

A Peek at Piquing EV Owners Interest in Off-Peak Charging: How Nudges Can Increase Awareness of Targeted Time-of-Use Rates

*Russell M. Meyer¹ and Beth Morgan, Opower (Oracle Energy and Water)
Ryan Cote, Rhode Island Energy*

ABSTRACT

Uptake of electric vehicles (EVs) is increasing, as is their share of the total vehicle miles traveled (VMT) and total energy consumption for personal transportation services. This accelerating adoption trend is an opportunity for utilities to provide additional energy services to their existing customer base. It also presents a challenge to distribution and generation infrastructure. On-peak vehicle charging exacerbates already stressed electricity delivery systems and can lead to unintended service disruptions if not managed with care. An alternative to expensive infrastructure upgrades is to encourage vehicle owners to smooth their EV charging by moving it to off-peak times. In a first-of-kind pilot program, Rhode Island Energy has provided incentive rewards to a group of EV households to encourage off-peak charging. Accompanying this incentive intervention, Opower created an educational and behavioral-nudging campaign for a segment of the population and leveraged a randomized control trial (RCT) to assess its effectiveness. This paper reports on the results of the first year of treatment by this behavioral load shifting program. We find an approximate 8% reduction in on-peak charging behavior by households who receive behavioral educational materials compared to control group households, though this point estimate does not meet our threshold for statistical significance. Nevertheless, we interpret this result as suggesting that the load-management effectiveness of variable price signals can be enhanced by nudging households through behavioral educational communications.

Introduction

The delivery mechanism for the energy that drives personal transportation services is undergoing change unmatched since the transition from horses to horsepower. Reference-case projections by the U.S. Department of Energy's Annual Energy Outlook forecast that the quantity of electricity used for light-duty vehicle (LDV) mobility will increase approximately ten-fold by 2040 and over 19-fold by 2050 compared to 2020 (US EIA 2021). Several side-cases show even greater rates of growth. The increase in transportation energy delivered through the medium of at-home electric charging for EVs has the potential to add material stress to existing transmission and distribution infrastructure; particularly if latent preferences for the timing of charging by electric vehicle owners is correlated with demand peaks, as seems likely (Morrissey, Weldon, and O'Mahony 2016). Investment in U.S. transmission infrastructure has accelerated, doubling twice over the period of 2005 to 2016 (US DOE 2020), but that may not be sufficient to avoid service disruptions caused by over-congestion even in a business-as-usual scenario (ASCE 2021).

Distribution infrastructure must be built to the scale of peak system demand, so one pathway to reduce the ultimate investment necessary to meet utility-company service obligations

¹ Corresponding author. The authors thank Sanem Kabaca, Luciana Coptly, Hai Trinh, Leela Bandaru, Tom Gray, and Alex Mazarredo of Opower, and Mark Siegal of Rhode Island Energy for comments on drafts of this work and/or data assistance.

is to smooth demand by end-use consumers. Time-of-use (TOU) pricing schemes are increasingly being deployed by utilities in order to encourage demand shifting to off-peak periods when electricity service delivery is less expensive for utility operators (e.g., see Trabish 2019). However, unless consumers are aware of their TOU rates, and of strategies available to them to adjust their energy consumption timing accordingly, the desired load shifting cannot occur (Prest 2020).

This paper reports results from an effort by Opower, along with National Grid Rhode Island, to pilot a program designed to encourage EV owners who have enrolled in a TOU rebate program to shift their charging demand by delivering behavioral and educational messaging about their energy consumption. The results show that layering behavioral educational materials on top of a TOU rebate can boost the effectiveness of time-specific price signals.

Pilot Design

The behavioral education pilot reported in this study is layered on top of an existing program, called SmartCharge Rhode Island, run by Rhode Island Energy (formerly, National Grid Rhode Island) to provide TOU rebates to EV owners for off-peak charging (see, NGRI 2021). This opt-in program provides an incentive to participants to install a FleetCarma (now Geotab) device in their EV which tracks and transmits details about each EV's use. In addition to the annual flat-rate incentive provided to participants, the FleetCarma device records EV charging data in order to facilitate rebate payments under the TOU rate. Participants receive a rebate on EV charging that occurs in the off-peak period of 9pm to 1pm, daily. This behavioral education pilot uses these data of the timing-of-charging events and the quantity of power consumed while charging to measure the effects of treatment.

The population of participating households who opted-in to the SmartCharge program (initially, $n=308$) were split, using random selection, into treatment and control groups ($n=154$ for each). The treatment group received the behavioral education communication materials of this pilot while the control group did not. Crucially, for the causal inference of this study, this RCT approach allows us to attribute differences we observe in charging behavior between the treatment group and control group following the start of treatment to the program. It also means that the effects we measure in the pilot are entirely additional to the effects of the SmartCharge program (which are not measured by this study but are reported on elsewhere—see ERS 2020). To ensure valid assignment to treatment and control groups for the purposes of effect attribution, a standardized randomization procedure was employed.

Randomization Procedure

Assignment to the RCT's treatment and control groups was done at the household level. In the sample population, there were 49 households with more than one participating EV; however, because behavioral treatment is directed to the occupants of the household, it is the household, and not the EV, that is the unit of analysis for this study.

To ensure that the random assignment created two statistically balanced groups, we follow Bruhn and McKenzie's (2009) "minimum maximum" rerandomization method. In so doing, we create a randomized assignment and compute t-tests of differences in means (or proportions, for binary variables) for several variables of interest. That randomization assignment and the maximum t-score from among the variables included in the balance check are saved, then a new randomization assignment is performed and new t-test scores are computed.

This is iterated 1,000 times, and the assignment with the smallest maximum t-test score is selected for final treatment and control group assignment.

This procedure was operationalized using the Stata *randomize* module (Kennedy and Mann 2015). The variables used in the balance check algorithm and the t-test values for the comparison of the assigned treatment and control groups are reported in Table 1. For all included variables, the P scores, representing the probabilities that the two groups are not different, are well above standard critical values for this measure.

Table 1: Results of the randomization balance check

Variable	mean (treatment)	mean (control)	st. dev. (treatment)	st. dev. (control)	t- score	P(T<=t) two-tail	P > 0.1?
luxury	0.253	0.273	0.436	0.447	-0.387	0.699	OK
BEV	0.571	0.571	0.496	0.496	0.000	1.000	OK
PHEV	0.455	0.455	0.500	0.500	0.000	1.000	OK
car_count	1.169	1.188	0.393	0.482	-0.389	0.698	OK
miles_per_day	26.087	25.224	15.624	14.909	0.496	0.620	OK
daily_peak_kwh_12mo	1.910	1.815	1.629	1.923	0.467	0.641	OK
daily_total_kwh	7.354	7.915	5.269	10.714	-0.583	0.560	OK
daily_peak_kwh	2.309	2.897	1.800	9.243	-0.775	0.439	OK
pct_peak	0.349	0.353	0.194	0.209	-0.174	0.862	OK
Level2	0.513	0.539	0.501	0.500	-0.455	0.649	OK
Level3	0.026	0.013	0.160	0.114	0.823	0.411	OK
oldTreat	0.468	0.513	0.501	0.501	-0.796	0.427	OK

In the table, the variables are defined as follows.

- Luxury is an indicator variable for the presence of a luxury EV in the household,
- BEV is an indicator for a full (battery) EV in the household,
- PHEV is an indicator for a plug-in hybrid EV in the household,
- car_count is a count of the number of EVs in the household,
- miles_per_day is the average daily miles driven by EV vehicles in the household prior to program launch,
- daily_peak_kwh_12mo is the average daily peak-period EV charging in kWh for the household in the 12-months prior to program launch,
- daily_total_kwh is the average daily EV charging in kWh for the household among all records prior to program launch,
- daily_peak_kwh is the average daily peak-period EV charging in kWh for the household among all records prior to program launch,
- pct_peak is the percentage of on-peak EV charging as a fraction of all EV charging for the household prior to program launch,
- Level2 is an indicator variable in which a Level-2 EV charger is present at the household,

- Level3 is an indicator variable in which a Level-3 EV charger is present at the household²,
- and oldTreat is an indicator variable for households previously included in the treatment group of a now concluded earlier study using this same household population (ERS 2020).

Description of Treatment Experience

Households included in the treatment group for this pilot received monthly email communications from Opower, with National Grid Rhode Island branding (as Rhode Island Energy was known at the time of the program’s launch), along with an initial welcome letter. These communications included modules of both dynamic personalized elements along with static elements intended to remind participants about the SmartCharge program as well as provide a graduated educational experience about EV charging. The purpose of these communications is to encourage a change in charging behavior consistent with the incentives provided by the TOU rebate program. Each of the monthly communications has the following five elements: Anchor module; Educator module; TOU Repeating Banner; EV Fun Facts & Tools module; and Rebate Summary module. Figure 1 is an example communication in which each of these five elements is identified.

Anchor

The Anchor module provides dynamic energy consumption comparisons, personalized to the household, designed to leverage the same proven behavioral-change strategies are used in other behavior-based energy programs. This includes a self-comparison, in which the households’ monthly on-peak EV charging consumption is compared to the consumption from the previous month. This gives the participant household a sense of the progress (or backsliding) they have made. The anchor also includes a cross-participant comparison (social norming), in which the households’ monthly on-peak EV charging consumption is compared to other similar participants in the program. For the purposes of this comparison, similar participants are defined as other EV users with a similar type of EV (BEV or PHEV).

Educator

The Educator module includes graduated topical themes that build over time to take the consumer from motivation to knowledge to action. Each group of three months (one quarter) focuses on a different theme, with each subsequent theme building on the previous one. For the first year of the Opower program, the four quarterly themes were 1) why shift charging, 2) how to shift charging, 3) make shifting easier, and 4) schedule your charging. Within each quarterly theme there are three messaging opportunities. The first two of these provide straightforward, easily understandable messaging related to the theme. The third and final educator module in each quarter includes a “myth-buster” or tip message. The messaging in the Educator modules can be dynamically personalized, depending on the content of the messages. For example, within the “how to shift charging” theme, details are populated that are specific to the manufacturer of

² See e.g., https://afdc.energy.gov/fuels/electricity_infrastructure.html for a definition of Level-2 and Level-3 chargers.

the EV owned by the household to educate participants about the specifics of automating their EV charging schedule.

TOU Repeating Banner

The TOU Repeating Banner element is a relatively static portion of the email that reminds the consumer of the start and end times of their off-peak charging window and encourages them to earn rewards with the program by charging their EV during that time. This banner provides a visual break to the email and develops an identifiable visual feel for the communication series. While this content is not dynamic relative to the household, it does change relative to the seasonal change in rebate rewards provided by the SmartCharge program. For example, in the summer this banner reminds the reader that extra rewards are available for participants who shift charging to the off-peak period during that critical time.

EV Fun-Facts & Tools

This module features a variety of content of interest to EV drivers in order to create a tailored “feel good” experience and reinforce SmartCharge program participation. Topics include timely EV news, apps and tools for locating charging stations and planning EV road trips, quick surveys, and more. Quarterly this module delivers a dynamic “community impact message” showcasing the total off-peak charging accomplishment across the entirety of the SmartCharge program. This aggregated off-peak charging total is then tied to messaging about the positive benefits that off-peak consumption has in terms of environmental stewardship and grid resiliency.

Rebate Summary

The Rebate Summary provides dynamic household-specific calculations of the rebates earned for off-peak charging over the previous month by the participants in the household. This helps to reinforce the self-interest element of program participation and concludes the messaging on a positive note for the participant.

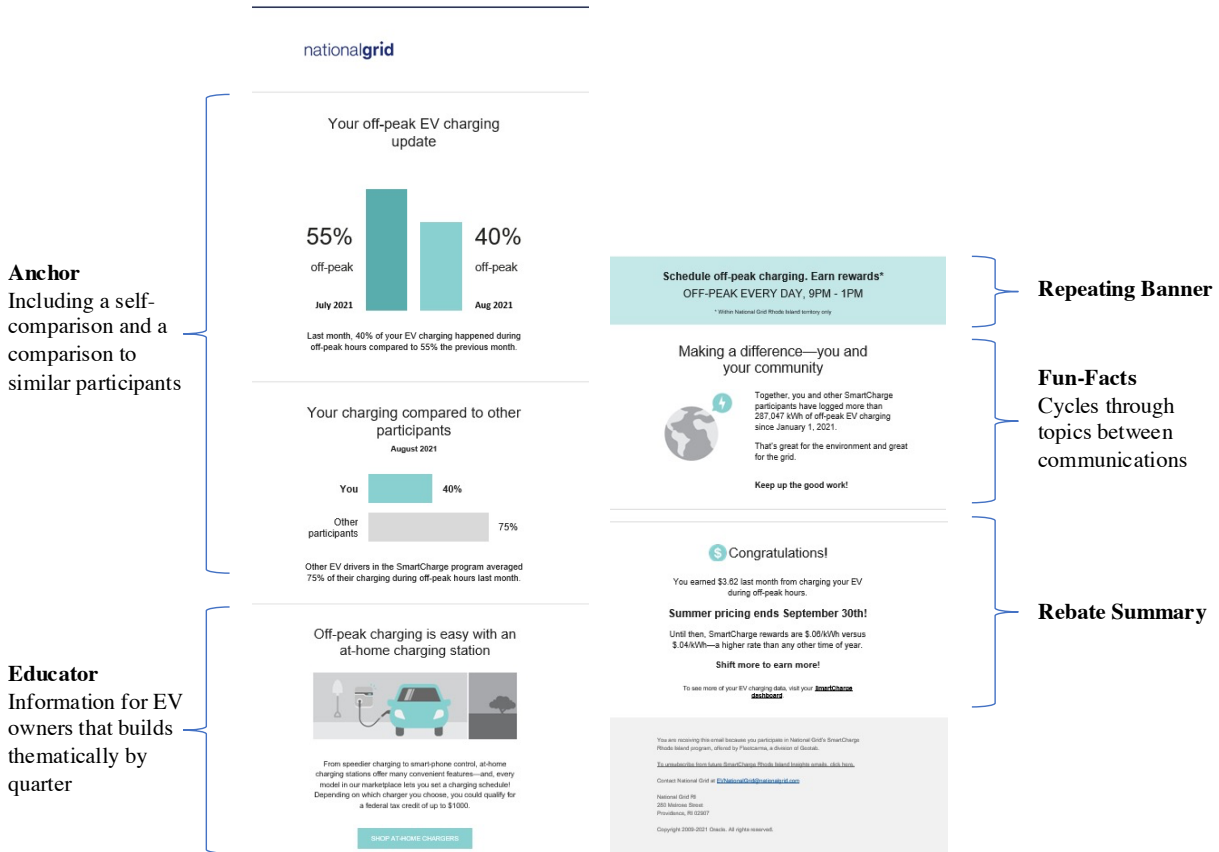


Figure 1. Treatment email example with each of the five elements that appear in all communications

Measurement Methods

To measure the effect of behavioral treatment on the treatment group households we use a lagged dependent variable (LDV) model. This model form is preferred to a fixed-effects (FE) model due to the increased efficiency in creating precise coefficient estimates (McKenzie 2012; Burlig, Preonas, and Woerman 2017). The model specification for estimating a single month's average treatment effect is given by Equation 1.

$$peak_charge_i = \alpha + \beta treatment_i + \sum \delta Y_{it} + \varepsilon_i$$

Equation 1. Lagged dependent variable model specification for monthly average effect.

Where

- the dependent variable, *peak_charge*, is the value for EV charging by household, *i*, in a given month measured in kWh;
- α is the model intercept;
- treatment* is an indicator variable that is equal to one for households in the treatment group, and the coefficient, β , is the estimate of interest for this model;
- Y_{it} is a vector of three LDV terms:
 - peak_charge_same_month* is the value for EV charging by the household in the same calendar month in the year prior to the start of program treatment

- *peak_charge_year_average* is the average monthly value for EV charging by the household over the course of the full year prior to the start of program treatment and,
- *peak_charge_prior_month* is the value for EV charging by the household in the month immediately preceding the start of program treatment (i.e., March 2021)
- ε is an idiosyncratic error term

The set of LDV terms included in this model were selected to be similar to the modeling approach of other behavioral energy programs administered by Opower (e.g., Allcott and Rodgers 2014). Equation 1 is used to estimate the effect of the program on treatment households, restricting the panel dataset to one post-treatment month per estimation run. Equation 2 is used to estimate the cumulative average treatment effect of the program from launch to-date. Equation 2 uses the same terms as Equation 1 but adds monthly indicator variables as well as interactions between those monthly indicators and the LDV terms. While Equation 1 is estimated with the dataset restricted to one month per estimation, Equation 2 is estimated using the full treatment-period dataset, with month indexed by the subscript, t .

$$peak_charge_{it} = \alpha + \beta treatment_i + \sum \gamma month_t + \sum \delta Y_{it} + \sum \zeta month_t Y_{it} + \varepsilon_{it}$$

Equation 2. Lagged dependent variable model specification for cumulative average effect.

Results

Treatment effect estimates from Equations 1 & 2 are presented in Table 2. The treatment coefficient represents the estimated value of β from Equations 1 & 2 and is reported in kWh per month. Reported standard errors are clustered robust at the household level. Treatment effects are also reported as a percentage of control group on-peak consumption for the time-period relevant to the treatment effect.

Table 2: Treatment effect estimates (to be updated with final results)

Equation	Month	Treatment coefficient	Standard Error	Treatment effect as %	N	R^2
1	April, 2021	-1.55	6.37	-2%	268	0.60
1	May, 2021	-19.00	9.15	-26%	257	0.40
1	June, 2021	-9.50	6.93	-14%	254	0.49
1	July, 2021	-1.96	11.24	-3%	250	0.29
1	August, 2021	-8.14	7.12	-12%	247	0.49
1	September, 2021	-5.74	7.75	-8%	242	0.44
1	October, 2021	-8.69	7.28	-11%	239	0.55
1	November, 2021	-5.20	9.15	-6%	236	0.44
1	December, 2021	3.06	8.30	4%	235	0.48
1	January, 2022	-3.26	6.98	-4%	228	0.61
1	February, 2022	6.20	7.66	10%	227	0.54
1	March, 2022	-5.53	10.01	-7%	221	0.38
1	April, 2022	-17.06	11.77	-19%	202	0.31
2	April-April	-5.86	4.61	-8%	3106	0.45

Discussion

The RCT experimental design of this program is layered on the SmartCharge program, with both treatment and control households receiving rebate payments as a result of off-peak EV charging. As a consequence, the effect estimated in this study is entirely additional to the effect of the price signal alone. This suggests that the demand effect of time-specific energy price signals can be materially amplified by coupling those programs with targeted information that goes beyond simple reminders about peak hours by engaging and educating consumers about how to manage their off-peak charging. Further, it suggests that existing estimates of the elasticity of demand for electricity across narrow time frames could be under-estimated for instances in which consumer awareness of the timing of their consumption patterns can be enhanced. Indeed, it is possible that the effect of the communication series is complementary to the price signal. Future research could investigate whether the communication effect on its own is greater or less without an accompanying TOU rate or incentive program. Note also that this program follows a previous program that provided communications to approximately half of the treatment group within this study. To the extent that the effects of that program persisted into the period of this study, the on-peak charging available to move to an off-peak period is reduced. Therefore, in a fresh population similarly treated, we would expect a program of this type to have the same or larger observed effect.

While the cumulative effect of the program has not, to date, reached statistical significance at the initially specified confidence interval threshold of 95%, both the magnitude and the directional effect observed in such a small sample size is encouraging, and is consistent with the finding of DNV (2021) that treatment households have changed the timing of the start of their charging sessions. Future work could seek larger populations to test the replicability of the outcomes observed by this study. Additional future work could include assessing the relative effect of economically identical price signals that are framed as a gain (rebates, as in this program) or as a loss (like most TOU rate charges) to identify if loss-aversion is an additional

motivating factor that could be leveraged by system operators to maximize the behavioral nudge delivered by a program like this one to relieve peak-period system stress. A limiting factor for future studies of this kind are the need for participants to install a data-gathering device in their vehicle in order to transmit data back to the utility. To the extent possible, vehicle manufacturers should incorporate this capability into the data logging that EVs are likely to do for other purposes in the future. Nevertheless, data-privacy safeguards should remain to ensure that third-party access to these data are based on affirmative participant opt-in.

As EV ownership continues to increase, solutions for managing the resulting demand growth will be necessary to ensure that the grid continues to operate with stability. To maximize the environmental benefits of wide-spread EV use, coinciding demand with renewable generation supply will be a critical pathway to achieve least-cost climate and system reliability goals. Behavioral nudges are an effective mechanism to contribute to this objective.

References

- Allcott, H., and Rogers, T. 2014. “[The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation](#).” *American Economic Review* 104(10):3003-3037.
- American Society of Civil Engineers (ASCE). 2020. “[Failure to Act: Electric Infrastructure Investment Gaps in a Rapidly Changing Environment](#).” Prepared by EBP US.
- Burlig, F., Preonas, L., and Woerman, M. 2017. “[Panel Data and Experimental Design](#)” Energy Institute at Haas working paper. WP 277.
- Bruhn, M., and McKenzie, D. 2009. “In Pursuit of Balance: Randomization in Practice in Development Field Experiments.” *American Economic Journal: Applied Economics*. 1(4): 200-232.
- DNV. 2021. “[Rhode Island Electric Transportation Initiative Evaluation Rate Year 3 Final Report](#).” October 25, 2021.
- Energy & Resource Solutions (ERS). 2020. “[Rhode Island Electric Transportation Initiative Evaluation Final Report – Rate Year 2](#).” North Andover, MA. October 23, 2020.
- Kennedy, C., and Mann, C.B. 2015. “[RANDOMIZE: Stata module to create random assignments for experimental trials, including blocking, balance checking, and automated rerandomization](#).” Statistical Software Components S458028, Boston College Department of Economics, revised 01 Jun 2017.
- McKenzie, D. 2012. “[Beyond Baseline and Follow-up: The Case for More T in Experiments](#)” Policy Research Working Paper 5639. The World Bank, Development Research Group.
- Morrissey, P., Weldon, P., and O’Mahony, M. 2016. “[Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour](#).” *Energy Policy*. Volume 89, Pages 257-270.

National Grid Rhode Island (NGRI). 2021. “[SmartCharge Rhode Island drives EV behaviors](#)” June 8, 2021.

Prest, B.C. 2020. “[Peaking Interest: How Awareness Drives the Effectiveness of Time-of-Use Electricity Pricing](#).” Journal of the Association of Environmental and Resources Economists. Volume 7, Number 1. January 2020.

Trabish, H.K. 2019. “[An emerging push for time-of-use rates sparks new debates about customer and grid impacts](#)” *Utility Drive*. January 28, 2019. Accessed, March 2022.

United States Department of Energy (US DOE). 2020. “[National Electric Transmission Congestion Study](#).” Washington, D.C.

United States Energy Information Administration (US EIA). 2021. “[Annual Energy Outlook \(Table 37: Light-Duty Vehicle Energy Consumption by Technology Type and Fuel Type – Multiple Cases\)](#).” Washington, D.C.

Appendix

Table A: Full regression results for Equation 2

	Variable	Coefficient Estimate	Standard Error	t-score	p-value
	Treatment	-5.86	4.61	-1.27	0.20
Month Indicators	May-21	9.28	6.45	1.44	0.15
	Jun-21	10.34	4.46	2.32	0.02
	Jul-21	16.23	5.98	2.72	0.01
	Aug-21	8.70	5.14	1.69	0.09
	Sep-21	14.96	7.02	2.13	0.03
	Oct-21	15.63	8.56	1.82	0.07
	Nov-21	22.51	7.04	3.20	0.00
	Dec-21	16.26	6.01	2.71	0.01
	Jan-22	6.96	5.29	1.32	0.19
	Feb-22	9.45	6.43	1.47	0.14
	Mar-22	20.85	7.38	2.82	0.01
	Apr-22	22.40	9.70	2.31	0.02
LDV Term 1 by Month	LDV Term 1	-0.27	0.19	-1.42	0.16
	May-21	-0.37	0.40	-0.92	0.36
	Jun-21	0.24	0.25	0.95	0.34
	Jul-21	0.10	0.20	0.48	0.63
	Aug-21	0.34	0.25	1.37	0.17
	Sep-21	0.35	0.21	1.67	0.10

	Oct-21	0.41	0.20	2.03	0.04
	Nov-21	0.56	0.26	2.11	0.04
	Dec-21	0.31	0.25	1.23	0.22
	Jan-22	0.43	0.22	1.95	0.05
	Feb-22	0.39	0.21	1.88	0.06
	Mar-22	0.30	0.34	0.87	0.39
	Apr-22	-0.11	0.56	-0.19	0.85
LDV Term 2 by Month Interactions	LDV Term 2	0.87	0.32	2.70	0.01
	May-21	0.73	0.73	1.00	0.32
	Jun-21	-0.05	0.39	-0.13	0.89
	Jul-21	0.53	0.43	1.24	0.22
	Aug-21	-0.27	0.40	-0.66	0.51
	Sep-21	-0.44	0.39	-1.13	0.26
	Oct-21	-0.43	0.30	-1.42	0.16
	Nov-21	-0.51	0.36	-1.43	0.15
	Dec-21	-0.40	0.37	-1.07	0.28
	Jan-22	-0.26	0.28	-0.92	0.36
	Feb-22	-0.65	0.38	-1.72	0.09
	Mar-22	-0.24	0.40	-0.60	0.55
	Apr-22	0.31	0.92	0.34	0.74
LDV Term 3 by Month Interactions	LDV Term 3	0.21	0.16	1.28	0.20
	May-21	-0.47	0.33	-1.39	0.16
	Jun-21	-0.17	0.18	-0.91	0.36
	Jul-21	-0.55	0.23	-2.33	0.02
	Aug-21	-0.05	0.20	-0.26	0.80
	Sep-21	0.05	0.21	0.25	0.81
	Oct-21	0.07	0.17	0.43	0.67
	Nov-21	0.02	0.21	0.11	0.91
	Dec-21	0.15	0.17	0.88	0.38
	Jan-22	0.01	0.18	0.05	0.96
	Feb-22	0.27	0.23	1.18	0.24
	Mar-22	(omitted due to collinearity with LDV 1)			
	Apr-22	-0.32	0.43	-0.73	0.47
	Constant	3.01	5.32	0.57	0.57

Reported standard errors are clustered robust at the household level. The month indicator for the first month, April 2021, is omitted to avoid collinearity. Similarly, the LDV3 interaction term for March 2022 is identical to the LDV1 term for that month so it is also omitted to avoid collinearity. Note that while many of the LDV by month interaction terms are not statistically significant individually, a Wald test of joint significance for each collection of LDV by month terms yields F-values greater than the critical value at standard levels of significance, reinforcing the justification of their joint inclusion.