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Impact of incentives for greener battery electric vehicle charging – A field experiment

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ABSTRACT

Battery electric vehicles generate a significant share of their greenhouse gas emissions during production and later, when in use, through the energy used for charging. A shift in charging behavior could substantially reduce emissions if aligned with the fluctuating availability of renewable energy. Financial incentives and environmental appeals have been discussed as potential means to achieve this. We report evidence from a randomized controlled trial in which cost-free and "green" charging was advertised via email notifications to customers of a charging service provider. Emails invited to charge during midday hours (11:00 to 15:00) of days with high predicted shares of renewable energy. Results show a significant increase in the number of charging processes in the critical time, and in the amount of energy charged (kWh), despite only marginal monetary savings of 5€ on average. A further increase in kWh charged was observed on weekends. Under the assumption that these charging processes replaced regular overnight charging at home, this represents reduction in CO_2 emissions of over 50%.

1. Introduction

Large-scale adoption of battery electric vehicles (BEVs) is often hailed as a way to reduce the climate impact of the transportation sector (Abdul-Manan, 2015; Faria et al., 2012; Laberteaux and Hamza, 2018). BEV-related greenhouse gas emissions occur during their manufacturing mainly from the battery production (Abdul-Manan, 2015; Nealer and Hendrickson, 2015), and from the generation of the required electricity for operating the BEVs. The latter depends heavily on the proportion of low-carbon renewable energy that is used to charge the vehicles (Abdul-Manan, 2015; Buekers et al., 2014; Manjunath and Gross, 2017). In Germany, a country marked by a relatively high capacity of renewable energy - 53% of total capacity for electricity production in 2019 according to the Bundesnetzagentur & Bundeskartellamt (2019) -, carbon intensity per kWh can fluctuate by an order of magnitude, with a mean for 2019 of 0.15 kg of CO_2 equivalent per kWh (SD = 0.09 kg, min = 0.03 kg, max = 0.54 kg) (Bundesnetzagentur, 2020), with a consumed share of renewable energy of 35% at total electricity consumption (BMWI, 2021). With increasing capacity for intermittent renewable energy production around the world, and an increasing share of BEVs on the roads (Irle, 2020), steering charging behavior has previously been suggested as an approach to increase consumed share from total capacity, and reduce emissions from BEV charging (Eider et al., 2017; Kacperski and Kutzner, 2020; Robinson et al., 2013; Schmalfuß et al., 2015; Tu et al., 2020; Zhang et al., 2018a).

The decision when and where to charge has reportedly been influenced by state-of-charge, dwell time, and price; among those factors, an inflexible and opportunity-driven pattern seems most pronounced, as most charging operations occur either on semi-public charging points at the workplace starting in the morning or, accounting for the largest share, at home charging points starting in the late afternoon (Jabeen et al., 2013; Lee et al., 2020; Morrissey et al., 2016; Robinson et al., 2013). Home charging usually combines convenience and economic benefits (Jabeen et al., 2013; Wen et al., 2016). In one large-scale study in 18 metropolitan areas in the US, 82% of all charging events were conducted at home (Smart and Schey, 2012).

EV drivers' charging behaviour has been steered successfully with directly BEV-related incentives such as optimization of charging station placement (Schmidt et al., 2020; Xu et al., 2017), free parking allocation (Robinson et al., 2013; Wolbertus et al., 2018), prioritization incentives at charging stations (Zhang et al., 2018a) and installation of fast-charging stations (Sun et al., 2016). Aligning charging with

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renewable production requires more flexible incentive systems, such as semi-instant financial or symbolic incentives that can impact BEV charging at a few hours' notice.

Studies that model how to manage electric vehicle charging have demonstrated that it is achievable to lower cost and/or minimize electricity consumption emissions (Kontou et al., 2017; Van Der Kam et al., 2019; Weis et al., 2015; Yang, 2013). Multiple simulation studies have proposed effects of monetary rewards on charging (Dallinger and Wietschel, 2012; Flath et al., 2013; Li et al., 2014; Zhang et al., 2018b). However, empirical research on incentive effects in the context of electric vehicle charging is rare. Self-reports reveal some price sensitivity regarding charging location, with preferences for home charging even more pronounced in the presence of particularly cheap electricity plans, and for workplace charging when it is provided for free (Chakraborty et al., 2019; Nicholas and Tal, 2015; Tal et al., 2014). In three instances, researchers analyzed charging data in the context of financial interventions as part of naturalistic studies of quasi-experimental design. For example, charging data from the US showed that switching from free charging to a $5 flat-rate fee increased the proportion of charge events taking place at low state of charge (Motoaki and Shirk, 2017). Similarly, using ChargePoint network billing data, free charging stations were found to be frequented at a four times higher rate than paid ones (Saxton, 2012). Most pertinent to smart charging, in the ECOtality project, a comparison of the effect of flat-rate vs. time-of-use electricity pricing between two cities was conducted, finding that demand peaks shifted from 4pm to midnight, coinciding with the beginning of the cheap off-peak electricity rate (Schey et al., 2012). While these studies support similar hypotheses, due to their quasi-experimental nature (i.e., lack of randomized allotment of participants to experimental and control group), they do not allow for a direct assessment of the causal link between price changes and charging behaviour. And while the study of consumer responses to incentives have been a prolific area of research in the context of electric vehicles when it comes to the purchase and promotion of BEVs (Jenn et al., 2018, 2020; Kwon et al., 2018; Zhang et al., 2018c), modelling customer responses to charging incentives is a novel contribution to the financial incentive literature.

A similar dearth of experimental evidence exists for environmentally focussed incentives. Pro-environmental attitudes have been found to be a positive predictor of BEV purchase (Li et al., 2017; Rezvani et al., 2015; Schuitema et al., 2013), and BEV usage is cited as a way to engage in pro-environmental behaviours (Graham-Rowe et al., 2012; Ingeborgrud & Ryghaug, 2019). Yet, the role of environmental incentive strategies has previously mostly been investigated in contexts of home energy saving and energy efficient driving and yielded small to moderately positive effects on intentions and behaviours (Asensio and Delmas, 2015; Dogan et al., 2014; Møller et al., 2019; Schwartz et al., 2015; Steinhorst and Klöckner, 2018). To the best of our knowledge, only one laboratory study has experimentally investigated individual decision-making in the context of BEV charging: monetary and symbolic-environmental incentives were both effective in changing behaviour towards 'greener' charging choices, despite a time penalty for doing so (Kacperski and Kutzner, 2020). The lack of field studies that investigate effects of incentives on charging behaviour is untimely, especially given the interest in rolling out charging programs by research and commercial actors alike (BMW *ChargeForward*, 2020; IRENA, 2019).

To address this gap, we carried out a field experiment in which groups of randomly chosen BEV drivers were offered an incentive. Specifically, we repeatedly carried out a lottery with customers of a charging service provider and offered to the selected customers an opportunity of "greener" charging at zero costs between 11:00 and 15:00.

Concepts and results from our experiment can be leveraged to design and implement more realistic incentives in order to encourage adoption of and more sustainable usage of BEVs, currently a highly topical issue in policy and regulatory contexts (Hardman et al., 2017; Liu and Xiao, 2018; Wu et al., 2021), particularly those that include both environmental and financial factors.

The combination of environmental and financial reward was chosen for two reasons: previous research on such incentives claims the combination of both to be the most effective, often with larger effects reported compared to each incentive alone (Allcott and Sweeney, 2017; Mizobuchi and Takeuchi, 2013; Møller et al., 2019; Petersen et al., 2007). Additionally, it maximizes external validity: policy-driven financial charging incentives will only BEVer be provided in combination with expected environmental benefits – our intervention was therefore designed as a mixed financial-environmental incentive.

We chose to provide completely free charging as opposed to reductions in charging costs for several reasons. A relatively larger impact can be expected from a free offer versus a simple reduction of costs of a similar amount (Shampanier et al., 2007) and variable or dynamic pricing runs the risk of eliciting negative consumer reactions (Haws and Bearden, 2006). Finally, the administrative effort of calculating and distributing minor savings was deemed too large considering the already minor expense of a single charging process (reported as around 5 Euros by the charging provider).

The feasibility of "all-charging-free" approach by subsidy has previously been modelled (Maness and Lin, 2019), and judged efficient in terms of greenhouse gas emission reduction per dollar of subsidy spent. The here proposed "free-when-green" approach augments economic value, if subsidized by higher prices in high-emission time slots, fine-tuned carbon tax programs, and increased BEV sales (Schneider and Sanguinetti, 2021; Zhang et al., 2018a). For charging station providers, customer retention, a possibility to conjoinedly incentivize smart and controlled charging to balance supply and demand (García-Villalobos et al., 2014; Haupt et al., 2020; Rubino et al., 2017), and vehicle-to-grid charging involving prosumers in microgrids (Parag and Sovacool, 2016; Wolinetz et al., 2018) could be considered potential avenues to make the proposed incentive a viable market measure.

2. Methods

2.1. Field study

The field experiment was conducted in collaboration with E-Wald, an electric mobility service provider originally founded as part of the research project "Modellregion Elektromobilität". E-Wald operates 150 publicly accessible charging stations with 500 charging points in an area of 7000 km^2 in rural and semi-rural districts in southern Germany, with mostly transportation, institutional, commercial, and industrial land use. The charging infrastructure combines the following types of charging technology: CCS fast charging, CHAdeMO fast charging, Type2 charging, Type1 charging and the F1 standard. This operator offers charging with a tariff system at flat 0.45 Euro/kWh for slow charging at a maximum charging power of 22 kW, or 0.55 Euro/kWh for fast charging above 22 kW. The study was carried out in line with ethics requirements of the German Ethics Board (DGPS) and the university ethics statute (Statut der Ethikkommission der Universität Mannheim, 2016), as well as European data protection guidelines (DGPR). Consent was obtained by the service provider during sign-up procedures, where customers were informed that anonymized charging station data would be made available to researchers and that they might be contacted for research trials and incentive schemes via email and newsletter.

318 customers had actively used this charging service within the previous year and were signed up to the E-Wald email newsletter. Based on information received from E-WALD regarding their customer base,

participants, who were required to hold E-WALD charging cards and are most commonly local residents, were driving for recreational, educational, or work purposes, so were in most cases not long-distance travelers. These participants received an email that a campaign would be taking place. This email[1] informed the customers that renewable energy would be a focus topic for the upcoming weeks, and that the operator would keep track of the energy mix in the power grid. Selected customers would be randomly gifted a free charge between 11:00 and 15:00[2] if renewable shares were particularly high on that day. Using this infrastructure, we implemented a 6-week event-based free charging intervention running February to mid-March.

On 13 days during the trial period when emissions were predicted to be particularly low, half of the sample (i.e., 159 customers, selected at random for each event day) received an email[3] in the afternoon, stating that on the next day between 11:00 and 15:00, charging would be free for them due to a high ratio of renewables in the grid. The number of clients that charged during these hours, the energy charged in kWh, and the emissions generated by these charges, were measured as outcome variables.

2.2. Event day selection based on emission prediction

The algorithm that selected the event days was built on the following procedure: every day at 16:00, we compared the predicted CO_2eq emissions of the current evening between 18:00 and 22:00 with the CO_2eq emissions of the following day between 11:00 and 15:00 (critical time). If the average hourly emissions were predicted to be at least 20% lower in the critical time, the charging service provider was notified automatically, and between 16:00 and 17:00, the notification email was sent to a randomly selected 50% sample of customers.[4] To forecast the respective hourly CO_2eq emissions, we used the algorithm provided by electricitymap.org via their API (*Electricity Map API*, 2020).

2.3. Data sources

Data on customers were provided by the charging service provider. These data contained the timestamp of when participants had plugged in their vehicle, the charging duration, and the number of kWh charged. No demographic data were available due to the provider's data protection regulations. Emission data were calculated using the TenneT system operator open source dataset provided by SMARD.de, multiplying the kWh generated from various energy sources (such as gas, solar, biomass etc.) with kg/kWh values of CO_2eq for Germany as suggested in the literature, and used by electricitymap.org in their predictive algorithms (Tranberg et al., 2019).

After the field trial was completed, a survey was sent to all customers who had at least charged once during the field trial in response to an intervention email: the trial participants were invited to answer a brief survey about their charging behavior (time of charging process, location of charging station, number of kWh), both for normal days and for the trial's event days. We also used the survey[5] to debrief participants on the research conducted and provided them with first results.

2.4. Hypotheses and experimental design

Conceptually, the experiment was a 2 (*intervention*: no email vs. email) x 2 (*time*: 15:00 to 11:00 vs. 11:00 to 15:00) experimental randomized controlled trial for the 13 event days, with 159 participants per condition. We measured two main response variables: charging processes conducted (dummy coded) and total energy charged in kWh. We also analyzed these data on the 28 no-event days for a comparison with no-event days charging behavior. We calculated emissions in kg of CO_2eq. In line with the predictive algorithm used, event days should show lower emissions in the critical time (11:00–15:00) as compared to the evening before. The difference should be particularly pronounced when compared to no-event days.

For regression analyses we used R (R Development Core Team, 2008), with the Linear mixed model (lmer with gaussian family for continuous dependent variables) and Generalized linear mixed-effects models (glmer, binomial family for dummy coded dependent variables), measuring the effect of the intervention in interaction with time.

The main hypothesis consists of two parts: We hypothesized that more charging processes would be logged during the critical time as a result of participants receiving an email and that they would charge more kWh in in this critical period, compared to the control group that did not receive an email (H1). Two further explorative analyses were conducted: We included workdays (7 days, 54%) versus weekends/holidays (6 days, 46%) as a predictor in interaction, hypothesizing that the intervention would have a stronger effect on non-workdays, based on the idea that participants might be more flexible temporally on weekends and holidays (H2). Finally, comparing charging behavior on no-event days versus event days, we expected to see a reduction in charging outside of critical hours on event days (compared to no-event days), as an indication that we had also moved customers in time for home-charging rather than in time *and* place, from home to the tracked public charging (H3).

We modelled repeated measurements from individual drivers by adding a random intercept per driver. We report Estimate betas, odds ratios as additional effect sizes and 95% confidence intervals in brackets. Appendix A.1. - A.3. hold the full model outputs, including standard errors, Wald z statistics and odds ratio confidence intervals. Appendix A.4. holds all means and standard deviations. We analyzed the survey following the trial to learn more about charging habits of our participants; the results are presented as aggregate statistics.

Emission projections were calculated by generating charging distributions in 15-min time series and multiplying them by the corresponding 15-min intervals of emissions in kg CO_2eq/kWh as reported by historical emission data (Bundesnetzagentur, 2020). As comparison we used the charging pattern on no-event days, and the charging behavior as reported in the survey. We hypothesized that emissions generated as a result of our intervention would be lower than if they had occurred at the times when public charging happens regularly, i.e. on no-event days, and lower than if they had occurred at the times survey participants reported they would have charged usually (H4).

3. Results

3.1. Field study

During the 41 days of the trial, 270 charging processes were logged, of which 23 were excluded due to the charging time lasting less than 1 min or charging less than 0.05 kWh. After the exclusion, we logged a combined total of 247 charging events from 90 customers.

Each afternoon at 16:00, the previously described algorithm predicted the next midday's emissions. Days with particularly low predicted emissions were designated as *event days*, on which at 17:00 the charging service provider sent the event email to a randomly selected

[1] "Dear customers! In the coming weeks, our focus will be on renewable energy. As part of a pilot project, we will watch the energy mix for you (see electricitymap.org). Whenever it's particularly "green", we will send you an email and charging will be free for you between 11am and 3pm (charge start)." (see Appendix B for German version).

[2] This timeslot was selected based on minimum emission timeslots calculated for 2015–2018, please see Appendix E for further information.

[3] „TOMORROW free charging between 11am and 3pm! Dear customers! Tomorrow there will be high quantities of renewables in the grid. Between 11am and 3pm TOMORROW (charge start), charging with your E-Wald customer card is free!".

[4] An illustration of the expected emission distribution can be found in Appendix C.

[5] Exact item wordings can be found in Appendix D.

50% sample of customers. On these 13 event days, 66 customers initiated a total of 129 charging operations, charged 1304.97 kWh, with a mean consumption per charge of 9.67 kWh (*Mdn* = 7.25 kWh, *SD* = 7.58 kWh, *Max* = 37.07 kWh).

Emissions generated by the production of power in the trial geographical area (TenneT provider, southern Germany) during the entire 41-day trial period was on average 0.13 kg of CO_2 equivalent (CO_2eq) per kWh (*Mdn* = 0.09 kg, *SD* = 0.11 kg, *Max* = 0.49 kg). Fig. 1 portrays the distinction between average emissions generated on event days (dashed line), and on no-event days (dotted line), starting at 17:00 until the same time the next day in 15-min intervals. The dashed line shows that the predictive algorithm led to a correct identification of days in which emissions were particularly low at midday (11:00–15:00) (*M* = 0.07 kg of CO_2eq per kWh) when compared to the evening before (*M* = 0.15 kg of CO_2eq per kWh), a 41% decrease.

Fig. 1 also shows the average number of charging processes undertaken per customer per trial day for each 15-min time interval, i.e., the probability density of a customer charging at an E-Wald charging station at this time during the trial. As the green curve illustrates, the critical timeframe between 11:00 and 15:00 was particularly attractive for participants that had received an email. The probability of charging processes on no-event days, and by customers that had not received an event notification are much more evenly distributed throughout the day.

Fig. 2 shows the sum of charging events (A) and the sum of kWh (B) on event days. We found a significant interaction of intervention and time for drivers that received an email, showing an increase in number of charging operations in the critical time between 11:00 and 15:00, $b = 2.46$ [1.40, 3.52], $p < .001$, $OR = 11.7$, as well as an increase in kWh charged, $b = 0.39$ [0.27, 0.51], $p < .001$, $OR = 1.47$ (H1). Again, the data illustrates that the critical time frame was magnitudes more attractive for participants that received the email.

We included weekdays in the previously reported regression analysis and found that our intervention increased the amount of kWh charged per person per day during the weekend as compared to weekdays, $b = -0.30$ [−0.53, −0.05], $p = .016$, $OR = 0.74$. There was no significant evidence that the intervention also increased the number of charging operations conducted on weekends as compared weekdays, $b = -0.88$ [−2.99, 1.24], $p = .415$, $OR = 0.42$ (H2). This is in line with the expectation that participants might have more time to leave their cars parked at charging stations on weekends.

Finally, we tested whether the intervention had reduced participants' use of charging stations outside the critical times. To do so, we compared the average number of charging processes per person and day outside of 11:00–15:00 on event days and on no-event days (c.f. Fig. 3, green versus blue series of "Other times"). We did not find a significant difference, $b = -0.32$ [−0.94, 0.30], $p = .308$, $OR = 0.72$ (H3); this indicates that instead of moving public charging customers from non-critical to critical times, charging operations between 11:00 and 15:00 were additional, and deducing from prior literature, most likely a change from home charging to public charging.

With regards to monetary savings for our participants, we found that the median incentive payout per charging event lay at 4.79 Euro (*M* = 5.51, *SD* = 3.38, *Min* = 0.84, *Max* = 16.68) with 75% of participants gaining savings below 8.04 Euro. Fig. 4 shows a histogram of the number of charging events with their respective savings.

3.2. Survey results

19 responses were recorded from participants. In line with previous literature, participants reported that, had they not charged between 11:00 to 15:00 during the event day, the majority 79% (15) would have charged at home; 84% (16) would have instead charged between 15:00 and 06:00. For participating respondents, the survey therefore further confirmed the findings regarding H3 mentioned above, i.e. they transferred their overnight home charging processes to the critical time and to a public charging station. Participants also reported that they usually charged on average 17.92 kWh per charging process (*Min* = 9.00 kWh, *Max* = 35.00 kWh), and conducted on average 4.53 charging processes per week (*Min* = 1, *Max* = 10), charging their battery to an average 57% SoC (*Min* = 20%, *Max* = 90%).

3.3. Emission projections

A total of 1136.43 kWh were charged by email recipients. Using the time series of the distribution of charging by these recipients, and the average emission intensity on event days, we calculated the average emissions in kg of CO_2eq generated by our intervention (see Fig. 5, green bar). We then projected the average CO_2eq emissions that would have been generated for the usual charging pattern at public E-Wald charging stations, i.e. charging behavior on no-event days (see Fig. 5, orange bar). We secondly considered the survey answers, i.e. the times participants indicated they would have charged if the trial had not taken place; based on this distribution, we also projected the amount of generated CO_2eq emissions (see Fig. 5, blue bar).

For additional comparisons, we added lines indicating three uniform charging distributions: a minimum line indicating the CO_2eq emissions

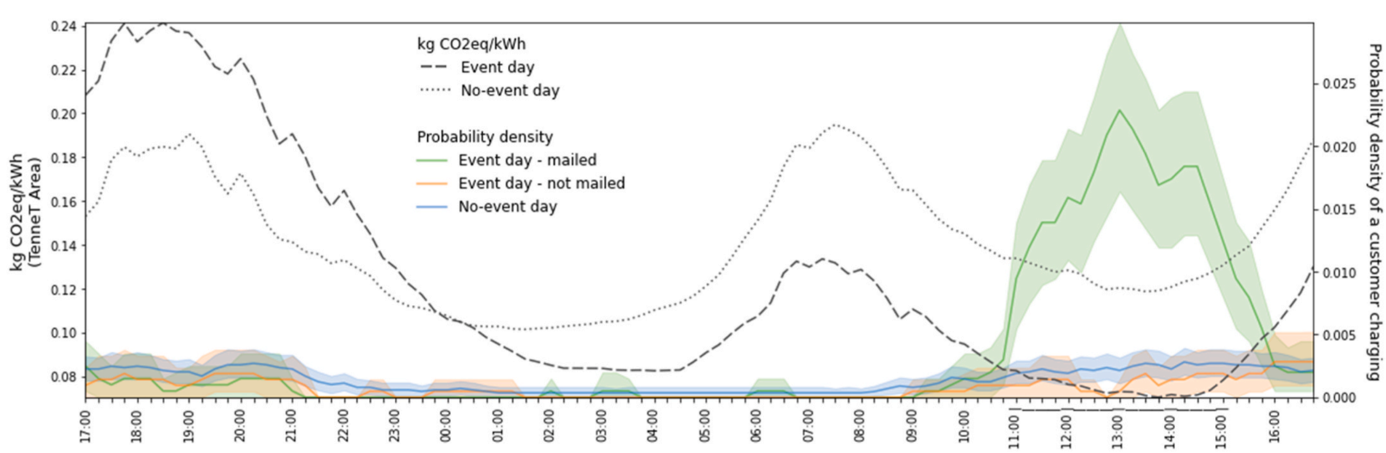

Fig. 1. Black lines: CO_2eq emissions for the trial period for event days (dashed line) and no-event days (dotted line). Event day CO_2eq emissions are higher in the evenings (17.00–22.00) and lower at midday (11:00–15:00) than the corresponding emissions on no-event days. Colored lines: Charging operations per customer per timeslot at an E-Wald charging station, for customers that received an email (green), customers on event days that did not receive an email (orange) and charging on no-event days (blue). In the critical time (11:00–15:00), a large spike of charging activity can be observed. Shaded areas indicate bootstrapped 95% confidence intervals (1000 iterations). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

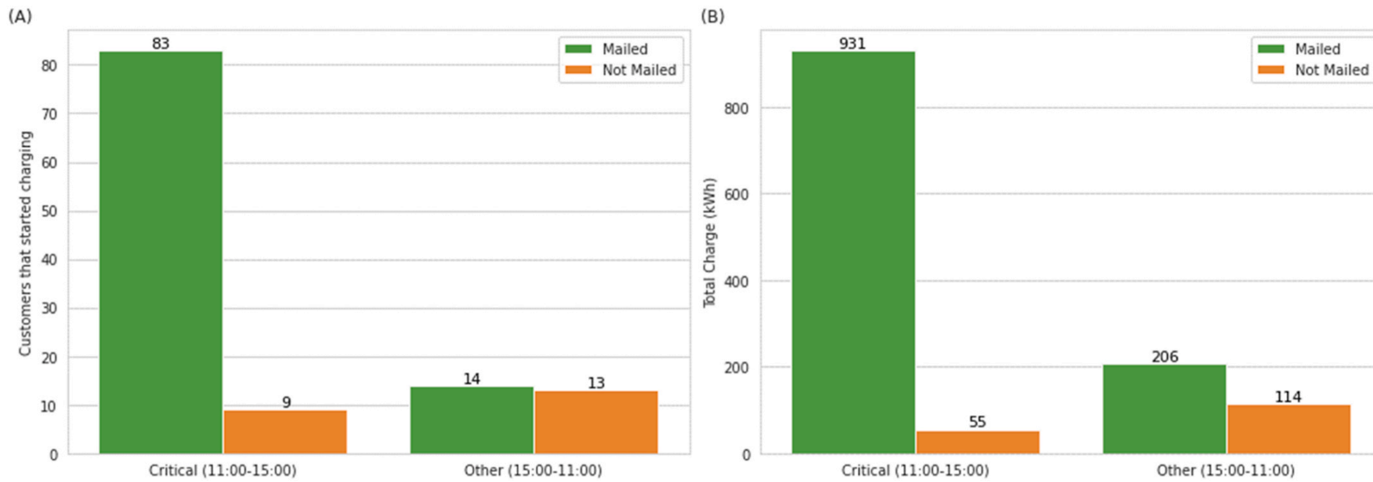

Fig. 2. Charges during critical times and other times on event days for customers who received an email about the incentive, and those who did not. The number of customers that charged (A) and the total kWh charged (B) show a noted increase in critical time (11:00–15:00) when an email was received, as compared to other times (15:00–11:00), and as compared to customers who did not receive the email.

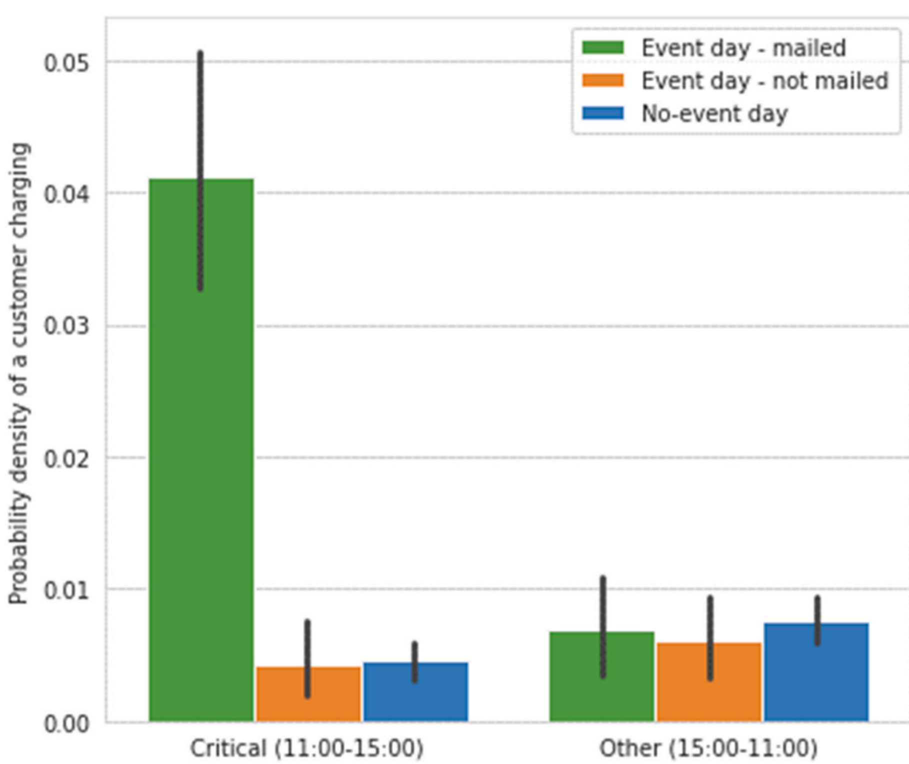

Fig. 3. Probability density of a customer charging during critical and other, i.e. non-critical, times; on average, a customer was more likely to charge in the event day critical timeslot. A customer that received an email was not less likely to charge outside of critical times (green bar, Other) than they were on baseline no-event days (blue bar, Other). Error bars indicate bootstrapped 95% confidence intervals (1000 iterations). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

generated if all charging processes had occurred at the time of least emissions (red line), the CO_2eq emissions generated if all charging processes had occurred spread evenly across the day (black line), and CO_2eq emissions generated if all charging processes had occurred at the time of highest emissions (blue line).

We find that if charging processes had occurred either at a regular charging station pace, or at home at night as reported by the majority of participants in the survey, roughly twice the emissions would have been generated, an increase from 81.96 kg CO_2eq to 163.56 kg CO_2eq for the public station charging distribution (99.6% increase) and to 163.16 kg CO_2eq for the survey-data based charging distribution (99.1% increase) (H4).

4. Conclusion and policy implications

We investigated whether offering a mixed financial-environmental incentive to BEV drivers, free charging advertised as “green”, would steer charging behavior towards times that would lead to emission reductions. Due to the incentive, eight times more charging processes were conducted during pre-specified event periods with low carbon intensity of the electricity charged. Twice the emissions would have been generated if BEV drivers had instead charged throughout the evening and night, using a distribution reported common for home charging in our follow-up survey and based on prior literature (Franke and Krems, 2013; Jabeen et al., 2013).

The study provides first evidence from a field experiment that a combination of financial and environmental incentives has the potential

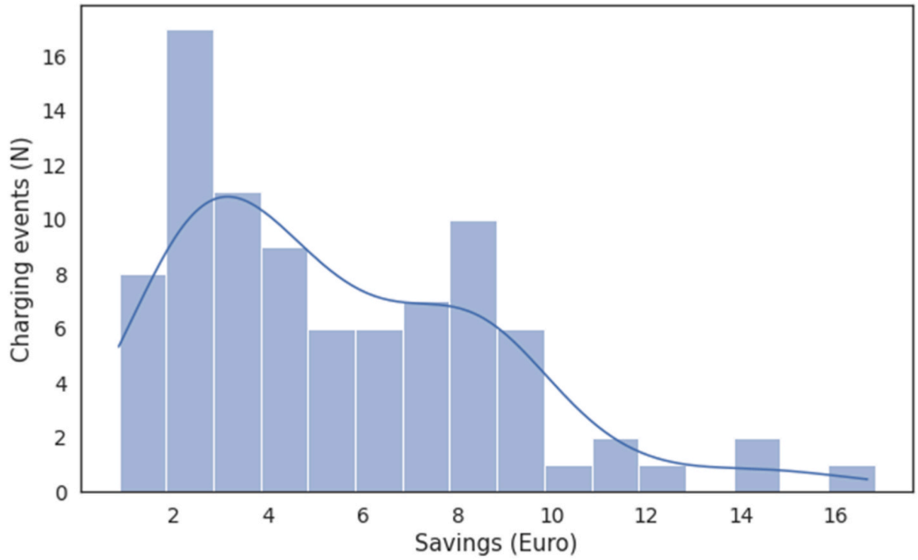

Fig. 4. Histogram of savings in Euro and corresponding numbers of charging events.

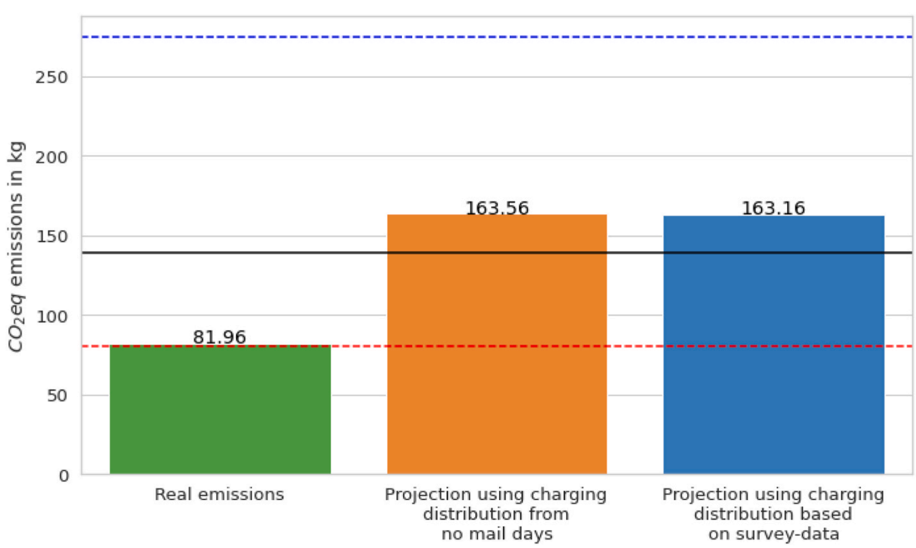

Fig. 5. CO_2eq emissions generated by email recipients (green bar), projected using the charging distribution on no-event days (orange bar) and projected using the charging distribution as suggested by the survey data (blue bar). Lines indicate projected CO_2eq emissions calculated for uniform minimum (red line), mean (black line) and maximum (blue line) distributions for the trial period. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

to reduce emissions from BEVs. As the climate impact of BEVs depends partially on low-carbon renewable energy that is used to charge the vehicles, studying the effects of such incentives is of utmost importance for policy makers and the general population (Abdul-Manan, 2015; Buekers et al., 2014). Utility companies and providers might, in reaction to policy instruments, demand pro-environmental changes and better renewables integration from charging infrastructure providers and managers. They, in turn, can take the incentive intervention designed here as a starting point to develop better market instruments to take advantage of lost time-of-use electricity prices. The implementation of a “free-when-green” approach in terms of market viability remains a topic for further investigation, though potential avenues such as carbon taxes, carbon trading, and ties with BEV sale profits have previously been proposed (W. Li et al., 2019; Maness and Lin, 2019; Schneider and Sanguinetti, 2021). In general, as pricing strategies are often discussed to counteract uncoordinated charging (Dallinger and Wietschel, 2012), this type of incentive design might be an important component for better grid and parking regulation as well (García-Villalobos et al., 2014; Parag and Sovacool, 2016). In this sense, the approach presented here should be interpreted as a proof of concept for the optimization of emission-related savings, showcasing that the incentive works to change behavior. It could potentially be adopted for solving problems in various situation, e.g., to balance an optimization of renewables, grid stability and parking availability at the same time. Relevant factors for a suitable application of our approach in certain scenarios are the current grid capacity utilization, grid stability (e.g., power quality) and renewable generation, as well as charging demand in the region of interest and within the respective time frame. With our approach, EV drivers could be motivated to adapt their charging behavior, tackling a variety of different grid- and energy-related challenges. It is also up to the grid operator to account for the uncertainty of the impact of behavior changes with additional measures such as curtailment.

Simulation studies could help to more effectively showcase how much flexibility would be required in different scenarios, and whether features such as charging station availability feedback, charging station reservations, and short notice push notifications, as well as a smarter communication between charging stations might be required.

Regarding the financial aspect of the selected incentive, while charging was offered for free, participants saved on average around 5 Euros (for an average charge of around 10 kWh in the critical 11:00 to

15:00 time slot). It is noteworthy that such a relatively small amount of savings was able to move persons into the desired direction when considering the time and effort of undertaking an extra charging process; especially in light of the typical socio-demographic profile of BEV owners (predominantly high-income, multi-car households, see Kumar and Alok, 2020; Priessner et al., 2018). This could be attributed to the previously mentioned findings that a free offer has a much stronger impact than a mere reduction of cost (Shampanier et al., 2007). As an alternative interpretation, it also supports the idea that the conversational nature of the incentive might play a role more than the value itself, in the sense that the free offer transmits a priority and urgency for the desired action (Grice, 1975; Kacperski and Kutzner, 2020). If it is indeed the financial value of such incentives that drives the effect, this might be expected to be stronger for financially more vulnerable populations. However, even relatively large financial savings might fail to change charging patterns for families with children, if previous research on household energy consumptions is any indication (Mizobuchi and Takeuchi, 2013; Møller et al., 2019; Nilsson et al., 2018)

Further, more kWh were charged during weekends as compared to weekdays following the incentive, probably due to the increased flexibility to leave the vehicle at the charging station for multiple hours. This is in line with the hypothesis that a higher flexibility of customers allows for more effective introduction of incentives and is noteworthy for researchers as well as policy makers deciding on effective charging interventions in the future. As the present study's critical time slot occurred during working hours in 53% of cases, many participants could be assumed to have been between work appointments, retired, working in a mobile service industry, and/or having flexible work hours or shift work. With higher expected work flexibility in the future (Smit et al., 2020), implementation of incentive programs that are based on renewable supply might become more feasible.

Finally, results seem to indicate that the incentive mainly moved charging from private to public charging stations and into critical times. Yet, in the presented study, data from home charging are missing to verify this claim. A possible future avenue of research could be to investigate how home charging patterns are affected by similar incentive strategies. While public charging incentives might lead to more investments into public charging infrastructure in the future, policy makers should ensure that it does not increase road traffic, and lead to potential grid issues as a consequence. A free-when-green charging model for home use could circumvent these issues, as smart chargers at home could optimize for renewable production – and potentially also take into account grid stability. A smarter charging infrastructure could include charging reservation systems in which positions in the queue are scheduled on demand, for example through an app that logs habitual car usage cycles.

Some limitations are noted. Firstly, at 318 initial customers, the number of participants is relatively low for an experimental field trial, though 99% power was achieved for the main model, as per a post-hoc power analysis (Judd et al., 2017). Secondly, the individual contributions of environmental and financial incentives cannot be teased apart with the current design. The decision to provide a mixed incentive, based on previous evidence of its effectiveness, and compare results between one intervention and control group, yielded here the high-powered experimental design we had targeted; however, future experiments using a 2 (environmental vs control) x 2 (financial vs control) design with a bigger sample would achieve more explanatory insights and could also attempt to collect demographic and mobility patterns among participants to further increase generalizability. The trial and incentive design provided in this study could be used by other researchers as a starting point. Finally, the here proposed charging station usage optimization scenario is ambitious; it requires a much smarter grid and user interaction and involvement, including possibly prioritization and automatic vehicle detection. However, the future grid, dominated by volatile renewable energy sources and increased demand through electric mobility can only be operated safely if many types or demand flexibilities are orchestrated. It is an objective worth targeting to approach maximum usage of renewable energy at peak generation.

In summary, in this first of its kind field experiment, BEV drivers were successfully steered towards greener charging with a financial-environmental incentive, while being directly confronted with the trade-offs that can be realistically expected in such scenarios. We highlight the need for further investigations into BEV drivers' decision-making and the measuring actual behavior in the field. Such studies are crucial to design better policies surrounding BEV adoption and usage.

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CRediT authorship contribution statement

Celina Kacperski: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Project administration. **Roberto Ulloa:** Methodology, Formal analysis, Writing – review & editing. **Sonja Klingert:** Conceptualization, Methodology, Writing – review & editing, Project administration. **Benedikt Kirpes:** Conceptualization, Methodology, Writing – review & editing. **Florian Kutzner:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – review & editing, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2021.112752.

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