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SHOW ME THE MONEY! INCENTIVES AND NUDGES TO SHIFT ELECTRIC VEHICLE CHARGE TIMING

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ABSTRACT

We use a field experiment to measure the effectiveness of financial incentives and moral suasion "nudges" to shift the timing of electric vehicle (EV) charging. We find EV owners respond strongly to financial incentives, while nudges have no statistically discernible effect. When financial incentives are removed, charge timing reverts to pre-intervention behavior, showing no evidence of habit formation and reinforcing our finding that "money matters". Our charge price responsiveness estimate is an order of magnitude larger than typical household electricity consumption elasticities. This result highlights the greater flexibility of EV charging over other forms of residential electricity demand.

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1 Introduction

Electric vehicle (EV) sales are on the rise. In 2023, the International Energy Agency estimates 18% of global vehicle sales will be electric, up from only 2% in 2018 (IEA, 2023). This growth is expected to continue as policies to electrify the transportation sector take hold (IPCC, 2022). However, this trend raises questions about the ability of electricity systems to serve the influx of large new demand from EVs. While much attention has been paid to the total quantity of new electric energy required to charge EVs, their impact on the cost and reliability of electricity delivery systems will depend largely on when they are charged.

To illustrate, consider two possible paths. In the first, EVs are charged when privately most convenient—between 5 and 8 PM when drivers return home from work. This "EV rush hour" adds to existing peak demand, requiring higher marginal cost and likely higher greenhouse gas (GHG) emitting generation to meet demand and, ultimately, an expansion of system capacity. In the second, EVs are charged during periods of surplus supply capacity—be it overnight when demand is low or during periods of the day with abundant renewable generation. This path improves the economic and environmental efficiency of the existing system and lessens the need for costly capacity expansions. The ability to achieve the latter path depends on the flexibility of EV owners to shift their charge timing.

In this paper, we use a field experiment and in-vehicle monitoring devices to assess the willingness of EV owners to shift within-day charging activity in response to financial incentives and moral suasion "nudges" (Thaler and Sunstein, 2009). While estimates of short-run electricity demand elasticities are notoriously inelastic (Reiss and White, 2005), there are reasons to believe EVs should be more flexible. Unlike most electric appliances where the service provided occurs simultaneously with the electric draw, EVs differ in that the service (driving) and electric draw (charging) are separated on account of their large batteries. Further, EV charging demand, at 7-10 kilowatts (kW) for a "Level 2" home charger, is considerably larger than that of other large household appliances, such as air conditioners, water heaters, and clothes dryers, which is typically in the range of 1 to 3kW. This suggests EVs could be a source of considerable demand flexibility, yet there is limited empirical evidence on whether this is true.

Our experiment consists of two phases. In Phase 1, we randomize participants into one of three groups: (1) a "Rewards" group that receives a financial incentive of 3.5 cents per kilowatt-hour (kWh)—roughly a 23% discount off the fixed retail price—on all off-peak (10 PM to 6 AM) charging; (2) a "Nudge" group that receives information on the societal benefits to the grid of charging in the off-peak hours; and (3) a "Control" group that does not receive any intervention but its hourly consumption is monitored.[1,2] We then estimate the effect of financial incentives and nudges on charging behavior using a difference-in-differences empirical design.

We find that financial rewards are effective at shifting EV charging behavior, but nudges are not. The Rewards group collectively shifts its average share of kilowatt-hours charged during off-peak hours of the day from 59% prior to the intervention to 77% afterward. However, the Nudge group shows no statistically detectable change in charging behavior and is statistically indistinguishable from the Control group. To put the Rewards group results in context, the resulting price elasticity of charge timing is a full order of magnitude larger than short-run price elasticity of electricity demand estimates from TOU experiments on household consumption that range from -0.10 to -0.20.[3] This large difference in price responsiveness is likely due to the fact that, historically most residential demand response comes from reducing or delaying the service an electric appliance provides. In contrast, large batteries in EVs allow shifting a significant amount of electricity consumption without sacrificing the service provided by the EV in most situations.

In Phase 2, we test for habit formation in the timing of EV charging behavior by performing a second randomization where half of the Rewards group are told they will no longer receive financial incentives for off-peak charging. The charge timing of customers whose payments are terminated reverts back to their pre-intervention behavior, a result consistent with the absence of habit formation. This finding further reinforces our central conclusion that financial incentives are key to eliciting changes in charge timing from EV owners.

Our research is most closely related to three recent studies. Burkhardt et al. (2019) use appliance-level data in a study of electricity demand response in Texas. While not exclusively focused on EVs, they find greater responsiveness to overnight price

[1]All currency references in this paper are to Canadian dollars. At time of writing (August 2023), 1 Canadian dollar ≈ 0.75 US dollar.

[2]The economic incentives for the Rewards group mimics Time-of-Use (TOU) pricing. We recognize that TOU tariffs are an imperfect reflection of time-varying nature of wholesale energy costs and may even lead to bunching of electricity consumption near the start and end of off-peak periods. Our study is not intended to advocate for TOU pricing, but rather to investigate the flexibility of EV charging in response to financial incentives. Such incentives, in practice, could potentially include more efficient designs, such as dynamic pricing or centrally-managed demand response (Bailey et al., 2022).

[3]Harding and Sexton (2017) survey these studies.

discounts from homes with EVs. Using household-level electricity consumption data in Arizona, Qiu et al. (2022) find households with EVs respond to time-of-use rates. In their setting, however, customers self-select into their preferred tariff. Finally, Ito et al. (2018) find financial incentives create a larger and more persistent reduction in household electricity consumption during peak hours than moral suasion nudges. Our results are perhaps more stark. We find no statistically significant evidence of a demand response to moral suasion nudges.

Our results provide three key insights. First, money matters. Saving even a small amount (3.5¢ per kWh, or an average of roughly $10 per month per participant) is key to eliciting behavior change. Second, though nudges remain a popular policy tool to address market failures and have been found effective in several energy conservation studies (Allcott and Rogers, 2014; Brandon et al., 2019; Reiss and White, 2008), in our setting we find moral suasion nudges to be ineffective. Third, we find no evidence of habit formation. When financial incentives are removed, charge timing quickly reverts back to pre-intervention behavior. This finding stands in contrast to that of Ito et al. (2018), who find that residential electricity consumers in Japan continue to conserve energy during peak hours after a series of critical peak pricing events. However, our results are consistent with the results from experiments in which short-term financial incentives were provided to increase exercise, quit smoking, and improve school performance (Gneezy et al., 2011; Royer et al., 2015). This finding reinforces the importance of financial incentives for EV drivers to shift charging behavior.

Finally, the magnitude of EV charging price responsiveness is noteworthy in its own right. Compared to typical household-level electricity price elasticity estimates, the elasticity we find reflects just how different EV charging flexibility is versus other forms of residential electricity demand. The ability to shift charging times without sacrificing driving capability in most situations stands in contrast to most residential appliances, for which the service and electric draw must occur simultaneously. Harnessing this considerable flexibility will be imperative as EV sales expand. Studies predicated on the assumption of inelastic EV demand are likely to overstate the cost of integrating EVs into the electric system.

The rest of the paper proceeds as follows. Section 2 outlines the experimental design. Section 3 summarizes the data and empirical methodology. Section 4 presents results from both descriptive and statistical analysis. Section 5 concludes with policy implications and a discussion of promising areas for future research.

2 Experimental Design

The field experiment is done in partnership with ENMAX Power, a municipally-owned distribution utility serving the residents of Calgary, a city of approximately 1.4 million people. Important for our study, residential retail electricity prices are time-invariant across hours of day in Alberta. Consumers can choose between a default tariff that varies monthly based on wholesale market conditions or multi-year fixed rate contracts offered by competitive retailers.[4]

In November 2021, households with EVs in ENMAX's service territory were recruited by voluntary sign-up to the utility-branded "ChargeUp" program. Recruitment was conducted using television, radio, and online marketing campaigns. EV owners were offered $100 ($20 upfront and $80 upon completion of the experiment) to participate and told their driving and charging behavior would be monitored for one year to help the utility better understand the impact of a growing share of EVs on the electricity system.

Within one week of signing up, participants were mailed a physical device with instructions on how to connect it to their vehicle's onboard diagnostic port. This device enables the monitoring of charging and driving data from the vehicle. The monitoring device was installed in 150 vehicles. This serves as our pool of participants that are randomized into our three groups—Rewards, Nudge and Control.

The experiment consists of two phases following a pre-period, which runs from device installation to March 31, 2022.[5] During the pre-period, charging behavior is monitored, but participants receive no interventions or communication from ENMAX.

For Phase 1, we assign participants to either the Rewards, Nudge, or Control group using a stratified randomization procedure leveraging data collected during the pre-period.[6] On March 31, 2022, participants in the experiment received emails with the following information:

- The Nudge group [45 vehicles] received information on the benefits to the grid of shifting EV charging from the peak hours of 5 PM–8 PM into the low demand

[4]As of January 2022, 76% of households in ENMAX's territory are on multi-year fixed rate contracts (MSA, 2023), with the remaining on plans that vary monthly.

[5]The installation of the monitoring devices occurred primarily throughout the months of December 2021 and January 2022. For our analysis, we begin our pre-treatment period on February 1, 2022, when the majority of vehicles (93%) had the monitoring device installed.

[6]We used a k-means clustering analysis to first cluster participants based on the similarity of their observable characteristics, then randomly assigned the EVs within each cluster to the three groups to ensure the balance of characteristics across these three groups.

period of 10 PM–6 AM.

- The Rewards group [68 vehicles] received the same information as the Nudge email plus an additional paragraph explaining that as of April 1, 2022, they would receive a 3.5¢/kWh discount for all kWh charged between the hours of 10 PM and 6 AM.[7]

- The Control group [37 vehicles] did not receive any intervention during the course of the experiment. Their charging behavior was simply monitored.

In Phase 2, we further randomized the Rewards group into two subgroups: "Rewards-Continue" [33 vehicles] and "Rewards-Stop" [35 vehicles]. The Reward-Stop group received an email on August 31, 2022, notifying them that they would no longer receive payments for their off-peak charging behavior. To ensure comparability of the salience of the experiment across groups, the Rewards-Continue group received an email at the same time reminding them of their continued payment for off-peak charging. Both emails also contained language emphasizing the value of continued off-peak charging. The experiment was concluded on December 31, 2022. The full text of all intervention emails can be found in Appendix B.

3 Data and Empirical Methodology

3.1 Data and Assessment of Balance

Our data for this study extend from February 1, 2022 to December 31, 2022. The monitoring devices provide time-stamped information on EV charging including kWhs charged and maximum charging power (in kWs), the location of charging (at home or away from home), and time-stamped information on driving activity that includes individual trip driving distances. Sign-up information provides data on vehicle make and model for each participant.

In addition, participants were sent a survey at the beginning of the experiment that asked an array of questions including the number and characteristics of vehicles at home, the number of drivers, whether the home has solar panels, and educational

[7] The discount comes in the form of a bill credit against their regular electricity bill. The discount represents an approximate 23% reduction in the variable delivered price of electricity in ENMAX's territory in 2022.

background. Approximately 75% of participants filled out this survey.[8] We also collected hourly temperature data for Calgary from Environment Canada to control for possible impacts of outdoor temperature on factors that impact EV charging.[9]

We use the monitoring and survey data to assess the quality of our randomization. We compare means across the three groups for various EV charging, driving, and vehicle characteristics to ensure we have balance on observables pre-treatment in Appendix Table A1. Using a one-way ANOVA test, the table shows there are no statistically significant differences in means of each variable across the three groups. Appendix Table A2 demonstrates that we achieve balance on the variables collected through the survey as well.

In Phase 2 of our analysis, we randomize the Rewards group participants into two subgroups: Rewards-Continue and Rewards-Stop. Appendix Table A4 demonstrates these two groups are also balanced on observable charging, vehicle, and driving characteristics during Phase 1, the pre-period for this portion of our analysis. Further, Appendix Table A5 demonstrates there are no statistically significant differences in survey responses across these two groups, with the exception of the number of drivers in the household, which is marginally significant, with a p-value of 0.06.

Our research design ensures strong internal validity across the different groups in our sample. However, we recognize the need to exercise caution when generalizing our results to a wider population of customers. Households in our sample display a high level of education, with over 80% reporting at least a bachelor's degree (see Table A2). In contrast, 37% of the broader population of Calgary has a bachelor's degree.[10] This high level of education among our sample aligns with the characteristics of early adopters of electric vehicles observed in other regions (Lee et al., 2019). As discussed in Section 5, future research is required to understand how charging behavior and responsiveness to incentives might differ among EV owners as EVs become more widespread.

[8] We perform balance tests using pre-period variables that were used for clustering to evaluate if the EV owners that did and did not respond to the survey are different. The results are presented in Appendix Table A3. We find no statistically significant differences in observable charging and driving behavior, with the one exception that EV owners that responded to the survey had a larger maximum kW charged at home.

[9] The data can be accessed here: https://climate.weather.gc.ca/historical_data/search_historic_data_e.html.

[10] Data on educational attainment are from Statistics Canada and can be accessed here: https://open.alberta.ca/opendata/educational-attainment-by-municipality#detailed.

3.2 Empirical Methodology

The sample period for Phase 1 covers February 1, 2022 to August 31, 2022. For this phase, we estimate the effect of randomly receiving either the Rewards or Nudge treatment via a difference-in-differences estimation strategy.

Using data for each hour t and vehicle i, we estimate the following equation:

$$y_{it} = \beta_0 Post_t \times Group_i + \beta_1 Post_t \times Group_i \times OffPeak_t + \alpha_i + \boldsymbol{\tau}_t + \gamma \mathbf{X}_t + \varepsilon_{it}, \quad (1)$$

in which y_{it} can one of our two dependent variables: (1) a "Charge Indicator" variable that equals 1 if vehicle i was charged in hour t and zero otherwise and (2) vehicle i's charge kWhs in hour t ("Charge kWhs").[11] $Post_t$ is an indicator variable that equals 1 starting on April 1, 2022, the day after households received emails corresponding to the Rewards and Nudge treatments (see Appendix B). $Group_i$ represents two indicator variables, for the Rewards and Nudge treatment groups. Because our main objective is to investigate changes in EV charge timing, we interact the $Post_t \times Group_i$ indicator variable with an off-peak hour indicator variable, $OffPeak_t$, that equals 1 if hour t falls between 10:00 PM and 6:00 AM and zero otherwise. This allows us to evaluate the impact of the Phase 1 treatment on both peak and off-peak charge timing and levels.

The α_i are vehicle fixed effects to control for time-invariant vehicle characteristics in y_{it}. The $\boldsymbol{\tau}_t$ represents a vector of time fixed effects for the month-of-sample, day-of-week, and hour-of-day. These fixed effects control for time-varying factors that impact charging decisions. $\mathbf{X}_t$ is a vector containing hourly heating degree and cooling degree covariates.[12] We include a third-order polynomial for both measures, allowing us to control flexibly for possible temperature-dependent factors that impact battery efficiency. For both dependent variables, the standard errors are clustered at the vehicle level.

Phase 2 of the experiment randomly splits the Rewards group into two subgroups: Rewards-Stop and Rewards-Continue. Between the period of April 1, 2022 to August 31, 2022, these vehicles were in the Rewards group during Phase 1 and were exposed to the same financial incentives and information. This serves as our pre-treatment

[11] Our regression is a linear probability model when Charge Indicator is the dependent variable. In the results reported below, we find few cases where the predicted values of the regression model fall outside of the bounds of $[0, 1]$ (approx. 1%).

[12] Heating (cooling) degrees captures the outdoor temperature below (above) 18 degrees Celcius (approx. 65 degrees Fahrenheit).

period for this phase of the analysis. After August 31, Rewards-Stop was subject to a new treatment in which the financial incentives for off-peak charging were removed. Rewards-Continue did not receive a new treatment. Consequently, we use the Rewards-Continue group as the "Control" group in this phase to estimate the impact of the Rewards-Stop intervention.

More formally, for this second phase we consider an analogous specification to that above (Equation 1), with the following two exceptions. First, the $Group_i$ variable is replaced with an indicator variable denoting if an EV is in the Rewards-Stop group, with Rewards-Continue serving as the control. Second, the $Post_t$ period refers to the period after August 31, 2022. The sample period for this analysis is limited to April 1 to December 31, 2022, and those in the Nudge and original Control groups are excluded.

Our primary objective in both phases is to understand how the various interventions affect the timing of EV charging, within-day. Given vehicle owners may be less able to adjust their charge timing when they are away from home, we restrict the main analysis to days when charging at home occurs.[13] Our identification strategy is valid with this subsetting if there is no differential change in the daily frequency or amount of charging at home across groups, post-treatment, compared to pre-treatment, which we address in Appendix C.[14] We also present and discuss the results of robustness checks where we include both home and away charging.

4 Results

4.1 Phase 1: Shifting EV Charging behavior

We begin with a descriptive analysis, investigating if there are observable changes in charging behavior in our three groups relative to their pre-treatment behavior. For each treatment group and day, we calculate the share of total kWhs charged at home in the off-peak hours before and after the Phase 1 intervention.[15] We nor-

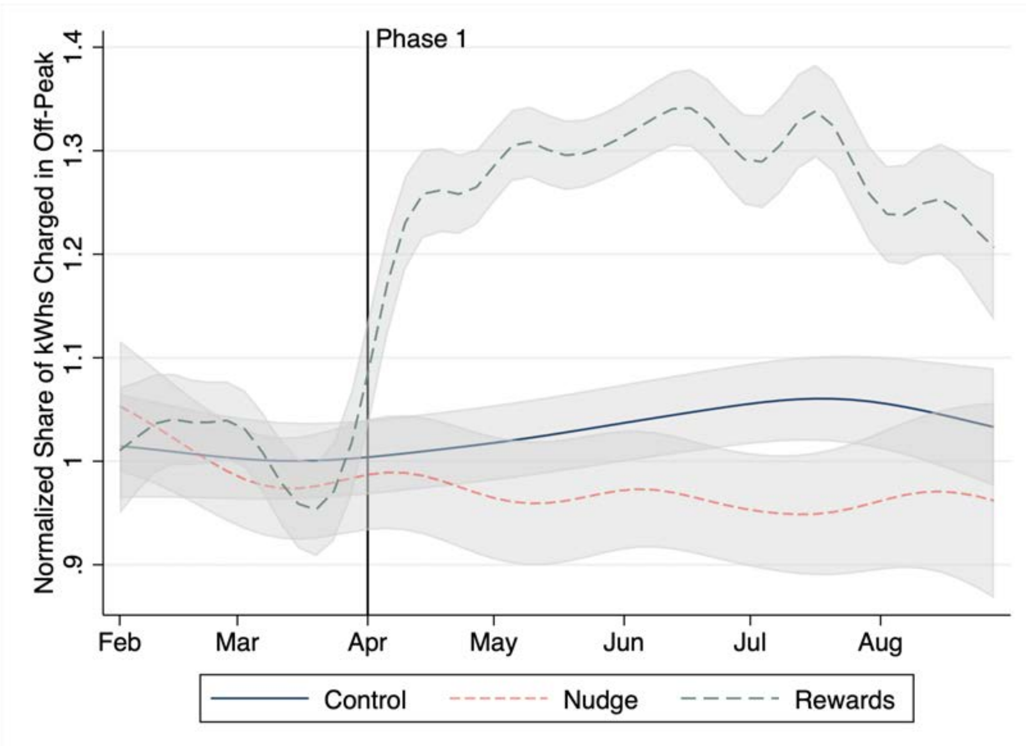
[13]We define a "day" as running from 9:00 AM to 8:59 AM the following day to capture shifts in charging that may occur overnight.

[14]Participants in the Rewards group receive their financial incentive for charging in the off-peak hours regardless of location, so there is no financial incentive for participants to shift where they charge, post-treatment. As shown in Table A1, across all treatment groups, approximately 81% to 86% of the pre-treatment charging sessions are at home.

[15]In contrast to our regression analysis in (1) that is at the vehicle-hour level, the descriptive analysis aggregates charging behavior to the treatment group-day level. More specifically, define Y^G_{ihd} to be the kWhs charged at home by vehicle i in hour h of day d in group G and OP to be the set of off-peak hours. For each day d, the share of kWhs charged in the off-peak for group G equals

malize each series such that a value of 1 indicates the off-peak share is equal to the group's pre-treatment daily mean. We smooth the normalized daily mean shares by a nonparametric regression and a 95% confidence interval.[16]

Figure 1. Share of kWhs Charged At Home in Off-Peak Hours (Phases 0 and 1)



Notes. This figure plots the daily share of kWhs charged at home in the off-peak by group, normalized by the group-specific pre-treatment mean of the off-peak share. The lines represent a kernel-weighted local polynomial nonparametric regression with 95% confidence intervals.

Figure 1 illustrates that, starting on April 1, the Rewards group's normalized off-peak share quickly increases to 1.3, demonstrating a 30% increase relative to its pre-treatment mean. In raw data terms, this brings the average off-peak share of charged kWhs for the Rewards group to 77% post-treatment, up from 59% pre-treatment. In contrast, we observe minimal changes for the Nudge and Control groups. These descriptive results suggest that the financial intervention motivated EV owners to adjust their charge timing and that the behavioral nudge had no discernible impact.

Table 1 provides the results of our regression analysis, which evaluates the effects

$Y_d^{OP,G}/Y_d^G$, where $Y_d^{OP,G} = \sum_{i \in G} \sum_{h \in OP} Y_{ihd}^G$ and $Y_d^G = \sum_{i \in G} \sum_{h=0}^{23} Y_{ihd}^G$.

[16] We estimate a kernel-weighted local polynomial regression with a Gaussian kernel, using the rule-of-thumb plug-in bandwidth parameter. See the documentation for the STATA *lpolyci* command for details.

of the Phase 1 intervention. Column (1) demonstrates that financial rewards reduced on-peak and increased off-peak charging frequency. Both effects are statistically significant at the 5% level. The financial intervention increased the off-peak charging frequency by approximately 10 percentage points, a 27% increase relative to its mean value during the pre-treatment period (0.3516), and decreased peak charging by 5 percentage points, a 30% reduction from its pre-treatment period mean (0.1706).[17] The Nudge group coefficients in column (1) are not statistically different from zero, consistent with this intervention not impacting charge timing.

Table 1. Estimated Treatment Effects - Phase 1

Group	Hours	(1) Charge Indicator	(2) Charge kWh
Rewards	Peak	-0.0509	-0.2008
		(0.0208)	(0.0558)
	Off-Peak	0.0958	0.4553
		(0.0296)	(0.1063)
Nudge	Peak	0.0090	0.0053
		(0.0238)	(0.0626)
	Off-Peak	-0.0225	-0.2216
		(0.0330)	(0.1282)
Mean Dep. Var. (Pre-Treatment)			
Rewards	Peak	0.1706	0.4091
	Off-Peak	0.3516	1.2280
Nudge	Peak	0.1990	0.5366
	Off-Peak	0.3386	1.0946

Notes. The data include charging at home only. The estimated treatment effects are separated into Peak and Off-Peak hours. The Mean Dep. Var. (Pre-Treatment) represents the mean value of each dependent variable between February 1, 2022 - March 31, 2022, separated into Peak and Off-Peak hours. All specifications include fixed effects at the vehicle, month, hour, and day-of-week. Standard errors are clustered at the vehicle level.

Column (2) shows that financial rewards led to a statistically significant increase

[17] It is important to note that the off-peak coefficient is approximately two times as large as the peak coefficient in column (1). This is driven by the fact that there are 16 peak hours and 8 off-peak hours, as well as underlying differences in the frequency of peak and off-peak charging pre-treatment. Figure A1 shows coefficient results by hour of day, which illustrate the impact of small per-hour reductions during the 16 peak hours, leading to larger per-hour increases during the 8 off-peak hours, as EV owners squeeze the same volume of electricity demand into a shorter time period. The same logic applies to the at-home Charge kWhs results for the Rewards group presented in column (2).

(decrease) in the off-peak (peak) at-home volume of electricity used for charging ("Charge kWhs"). The financial incentive increased off-peak at-home Charge kWhs by approximately 37% relative to the mean at-home value for the Rewards group pre-treatment (1.2280) and decreased peak charging by 49% from its pre-treatment mean (0.4091).

Using the Charge kWhs as a dependent variable has the advantage of allowing us to estimate a price elasticity of off-peak charging.[18] The estimated off-peak price elasticity for the Rewards group equals -1.59.[19] This is orders of magnitude larger than estimated price elasticities of household-level consumption from time-of-use price signals, which are often in the range of -0.10 to -0.20 (Harding and Sexton, 2017).

Column (2) shows that the Nudge group did not significantly change its peak charging kWh post-treatment, compared to the Control. We conducted a series of analyses that suggest this is due to the Nudge group charging more away from home post-treatment than the other groups.[20]

When both home and away charging are included, we continue to find statistically significant evidence of a shift from peak to off-peak charging for the Rewards group for both the Charge Indicator and Charge kWh variables (see Table A6 in the Appendix). For the Nudge group, there is no evidence of a change in the timing of charging when using either dependent variable.

We also consider a flexible specification that estimates hour-of-day specific treatment effects by group.[21] Figures A1 and A2 in the Appendix present estimated hourly treatment effects using Charge Indicator and Charge kWh as the dependent variables,

[18]This elasticity is, of course, estimated from and applicable to days when EV owners plug in their vehicles to charge.

[19]This price elasticity is the estimated percentage change in off-peak Charge kWhs in response to the financial intervention divided by the percentage change in the price of off-peak charging. Using our regression results (see Table 1), the percentage change in off-peak at-home Charge kWhs is $0.4553/1.2280 \approx 0.3707$. The percentage change in the off-peak price is $-0.035/0.15 \approx -0.2333$, using the average 2022 retail rate in ENMAX for a residential customer on a 3-year fixed rate plan and prevailing variable transmission, distribution and local access fees. This results in the off-peak price elasticity $(0.3707)/(-0.2333) \approx -1.59$.

[20]First, when we include both home and away charging and estimate Equation (1), the off-peak coefficient for the Nudge group loses statistical significance (Appendix Table A6). Additionally, in Appendix C, we investigate whether the daily charge frequency and/or charged kWhs changes differentially across the treatment groups, post-treatment. This analysis reveals that the Nudge group reduces its at-home Charge kWhs during Phase 1, relative to the Control. This is driven by an increased amount of away charging sessions that typically occur at level 3 chargers. When away charging is included, we observe no difference in the intensity of daily charged kWhs for the Nudge group relative to the Control.

[21]More specifically, we adjust the specification in (1) to interact $Post_t^1 \times Group_i$ with a vector of indicators for each hour of the day, removing the interaction with the $OffPeak_t$.

respectively. For the Rewards group, we observe a statistically significant reduction in evening charging between 4 PM - 9 PM and an increase in most off-peak hours for both measures. Whereas, for the Nudge group, there is no evidence of a statistically significant decrease (increase) in any peak (off-peak) hours.[22] Taken together, these results support the conclusion that the financial incentives led to a sizable shift in charging to the off-peak hours, while there is no statistically significant evidence that our intervention reduced the Nudge group's peak period charging.

4.2 Phase 2: Testing for Habit Formation

With the Phase 2 data, we test for the presence of habit formation when financial incentives are removed. Figure 2 plots the share of at-home kWhs charged in the off-peak hours by group over Phases 1 and 2, normalized by each group's mean in the initial pre-treatment period (i.e., Phase 0). This figure is analogous to Figure 1, except the Rewards group is split into its two Phase 2 subgroups, the absence of the Nudge group, and different sample periods.

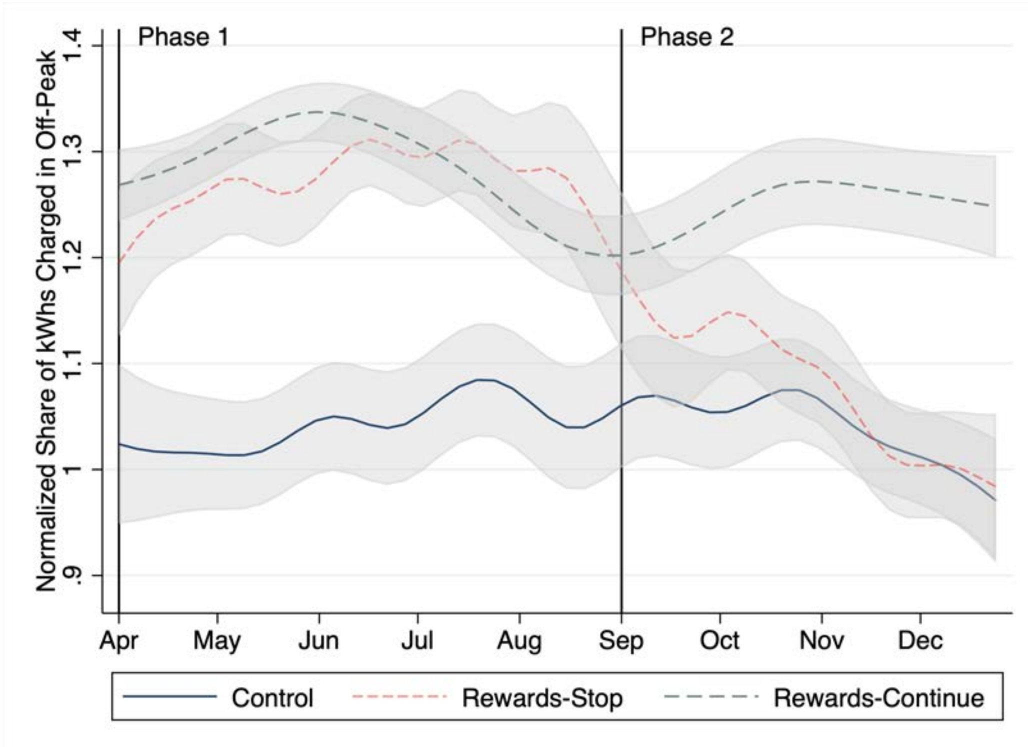
Figure 2 demonstrates that during Phase 1, Rewards-Continue and Rewards-Stop EVs have similar patterns for their share of off-peak charging. Over this time period, these two groups received the same treatment (financial reward for charging in the off-peak). As described in Section 3.2, these descriptive results support the use of the Rewards-Continue group as a valid control for the Rewards-Stop group, as the Rewards-Continue group displays a Phase 1 off-peak charging share that is not statistically different than the Rewards-Stop group.

After the Phase 2 intervention on August 31, 2022, we see a decline in the off-peak charging share for the Rewards-Stop group, while the Rewards-Continue group maintains a high level of off-peak charging. By the end of the sample period, the Rewards-Stop group converges to the same share of kWhs charged in the off-peak as the Control group; both groups' values are near their initial pre-period mean off-peak shares. These descriptive statistics provide evidence that the EV owners did not form and maintain habits on charge timing, absent financial incentives.

Table 2 presents the results of estimating Equation (1) (with the Phase 2 procedure described in Section 3.2) to evaluate the impact of removing financial incentives in Phase 2. Column (1) shows a statistically significant increase (decrease) in peak

[22] In fact, there is some evidence that the Nudge group charges less (in terms of frequency and kWhs) in off-peak hours compared to the Control post-treatment. As explained above, this is attributable to the shift to more away from home charging in the Nudge group, post-treatment, relative to the Control.

Figure 2. Share of kWhs Charged At Home in the Off-Peak - Phase 2 Analysis



Notes. This figure plots the daily share of kWhs charged at home in the off-peak by group, normalized by the group-specific Phase 0 mean of the off-peak share. The lines represent a kernel-weighted local polynomial nonparameteric regression with 95% confidence intervals.

(off-peak) charging frequency for the Rewards-Stop group relative to the Rewards-Continue group, post-treatment. These effects are also economically significant. The mean charging frequency for the Rewards-Stop group during peak hours increased by approximately 42% after their financial incentives to shift to off-peak were removed.

Column (2) presents the results using Charge kWhs as the dependent variable. There is a positive and statistically and economically significant increase in peak-hour charged kWhs during Phase 2 for the Rewards-Stop group. Peak charging for this group increased by approximately 51% after they stopped receiving the incentive to charge in the off-peak. There is also evidence of a reduction in off-peak charged kWhs, but the estimate is imprecisely estimated.

These results are consistent with those presented in Figure 2 and demonstrate there was a large increase in peak hour charging after the financial incentives were removed. These findings indicate there is no empirical evidence of habit formation as a result of the Phase 1 treatment. Once the financial incentives were removed, EV

Table 2. Estimated Treatment Effects - Phase 2

Group	Hours	(1) Charge Indicator	(2) Charge kWh
Rewards-Stop	Peak	0.0415	0.1275
		(0.0202)	(0.0632)
	Off-Peak	-0.0817	-0.2299
		(0.0298)	(0.1677)
Mean Dep. Var. (Pre-Treatment, Phase 1)			
Rewards-Stop	Peak	0.0999	0.2497
	Off-Peak	0.3582	1.5984

Notes. The data include charging at home only. The estimated treatment effects are separated into Peak and Off-Peak hours. The Mean Dep. Var. (Pre-Treatment, Phase 1) represents the mean value of each dependent variable between April 1, 2022 - August 31, 2022, separated into All Hours, Peak, and Off-Peak only. All specifications include fixed effects at the vehicle, month, hour, and day-of-week. Standard errors are clustered at the vehicle level.

owners increased their charging during peak hours.

We also perform analysis that includes both home and away charging data that shows a statistically significant reduction in off-peak charging frequency for the Rewards-Stop group compared to its control, post-treatment (see Table A7 in the Appendix). However, there is no longer a statistically significant increase in peak charging frequency or kWhs. The lack of significance is likely driven in part by the fact that, unlike home charging, away charging is largely inflexible, with timing determined by other factors (e.g., the timing of travel).

5 Conclusion

Understanding the flexibility of EV charging, and which policies are effective at achieving it, are crucial given the rapidly growing share of EVs and associated electricity demand. Charging EVs during high-demand times can potentially destabilize electricity delivery and necessitate substantial investments in grid infrastructure.

We find that financial incentives are very effective in shifting the timing of EV charging, whereas we do not find a statistically significant effect from the nudge in our experiment. We estimate that the receipt of a 3.5¢/kWh credit, or roughly a 23% discount on the retail price, led to a 37% increase in off-peak charged kWhs and commensurate decrease in peak charging. This 3.5¢/kWh discount was cost-effective for retailers serving these customers because the wholesale market price difference between peak and off-peak hours in Alberta in 2022 was 8.9¢/kWh (AESO, 2023).

Our findings highlight the large flexibility of EVs to shift their electricity demand as compared to other forms of residential electricity demand. As previously mentioned, there are several reasons for this greater flexibility. First, unlike most residential appliances where electricity demand response comes from delaying or sacrificing the underlying service the appliance provides, the large batteries in EVs allow for electricity demand to shift in time without drivers having to sacrifice the service (driving) in most situations. Second, EV charging loads are significantly larger than other residential loads, leading to potentially more attention and salience of their electricity use.

While several studies have attempted to quantify the impact of the growth of EVs on electric grids (e.g., Jones et al. (2022)), most rely on simulations of EV charging behavior in response to TOU incentives. Our paper provides well-identified empirical estimates through the use of a randomized controlled trial of how incentives impact EV charge timing. These estimates can be used in future work on the impact of EVs on the electric grid. With the large instantaneous electric demand from EV chargers (roughly 10kW for a "Level 2" charger), encouraging a shift to charging when there is surplus system capacity offers the potential to dramatically reduce the cost of EV integration. Studies predicated on the assumption of inelastic charging demand will grossly overstate the impact of the pending growth in EVs.

To give a sense of scale, and the potential benefits of flexible EV charging, consider the following. If one-third of Alberta's registered vehicles were to be electric and all charging simultaneously on Level 2 (10kW) chargers, it would double the province's current electric system peak (≈12,000MW). Obviously this is an extreme example—all vehicles charging at once is extremely unlikely and that level of EV penetration remains a long ways away—but nevertheless enabling flexible EV charging can ensure electricity demand from EVs gets spread across hours with surplus capability, minimizing strain on the system. Such flexibility can greatly reduce future electric system costs arising from a rapidly decarbonizing transportation sector.

In our setting, EV charging flexibility is unlocked via financial incentives; nudges do not prove effective at eliciting a noticeable change in our experiment. More research is needed to understand how these results might generalize beyond EV early adopters and static TOU block rates. As electricity systems evolve, more supply variability from growing shares of renewable generation will place greater emphasis and importance on demand flexibility. Moreover, given just how large the power draw is from a "Level 2" charger, avoiding coincident charging of numerous EVs on a distribution circuit becomes essential to avoid costly infrastructure upgrades. Future work can extend our results to consider more dynamic schemes, such as dynamic pricing and active charge management, that can better align charging decisions with ever-changing marginal system costs and overcome the aforementioned coordination challenges.[23] Nonetheless, our study makes clear there is significant EV charging flexibility ready to be unlocked by the right policy incentives.

[23]There are several pilot programs and studies analyzing the effectiveness of management of household appliances, including EVs, in jurisdictions such as California, Massachusetts, and in Canada (SEPA, 2019; Larcher and Piero, 2021; Bailey et al., 2022).

References

AESO (2023). Aeso 2022 annual market statistics. Accessed June 15, 2023. https://www.aeso.ca/assets/Uploads/market-and-system-reporting/2022_Annual_Market_Stats_Final.pdf.

Allcott, H. and T. Rogers (2014). The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation. *American Economic Review 104*(10), 3003–3037.

Bailey, M., D. Brown, B. Shaffer, and F. Wolak (2022). Centralized vs Decentralized Demand Response: Evidence from a Field Experiment. *Working Paper*.

Brandon, A., J. A. List, R. D. Metcalfe, M. K. Price, and F. Rundhammer (2019). Testing for Crowd Out in Social Nudges: Evidence From a Natural Field Experiment in the Market for Electricity. *Proceedings of the National Academy of Sciences 116*(12), 5293–5298.

Burkhardt, J., K. Gillingham, and P. K. Kopalle (2019). Experimental Evidence on the Effect of Information and Pricing on Residential Electricity Consumption. *National Bureau of Economic Research Working Paper No. w25576*.

Gneezy, U., S. Meier, and P. Rey-Biel (2011). When and Why Incentives (Don't) Work to Modify Behavior. *Journal of Economic Perspectives 25*(4), 191–210.

Harding, M. and S. Sexton (2017). Household response to time-varying electricity prices. *Annual Review of Resource Economics 9*, 337–359.

IEA (2023). Global ev outlook 2023. Accessed May 17, 2023. https://www.iea.org/reports/global-ev-outlook-2023.

IPCC (2022). *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York, NY, USA: Cambridge University Press.

Ito, K., T. Ida, and M. Tanaka (2018). Moral suasion and economic incentives: Field experimental evidence from energy demand. *American Economic Journal: Economic Policy 10*(1), 240–267.

Jones, C. B., W. Vining, M. Lave, T. Haines, C. Neuman, J. Bennett, and D. R. Scoffield (2022). Impact of electric vehicle customer response to time-of-use rates on distribution power grids. *Energy Reports 8*, 8225–8235.

Larcher, R. and J. Piero (2021). Intelligent Vehicle Integration. California Energy Commission. Publication Number: CEC-500-2022-013.

Lee, J. H., S. J. Hardman, and G. Tal (2019). Who is Buying Electric Vehicles in California? Characterising Early Adopter Heterogeneity and Forecasting Market Diffusion. *Energy Research & Social Science 55*, 218–226.

MSA (2023). Retail statistics, alberta market surveillance administrator. Accessed February 15, 2023. https://www.albertamsa.ca/documents/retail-and-rate-cap/retail-statistics/.

Qiu, Y. L., Y. D. Wang, H. Iseki, X. Shen, B. Xing, and H. Zhang (2022). Empirical grid impact of in-home electric vehicle charging differs from predictions. *Resource and Energy Economics 67*, 101275.

Reiss, P. and M. White (2005). Household Electricity Demand, Revisited. *The Review of Economic Studies 72*(3), 853–883.

Reiss, P. C. and M. W. White (2008). What Changes Energy Consumption? Prices and Public Pressures. *The RAND Journal of Economics 39*(3), 636–663.

Royer, H., M. Stehr, and J. Sydnor (2015). Incentives, Commitments, and Habit Formation in Exercise: Evidence From a Field Experiment With Workers at a Fortune-500 Company. *American Economic Journal: Applied Economics 7*(3), 51–84.

SEPA (2019). A Comprehensive Guide to Electric Vehicle Managed Charging. Smart Electric Power Alliance.

Thaler, R. H. and C. R. Sunstein (2009). *Nudge: Improving decisions about health, wealth, and happiness*. Penguin.

A Additional Tables and Figures

Table A1. Pre-Treatment (Phase 0) Comparison of Means by Group - Cluster Variables

Variable	Control	Nudge	Rewards	ANOVA (p-value)
Home Charging (%)	81.25	83.43	85.66	0.69
	(28.52)	(25.96)	(22.63)	
Daily Charging Sessions (Count)	1.77	1.48	1.70	0.78
	(2.45)	(1.26)	(2.08)	
Energy Charged Per Session (kWh)	8.80	11.05	10.04	0.37
	(6.73)	(8.45)	(6.15)	
Max kW Charge at Home	6.52	5.63	6.03	0.49
	(2.86)	(3.12)	(3.06)	
Modal Hour of Charge (Start Time)	6.73	6.00	5.14	0.48
	(6.74)	(6.53)	(6.39)	
Charge Duration Per Session (Minutes)	115.61	137.47	154.07	0.25
	(64.70)	(80.05)	(146.38)	
Percent Tesla	56.76	53.33	59.09	0.84
	(50.22)	(50.45)	(49.54)	
Average Daily Distance Driven (KMs)	42.11	54.66	48.99	0.30
	(27.02)	(40.28)	(37.73)	
Number of EVs	37	45	68	

Notes. This table compares pre-treatment (Phase 0) average values of the variables used in the clustering procedure across the three different groups. Parentheses contain the standard deviations. Home Charging captures the percentage of charging sessions that were at home, Daily Charging Sessions is the number of times the car was charged each day, Energy Charged Per Session is the cumulative number of kWhs charged each session, Max kW Charge at Home is the maximum kW draw from the charger at home in a charging session, Modal Hour of Charge is the modal hour that charging started, Charge Duration reflects the minutes of charging each charge session, Percent Tesla is the percentage of EVs that are Teslas, Average Daily Distance Driven is the average daily KMs traveled. ANOVA (p-value) reports the p-value from one-way ANOVA tests for differences in means across groups.

Table A2. Comparison of Means by Group - Survey Variables

Variable	Control	Nudge	Rewards	ANOVA (p-value)
Pre-Schedule (%)	65.38	43.75	60.38	0.20
	(48.52)	(50.40)	(49.38)	
Charge Outside of Home (%)	69.23	62.50	62.26	0.82
	(47.07)	(49.19)	(48.94)	
Number of Electric/Hybrid Vehicles	1.15	1.13	1.28	0.17
	(0.37)	(0.34)	(0.45)	
Number of Other Vehicles	0.92	0.97	0.94	0.98
	(0.80)	(0.69)	(0.91)	
Solar Panels (%)	11.54	28.13	22.64	0.31
	(32.58)	(45.68)	(42.25)	
Number of Drivers	1.85	2.06	2.09	0.13
	(0.46)	(0.25)	(0.66)	
Percent with at least Bachelors	84.62	84.38	88.68	0.82
	(36.79)	(36.89)	(31.99)	
Percent with Graduate Degrees	30.77	37.50	32.08	0.84
	(47.07)	(49.19)	(47.12)	
Count	26	32	53	

Notes. This table compares average values from the survey responses across the three different groups. Parentheses contain the standard deviations. Pre-Schedule represents the percentage of EV owners that reported using pre-scheduling to determine their EV charge timing, Charge Outside of Home is the percentage of EV owners that reported ever charging outside of their home, Number of Electric/Hybrid Vehicles is the number of EVs or hybrid vehicles, Number of Other Vehicles is the number of non-EV/hybrid vehicles, Solar Panels represents the percentage of EV owners that also have solar panels, Number of Drivers is the number of drivers in the household, Percent with at least Bachelors is the percentage of EV owners with a Bachelors, Master's, or Ph.D., and Percent with Graduate Degrees is the percentage of EV owners with a Master's or a Ph.D. ANOVA (p-value) reports the p-value from one-way ANOVA tests for differences in means across groups.

Table A3. Pre-Treatment (Phase 0) Comparison of Means by Survey Response

Variable	Response	Non-Response	p-value
Home Charging (%)	85.18	80.23	0.29
	(24.58)	(26.52)	
Daily Charging Sessions (Count)	1.75	1.38	0.32
	(2.20)	(1.06)	
Energy Charged Per Session (kWh)	10.09	9.90	0.89
	(7.23)	(6.69)	
Max kW Charge at Home	6.40	5.09	0.03
	(2.96)	(3.03)	
Modal Hour of Charge (Start Time)	6.02	5.18	0.49
	(6.56)	(6.42)	
Charge Duration Per Session (Minutes)	134.81	152.23	0.41
	(119.26)	(91.18)	
Percent Tesla	55.96	58.97	0.75
	(49.87)	(49.83)	
Average Daily Distance Driven (KMs)	49.73	48.18	0.82
	(34.38)	(41.33)	
Number of EVs	111	39	

Notes. This table compares the pre-treatment (Phase 0) average values of the variables used in the clustering procedure for the EVs by whether they responded to the survey (Response) or did not respond (Non-Response). Parentheses contain the standard deviations. Home Charging captures the percentage of charging sessions that were at home, Daily Charging Sessions is the number of times the car was charged each day, Energy Charged Per Session is the cumulative number of kWhs charged each session, Max kW Charge at Home is the maximum kW draw from the charger at home in a charging session, Modal Hour of Charge is the modal hour that charging started, Charge Duration reflects the minutes of charging each charge session, Percent Tesla is the percentage of EVs that are Teslas, Average Daily Distance Driven is the average daily KMs traveled. P-value reports the p-value from a difference in means test across the two groups.

Table A4. Phase 1 Comparison of Means by Rewards-Continue and Rewards-Stop

Variable	Rewards-Continue	Rewards-Stop	p-value
Home Charging (%)	78.62	73.60	0.46
	(24.91)	(29.36)	
Daily Charging Sessions (Count)	1.17	1.09	0.71
	(0.97)	(0.70)	
Energy Charged Per Session (kWh)	11.59	12.54	0.63
	(7.83)	(7.75)	
Max kW Charge at Home	5.47	6.25	0.35
	(3.31)	(2.91)	
Modal Hour of Charge (Start Time)	1.95	4.03	0.16
	(4.31)	(7.28)	
Charge Duration Per Session (Minutes)	182.69	148.57	0.28
	(131.63)	(121.18)	
Percent Tesla	58.06	57.14	0.94
	(50.16)	(50.21)	
Average Daily Distance Driven (KMs)	52.72	54.70	0.87
	(56.39)	(36.88)	
Number of EVs	33	35	

Notes. This table compares the average values of the variables used in the clustering procedure over the period April 1, 2022 - August 31, 2022 (Phase 1) for the Rewards-Continue and Rewards-Stop groups. Parentheses contain the standard deviations. Home Charging captures the percentage of charging sessions that were at home, Daily Charging Sessions is the number of times the car was charged each day, Energy Charged Per Session is the cumulative number of kWhs charged each session, Max kW Charge at Home is the maximum kW draw from the charger at home in a charging session, Modal Hour of Charge is the modal hour that charging started, Charge Duration reflects the minutes of charging each charge session, Percent Tesla is the percentage of EVs that are Teslas, Average Daily Distance Driven is the average daily KMs traveled. P-value reports the p-value from a difference in means test across the two groups.

Table A5. Comparison of Means by Rewards-Continue and Rewards-Stop - Survey Variables

Variable	Rewards-Continue	Rewards-Stop	P-value
Pre-Schedule (%)	57.69	62.96	0.70
	(50.38)	(49.21)	
Charge Outside of Home (%)	65.38	59.26	0.65
	(48.52)	(50.07)	
Number of Electric/Hybrid Vehicles	1.31	1.26	0.70
	(0.47)	(0.45)	
Number of Other Vehicles	0.85	1.04	0.45
	(1.12)	(0.65)	
Solar Panels (%)	23.08	22.22	0.94
	(42.97)	(42.37)	
Number of Drivers	1.92	2.26	0.06
	(0.69)	(0.59)	
Percent with at least Bachelors	84.62	92.59	0.37
	(36.79)	(26.69)	
Percent with Graduate Degrees	30.77	33.33	0.85
	(47.07)	(48.04)	
Count	26	27	

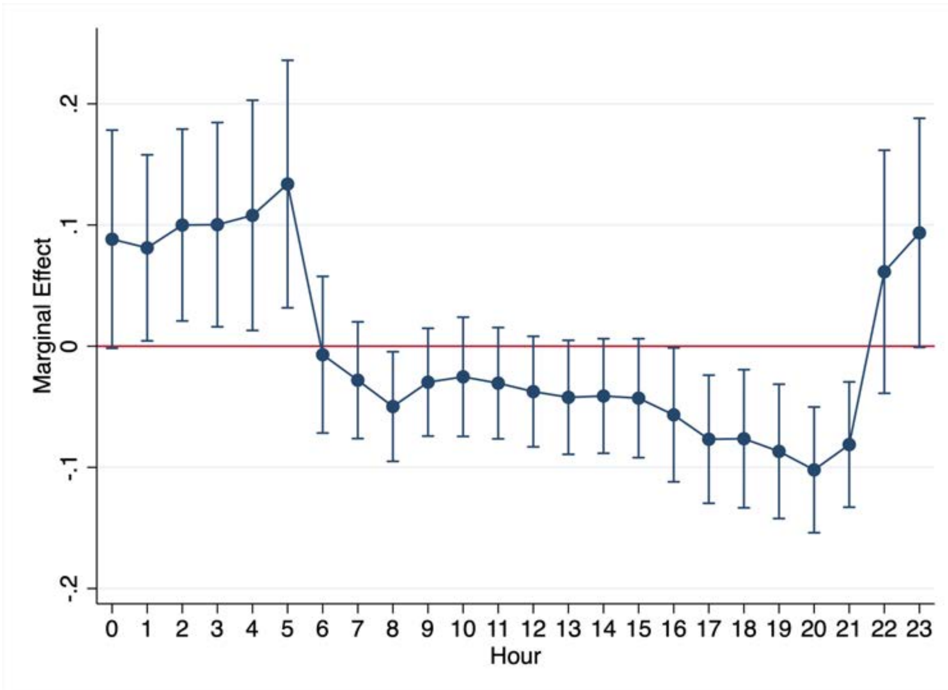
Notes. This table compares average values from the survey responses for the Rewards-Continue and Rewards-Stop groups. Parentheses contain the standard deviations. Pre-Schedule represents the percentage of EV owners that reported using pre-scheduling to determine their EV charge timing, Charge Outside of Home is the percentage of EV owners that reported ever charging outside of their home, Number of Electric/Hybrid Vehicles is the number of EVs or hybrid vehicles, Number of Other Vehicles is the number of non-EV/hybrid vehicles, Solar Panels represents the percentage of EV owners that also have solar panels, Number of Drivers is the number of drivers in the household, Percent with at least Bachelors is the percentage of EV owners with a Bachelors, Master's, or Ph.D., and Percent with Graduate Degrees is the percentage of EV owners with a Master's or a Ph.D. P-value reports the p-value from a difference in means test across the two groups.

Table A6. Estimated Treatment Effects - Phase 1 (Home and Away)

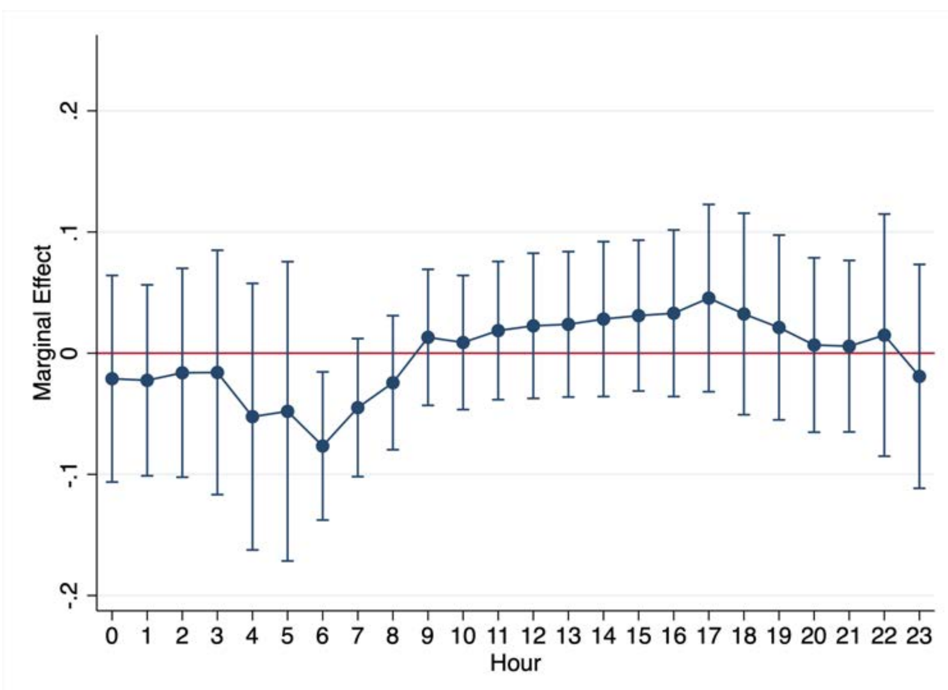
Group	Hours	(1) Charge Indicator	(2) Charge kWh
Rewards	Peak	-0.0408	-0.1327
		(0.0215)	(0.0634)
	Off-Peak	0.1027	0.4363
		(0.0305)	(0.0994)
Nudge	Peak	0.0022	0.0187
		(0.0245)	(0.0775)
	Off-Peak	-0.0115	-0.1545
		(0.0333)	(0.1194)
Mean Dep. Var. (Pre-Treatment)			
Rewards	Peak	0.2021	0.6181
	Off-Peak	0.3497	1.2241
Nudge	Peak	0.2278	0.7406
	Off-Peak	0.3495	1.0701

Notes. The data include charging at home and away. The estimated treatment effects are separated into Peak and Off-Peak hours. The Mean Dep. Var. (Pre-Treatment) represents the mean value of each dependent variable between February 1, 2022 - March 31, 2022, separated into Peak and Off-Peak hours. All specifications include fixed effects at the vehicle, month, hour, and day-of-week. Standard errors are clustered at the vehicle level.

Figure A1. Estimated Treatment Effects by Hour (Charge Indicator, Home-Only) - Phase 1



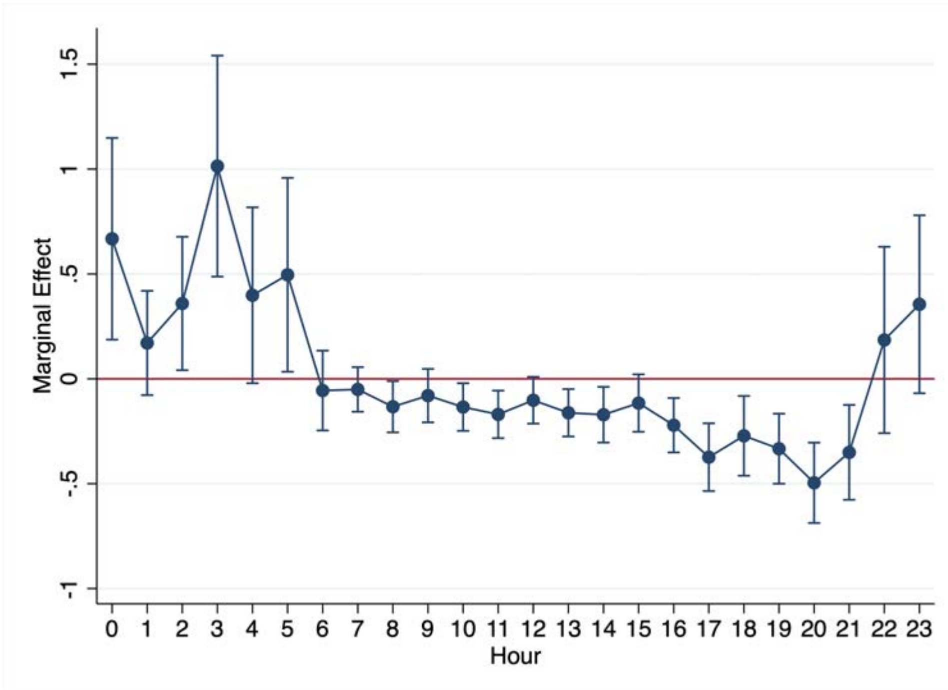
(a) Rewards Group



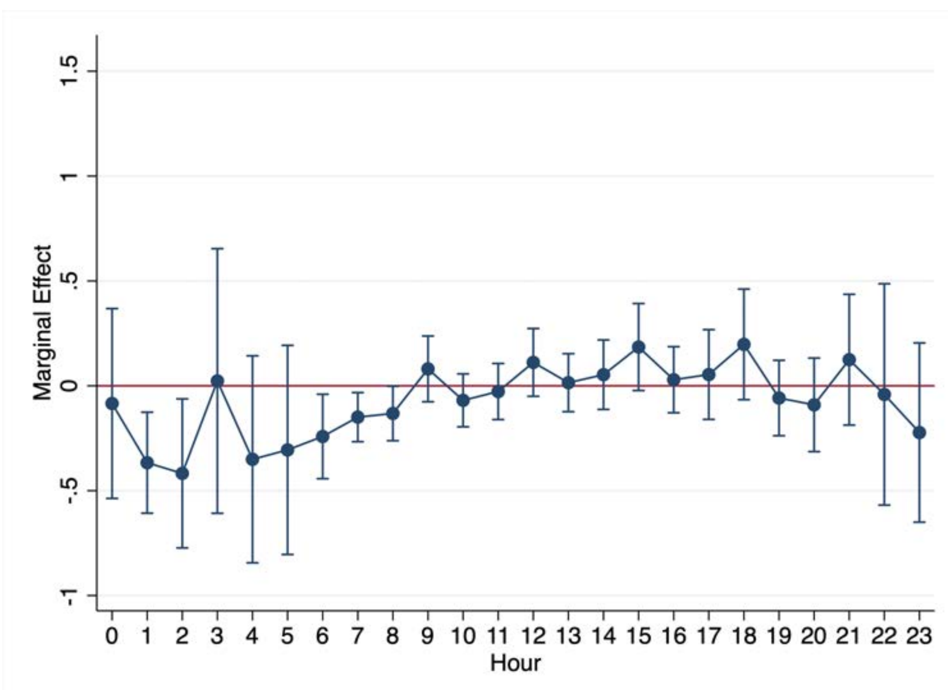
(b) Nudge Group

Notes. The treatment effects are estimated using the dependent variable Charge Indicator and the specification in (1) adjusted to interact $Post_t^1 \times Group_i$ with a vector of indicators for each hour in place of the interaction with $OffPeak_t$. The data only consider at-home charging.

Figure A2. Estimated Treatment Effects by Hour (Charge kWhs, Home-Only) - Phase 1



(a) Rewards Group



(b) Nudge Group

Notes. The treatment effects are estimated using the dependent variable Charge kWhs and the specification in (1) adjusted to interact $Post_t^1 \times Group_i$ with a vector of indicators for each hour in place of the interaction with $OffPeak_t$. The data only consider at-home charging.

Table A7. Estimated Treatment Effects - Phase 2 (Home and Away)

Group	Hours	(1) Charge Indicator	(2) Charge kWh
Rewards-Stop	Peak	0.0172	-0.0051
		(0.0191)	(0.0956)
	Off-Peak	-0.0587	-0.1235
		(0.0261)	(0.1390)
Mean Dep. Var.	(Pre-Treatment, Phase 1)		
Rewards-Stop	Peak	0.1442	0.5241
	Off-Peak	0.3803	1.5475

Notes. The data include charging at both home and away. The estimated treatment effects are separated into Peak and Off-Peak hours. The Mean Dep. Var. (Pre-Treatment, Phase 1) represents the mean value of each dependent variable between April 1, 2022 - August 31, 2022, separated into All Hours, Peak, and Off-Peak only. All specifications include fixed effects at the vehicle, month, hour, and day-of-week. Standard errors are clustered at the vehicle level.

B Email Text to Participants

In this section, we present the text from the emails sent to the participants during Phase 1 and Phase 2 of the experiment.

B.1 Phase 1

The following text is the email sent to the Nudge group:

> **Thank you for participating in Charge Up by ENMAX.**
>
> Through the first three months of the program, we have collected more than 150,000 data points on EV charging in Calgary. Your participation is ensuring ENMAX has a comprehensive EV strategy in place for the growing demand we expect to see in the coming years.
>
> **What we have learned so far**
>
> **Did you know that most EV drivers plug their vehicles in at 5:00 PM?** This timing coincides with existing system load peaks and can lead utilities to upgrade wires and equipment ahead of schedule to meet this growing peak demand.
>
> To help **reduce costs** for all Calgarians and **reduce strain on electric infrastructure**, EV drivers can use their EV scheduled charging feature to charge **between 10:00 PM and 6:00 AM** when grid demand is low, or **wait until 10:00 PM to plug in**. This simple change can make a big impact and will benefit the entire system as EV adoption continues.
>
> **Rewarding your Participation**
>
> ENMAX will continue to collect data through this program until the end of December 2022. For your continued participation in this program you will receive an **$80 reward** that will be issued to you through the SmartCharge Rewards platform at the end of December.

The following text is the email sent to the Rewards group:

Thank you for participating in Charge Up by ENMAX.

Through the first three months of the program, we have collected more than 150,000 data points on EV charging in Calgary. Your participation is ensuring ENMAX has a comprehensive EV strategy in place for the growing demand we expect to see in the coming years.

What we have learned so far

Did you know that most EV drivers plug their vehicles in at 5:00 PM? This timing coincides with existing system load peaks and can lead utilities to upgrade wires and equipment ahead of schedule to meet this growing peak demand.

To help **reduce costs** for all Calgarians and **reduce strain on electric infrastructure**, EV drivers can use their EV scheduled charging feature to charge **between 10:00 PM and 6:00 AM** when grid demand is low, or **wait until 10:00 PM to plug in**. This simple change can make a big impact and will benefit the entire system as EV adoption continues.

Rewarding your Participation

ENMAX will continue to collect data through this program until the end of December 2022. For your continued participation in this program you will receive an **$80 reward** that will be issued to you through the SmartCharge Rewards platform at the end of December.

In addition, to encourage you to charge during off-peak hours, effective immediately **ENMAX will issue you a 3.5¢/kWh reward for charging that takes place between 10:00 PM and 6:00 AM**. This reward will be paid monthly through the SmartCharge Rewards platform. You are still free to charge your car whenever you like, and there will be no changes to your electric service.

B.2 Phase 2

The following text is the email sent to the Rewards-Continue group:

> **Thank you for your continued participation in ENMAX's Charge Up program**
>
> To date, we have collected more than one million data points on EV charging in Calgary. Your participation will ensure ENMAX has a comprehensive EV strategy in place as demand for electric vehicles grows in the coming years.
>
> **What we have learned so far**
>
> To help **reduce strain on electric infrastructure and reduce costs** for all Calgarians, EV drivers can use their EV scheduled charging feature to charge between 10:00 PM and 6:00 AM when grid demand is low, or **wait until 10:00 PM to plug in**. This simple change can make a big impact and will benefit the entire system as EV adoption continues.
>
> **Rewarding your Participation**
>
> You will continue to receive **3.5 ¢/kWh reward for charging that takes place between 10:00 PM and 6:00 AM**. This reward will be paid monthly through the SmartCharge Rewards platform. You are still free to charge your car whenever you like, and there will be no changes to your electric service.
>
> ENMAX will continue to collect data through this program until the end of December 2022. For your continued participation in this program, you will receive an **$80 reward** that will be issued to you through the SmartCharge Rewards platform at the end of December.

The following text is the email sent to the Rewards-Stop group:

> **Thank you for your continued participation in ENMAX's Charge Up program**
>
> To date, we have collected more than one million data points on EV charging in Calgary. Your participation will ensure ENMAX has a comprehensive EV strategy in place as demand for electric vehicles grows in the coming years.
>
> **What we have learned so far**
>
> To help **reduce strain on electric infrastructure and reduce costs** for all Calgarians, EV drivers can use their EV scheduled charging feature to charge between 10:00 PM and 6:00 AM when grid demand is low, or **wait until 10:00 PM to plug in**. This simple change can make a big impact and will benefit the entire system as EV adoption continues.
>
> **Rewarding your Participation**
>
> As of August 31, **we are ENDING the 3.5 ¢/kWh financial reward for charging that takes place between 10:00pm and 6:00AM**. ENMAX will continue to collect data through this program until the end of December 2022. For your continued participation in this program, you will receive an **$80 reward** that will be issued to you through the SmartCharge Rewards platform at the end of December.

C Extensive Margin Analysis

Because we are interested in identifying the impact of our treatments on the timing of EV charging within-day, our empirical analysis only includes days when vehicles are charged at home. With this subsetting on days, our identification strategy is valid if there is no differential change in the daily frequency or amount of charging at home across groups, post-treatment, compared to pre-treatment. In this section, we evaluate whether the frequency or intensity of daily charging changed differentially across the treatment groups, post-treatment with a difference-in-differences empirical strategy. We carry out this analysis by considering all days (regardless of charging status) and two specifications that include either at-home charging only or on both home and away charging. We continue to define a "day" as the period from 9:00 AM - 8:59 AM the following day.

We first consider the period February 1, 2022, to August 31, 2022, to evaluate if there was a differential change in the extensive margin of the daily charging frequency or intensity across the treatment groups associated with the treatment during Phase 1. We estimate the following equation using data for each day d and vehicle i:

$$y_{id} \;=\; \beta\, Group_i \times Post^1_d + \alpha_i + \tau_d + \varepsilon_{dt} \tag{2}$$

in which y_{id} represents our two dependent variables: (1) a Charge Indicator variable that equals 1 if vehicle i is charged during day d and 0 otherwise and (2) the vehicle's charged kWhs in day d ("Charge kWhs"). Similar to the main specification in our analysis of Phase 1, $Group_i$ represents two indicator variables for the Rewards and Nudge treatment groups, and $Post^1_d$ is an indicator variable that equals 1 starting on April 1, 2022, and 0 otherwise. α_i are vehicle fixed effects and τ_d include month and day-of-week fixed effects. Standard errors are clustered at the vehicle level.

Table A8 presents the results of the extensive margin analysis for Phase 1, using at-home charging only. The results in column (1) illustrate that there is no statistically significant change in the daily at-home charge frequency after the Phase 1 treatment begins for either the Rewards or Nudge groups, compared to the Control. In column (2), we see no evidence of a change in at-home charged kWhs for the Rewards group. Alternatively, we find a marginal statistically significant reduction in at-home charged kWhs for the Nudge group post-treatment, compared to the Control. As we will show below, this effect is no longer significant when we include away charging. In the data, we observe an idiosyncratic increased frequency of away charging by the Nudge group in the summer months post-treatment. We suspect this is due to summer travel, and because away charging typically occurs at level 3 chargers on road trips, this coincides with a large amount of charged kWhs.

Table A8. Extensive Margin Analysis - Phase 1 (Home Only)

Group	(1) Charge Frequency	(2) Charge kWhs
Rewards	-0.0480	-0.5652
	(0.0367)	(0.6615)
Nudge	-0.0189	-1.4053
	(0.0437)	(0.7176)
Mean Dep. Var. (Pre-Treatment)		
Rewards	0.6057	9.8104
Nudge	0.5544	9.5171

Notes. The data include charging at-home only. The Mean Dep. Var. (Pre-Treatment) is the mean value of each dependent variable between February 1, 2022 - March 31, 2022. All specifications include vehicle, month, and day-of-week fixed effects. Standard errors are clustered at the vehicle level.

Table A9 presents the results from estimating Equation (2) for Phase 1 when we include both home and away charging. Column (1) shows no evidence of a statistically significant change in the daily charge frequency for either treatment group, compared to the Control. In contrast to the results when we include at-home charging only, column (2) demonstrates that there is no statistically significant evidence of a change in the charged kWhs for either treatment group compared to the Control.

Table A9. Extensive Margin Analysis - Phase 1 (Home and Away)

Group	(1) Charge Frequency	(2) Charge kWhs
Rewards	-0.0150	0.6680
	(0.0349)	(0.9229)
Nudge	-0.0178	-1.1730
	(0.0423)	(1.0328)
Mean Dep. Var. (Pre-Treatment)		
Rewards	0.6595	12.8387
Nudge	0.6251	12.6434

Notes. The data include both at-home and away charging. The Mean Dep. Var. (Pre-Treatment) is the mean value of each dependent variable between February 1, 2022 - March 31, 2022. All specifications include vehicle, month, and day-of-week fixed effects. Standard errors are clustered at the vehicle level.

Next, we evaluate if there is evidence of a change in the daily charging frequency or intensity for the Rewards-Stop compared to the Rewards-Continue group during Phase 2. As with our main analysis of Phase 2, we consider the period from April 1, 2022 to December 31, 2022, with the Phase 2 treatment beginning on September 1st. Additionally, the analysis only includes vehicles in the Rewards-Continue and Rewards-Stop groups. We estimate an equation analogous to Equation (2), with the exceptions that (1) $Group_i$ is replaced by a Rewards-Stop indicator variable that equals 1 if vehicle i is in the Rewards-Stop group and 0 if the vehicle is in the Rewards-Continue group, and (2) $Post_d^1$ is replaced with $Post_d^2$ that equals 1 starting on September 1, 2022 and 0 otherwise.

Tables A10 and A11 present the results of this analysis with at-home charging only and with both home and away charging, respectively. In both cases, we find no evidence of a statistically significant difference in the daily charge frequency or charged kWhs for the Rewards-Stop group compared to the Rewards-Continue group associated with the change in treatment at the start of Phase 2.

Table A10. Extensive Margin Analysis - Phase 2 (Home Only)

Group	(1) Charge Frequency	(2) Charge kWhs
Rewards-Stop	0.0426	0.4552
	(0.0466)	(1.0055)
Mean Dep. Var. (Pre-Treatment, Phase 1)		
Rewards-Stop	0.4787	8.0298

Notes. The data include charging at-home only. The Mean Dep. Var. (Pre-Treatment, Phase 1) is the mean value of each dependent variable between April 1, 2022 - August 31, 2022. All specifications include vehicle, month, and day-of-week fixed effects. Standard errors are clustered at the vehicle level.

Table A11. Extensive Margin Analysis - Phase 2 (Home and Away)

Group	(1) Charge Frequency	(2) Charge kWhs
Rewards-Stop	0.0502	0.2598
	(0.0381)	(1.3106)
Mean Dep. Var. (Pre-Treatment, Phase 1)		
Rewards-Stop	0.5636	11.6775

Notes. The data include both at-home and away charging. The Mean Dep. Var. (Pre-Treatment, Phase 1) is the mean value of each dependent variable between April 1, 2022 - August 31, 2022. All specifications include vehicle, month, and day-of-week fixed effects. Standard errors are clustered at the vehicle level.