by consumers. Similarly, large industrial electricity consumers can sign long-term purchasing power agreements, which would stabilize electricity prices. This is not true for fuel prices, which tend to respond to changes in the oil price immediately. To take this into account, we consider in this scenario electricity price changes relative to the period 2020 - 2023 and fuel prices relative to their 2022 levels.

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

Table G.1: Period-ATTs Relative to Estimated ATTs [%]

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

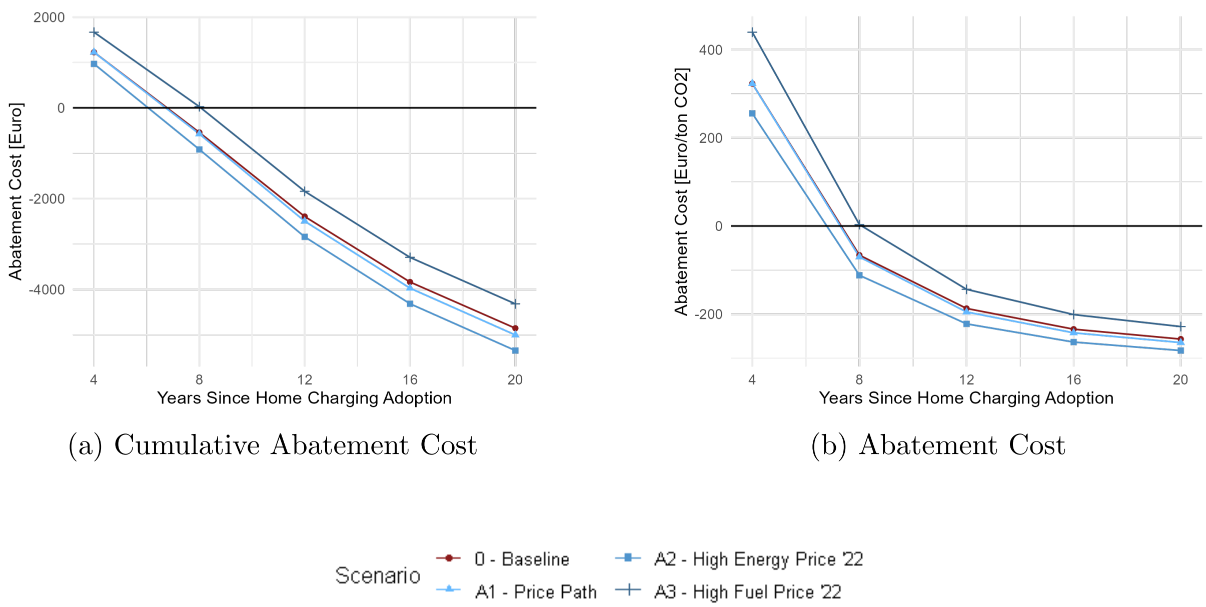
Notes: Price path relative to reference period, as described in scenarios Baseline and A1 - A3. Electricity price path is obtained by dividing the projection for the average wholesale electricity price in the period by the reference point corresponding to the scenario. Fuel price path is obtained by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

Table G.2: ATT on Energy Use and Energy Cost, Divided by Electricity and Fossil Fuels

	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
Eyployee FE	X	X	X	X	X
Time FE	X	X	X	X	X

Notes: Estimator θ^{O}_{sel} from (Callaway & Sant'Anna, 2021) as in Equation 2. "Energy" corresponds to electricity, diesel and gasoline. "Fuel" corresponds to both diesel and gasoline. "Periods" are quarters. "Groups" are groups of employees receiving home charging in the same quarter. The analysis is clustered at the level of the participating employee. We allow for an unbalanced panel, which is necessary, since each month, some employees could potentially order a new car. 95 % confidence intervals are indicated (bootstrapped standard errors, 1000 draws). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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



(a) Cumulative Abatement Cost

(b) Abatement Cost

Notes: Estimates for the dynamic ATT, aggregating treatment effects on PHEV and BEV use and BEV adoption under different assumptions for PHEV and BEV diffusion (cf. Appendix **??**). Scenario 0 is the baseline scenario. In scenario A1, projections for the future development of electricity prices and carbon prices for gasoline are considered. In scenario A2, we assume our estimates were affected by high energy prices during 2022. We adjust by scaling the estimated treatment effects on fuel and electricity using the ratio between i) the fuel price implied by the treatment effects in Table G.2 and ii) the wholesale electricity price in 2022 and the corresponding prices over the period 2020 - 2023, based on the sources indicated in Table C.1. In scenario A3, we adjust only the fuel price in that way.