Shifted or additional charging of electric vehicles? The effect of smart charging on German prosumers

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***Abstract*— Special smart charging modes are an energy service that enables prosumers to charge their electric vehicle exclusively with self-generated electricity. In this paper, we evaluate empirically how 39 prosumer households adjusted their charging behaviour after introducing this smart charging mode under real-life conditions in a field trial in Germany. With a panel-data regression strategy and rich set of household-level charging data, we test the following hypotheses: With the smart charging mode, prosumers charge (i) more during the midday PV peak (11am – 3pm), but (ii) their charging remains the same during off-peak hours (4 - 8pm).**

The smart charging mode led to changes in the participants' charging behavior that confirm the first part (i) of our hypothesis and partially the second part (ii). We find strong evidence of an increase during the midday peak by 16%. In line with our hypothesis, this shift was not offset by a corresponding decrease during off-peak hours. However, we identify a significant increase in the off-peak load during the treatment when we apply the morning load as a reference period. This intraday shift from the morning may be explained by a coincidence of participants' presence at home and PV generation at the start of the off-peak hours (around 4pm). Overall, our results provide micro-level evidence that the introduction of smart charging based on PV production induces load shifting, but that the response is more complex than a mere shift from evening to midday.

***Index* - Smart charging, charging behavior, prosumer, smart meter data, field trial**

I. Introduction

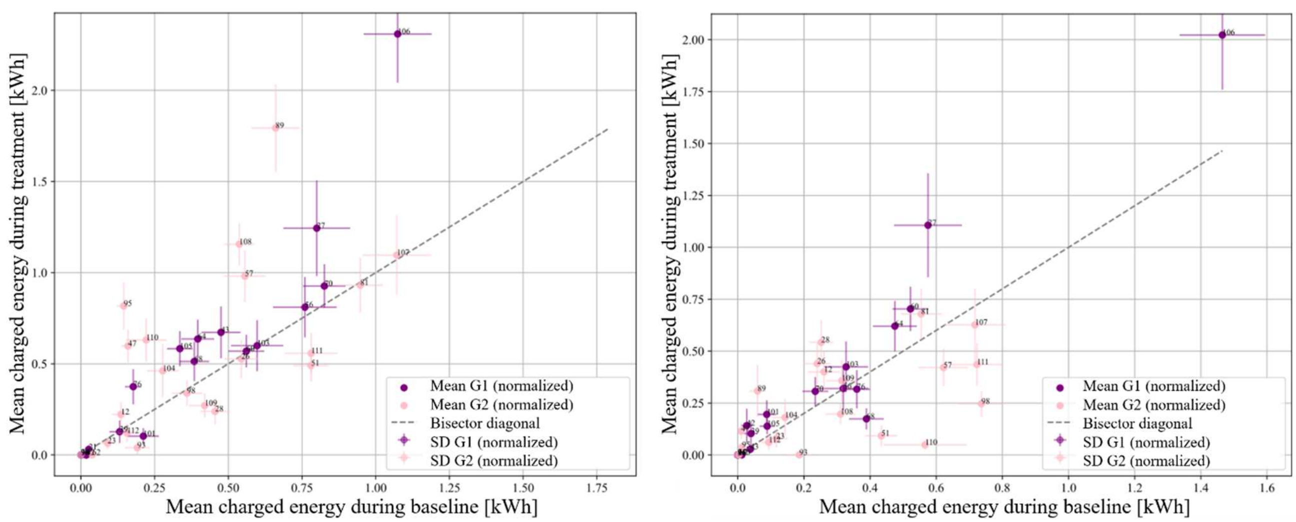
Owning a rooftop photovoltaic (PV) system makes it more attractive for households to purchase a plug-in electric vehicle (PEV) [1]. With a special smart charging mode as part of a new data-driven energy service, prosumers can charge their PEV exclusively with self-generated electricity during times of high PV production. They can reduce their impact on the distribution grid as a system-level benefit, while saving on charging costs as an individual benefit [2]. We provide experimental evidence on the effects of smart charging on prosumer behavior. Specifically, we test how 39 prosumers adjusted their charging behavior after introducing this smart charging mode using smart meter data, which were collected as part of the Horizon 2020 project NUDGE from 2021-2023 [3]. Previous findings from the same field trial were focused on aggregated consumption patterns. Those results demonstrated that prosumers using this mode increase the amount of self-consumed and overall consumed electricity on an aggregated household level by up to 15% [4]. The present conference contribution examines the extent to which the increase results from an adjusted charging behavior after the introduction of the smart service, thereby providing novel insights on an important sector-coupling technology for prosumer flexibility.

If charging with self-generated electricity becomes more easily accessible with the smart charging mode, two adjustments in charging behavior are possible [5]-[7]: (i) prosumers shift their charging from off-peak- to peak production hours, or (ii) prosumers charge more than before. While adjustment (i) describes intraday load shifts, (ii) outlines an increase in consumption after expected charging cost savings (i.e., rebound effects). Assuming both kinds of adjustments based on the previous findings, we test the following hypotheses with the field trial data: With the smart charging mode, prosumers charge (i) more during the midday PV peak, but (ii) their charging remains the same during off-peak hours.

II. Material & Method

A. Data

We analyze the charged energy of 39 prosumer-households living in, or close to, the German city of Mannheim. The average installed PV capacity per participating household is 7.78 kWp [8]. Most households are families with children living in a single- or semi-detached house [8]. All participants are equipped with a PEV and a smart charging tool. A basic charging mode is included in the tool before and during the field



Midday (11am-3pm)

Evening (4pm-8pm)

Figure 1: Comparison between the charged energy of every participant before (x-axis) and during the treatment (y-axis)

Notes: Points above the bisector diagonal indicate higher charged energy during treatment than baseline. Crosses show SD normalized by the number of measurements (per participant). Purple crosses are participants assigned to G1 & pink to G2.

trial. It enables participants to decide between charging the EV immediately to each the targeted State-of-Charge (SoC, default setting) or spread the charging process between the plug in and departure time to maximise the self-consumption.

With the new smart charging mode, participants charge their PEVs exclusively with their self-generated electricity once they plug them in at home. If too little self-generated electricity is available to reach the targeted SoC, participants risk not covering their mobility needs. As the intervention in the field trial, this new charging mode is introduced and set as a default mode[1]. The participants need to overrule the default if they want the basic charging mode to charge their PEVs up to the targeted SoC. In other words, if treated households plug in their PEV, it is charged to the extent that self-generated electricity is available, thus helping households increase self-consumption with an automated strategy. Yet if the households want their PEV to reach a certain SoC until the departure time, they need to manually revert to the basic charging mode.

The intervention is implemented for alternating treatment groups after a baseline period (7th September '22 to 22nd February'23). This means that a first group (G1, n=18) is treated in the period from 23rd February to 19th April ' 23. The second group (G2, n=21) receives the same treatment from 20th April to 14th June ' 23. The group not treated now acts as a control group, while the baseline period is common to both groups.

Both groups have similar socio-technical characteristics: Both infrequently use their smart charging device. A minor share owns heat pumps (G1: 17%, G2: 18%). They have, on average, a similar installed capacity of rooftop PV (G1:7.3 kWp, G2: 8.2 kWp) and wall box (G1: 17.8 kW, G2: 15.6 kWp). Both groups experienced similar retail price increases. G1 (5.8 days) spends on average slightly more days per week at home than G2 (5.0 days).

We evaluate whether the charged energy changes in response to the intervention. Charged energy as a dependent variable is based on minutely smart meter data and aggregated to hourly weighted average values. We control for confounding factors with socio-demographic data collected from the participants in a survey and weather data, which was downloaded from the Copernicus platform[2].

The hypotheses about the changes in the charged energy (i) during midday and (ii) during the evening is approached with two kinds of descriptive analysis. First, we compare the charged energy mean of the two groups (G1 and G2) during the baseline period and treatment period (pooling the two group-specific treatment times). Concerning the measurements during midday (11am-3pm), G2 (398.16 Wh) charged slightly more than G1 (374.49 Wh) before the treatment. During the treatment of G1, G1 (528.72 Wh) increased the charged energy compared to G2 (349.29 Wh). During the treatment of G2, G2 (526.43 Wh) surpassed the charged energy of G1 (521.88 Wh). The mean of the evening measurements (4pm-8pm, 257.08-363.81 Wh) is generally lower than the midday measurements. Also, the evening measurements during the G2 treatment are characterized by slightly lower means of both groups (G1 – 257.08 Wh, G2 – 263.18 Wh) than during baseline (G1 – 265.56 Wh, G2 – 276.87 Wh). Apart from these two aspects, the evening values follow a similar pattern to the midday values: higher charged energy of G1 than G2 before the

[1] The special charging mode is activated as default after the participants activated it for the first time in a web application.

[2] For more information, visit: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview (last visited: 10/03/24)

treatment, G1 (363.81 Wh) surpassing G2 (289.86 Wh) during the G1 treatment, G2 slightly higher than G1 during the G2 treatment.

Second, we visually compare the mean charged energy of every participant before (x-axis) and during the treatment (y-axis). If participants charge more during the treatment than before, their points are above the bisector diagonal. We observe no strong tendency for the midday (left) and evening measurements (right, see

Figure 1) in these descriptives, i.e., most measurements are close to the bisector diagonal. Hence, the descriptive data give no indication for the first part of the hypothesis that (i) more electricity is charged during the midday PV peak, but rather support the second part, that (ii) their charging remains the same during off-peak hours. Moreover, the depiction indicates that prosumers' charging behavior is idiosyncratic *across* households and highly variable even *within* households when comparing the respective means and the standard deviations.

Moreover, the measurements of most participants are relatively close to each other in the sense that the pattern is similar across the two groups despite the different time periods of the treatment. This supports our regression strategy to combine the two groups and estimate a single treatment effect (staggered design). The measurements of participants that are more distanced from the accumulated measurements are also characterized by a higher standard deviation (larger crosses).

B. Regression Strategy

For the regression, we use the household-specific hourly charged energy (in kWh) as the outcome and conduct a sample split to look at two periods: the midday (peak, 11am-3pm) and the evening (off-peak, 4pm-8pm). We pursue two approaches to estimating the treatment effect. First, the comparison of the baseline period with the treatment period, i.e., identification over time. Second, the comparison between the treatment and control group during the treatment period(s). The first is potentially more sensitive to weather and other time-varying factors, whereas the second has limitations due to the small cross-section. Conducting both approaches shows robustness around the main result.

Formally, the regression equation (1) is:

$$y_{it} = \alpha_0 + \beta \quad T_{it} + \boldsymbol{X}_i\gamma + \boldsymbol{Z}_t\delta \; + e_{it} \qquad (1)$$

Where i indicates individuals and t indicates hourly periods. The indicator T equals 1 when the treatment is active, and zero otherwise. The coefficient of interest is β , which represents the effect of smart charging, but is interpretable as an effect over time or between groups depending on how T is defined. $\boldsymbol{X}$ is a vector of household-specific controls, namely: an indicator for retired participants, the dwelling size (m^2), self-reported weekly home days (1 to 7), and the size of the PV plant (in kwp). $\boldsymbol{Z}$ is a vector of time-varying controls, which includes the weather, defined as the logarithm of solar radiation in kWh/m^2 (adding 1 unit to all observations to preserve the zeroes during night times), and an interaction between weather and the size of households' PV.

We run the regression for both definitions of treatment, and an additional specification that uses the morning (6am to 10am) as a reference period for midday and evening, hence capturing the relative effect from intraday load shifts. This is implemented with an additional interaction term between T and the block-of-day dummy B, which equals one during either midday or evening and zero during the morning (the simple block-of-day dummy is also included). The coefficient of interest is then the interaction term, which indicates the *differential* development of the treatment during the midday / evening relative to the morning.

Robust standard errors are calculated with the common Huber-White adjustment.

Besides these preferred specifications, we conduct a series of additional robustness checks: (1) using only household- or (2) time-specific controls, and (3) replacing the household characteristics with household fixed effects. These additional results are not shown here but are motivated by previous findings with the same sample revealing that time- and household variation can be very influential in the prosumer field trial (Pelka et al., 2024).

III. Results

Table 1 reports the regression results. The upper panel refers to the results during the midday; the lower panel refers to the evening. Within each panel, rows (1) and (2) show the results for the simple comparison, rows (3) and (4) show the results relative to the morning period. For the latter, the reported coefficient is the interaction term between block-of-day and treatment.

Across all specifications for the midday period in Panel A, the smart charging treatment has a positive effect on the hourly loads, i.e. households charge more with the smart charging. The effects are robust to the definition of the treatment period (rows 1 and 2), but slightly larger for the intraday comparison (rows 3 and 4). All effects are statistically significant at the 5% level of confidence, and economically relevant. For example, the coefficient of 0.0708 represents an increase by 70 Wh on an hourly basis, which is an increase of ca. 16% when evaluated against the baseline mean of 436 Wh. For the interaction specification, the estimated increase is ca. 110 Wh, which corresponds to 26% of the mean value.

Regarding the evening period in Panel B, the results differ from midday. The coefficients are smaller, and not statistically significant for the simple comparison (rows 1 and 2). Nevertheless, the coefficient magnitudes are again relatively robust to the choice of treatment definition. For the intraday load shifting (rows 3 and 4), the results are statistically significant and in the range of 35-40 Wh, which is smaller than midday. To give an economic interpretation, the (significant) increase by 35 Wh in row 3 is 12% of the mean (284 Wh). Note that the Wh-differences between midday and evening are substantial, while the expression in % differs less due to the lower average charged energy in the evening. Overall, we find no strong evidence that households recorded higher loads during the evening periods, in line with the hypothesis. When adding the intra-day comparison, the results suggest that there is a small shift towards the evening, but on a much larger smaller scale than for midday.

Combining the midday and evening results, we do find strong evidence of an increase during the midday peak, but this

Table 1: Effect of the smart charging treatment on hourly charged energy – treatment coefficients for four regression specifications

Panel A: Regression Results for Midday (11am to 3pm)				
	Coefficient	Std. Error	F-Stat.	Adj. $R2$
(1) Baseline vs. Treatment Period	**0.0708***	0.016	13.76	0.002
(2) Control vs. Treatment Group	**0.1124***	0.021	15.30	0.002
(3) Interaction[1]: Basel. vs. Treat.	**0.0898***	0.017	180.1	0.016
(4) Interaction[1]: Control vs. Treat. Gr.	**0.1187***	0.023	179.5	0.016
Panel B: Regression Results for Evening (4pm to 8pm)				
(1) Baseline vs. Treatment Period	**0.0121**	0.013	119.4	0.005
(2) Control vs. Treatment Group	**0.0298**	0.017	119.5	0.005
(3) Interaction[1]: Basel. vs. Treat.	**0.0345***	0.015	126.3	0.009
(4) Interaction[1]: Control vs. Treat. Gr.	**0.0390***	0.019	111.2	0.009

Notes: The four regression specificatio are about comparisons over time (rows 1 & 3) and between groups (2 & 4). For each type of comparison, there is a simple specification *without* morning as reference period (1 & 2), and the interaction specification that uses the morning as a reference period (3 & 4). [1] In the interaction specifications, the treatment coefficient is the interaction term between the treatment dummy and the block-of-day dummy (morning = 0). Time- and household-specific controls are included in each regression but not displayed in the table. Dependent variable is charged energy in kWh at hourly frequency. (*) Indicates significance at the 5%-level with robust std. errors.

shift was *not* offset by a corresponding decrease in the evening. As a general remark, it is notable that the effect sizes are stable across specifications despite the small cross-section and the low R2. Charged energy varies substantially on an hour-by-hour basis across and within households for factors outside of the regression model (as expected), but the average effect of the smart charging can still be extracted with robustness.

IV. Discussion & Conclusion

The results of the regression analysis based on the charging data of 39 prosumers confirm the hypothesis that prosumers charge more during the midday PV peak. The results are inconclusive for the evening period, where the null hypothesis was no change in charging behavior. In particular, the charged energy in the evening during the treatment does not significantly change when we compare it only to the baseline period or the control group. However, it does increase when compared to the charged energy in the morning. Despite these differences, there is no evidence that the estimated midday increase reflects intertemporal substitution from the evening. One possible explanation for the intraday shift relative to the morning is the likely coincidence of participants' presence at home and PV generation at the start of the off-peak hours (around 4pm). Overall, the results do not show an intraday shift of the charged energy from evening to midday, but rather a shift from morning to midday and to a lesser extent also to the evening, supporting an overall rebound effect that is however aligned with better utilization of self-generated electricity.

Two aspects of the field trial scope and sample need to be considered when interpreting the increased charged energy during the midday PV peak and its intraday shift from the morning hours. First, we did not consider how the smart charging mode affected charging behavior in places other than home. The participants may shift their charging during the day and spatially (e.g., charge less at work or publicly because of the new charging mode shifting relative prices between these options). Second, the participants are self-selected into the field trial and are characterized by relatively high energy literacy and advanced household equipment [9]. The self-selection bias can impact the presented effects in both directions. On the one hand, participants already had a higher charged energy during midday than the evening before the intervention, perhaps limiting the margin for further increase with the smart charging mode. On the other hand, these households are likely better equipped to optimize their charging than the average German household.

Individual- and time-dependent factors pre-determine larger parts of the variation. There are differences between the coefficients when comparing the identification over time and across groups, for instance, the group comparison (happening at the same point in time, row 2) reveals larger coefficients than the comparison over time (row 1). However, the directions and effect sizes remain robust despite the small cross-section. In line with the descriptives showing large variation across and within household charged energys (Figure 1), the adjusted R2 is low across all specifications. This indicates that charging behavior is highly idiosyncratic across time and households even after controlling for weather and household characteristics. The residual variability is much higher than for the preceding analysis of overall self-consumption with the same data.

In summary, the smart charging mode led to changes in the charging behavior. The introduction had substantial additional effects on electricity patterns, even in a sample of prosumers that already had digital tools for adjusting behavior before the smart charging intervention. In particular, we find strong evidence of an increase during the midday peak. A corresponding decrease in the evening did not offset this shift. How these findings are impacted by charging outside the home and PV generation during the early evening is however subject to further research. Our findings are highly relevant for understanding the potential of demand-side flexibility from electric vehicles. The smart charging mode makes it easier for prosumers to better utilize their own production, in line with the literature pointing to demand for low-effort solutions for end-consumers [10]. More broadly, evidence on the effects of data-driven energy services among these early adopters is important in light of the expected diffusion of related concepts to a broader population [11].

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