American Economic Journal: Economic Policy 2025, 17(2): 259–284
https://doi.org/10.1257/pol.20230653

Show Me the Money! A Field Experiment on Electric Vehicle Charge Timing†

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We use a field experiment to measure the effectiveness of financial incentives to shift the timing of electric vehicle (EV) charging. EV owners respond strongly to financial incentives, reducing charging during peak hours by 49 percent by shifting to off-peak hours. In contrast, a prosocial information treatment has no discernible effect. When financial incentives are removed, charge timing reverts to pre-intervention behavior, reinforcing that "money matters." Our findings highlight the substantial flexibility of EV charging compared to other forms of electricity demand. Such flexibility has the potential to greatly reduce future electric system costs arising from a rapidly decarbonizing transportation sector. (*JEL* C93, D12, D91, L92, L94, Q48)

The International Energy Agency estimates that in 2023, 18 percent of global vehicle sales will be electric, up from only 2 percent in 2018 (IEA 2023). This growth is expected to continue as policies to electrify the transportation sector take hold (Working Group III, IPCC 2022). However, this trend raises questions about the ability of electricity systems to serve the influx of large new demand from electric vehicles (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

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† Go to https://doi.org/10.1257/pol.20230653 to visit the article page for additional materials and author disclosure statement(s).

and likely higher greenhouse gas–emitting generation to meet demand and, ultimately, an expansion of generation, transmission, and electric distribution system capacity. In the second, EVs are charged during periods of surplus supply—be it overnight when demand is low or during periods of the day when renewable generation is abundant. This path improves the economic and environmental efficiency of the existing system and lessens the need for costly capacity expansions (Imelda, Fripp, and Roberts 2024).[1] The ability to achieve the latter path depends on the willingness of EV owners to shift their charge timing.

One reason to believe EV charging has the potential to be flexible is because 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 in time 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 3 kW. This suggests EVs could be a source of considerable demand flexibility, yet there is limited empirical evidence on whether this is true.

In this paper, we partner with an electric distribution utility in Calgary, Canada, to conduct a field experiment to assess the willingness of EV owners to shift within-day charging activity in response to financial incentives and prosocial information. Our experiment begins with collecting baseline charging behavior from participants who installed in-vehicle monitoring devices that record charging and driving data, followed by two experimental phases. In Phase 1 we randomize participants into one of three groups: (i) a "Rewards" group that receives a financial payment of 3.5 cents per kilowatt-hour (kWh)—equivalent to roughly a 23 percent reduction in the retail price—on all off-peak (10 PM to 6 AM) charging; (ii) an "Info" group that only receives information on the societal benefits to the grid of charging in the same off-peak hours; and (iii) a "Control" group that does not receive any intervention but has its hourly consumption monitored.[2,3]

We find that financial rewards are very effective at shifting EV charging behavior, but our prosocial information intervention is not. The Rewards group decreased peak-time charging kWh by 49 percent from its pretreatment mean, shifting charging to off-peak hours on days when charging occurred, in response to the financial

[1] The potential cost savings associated with shifting EV charging away from peak hours has been noted as far back as the 1915 US Census report in this prescient passage: "At the meeting of the Illinois Electrical Association in 1912 it was stated by Mr. George Jones that if half the horses in use in Chicago were replaced by electric vehicles, the central station load created would amount to 94,000,000 kilowatt hours per annum. As such vehicles are usually charged late at night, when the ordinary demand for current is small, no additional investment in central station apparatus would be necessary, and this "off-peak" business would improve the general load factor about 13 per cent" (US Bureau of the Census 1915).

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

[3] The economic incentives for the Rewards group mimic time-of-use (TOU) pricing. We recognize TOU tariffs are an imperfect reflection of the time-varying nature of wholesale energy costs and may even lead to a 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 include more efficient designs, such as dynamic pricing or centrally-managed demand response (Bailey et al. 2024).

rewards intervention. However, our Info group shows no statistically detectable change in charge timing relative to the the Control group.

In Phase 2, we perform 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.[4] This finding further reinforces our central conclusion that financial incentives are key to eliciting changes in charge timing from EV owners.

Our estimates of the price responsiveness of EV charge timing are larger than typical estimates for residential electricity demand (Harding and Sexton 2017). This likely reflects several factors. First, as noted above, EVs break the contemporaneous link between electricity consumption and an electric device's underlying service. Whereas, historically, demand response from most residential appliances required delaying or sacrificing the service the device provides (e.g., cooking in an oven, using a hair dryer, etc.), the large batteries in EVs allow households to shift electricity consumption with minimal impact on the ability to meet their driving needs. Second, the larger magnitude of electricity demand from EV charging as compared to most other residential devices makes the potential gains from demand response more meaningful and salient, which may help overcome barriers to taking these actions.

Our research is most closely related to three recent studies. Burkhardt, Gillingham, and Kopalle (2023) 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 discounts from homes with EVs. Qiu et al. (2022) use household-level electricity consumption data in Arizona and find households with EVs respond to time-of-use rates. In their setting, however, customers self-select into their preferred tariff. Finally, Ito, Ida, and Tanaka (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 consistent with and reinforce these earlier findings.

Our results provide several 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, we find our prosocial information treatment to be ineffective. Third, when financial incentives are removed, charge timing quickly reverts back to pre-intervention behavior. Finally, the magnitude of flexibility in EV charge timing is noteworthy in its own right. Compared to typical estimates of household-level electricity price responsiveness, the greater degree of price responsiveness we find reflects just how different EV charging flexibility is versus other forms of residential electricity demand. Harnessing this considerable flexibility will be imperative as EV sales expand to reduce the cost of integrating

[4] EV owners in our sample may use prescheduling within an app to automate charge timing. In this setting, scheduled charging to earn the off-peak charging incentives would reflect a passive form of habit formation achieved via automation. We cannot observe if an EV owner uses automation to determine its charge timing. However, in our presentation of the Phase 2 results, we discuss efforts to evaluate the extent of automation and how it varies over our sample period.

EVs into the electric system. Collectively, our findings reinforce the importance of financial incentives to elicit this flexibility and shift EV charging behavior.

The rest of the paper proceeds as follows. Section I outlines the experimental design. Section II summarizes the data and provides an assessment of balance from the randomization. Section III outlines the empirical methodology and Section IV presents our main results. We present several robustness checks in Section V. Section VI concludes with policy implications and a discussion of promising areas for future research.

I. Experimental Design

The field experiment is done in partnership with ENMAX Power, a municipally-owned distribution utility serving the residents of Calgary, Canada, a city of approximately 1.4 million people. Important for our study, residential retail electricity prices faced by ENMAX customers are time-invariant (constant) across all hours of the day within a billing cycle. Consumers can choose between a default tariff that varies monthly based on wholesale market conditions or multiyear fixed rate contracts offered by competitive retailers.[5] For context, the average residential electricity consumption in Alberta is estimated to be approximately 510 kWh per month (MSA 2023a). The average monthly at-home EV charging electricity consumption adds approximately 250 kWh per month over our entire sample period.

In November 2021, households with EVs in ENMAX's service territory were recruited to sign up for 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 were 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. A total of 217 vehicles signed up for the program.

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, via Wi-Fi transmission to ENMAX. The monitoring device was successfully installed in 150 vehicles.[6] This serves as our pool of participants that are randomized into our three groups—Rewards, Info, and Control.[7]

The experiment consists of two phases following a pre-period, which runs from device installation to March 31, 2022. The installation of the monitoring devices occurred primarily throughout the months of December 2021 and January 2022. For our analysis, we begin our pretreatment period on February 1, 2022, when the

[5] As of January 2022, 76 percent of households in ENMAX's territory are on multiyear fixed rate contracts (MSA 2023b), with the remaining on plans that vary monthly.

[6] To participate in the pilot, vehicle owners had to physically install the monitoring device by connecting it to their vehicle's onboard diagnostic port. This action proved to be an obstacle for some EV owners who initially signed up for the program.

[7] Data provided by the Alberta Ministry of Transportation (2023) shows 1,695 Electric Vehicles registered in the City of Calgary at the end of 2021. This implies our final sample size covered 8.8 percent of the existing EV pool in Calgary.

majority of vehicles (93 percent) had the monitoring device installed.[8] This period will be referred to as Phase 0 throughout. During Phase 0, charging behavior was monitored, but participants received no interventions or communication from ENMAX.

A. *Phase 1*

For Phase 1, we assign participants to either the Rewards, Info, or Control group using a stratified randomization procedure leveraging data collected during the pre-period.[9] On March 31, 2022, participants in the experiment received emails with the following information.

- The Info 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 period of 10 PM–6 AM.[10] Info group participants received the following email text:

> **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 Rewards group (68 vehicles) received the same information as the Info email plus an additional paragraph explaining that as of April 1, 2022, they would receive a 3.5¢/kWh reward for all kWh charged between the hours of

[8] For the remaining 7 percent of EVs who installed their devices after February 1, 2022, we use all available pretreatment data in our analyses.

[9] We stratified the 150 enrolled EVs using 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 facilitate the balance of characteristics across these three groups.

[10] It must be noted that we cannot be certain as to whether participants actually read their email or not.

10 PM–6 AM[11,12] As will be described in Section IB, the greater number of EVs in this group allowed us to implement a second phase of our experiment where we remove the financial incentives for a subset of the EVs. The 3.5¢/kWh financial reward was selected based on it being (i) in the realm of average historical wholesale peak to off-peak price spreads and (ii) manageable within the budget for the field experiment. The full text of the email sent to Rewards group participants is here:

> **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.

[11] Total rewards were paid monthly to participants via PayPal. While we do not have residential billing data for the customers in our experiment, we assume that they paid the 2022 one-year fixed rate and prevailing variable transmission, distribution and local access fees, resulting in a per kWh charge of $0.15; which implies that the 3.5¢/kWh reward is equivalent to an approximate 23 percent reduction in the variable price of electricity in ENMAX's territory in 2022. Historic electricity rates can be found here: https://ucahelps.alberta.ca/historic-rates.aspx. Transmission, distribution, and local access fees can be found at: https://www1.enmax.com/rro/tariffs. Of note, this 3.5¢/kWh payment for off-peak charging would be an improvement in making the generation market more efficient, as the wholesale market price difference between peak and off-peak hours in Alberta in 2022 was 8.9¢/kWh (AESO 2023).

[12] Burkhardt, Gillingham, and Kopalle (2023) note there may be a difference in the way consumers respond to discounts versus rewards. If, for example, the reward payment is more or less salient than an on-bill discount, they may respond differently. We acknowledge this possibility and see "rewards vs discounts" as a fruitful area for future research.

- The Control group (37 vehicles) did not receive any intervention (i.e., no emails) during the course of the experiment. Their charging behavior was simply monitored.

B. *Phase* 2

In Phase 2, we further randomized the Rewards group into two subgroups: "Rewards-Continue" (33 vehicles) and "Rewards-Stop" (35 vehicles). The Rewards-Stop group received an email on August 31, 2022 notifying them that they would no longer receive the 3.5¢/kWh rewards for their off-peak charging kWh. 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 following text is the Phase 2 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 10:00 PM and 6:00 AM**. 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 Phase 2 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.
>
> (*continued*)

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.

II. Data and Assessment of Balance across Groups

The data for charging activity used in this study extend from February 1, 2022, to December 31, 2022 (Bailey et al. 2025). The monitoring devices provide time-stamped information on EV charging, including kWh charged and maximum charging power (in kW), 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 background of the participant. Approximately 75 percent of participants filled out this survey.[13] 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.[14]

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 pretreatment (in Phase 0) in Table 1. Table 1 demonstrates a number of notable features of the pretreatment period, including that the majority of charging occurs at home, over half of the EVs in our sample are Teslas, EVs have approximately 1.5 to 1.75 charging sessions on average per day, and between 44 percent to 56 percent of at home charged kWh arise in the off-peak period. We observe a higher charging frequency and hourly

[13] We perform balance tests using pre period variables to evaluate if the EV owners who did and did not respond to the survey are different. The results are presented in Table C2 of the Supplemental Appendix. We find limited differences in observable charging and driving behavior.

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

TABLE 1—PRETREATMENT (PHASE 0) COMPARISON OF MEANS BY GROUP

Variable	Control	Info	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 (km)	42.11	54.66	48.99	0.30
	(27.02)	(40.28)	(37.73)	
Charge frequency	0.19	0.25	0.23	0.13
	(0.12)	(0.12)	(0.12)	
Hourly charge kWh	0.63	0.83	0.71	0.13
	(0.38)	(0.52)	(0.42)	
Percent kWh charged in off-peak	54.47	44.18	56.40	0.13
	(34.18)	(33.50)	(28.47)	
Number of EVs	37	45	68	

Notes: This table compares pretreatment (Phase 0) average values of vehicle-level variables across the three 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 plugged in to charge each day looking across all days (i.e., including days where the EV was not charged), energy charged per session is the cumulative number of kWh 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 km traveled, charge frequency reflects the proportion of hours the EVs were being charged at home on days when there is at least one hour of at-home charging, hourly charge kWh is the mean hourly kWh charged at home on days when there is at least one hour of at-home charging, and percent kWh charged in off-peak represents the share of total kWh charged at home in the off-peak hours. ANOVA (p-value) reports the p-value from one-way ANOVA tests for differences in means across groups.

charged kWh for the EVs in the Info group on days when there is a positive charge at home, but a lower percentage of kWh charged in the off-peak. However, using a one-way ANOVA test, the table shows no significant differences in the means of each variable across the three groups. Supplemental Appendix Table C1 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. Table C3 in the Supplemental Appendix finds 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, Table C4 in the Supplemental Appendix finds that there are limited significant differences in survey responses across these two groups.

It is important 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 percent reporting at least a bachelor’s degree (see Table C1 in the

Supplemental Appendix). In contrast, 37 percent of the broader population of Calgary has a bachelor's degree.[15] This high level of education among our sample aligns with the characteristics of early adopters of electric vehicles observed in other regions (Lee, Hardman, and Tal 2019). As discussed in Section VI, future research is required to understand how charging behavior and responsiveness to incentives might differ as EVs become more widespread.

III. Empirical Methodology

The sample period to analyze the impact of the treatments introduced in Phase 1 covers February 1, 2022, to August 31, 2022. For each hour t and vehicle i, using all EVs in our sample, we estimate the following equation:

$$(1)\quad y_{it} = \beta_0^{RW} Post1_t \times Rewards_i + \beta_1^{RW} Post1_t \times Rewards_i \times OffPeak_t + \beta_0^{IN} Post1_t \times Info_i + \beta_1^{IN} Post1_t \times Info_i \times OffPeak_t + \alpha_i + \tau_t + \boldsymbol{\gamma}' \mathbf{X}_t + \varepsilon_{it},$$

in which y_{it} can be one of our two dependent variables: (i) a "Charge Indicator" variable that equals 1 if vehicle i was charged in hour t and 0 otherwise and (ii) vehicle i's charge kWh in hour t ("Charge kWh").[16] $Post1_t$ is an indicator variable that equals 1 starting on April 1, 2022, the day after households received emails corresponding to the Rewards and Info treatments, and 0 otherwise. $Rewards_i$ and $Info_i$ are indicator variables that equal 1 if vehicle i is assigned to the Rewards or Info groups, respectively, and 0 otherwise. Because our main objective is to investigate changes in EV charge timing, we interact the $Post1_t \times Rewards_i$ and $Post1_t \times Info_i$ indicator variables 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 0 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 τ_t represents 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.[17] We include a third-order polynomial for each measure, 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.

We also consider a flexible specification that estimates hour-of-day specific treatment effects by group for the Phase 1 analysis. More specifically, we adjust the specification in equation (1) to interact $Post1_t \times Rewards_i$ and $Post1_t \times Info_i$

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

[16] 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 percent).

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

with a vector of indicators for each hour of the day, removing the interaction with the $OffPeak_t$. This analysis provides a detailed view of how charge timing changed throughout the day due to each intervention.

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 pretreatment period for this phase of the analysis. Starting on September 1, 2022, EVs in the Rewards-Stop group were 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.

For the Phase 2 analysis, using only EVs in the Rewards-Continue and Rewards-Stop groups, we estimate the following equation for each hour t and vehicle i:

$$(2)\quad y_{it} = \beta_0^S Post2_t \times Stop_i + \beta_1^S Post2_t \times Stop_i \times OffPeak_t + \alpha_i + \tau_t + \gamma' \mathbf{X}_t + \varepsilon_{it},$$

in which $Stop_i$ is an indicator variable that equals 1 if vehicle i is assigned to the Rewards-Stop group and 0 otherwise. $Post2_t$ is an indicator that equals 1 starting on September 1, 2022, and 0 otherwise. All other aspects of the regression analysis, including the two dependent variables, fixed effects, and temperature controls are the same as those specified in equation (1). The sample period for this analysis is limited to April 1, 2022, to December 31, 2022, and EVs in the Info and original Control groups are excluded from the sample. The standard errors are clustered at the vehicle level.

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 analyses of both phases to days when charging at home occurs.[18] Our analysis assumes that there is no differential change in the daily frequency or amount of charging at home across groups, posttreatment, compared to pretreatment. We find no empirical evidence against this assumption as explained in Section V. It is important to note that 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, posttreatment. Throughout the results, we also present and discuss the results when we include both home and away charging.

To shed light on how the treatment effects vary by vehicle characteristics and driving behavior, we conduct additional heterogeneity analyses for the Phase 1 analysis, which we present in the Supplemental Appendix.[19] First, we evaluate if

[18] As shown in Table 1, across all treatment groups, approximately 81 percent to 86 percent of the pretreatment charging sessions are at home. We define a "charging day" as running from 9:00 AM to 8:59 AM the following day to capture shifts in charging that may occur overnight.

[19] For the Phase 2 analysis, we do not have a sufficiently large sample size to estimate heterogeneous treatment effects.

our results vary by whether the EVs are Tesla or non-Tesla. Second, an individual's ability to alter their charge timing may depend on how much they drive their car.

IV. Results

A. *Phase 1: Shifting EV Charging Behavior*

We begin with a graphical presentation of the data, investigating if there are observable changes in charging behavior in our three groups relative to their pretreatment behavior. For each treatment group and day, we calculate the share of total kWh charged at home in the off-peak hours before and after the Phase 1 intervention.[20] We normalize each series such that a value of 1 indicates the off-peak share is equal to the group's pretreatment daily mean. This corrects for any differences in pretreatment means across the groups and allows for a visual focus on the change post-intervention. We smooth the normalized daily mean shares by a nonparametric regression and calculate a 95 percent confidence interval.[21]

Figure 1 illustrates that, starting on April first, the Rewards group's normalized off-peak share quickly increases to 1.3, demonstrating a 30 percent increase relative to its pretreatment mean. In raw data terms at the vehicle level, this brings the average off-peak share of charged kWh for the Rewards EVs to 74 percent posttreatment, up from 56 percent pretreatment. In contrast, we observe minimal changes for the Info and Control groups. These results suggest that the financial intervention motivated EV owners to adjust their charge timing and that our prosocial information treatment had no discernible impact.

Table 2 provides the results of our regression analysis detailed in equation (1), which evaluates the effects of the Phase 1 intervention. Column 1 demonstrates that financial rewards reduced on-peak and increased off-peak charging frequency. Both effects are significant at the 5 percent level. The financial intervention increased the off-peak charging frequency by approximately 10 percentage points, a 27 percent increase relative to its mean value during the pretreatment period,[22] and decreased peak charging by 5 percentage points, a 30 percent reduction from its pretreatment period mean.[23] The Info group coefficients in column 1 are not statistically different

[20] 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 kWh 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 kWh charged in the off-peak for group G equals $Y^{OP,G}_d / Y^G_d$, where $Y^{OP,G}_d = \sum_{i \in G} \sum_{h \in OP} Y^G_{ihd}$ and $Y^G_d = \sum_{i \in G} \sum_{h=0}^{23} Y^G_{ihd}$.

[21] 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.

[22] Using Table 2, the 27 percent increase reflects the Reward group's off-peak coefficient estimate of 0.0959 in column 1, divided by the off-peak pretreatment mean of the dependent variable for the Reward group equal to 0.3516. Similar calculations will be provided throughout the presentation of our results.

[23] 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 pretreatment. Figure 2 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 kWh results for the Rewards group presented in column 2.

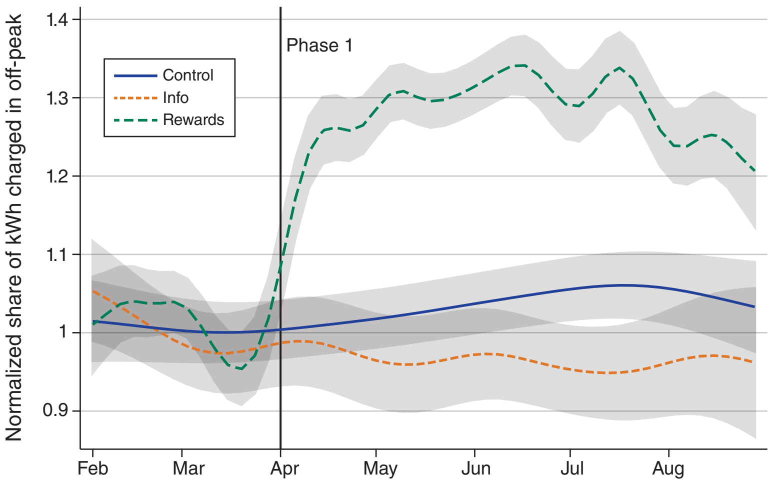

Figure 1. Share of kWh Charged at Home in Off-Peak Hours (Phases 0 and 1)

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

from zero, consistent with the graphical evidence above that this intervention had a limited impact on charge timing.

Column 2 shows that financial rewards led to a significant increase (decrease) in the off-peak (peak) at-home volume of electricity used for charging ("Charge kWh"). The financial incentive increased off-peak at-home Charge kWh by approximately 37 percent relative to the mean at-home value for the Rewards group pretreatment and decreased peak charging by 49 percent from its pretreatment mean.

Column 2 shows that the Info group did not significantly change its peak charging kWh posttreatment, compared to the Control. However, the off-peak coefficient is significant at the 10 percent level. We conducted a series of analyses that suggest this is due to the Info group charging more away from home posttreatment than the other groups.[24]

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 C5 in the Supplemental Appendix). For the Info group, there is no evidence of a change in the timing of charging when using either dependent variable.

[24] First, when we include both home and away charging and estimate equation (1), the off-peak coefficient for the Info group loses statistical significance (Supplemental Appendix Table C5). Additionally, in the extensive margin analysis outlined in Section V, we investigate whether the daily charge frequency and/or charged kWh change differentially across the treatment groups posttreatment. The results of this analysis reveals that the Info group reduces its at-home Charge kWh during Phase 1, relative to the Control. This is driven by an increased amount of away charging sessions that often occur at level 3 chargers that entail a large amount of kWh charged. When away charging is included, we observe no difference in the intensity of daily charged kWh for the Info group relative to the Control.

Table 2—Estimated Treatment Effects—Phase 1 (Home Only)

Group	Hours	Charge indicator (1)	Charge kWh (2)
Rewards	Peak	−0.0509	−0.2008
		(0.0208)	(0.0558)
	Off-peak	0.0959	0.4553
		(0.0296)	(0.1063)
Info	Peak	0.0090	0.0053
		(0.0238)	(0.0626)
	Off-peak	−0.0225	−0.2216
		(0.0330)	(0.1282)
Mean dependent variable (pretreatment)			
Rewards	Peak	0.1706	0.4091
	Off-peak	0.3516	1.2280
Info	Peak	0.1990	0.5366
	Off-peak	0.3386	1.0946

Notes: The results reflect the estimation of equation (1). The data include charging at home only and days where charging occurred. The estimated treatment effects are separated into peak and off-peak hours. The mean dependent variable (pretreatment) represents the mean value of each dependent variable between February 1, 2022 and March 31, 2022, separated into peak and off-peak hours. All specifications include fixed effects at the vehicle, month-of-sample, hour-of-day, and day-of-week, as well as temperature control variables up to a third-order polynomial. Standard errors are clustered at the vehicle level.

Figure 2 and Figure 3 present estimated hourly treatment effects using the Charge Indicator and Charge kWh as the dependent variables, respectively. For the Rewards group, we observe a significant reduction in evening charging between 4 PM–9 PM and an increase in most off-peak hours for both measures. In contrast, for the Info group, there is no evidence of a significant decrease in peak hours.[25] 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 Info group's peak period charging.

Finally, in the Supplemental Appendix, we present detailed results of our heterogeneous treatment effects analyses. We find that there is limited evidence of heterogeneous treatment effects by whether or not the EV was a Tesla. We find that the response to the financial incentives was larger for EV owners who were heavier drivers pretreatment when using the Charge kWh as the dependent variable. This is consistent with the fact that these drivers systematically charge more kWh on average. This result is likely driven by the fact that when these EVs respond to the financial incentives, they have more kWh to shift. However, when using the Charge Indicator variable, there are no statistically significant differences in the estimated treatment effects by pretreatment driving behavior.

Price Responsiveness of EV Charge Timing.—The estimates of consumption changes allow us to calculate a measure of price elasticity of EV charge timing on

[25] In fact, there is some evidence that the Info group charges less (in terms of frequency and kWh) in off-peak hours compared to the Control posttreatment. As will be shown in Section V, this is attributable to a modest shift to more away from home charging in the Info group, posttreatment, relative to the Control.

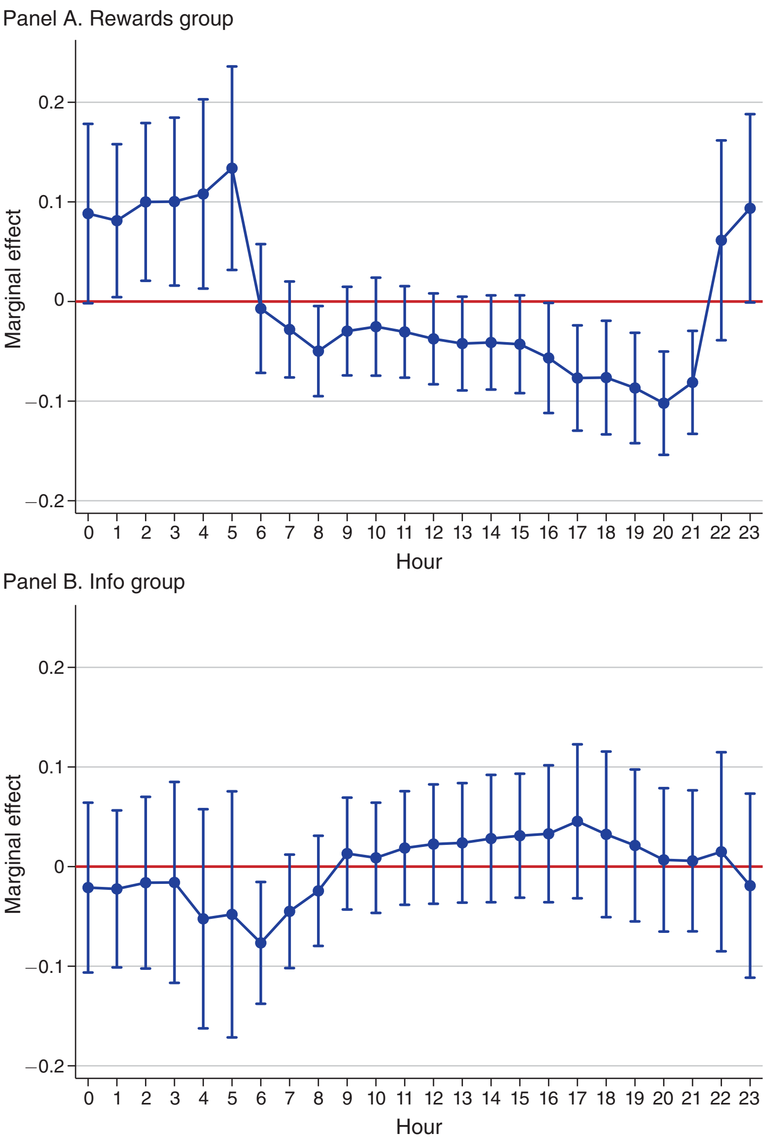

FIGURE 2. ESTIMATED TREATMENT EFFECTS BY HOUR (CHARGE INDICATOR, HOME-ONLY)—PHASE 1

Notes: The treatment effects are estimated using the dependent variable charge indicator and the specification in equation (1) adjusted to interact $Post1_t \times Rewards_i$ and $Post1_t \times Info_i$ with a vector of indicators for each hour in place of the interaction with $OffPeak_t$. All specifications include fixed effects at the vehicle, month-of-sample, hour-of-day, and day-of-week, as well as temperature control variables up to a third-order polynomial. The data only consider at-home charging and days where charging occurred. The bars represent the 95 percent confidence intervals.

charging days. We preface these calculations with several caveats. First, the direct comparability of our estimates to typical estimates of short-run price elasticities requires some nuance. In the case of EV charging, and certainly our experiment, the objective is to shift the timing of charging away from peak hours, not to generate an

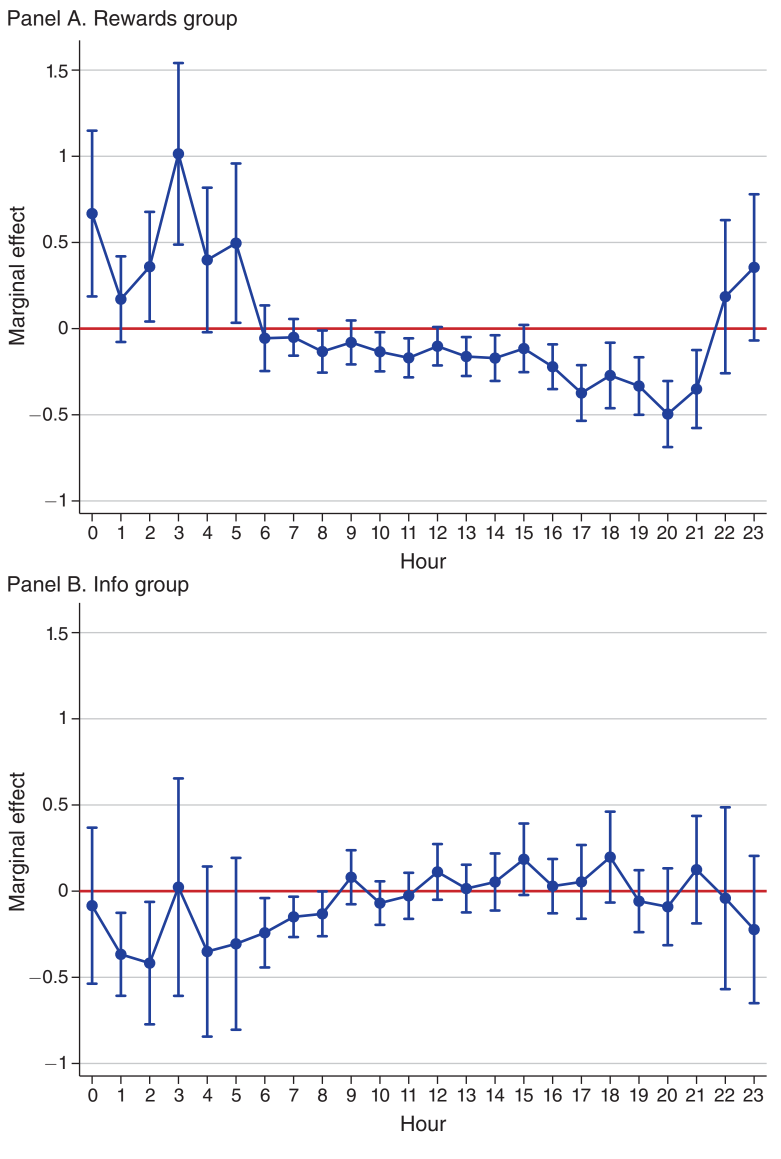

Figure 3. Estimated Treatment Effects by Hour (Charge kWh, Home-Only)—Phase 1

Notes: The treatment effects are estimated using the dependent variable charge kWh and the specification in equation (1) adjusted to interact $Post1_t \times Rewards_i$ and $Post1_t \times Info_i$ with a vector of indicators for each hour in place of the interaction with $OffPeak_t$. All specifications include fixed effects at the vehicle, month-of-sample, hour-of-day, and day-of-week, as well as temperature control variables up to a third-order polynomial. The data only consider at-home charging and days where charging occurred. The bars represent the 95 percent confidence intervals.

overall change in demand. For this reason, our estimation sample only includes days that drivers charge their EV at home, as per our main specification. Second, elasticities may be highly nonlinear. That is, EV owners may respond to *any* financial incentive in the off-peak with similar consumption changes (noted more generally for time-of-use rates by Prest 2020). This would imply large elasticity estimates from small price changes and smaller estimates from large price changes.

With the above caveats in mind, we report various measures of price elasticity to highlight the large flexibility of EV charging to shift within charging days that occurred in response to the price changes in our experiment. The 37 percent increase in off-peak consumption for the Rewards group, in response to the 23 percent decrease in off-peak prices, results in a -1.59 own-price elasticity of off-peak EV charge timing. This is considerably larger than typical time-of-use price elasticity estimates of household electricity demand (Harding and Sexton 2017). We note the latter literature estimates stem in part from an overall change in the level of consumption, whereas our results come almost entirely from a *shift* in the timing of consumption. (This is seen in Section V that shows no change in the overall intensity of charging after consumers were exposed to the financial incentives.) Regardless, if the primary goal is to move consumption from or to a particular hour, it is of little import whether that occurs from a shift or an absolute change in the level of consumption. Both are equally useful in achieving the goal, and the large magnitude we find matters.

From a policy standpoint, the response of peak consumption to changes in off-peak prices is likely of more interest. We calculate a cross-price elasticity of peak EV charging to off-peak prices of 2.10 based on the 49 percent reduction in peak charging kWh for the Rewards group on charging days. Taken together, these results emphasize the large shift in charging that occurs within charging days as a result of the relative price change, as well as the considerable flexibility of EV charge timing.

B. *Phase 2: Removing Financial Incentives*

With the Phase 2 data, we investigate charging behavior when financial incentives are removed. We begin with a graphical presentation of the data. Figure 4 plots the share of at-home kWh charged in the off-peak hours by group over Phases 1 and 2, normalized by each group's mean in the initial pretreatment 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 Info group, and different sample periods.

Figure 4 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 (i.e., the financial reward for charging in the off-peak). As described in Section 3, these 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 distinctly different than the Rewards-Stop group.[26]

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

[26] Supplemental Appendix Tables C.3 and C.4 compare observable vehicle, driving, or charging characteristics over the Phase 1 period of our experiment and finds limited statistically significant differences. This further supports the comparability of these groups prior to the Phase 2 intervention.

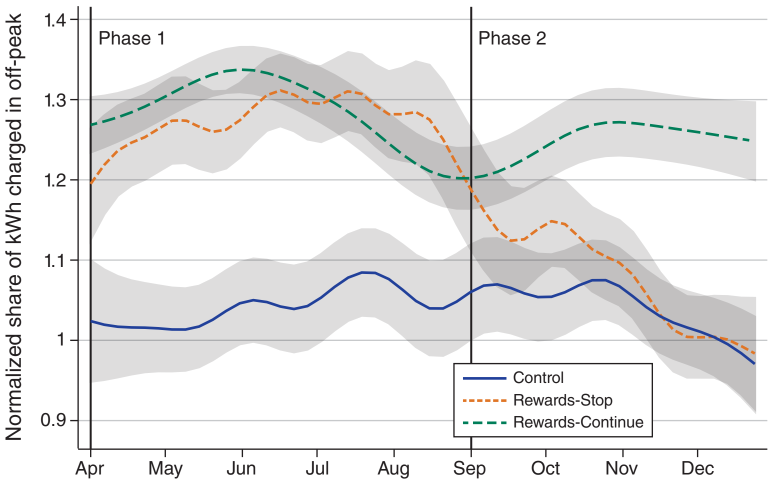

Figure 4. Share of kWh Charged at Home in the Off-Peak—Phase 2 Analysis

Notes: This figure plots the daily share of kWh 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 percent confidence intervals.

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 kWh 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 suggestive evidence that the EV owners did not form and maintain habits on charge timing, absent financial incentives.

Table 3 presents the results of estimating equation (2) to evaluate the impact of removing financial incentives. Column 1 shows a statistically significant increase (decrease) in peak (off-peak) charging frequency for the Rewards-Stop group relative to the Rewards-Continue group, posttreatment. These effects are also economically significant. The mean charging frequency for the Rewards-Stop group during peak hours increased by approximately 42 percent after their financial incentives to shift to off-peak were removed, relative to the pretreatment mean value in peak hours.

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

These results are consistent with those presented in Figure 4 and demonstrate there was a large increase in peak hour charging after the financial incentives were removed. These findings are consistent with the absence of habit formation due to the Phase 1 treatment. Once the financial incentives were removed, EV owners

Table 3—Estimated Treatment Effects—Phase 2 (Home Only)

Group	Hours	Charge indicator (1)	Charge kWh (2)
Rewards-stop	Peak	0.0415	0.1275
		(0.0202)	(0.0632)
	Off-peak	−0.0817	−0.2299
		(0.0298)	(0.1677)
Mean dependent variable (pretreatment, phase 1)			
Rewards-stop	Peak	0.0999	0.2497
	Off-peak	0.3582	1.5984

Notes: The results reflect the estimation of equation (2). The data include charging at home only and days where charging occurred. The estimated treatment effects are separated into peak and off-peak hours. The mean dependent variable (pretreatment, phase 1) represents the mean value of each dependent variable between April 1, 2022 and August 31, 2022, separated into all hours: peak and off-peak only. All specifications include fixed effects at the vehicle, month-of-sample, hour-of-day, and day-of-week, as well as temperature control variables up to a third-order polynomial. Standard errors are clustered at the vehicle level.

increased their charging during peak hours, reverting to their original, or pre-period, charging behavior.

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, posttreatment (see Table C6 in the Supplemental Appendix). However, there is no longer a statistically significant increase in peak charging frequency or kWh. 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).

We acknowledge that habit formation could arise from actively adjusting charging behavior or using an in-app charge scheduling program. In the latter case, this would reflect a more passive form of habit formation. We do not observe if an EV owner uses scheduled charging for a given charge session. In addition, our charging data only provides charging information in 15-minute intervals, limiting our ability to evaluate if charging systematically occurs at the start of an hour (e.g., at exactly 10 PM), which would be consistent with scheduled charging.

Despite these data limitations, we develop methods to evaluate the extent of scheduled charging. Details are provided in the Supplemental Appendix. While we detect a certain extent of scheduled charging, there is considerable variability in charging behavior at the vehicle level. We present evidence that EV owners in our sample were not systematically relying on scheduled charging. As a result, it is unlikely that the results of Phase 2 are largely driven by disproportionate changes in the use of automation from the Rewards-Stop group. However, we cannot rule out this possibility due to data limitations.

We conclude that there is no evidence of habit formation after the financial incentives are lifted, whether that habit formation is determined by active behavior or more passive use of an in-app scheduler. Relatedly, the convergence of the Rewards-Stop group charging behavior to that of the Control group during Phase 2 likely did not require a large proportion of participants to actively change their automated charge schedule; instead, it is likely driven by a reversion to pre-intervention habits.

V. Robustness Checks

In this section, we present a series of robustness checks. We begin by evaluating if EV owners in the treatment groups differentially adjusted their daily frequency or amount of charging kWh, posttreatment, either at home or in aggregate (i.e., including home and away charging). We then evaluate if our Phase 1 results are robust to alternative temperature controls or the removal of EV owners who reported having rooftop solar panels that create unique financial incentives.

Extensive Margin Analysis.—We evaluate whether the frequency or intensity of daily charging changed differentially across the treatment groups, posttreatment. We conduct this extensive margin analysis by considering all days regardless of whether charging occurred and two specifications that include either at-home charging only or both home and away charging. This also allows us to evaluate if there was a change in the location of charging (e.g., a shift from home to away).

We first consider the period from February 1, 2022, to August 31, 2022, to evaluate if there was a differential change in the extensive margin in response to the treatment during Phase 1. We estimate the following equation, using all EVs in our sample, for each day d and vehicle i:

$$(3)\quad y_{id} = \beta^{RW} Rewards_i \times Post1_d + \beta^{IN} Info_i \times Post1_d + \boldsymbol{\gamma}' \mathbf{X}_d + \alpha_i + \tau_d + \varepsilon_{id},$$

in which y_{id} represents our two dependent variables: (i) a Charge Indicator variable that equals 1 if vehicle i is charged during day d and 0 otherwise and (ii) the vehicle's total charged kWh in day d ("Charge kWh"). We consider a specification with at-home charging only and one with both home and away charging. Similar to the main specification in our analysis of Phase 1, $Post1_d$ is an indicator variable that equals 1 starting on April 1, 2022, and 0 otherwise, and $Rewards_i$ and $Info_i$ are indicator variables that equal 1 if vehicle i is assigned to the Rewards or Info groups, respectively, and 0 otherwise. $\mathbf{X}_d$ is a vector of mean daily heating and cooling degrees, allowing for a flexible third-order polynomial of each variable. α_i are vehicle fixed effects and τ_d includes month-of-sample and day-of-week fixed effects. Standard errors are clustered at the vehicle level.

We also 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, with an at-home-only and home and away charging specification. As with our main analysis of Phase 2 specified in equation (2), we consider the period from April 1, 2022 to December 31, 2022. Additionally, the analysis only includes vehicles in the Rewards-Continue and Rewards-Stop groups.

More formally, we estimate the following equation, using vehicles in the Rewards-Continue and Rewards-Stop groups, for each day d and vehicle i:

$$(4)\quad y_{id} = \beta^{S} Stop_i \times Post2_d + \boldsymbol{\gamma}' \mathbf{X}_d + \alpha_i + \tau_d + \varepsilon_{id},$$

Table 4—Extensive Margin Analysis—Phase 1 (Home Only)

Group	Charge frequency (1)	Charge kWh (2)
Rewards	−0.0480	−0.5642
	(0.0367)	(0.6619)
Info	−0.0188	−1.3994
	(0.0437)	(0.7179)
Mean dependent variable (pretreatment)		
Rewards	0.6057	9.8104
Info	0.5544	9.5171

Notes: The results reflect the estimation of equation (3). The data include charging at home only and consider all days regardless of whether or not charging occurred. The mean dependent variable (pretreatment) is the mean value of each dependent variable between February 1, 2022 and March 31, 2022. All specifications include vehicle, month-of-sample, and day-of-week fixed effects, as well as temperature control variables up to a third-order polynomial. Standard errors are clustered at the vehicle level.

in which $Stop_i$ is an indicator that equals 1 if vehicle i is in the Rewards-Stop group and 0 otherwise, and $Post2_d$ is an indicator variable that equals 1 starting on September 1, 2022, and 0 otherwise. The dependent variables, fixed effects, and temperature controls are analogous to those specified in equation (3). Standard errors are clustered at the vehicle level.

Table 4 presents the results of the extensive margin analysis for Phase 1 detailed in equation (3), 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 Info groups, compared to the Control. In column 2, we see no evidence of a change in at-home charged kWh for the Rewards group. Alternatively, we find a marginal statistically significant reduction in at-home charged kWh for the Info group posttreatment, 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 increase in away charging kWh by the Info group in the summer months posttreatment. 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 kWh.

Table 5 presents the results from estimating equation (3) 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 kWh for either treatment group compared to the Control.

Table 6 and Table 7 present the results of the extensive margin analysis for Phase 2 detailed in equation (4), 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 kWh for the Rewards-Stop group compared to the Rewards-Continue group associated with the change in treatment at the start of Phase 2.

TABLE 5—EXTENSIVE MARGIN ANALYSIS—PHASE 1 (HOME AND AWAY)

Group	Charge frequency (1)	Charge kWh (2)
Rewards	−0.0150	0.6694
	(0.0349)	(0.9230)
Info	−0.0177	−1.1663
	(0.0423)	(1.0328)
Mean dependent variable (pretreatment)		
Rewards	0.6595	12.8387
Info	0.6251	12.6434

Notes: The results reflect the estimation of equation (3). The data include both at-home and away charging and considers all days regardless of whether or not charging occurred. The mean dependent variable (pretreatment) is the mean value of each dependent variable between February 1, 2022 and March 31, 2022. All specifications include vehicle, month-of-sample, and day-of-week fixed effects, as well as temperature control variables up to a third-order polynomial. Standard errors are clustered at the vehicle level.

TABLE 6—EXTENSIVE MARGIN ANALYSIS—PHASE 2 (HOME ONLY)

Group	Charge frequency (1)	Charge kWh (2)
Rewards-Stop	0.0426	0.4552
	(0.0466)	(1.0056)
Mean dependent variable (pretreatment, phase 1)		
Rewards-Stop	0.4787	8.0298

Notes: The results reflect the estimation of equation (4). The data include charging at home only and considers all days regardless of whether or not charging occurred. The mean dependent variable (pretreatment, phase 1) is the mean value of each dependent variable between April 1, 2022 and August 31, 2022. All specifications include vehicle, month-of-sample, and day-of-week fixed effects, as well as temperature control variables up to a third-order polynomial. Standard errors are clustered at the vehicle level.

TABLE 7—EXTENSIVE MARGIN ANALYSIS—PHASE 2 (HOME AND AWAY)

Group	Charge frequency (1)	Charge kWh (2)
Rewards-Stop	0.0502	0.2598
	(0.0382)	(1.3108)
Mean dependent variable (pretreatment, phase 1)		
Rewards-Stop	0.5636	11.6775

Notes: The results reflect the estimation of equation (4). The data include both at-home and away charging and considers all days regardless of whether or not charging occurred. The mean dependent variable (pretreatment, phase 1) is the mean value of each dependent variable between April 1, 2022 and August 31, 2022. All specifications include vehicle, month-of-sample, and day-of-week fixed effects, as well as temperature control variables up to a third-order polynomial. Standard errors are clustered at the vehicle level.

Table 8—Estimated Treatment Effects—Charge Indicator—Phase 1 (Home Only)

Group	Hours	Main specification (1)	Linear temp (2)	No temp (3)	Removing solar (4)
Rewards	Peak	−0.0509	−0.0503	−0.0497	−0.0572
		(0.0208)	(0.0208)	(0.0208)	(0.0223)
	Off-peak	0.0959	0.0948	0.0944	0.1100
		(0.0296)	(0.0296)	(0.0296)	(0.0338)
Info	Peak	0.0090	0.0096	0.0100	0.0059
		(0.0238)	(0.0238)	(0.0237)	(0.0262)
	Off-peak	−0.0225	−0.0236	−0.0242	−0.0064
		(0.0330)	(0.0331)	(0.0331)	(0.0365)
Mean dependent variable (pretreatment)					
Rewards	Peak	0.1706	0.1706	0.1706	0.1743
	Off-peak	0.3516	0.3516	0.3516	0.3921
Info	Peak	0.1990	0.1990	0.1990	0.2044
	Off-peak	0.3386	0.3386	0.3386	0.3557

Notes: The results reflect the estimation of equation (1). The data include charging at home only and days where charging occurred. The estimated treatment effects are separated into peak and off-peak hours. The mean dependent variable (pretreatment) represents the mean value of the dependent variable between February 1, 2022 and March 31, 2022, separated into peak and off-peak hours. All specifications include fixed effects at the vehicle, month-of-sample, hour-of-day, and day-of-week. Columns 1 and 4 have temperature control variables up to a third-order polynomial. Standard errors are clustered at the vehicle level.

These results demonstrate that there is limited evidence of a systematic differential change in the extensive margin for our treatment groups over our sample period. This suggests that the main response to the treatments are a change in the timing of charging rather than an adjustment in the frequency of daily charging and/or the amount of charging kWh that occurred at home versus away.

Temperature Controls.—We provide the results of our Phase 1 analysis with linear and no temperature control variables. This alleviates concerns that the functional form of our temperature variables may be impacting our main estimated treatment effects.

Table 8 and Table 9 report the results of running our main specification from equation (1) with linear as well as no included temperature control variables, in columns 2 and 3, respectively. Column 1 shows the results from our main specification for comparison purposes. For the regressions using the Charge Indicator as our dependent variable (Table 8), our results are consistent across each specification. There are minimal differences in the magnitudes and no differences in statistical significance. For the regressions using Charge kWh as the dependent variable (Table 9), the results for the Rewards group are highly robust. For the Info group, the only difference arises from a loss of marginal statistical significance on the negative off-peak coefficient in column 3.

Excluding Homes with Solar.—As shown in Table C1 in the Supplemental Appendix, our survey variables have no significant difference between groups. However, one may be concerned about the notable difference in the share of homes that have solar panels across groups. Only 24 participants who responded to our

Table 9—Estimated Treatment Effects—Charge kWh—Phase 1 (Home Only)

Group	Hours	Main specification (1)	Linear temp (2)	No temp (3)	Removing solar (4)
Rewards	Peak	−0.2008	−0.1987	−0.1983	−0.1994
		(0.0558)	(0.0558)	(0.0556)	(0.0604)
	Off-peak	0.4553	0.4511	0.4527	0.4680
		(0.1063)	(0.1060)	(0.1058)	(0.1184)
Info	Peak	0.0053	0.0074	0.0073	−0.0152
		(0.0626)	(0.0627)	(0.0624)	(0.0678)
	Off-peak	−0.2216	−0.2260	−0.2248	−0.1654
		(0.1282)	(0.1280)	(0.1274)	(0.1433)
Mean dependent variable (pretreatment)					
Rewards	Peak	0.4091	0.4091	0.4091	0.3744
	Off-peak	1.2280	1.2280	1.2280	1.3157
Info	Peak	0.5366	0.5366	0.5366	0.4991
	Off-peak	1.0946	1.0946	1.0946	1.0813

Notes: The results reflect the estimation of equation (1). The data include charging at home only and days where charging occurred. The estimated treatment effects are separated into peak and off-peak hours. The mean dependent variable (pretreatment) represents the mean value of the dependent variable between February 1, 2022 and March 31, 2022, separated into peak and off-peak hours. All specifications include fixed effects at the vehicle, month-of-sample, hour-of-day, and day-of-week. Columns 1 and 4 have temperature control variables up to a third-order polynomial. Standard errors are clustered at the vehicle level.

survey reported having solar PV. There were 3 in the Control, 9 in the Info, and 12 in the Rewards group. Homeowners with solar may be less flexible than others in changing their EV charge timing, as consumers in ENMAX territory have net billing for solar panels. In this setting, if consumers use their own solar-generated electricity (e.g., to charge their EVs), they avoid variable transmission and distribution charges, saving approximately 6¢/kWh, on top of avoiding the energy charge. Alternatively, they receive only the energy price if they export solar generation to the grid. A higher share of homes with solar in the Reward group compared to the Control group may cause a downward bias in the estimated response to financial incentives provided in the off-peak nighttime hours if EV owners with solar panels are charging midday in response to the net billing incentive. We run a robustness check in which we drop homes with solar from the analysis to assess the potential implications of these incentives.

Tables 8 and 9 also report the results of excluding homes with solar panels from our main analyses in column 4, for our Charge Indicator and Charge kWh variables, respectively. (Column 1 shows the results from our main specification for comparison purposes.) Results are robust to the exclusion of homes with solar; the only significant change is the loss of marginal statistical significance on the negative off-peak coefficient for the Info group.

VI. Conclusion

Shifting EV charging from periods when the electricity generation and delivery systems are strained to periods of surplus capacity has the potential to be a game changer in lowering the cost of electrifying the transportation sector. Understanding the willingness of EV owners to shift when they charge their vehicles, as well as identifying effective policies to achieve charging time flexibility, is increasingly important as the number of EVs grows along with their associated large electricity demand.

We find EV owners respond strongly to financial incentives. The receipt of a relatively modest reward for off-peak charging results in a substantial shift in charge timing from peak to off-peak hours, with no discernible change in the overall daily amount of electricity charged. In contrast we find no evidence of a change in charging behavior for those who received the prosocial information treatment in our experiment. The "money matters" result is reinforced by our finding that charging behavior reverts to pre-intervention patterns when financial rewards are removed.

Our paper uses a randomized controlled trial to provide empirical estimates of EV charging behavior in response to incentives. These estimates can be used in simulation studies that rely on assumptions about EV charging flexibility to quantify the impact of the growth of EVs on electric grids. Studies predicated on the assumption of inelastic charging behavior are likely to overstate the cost of integrating EVs into the electric system.

In our setting, EV charging flexibility is unlocked via financial incentives. More research is needed to understand how these results might generalize beyond EV early adopters and to more sophisticated financial incentives and programs. Dynamic pricing, for example, offers the potential to better align charging behavior with ever-changing system conditions, including variations in supply due to growing shares of renewable sources. At a local level the geographic concentration of EV adoption means coordinated programs, such as active charge management, that sequence charging may be needed to avoid the problem of too many EV owners attempting to charge at the same time and overloading local distribution circuits. Future work can extend our research to these other pricing and management schemes. Nonetheless, our study makes clear that there is significant EV charging flexibility ready to be unlocked by the right policy incentives.

REFERENCES

AESO. 2023. *AESO 2022 Annual Market Statistics*. https://www.aeso.ca/assets/Uploads/market-and-system-reporting/2022_Annual_Market_Stats_Final.pdf (accessed June 15, 2023).

Alberta Ministry of Transportation. 2023. *Vehicle Registrations by Fuel Type in Alberta by 6-Digit Postal Code, by Year, from 2017 to 2022*. Provided by personal correspondence.

Bailey, Megan, David P. Brown, Blake Shaffer, and Frank A. Wolak. 2022. "Incentives vs. Nudges to Shift EV Charging Behaviour." AEA RCT Registry. https://doi.org/10.1257/rct.10282-1.0.

Bailey, Megan, David P. Brown, Blake Shaffer, and Frank A. Wolak. 2024. "Centralized vs Decentralized Demand Response: Evidence from a Field Experiment." Unpublished.

Bailey, Megan, David P. Brown, Blake Shaffer, and Frank A. Wolak. 2025. *Data and Code for: "Show Me the Money! A Field Experiment on Electric Vehicle Charge Timing."* Nashville, TN: American Economic Association; distributed by Inter-university Consortium for Political and Social Research, Ann Arbor, MI. https://doi.org/10.3886/E202941V1.

Burkhardt, Jesse, Kenneth T. Gillingham, and Praveen K. Kopalle. 2023. "Field Experimental Evidence on the Effect of Pricing on Residential Electricity Conservation." *Management Science* 69 (12): 7784–98.

Harding, Matthew, and Steven Sexton. 2017. "Household Response to Time-Varying Electricity Prices." *Annual Review of Resource Economics* 9: 337–59.

IEA. 2023. *Global EV Outlook 2023*. IEA.

Imelda, Matthias Fripp, and Michael J. Roberts. 2024. "Real-Time Pricing and the Cost of Clean Power." *American Economic Journal: Economic Policy* 16 (4): 100–41.

Ito, Koichiro, Takanori Ida, and Makoto Tanaka. 2018. "Moral Suasion and Economic Incentives: Field Experimental Evidence from Energy Demand." *American Economic Journal: Economic Policy* 10 (1): 240–67.

Lee, Jae Hyun, Scott J. Hardman, and Gil Tal. 2019. "Who is Buying Electric Vehicles in California? Characterising Early Adopter Heterogeneity and Forecasting Market Diffusion." *Energy Research & Social Science* 55: 218–26.

Market Surveillance Administrator (**MSA**)**.** 2023a. *Quarterly Report for Q2 2023*. Alberta Market Surveillance Administrator.

Market Surveillance Administrator (**MSA**)**.** 2023b. *MSA Retail Statistics*. Alberta Market Surveillance Administrator. https://www.albertamsa.ca/documents/retail-and-rate-cap/retail-statistics/ (accessed February 15, 2023).

Prest, Brian C. 2020. "Peaking Interest: How Awareness Drives the Effectiveness of Timeof-Use Electricity Pricing." *Journal of the Association of Environmental and Resource Economists* 7 (1): 103–43.

Qiu, Yueming Lucy, Yi David Wang, Hiroyuki Iseki, Xingchi Shen, Bo Xing, and Huiming Zhang. 2022. "Empirical Grid Impact of In-Home Electric Vehicle Charging Differs from Predictions." *Resource and Energy Economics* 67: 101275.

United States Bureau of the Census. 1915. *Central Electric Light and Power Stations and Street and Electric Railways with Summary of the Electrical Industries*. US Government Printing Office.

Working Group III, IPCC. 2022. *Climate Change 2022: Mitigation of Climate Change*. IPCC.