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APPENDIX

Insights from Smart Meters: Ramp-up, dependability, and short-term persistence of savings from Home Energy Reports

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Appendices

These Appendices provide detailed descriptions as an addendum to the paper: “Insights from Smart Meters: Ramp-up, dependability, and short-term persistence of savings from Home Energy Reports.” In Appendix A, we provide a detailed description of Home Energy Reports (HERs) and the experimental design (a Randomized Controlled Trial, (RCT)). Appendix B describes the data used in the analysis, and Appendix C provides summary statistics and a validation of the randomization. In Appendix D we describe our analytical approach and present the results in a table format (graphical representations are available in the main body of the paper).

Appendix A: Program description and experimental design

In this section we provide an overview of Opower's Home Energy Reports program that was implemented at PG&E, the program design employed, and a general overview of our analysis methods and the available data.

A.1 Description of Home Energy Reports

Opower worked with PG&E to provide its residential customers with periodic Home Energy Reports (HERs) by mail that contain energy usage feedback and behavioral suggestions (see Figure A-1 for an example). Specifically, the HER compares a customer's monthly electric and/or gas usage to an average of similar homes' usage as well as to an average of the most efficient 20% of similar homes' usage. These "neighbor comparisons" are based on a variety of customer characteristics, including location, home floor area, presence of high energy consuming devices (e.g., pool), and type and number of air conditioning and/or heating units.

The neighbor comparison is used to give the customer one of three ratings:

- *Great* – the customer is more efficient than both average neighbors and efficient neighbors
- *Good* - the customer is more efficient than average neighbors but less efficient than their efficient neighbors
- *Using More than Average* - the customer is less efficient than both average and efficient neighbors

If a customer receives a rating of "Good" or "More than Average," the HER will include a dollar amount of savings that the customer could realize on their annual energy bills by matching their efficient neighbors' usage. A HER also provides a list of several energy savings tips and their potential annual dollar savings. For customers receiving reports on their electric usage, the reports include a graph of their load shape by hour for an average day from the last month of usage. Load shapes are not provided for natural gas usage because gas usage data are generally not collected hourly.

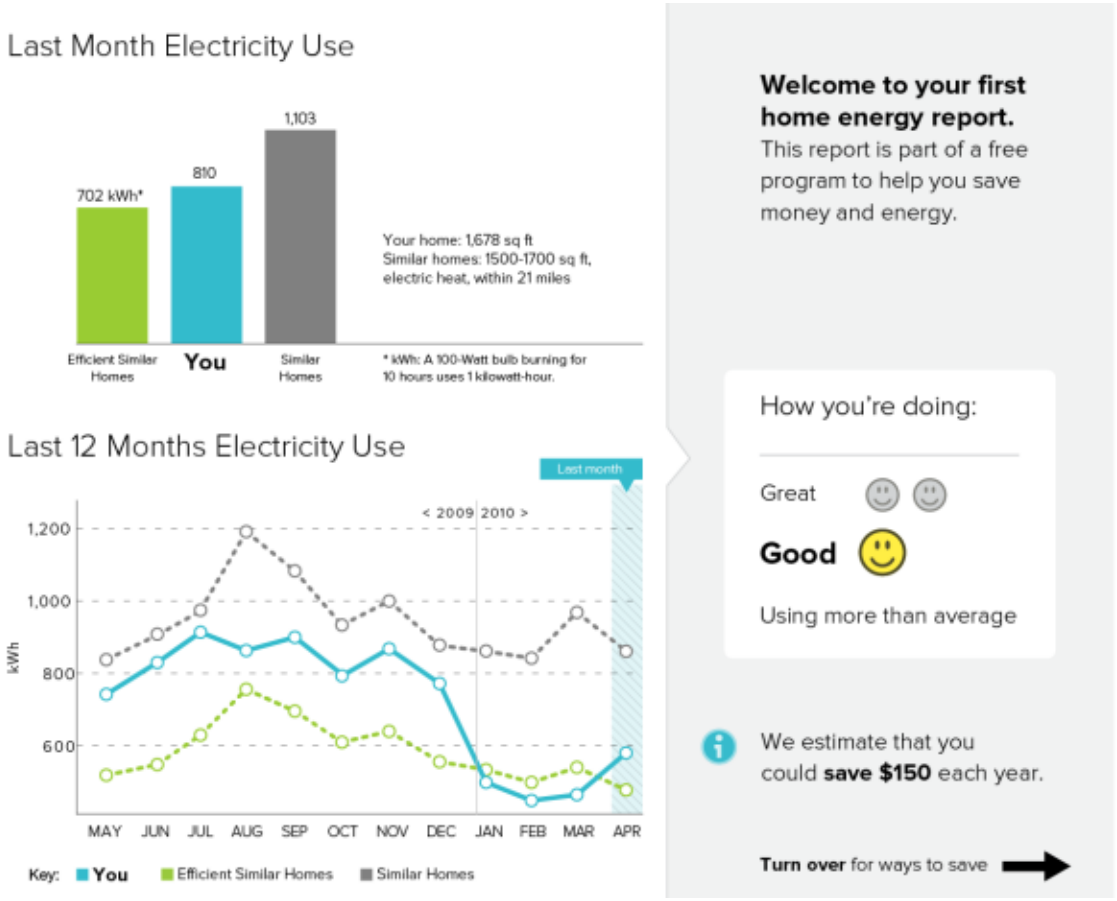

Figure A-1. Example of a Home Energy Report

A.2 Experimental Design

Opower's HER program in PG&E's service territory was designed as a field experiment that employed a randomized controlled trial (RCT). An RCT is a type of experimental design in which households in a given population are randomly assigned to two groups: a treatment group that receives the reports and a control group that does not.

The HER program utilizes an opt-out recruiting process. HERs are sent out to customers assigned to the treatment group without their prior knowledge or approval. These customers can elect to opt-out of receiving future HERs, if they wish by contacting PG&E.[1] Customers in the treatment group can then decide for themselves if and how to best respond to the energy usage feedback and behavioral suggestions contained in the HER. Customers in the control group are likely not aware that an experiment is occurring, since they are likely unaware their

[1] PG&E reports that the HERs generate very few complaints and opt-outs.

peers in the treatment group are receiving HERs, and are therefore unlikely to become dissatisfied.

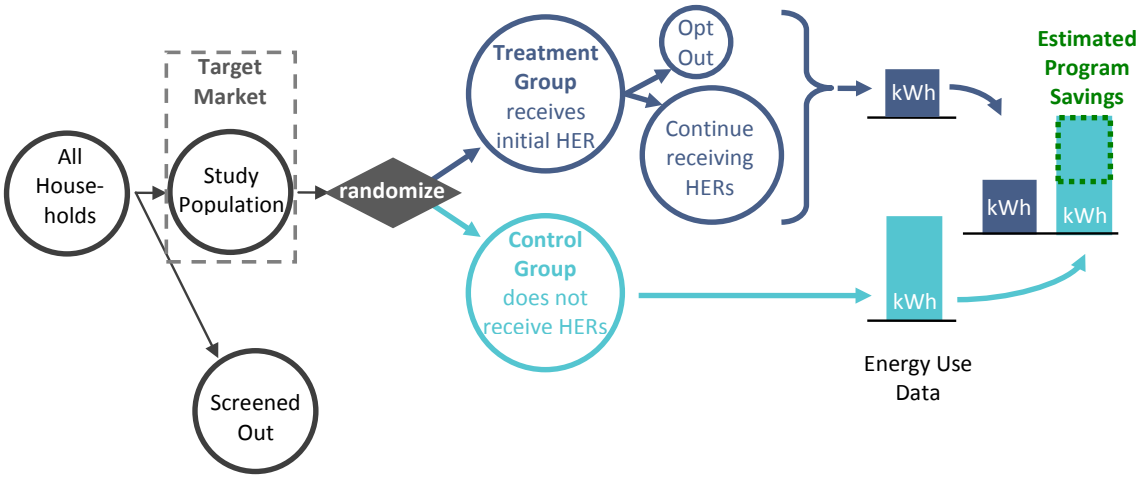

Figure A-2. Experimental design: opt-out randomized controlled trial

Because HERs are designed as RCTs, we can readily compare energy use data from customers in the treatment group to those in the control group in order to produce valid and unbiased statistical estimates of the total electricity savings, the peak demand savings, and the hour-by-hour electricity savings.

A.3 Screening criteria

PG&E's residential customers were screened into the study population using certain inclusion criteria (in addition to satisfying geographic or energy usage criteria discussed in Appendix B:). Customers must: have a full year of bills (to provide pre-treatment data for savings estimation); have had a functioning smart meter for more than one year; be on selected rate schedules—either PG&E's standard residential rate schedule or one of its residential time-of-use rates; neither be on a medical baseline rate, nor flagged as "vulnerable or disabled" in PG&E databases; not be master metered;[2] not be net metered;[3] not live in a mobile home; not be on an electric vehicle rate; not be on a natural gas vehicle rate; not be in another HER pilot program; not live in a multifamily dwelling; not be billed by a municipality; and have not previously requested that PG&E cease sending them any and all marketing materials.

[2] Master metered means that several homes share one meter—such as in a trailer park.

[3] Net metered homes have the ability to generate as well as consume power.

Appendix B: Data description

In this study, we analyze hourly interval electricity consumption data for one particular HER program pilot rollout within the broader set of HER programs implemented in PG&Es service territory (called "Gamma Wave" by PG&E; see Table B-1). It includes around 145,000 households, from all energy usage levels, drawn from five geographic regions in PG&E's service territories (see Figure B-1 for more information about PG&E's geographic territories). The Gamma Wave rollout began November 4, 2011, and we obtained data from the beginning of the rollout to September 31, 2012.

Table B-1. Overview of the Wave One dataset

	# Treat	# Control	Launch Date	Hourly interval data available	PG&E territory	Quartile of energy use[4]	Service received from PG&E
Gamma Wave	72,300	72,3000	Nov 2011	Nov 4, 2011 – Sept 31, 2012	R, S, T, W, X	All quartiles	Electric & gas service, and electric-only service

[4] The top (4th or highest) quartile refers to the 25% of energy users who use the most total annual energy on average (using the most energy as compared to the rest of the population). The quartiles were determined based on a combined electric and gas usage index.

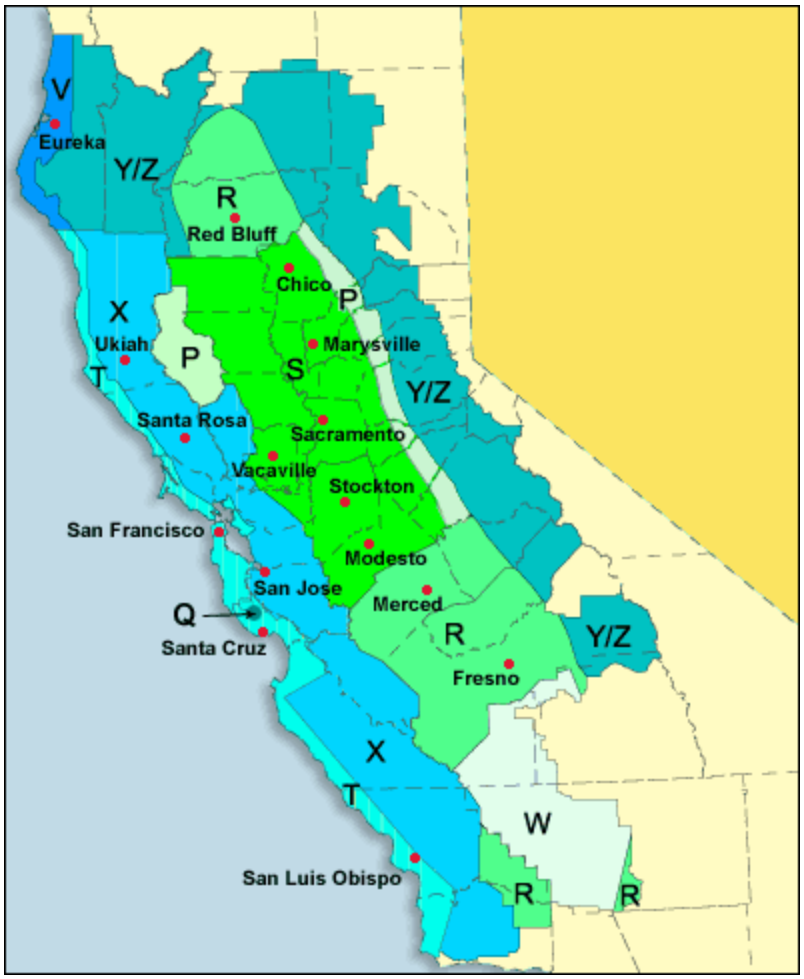

Figure B-1. PG&E Territory Map

Appendix C: Descriptive statistics and validation of randomization

In this section we present descriptive statistics of the pilot and pre-pilot study waves, and validate the comparability between the control and treatment groups through randomization.

Table C-1 demonstrates the successful randomization of customers onto control and treatment groups, as well as showing basic summary statistics. The table shows both the percentage of customers with observed characteristics as well as mean values for quantitative variables.[5] The observed characteristics in the table include baseline territory, CARE status (a program for low-income households offering subsidized rates), income level as estimated by a third party, homeownership status as estimated by a third party, home attributes, and monthly electricity usage prior to treatment. As the table shows, the distribution of each characteristic is similar across treatment and control groups.

The table also shows the results of statistical tests that tell us whether there is any evidence that the distribution of a given characteristic is correlated with treatment status. For binary variables, a z-test on the difference in means was used and the p-value for equality of means is shown. For metrics with more than two categories, the test used was Fisher's exact test and the p-value for independence of category with respect to treatment and control is shown.

Table C-1 shows the number of customers that were sent the first mailing in each wave; the number of months since wave inception through December 2012; and the average monthly attrition rate due to account closure from the beginning of the wave through December 2012. It is our understanding that account closure occurs primarily due to customers moving. In our analysis, we assume that moving (and any other source of account closure) is independent of being in the treatment or control groups.

[5] Data for tables C-1 and C-2 come from a combination of PG&E and third party databases licensed by PG&E.

Table C-1. Distributions of Characteristics across Treatment and Control Groups (Gamma Wave)

Metric	Category	Unit	Treatment	Control	P-value
Baseline Territory	R	(% of group)	22.0%	22.0%	1.00
	S	(% of group)	21.2%	21.2%	
	T	(% of group)	18.0%	18.0%	
	W	(% of group)	22.0%	22.0%	
	X	(% of group)	16.8%	16.8%	
CARE Rate		(% of group)	36.6%	36.6%	0.91
Estimated Household Income	<$30k	(% of group)	20.8%	20.8%	0.43
	$30k-$50k	(% of group)	18.1%	18.2%	
	$50k-$80k	(% of group)	30.1%	30.5%	
	>$80k	(% of group)	31.0%	30.6%	
Renter Status		(% of group)	6.8%	6.8%	0.91
Presence of Pool or Spa		(% of group)	13.8%	13.8%	0.69
Estimated Number of Residents		(number of residents)	2.7	2.7	0.16
Living Space		(square feet)	1651.7	1649.2	0.71
Year Home Built		(year)	1968.6	1968.4	0.21
Estimated Age of Head of Household		(years)	53.3	53.3	0.95

Pre-HER Usage	Oct-10	(monthly kWh)	558	555	0.21
	Nov-10	(monthly kWh)	531	529	0.26
	Dec-10	(monthly kWh)	597	595	0.31
	Jan-11	(monthly kWh)	575	574	0.40
	Feb-11	(monthly kWh)	493	492	0.31
	Mar-11	(monthly kWh)	518	516	0.20
	Apr-11	(monthly kWh)	477	476	0.24
	May-11	(monthly kWh)	508	507	0.40
	Jun-11	(monthly kWh)	675	673	0.42
	Jul-11	(monthly kWh)	834	831	0.45
	Aug-11	(monthly kWh)	836	833	0.39
	Sep-11	(monthly kWh)	718	716	0.46
	Oct-11	(monthly kWh)	558	556	0.29

Table C-2. Monthly Attrition Rate

Wave		Gamma
# of Customers at Launch of Wave	Control	70,529
	Treatment	70,518
# of Months of HERs*		14
Monthly Rate of Attrition (%)	Control	0.9%
	Treatment	0.9%

Appendix D: Analysis and results

In this section, we describe our analytical approach used to estimate the savings on each day after each report is mailed.

D.1 Creating "predicted mailing dates" for the control group

Every household did not receive their reports at the same time; they were mailed out based on billing dates. To estimate the savings for each day after the mailing of each report, we aligned the various mailing dates of different customers in order to estimate the savings on the first, second, third, etc. day after each report was mailed, even if those days are associated with different calendar dates. This alignment presents a challenge as to what segment of control group customers is appropriate to use as a comparison group for treatment group customers that receive their reports on a certain day, because billing dates may not be random within customer segments. We solved this issue by estimating "predicted mailing dates" for control customers based on their billing dates.

Fortunately, we have billing dates for all of the customers. The vast majority (97.6%) of treatment and control group customers fall into one of 15 billing groups, with between 10,000-20,000 customers in each group. For example, all customers in billing group A received their bills on August 4, September 2, October 3, November 5, etc. The 3.4% of customers that did not fit into one of the 15 groups were billed at what appeared to be random dates and were dropped from our dataset.

Within each billing group, almost every treatment customer was mailed reports on the same dates. We define these dates as *predicted mailing dates* for each billing group. Customers in the control group were also given predicted mailing dates according to the billing group that they are in; these are the dates that they would have been mailed reports had they been in the treatment group.

However, some customers were sent reports on dates that did not match the rest of their billing group: 4.65% of customers had actual mailing dates that were different than the predicted mailing dates of their billing group. Because we do not know why these customers were taken out of their billing group and sent reports on different days, and therefore cannot determine which control customers should also be taken out of their billing group, in all analyses we preserve the observable billing group by using the predicted mailing dates rather

than actual mailing dates.

D.2 Specification and results

We used the following regression specification, which was estimated separately for each mailing m (so there were four regressions, for $m = 1,2,3,4$): [6]

$$kwh_{id} = \sum_{d=1}^{D} b_d^m D_d^m T_i + \sum_{d=1}^{D} a_d^m D_d^m + e_{it} \quad (0.1)$$

Where:

- i indicates each household;
- m indicates each mailing;
- d indicates each day after each mailing m;
- kwh_{id} indicates electricity use for household i on day d;
- D_d^m is an indicator variable for each day d after each mailing m;
- T_i is an indicator variable for households in the treatment group;
- b_d^m is the coefficient of interest: the estimated average treatment effect for each day d after each mailing m; and
- Standard errors are robust and clustered at the household level, within each regression, to account for correlation within customers across days.

Table D-1 displays the results; a graphical representation is in the main body of the report.

[6] Pre-treatment data was not available and thus we could not perform a difference-in-differences approach. Because this is a randomized controlled trial, we would expect that adding pre-treatment data for a difference-in-difference analysis would increase the precision but not affect the estimates of savings.

Table D-1. Savings estimates on each day after each report is mailed

	Days after Report 1 mailed kwh		Days after Report 2 mailed kwh		Days after Report 3 mailed kwh		Days after Report 4 mailed kwh	
1 days after	-0.1484*	(.0595)	-0.2910***	(.0657)	-0.3455***	(.0584)	-0.3144***	(.0521)
2 days after	-0.2193**	(.0709)	-0.2986**	(.0941)	-0.2823***	(.0704)	-0.3041***	(.052)
3 days after	-0.2405**	(.0796)	-0.2565*	(.1251)	-0.2896***	(.0697)	-0.2880***	(.0517)
4 days after	-0.1509*	(.067)	-0.3358***	(.0727)	-0.3653***	(.0574)	-0.2805***	(.0509)
5 days after	0.0682	(.136)	-0.3491***	(.0758)	-0.5134***	(.0994)	-0.6437*	(.2572)
6 days after	0.0101	(.1356)	-0.3208***	(.0747)	-0.4646***	(.0952)	-0.5050	(.278)
7 days after	-0.1097	(.0669)	-0.3570***	(.0653)	-0.3323***	(.0591)	-0.3458***	(.0537)
8 days after	-0.1505*	(.0673)	-0.3818***	(.0665)	-0.4000***	(.0587)	-0.3583***	(.0509)
9 days after	-0.2087**	(.0743)	-0.4127***	(.0878)	-0.3819***	(.0714)	-0.3293***	(.0512)
10 days after	-0.2391***	(.0653)	-0.3271**	(.1187)	-0.4312***	(.0718)	-0.3612***	(.0531)
11 days after	-0.2123***	(.0623)	-0.5030***	(.0823)	-0.3819***	(.0571)	-0.3579***	(.0527)
12 days after	-0.1002	(.1385)	-0.4403***	(.0819)	-0.5227***	(.101)	-0.4165	(.2292)
13 days after	-0.1913	(.1398)	-0.4508***	(.0752)	-0.5602***	(.0985)	-0.4254	(.2637)
14 days after	-0.3016***	(.0649)	-0.4212***	(.0641)	-0.3861***	(.0606)	-0.3962***	(.0514)
15 days after	-0.3462***	(.0659)	-0.3936***	(.0617)	-0.3913***	(.0571)	-0.3953***	(.0492)
16 days after	-0.3769***	(.0755)	-0.3566***	(.0896)	-0.3663***	(.0683)	-0.3287***	(.0502)
17 days after	-0.3913***	(.0841)	-0.3650**	(.1289)	-0.3124***	(.0667)	-0.3705***	(.0515)
18 days after	-0.3282***	(.0717)	-0.4490***	(.0729)	-0.3455***	(.0547)	-0.3376***	(.0528)
19 days after	-0.2655	(.1431)	-0.4470***	(.074)	-0.4497***	(.0932)	-0.3704	(.2553)
20 days after	-0.2361	(.1429)	-0.4435***	(.0724)	-0.4849***	(.0891)	-0.3893	(.2343)
21 days after	-0.4202***	(.0732)	-0.4144***	(.064)	-0.3959***	(.0571)	-0.3228***	(.0498)
22 days after	-0.3859***	(.0749)	-0.4219***	(.0642)	-0.3561***	(.055)	-0.3043***	(.0472)
23 days after	-0.4293***	(.0815)	-0.3416***	(.0951)	-0.3228***	(.0683)	-0.3149***	(.0488)
24 days after	-0.3688***	(.0733)	-0.3394*	(.1366)	-0.3351***	(.0671)	-0.3223***	(.0507)
25 days after					-0.3526***	(.0545)	-0.3270***	(.0521)
26 days after					-0.4194***	(.0947)	-0.4040	(.2424)
27 days after					-0.4445***	(.095)	-0.7441**	(.2698)
28 days after					-0.3737***	(.0578)	-0.2896***	(.0532)
29 days after					-0.3434***	(.056)	-0.3309***	(.0521)
30 days after					-0.3191***	(.0691)	-0.2867***	(.0486)
31 days after					-0.2819***	(.0693)	-0.3014***	(.0503)
32 days after					-0.3149***	(.055)	-0.3219***	(.0514)
33 days after					-0.3931***	(.0905)	-0.2581	(.2204)
34 days after					-0.3849***	(.0855)	-0.3182	(.2217)
35 days after					-0.3277***	(.0542)	-0.2987***	(.053)
36 days after					-0.3312***	(.0548)	-0.2810***	(.0495)
37 days after					-0.2949***	(.0734)	-0.2754***	(.0508)
38 days after					-0.3238***	(.0712)	-0.2714***	(.0495)
39 days after					-0.3644***	(.056)	-0.3170***	(.0525)

40 days after			-0.5006***	(.0971)	-0.9212*	(.3595)
41 days after			-0.4751***	(.0977)	-0.6955*	(.343)
42 days after			-0.3480***	(.0542)	-0.3107***	(.0566)
43 days after			-0.3434***	(.0537)	-0.3244***	(.0549)
44 days after			-0.2691***	(.0663)	-0.2675***	(.0552)
45 days after			-0.2600***	(.0628)	-0.2171***	(.0527)
46 days after			-0.3178***	(.0508)	-0.2818***	(.0561)
47 days after			-0.4052***	(.0886)	-0.6583*	(.328)
48 days after			-0.3775***	(.0909)	-0.5293	(.3607)
49 days after			-0.3577***	(.0569)	-0.2977***	(.0573)
50 days after			-0.3265***	(.0533)	-0.2680***	(.0536)
51 days after			-0.3322***	(.0656)	-0.3051***	(.0578)
52 days after			-0.3355***	(.0646)	-0.2602***	(.0555)
53 days after			-0.3520***	(.0531)	-0.2582***	(.052)
Day after Mailing FE	Yes	Yes	Yes		Yes	
R-squared	.0091704	.0017687	.003325		.0080698	
Number of Households	193064	193038	193040		192995	

Standard errors in parentheses
Note: SE clustered at household level for each regression
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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