SUPPORTING INFORMATION

Materials and Methods

We outfitted 118 family apartments with wireless energy metering technology at a residential housing community in Los Angeles. We measured electricity use data in real-time 24 hours a day at the appliance level. The randomized controlled trial was conducted from October 2011 to July 2012 and weekly treatment messages were sent to participants. The first group of apartments was given detailed energy use feedback along with information about monetary savings. The second group was given feedback with a health message about emissions and its air quality impacts such as childhood asthma. The third group served as a statistical control following a six-month baseline period and random assignment. Fig. S1 shows screen shots of the website shown to participants and Fig. S2 shows a time series of the community consumption. No financial transfers or monetary rewards were offered for participation.

Field Site. Our field experimental site, University Village, is a large residential community located in proximity to public transportation, local businesses, parks and schools. It is a multiple building, family apartment/condo-style housing complex with 1,102 units. The community spans two census block groups serviced by the Los Angeles Department of Water and Power (LADWP), the nation's largest public utility. Although the facilities are owned and operated by the University of California, the University does not subsidize living costs for the community and offers market-based rental rates. All utilities are paid by the tenant, including electricity. While apartments vary in size and layout, all units are furnished with a common set of appliances—a refrigerator, gas stove, dishwasher, and microwave oven. This allows for standardization in the housing capital stock. We monitor direct electricity usage in each of the participant households.

Treatment Messages. Information treatments received by households contain: (i) a neighbor comparison, which provides a reference point for their household consumption, and (ii) a stated impact of electricity use, either in terms of potential cost savings or public health externalities. The specific treatment messages are listed in Table S1. Neighbor comparisons are standardized in the following form: "Last week, you used ___% more/less electricity than your efficient neighbors" Neighbor comparisons in the energy conservation context have gained broad use in (i) small-scale lab or field studies, typically in applied social psychology, building-science and engineering, and (ii) utility-scale pilot projects, typically in economics and related fields. Impacts described were presented to households in numerical and scientifically verifiable terms. Unlike many lab studies where numerical impacts may be the subject of manipulation, we provided households with factual evidence-based numbers that depend on their weekly consumption. Equivalent cost savings were calculated using household-level consumption data and the published LADWP electric rate schedules for residential customers. Equivalent pounds of air pollutant emissions were calculated using emission factors from the Emissions & Generation Resource Integrated Database (eGRID) maintained by the U.S. EPA and based on LADWP electricity fuel mix. Treatment messages were also pre-tested in a series of questionnaires for clarity, comprehension and stated willingness-to-save energy with independent populations.

Participant Recruitment. Households were recruited to participate in the study. In order to prevent biases in recruitment selection, no direct environmental messaging was used. The recruitment process occurred within the context of several community events and information campaigns during the summer months prior to the start of the 2011-2012 academic year. To meet all Institutional Review Board (IRB) ethics requirements regarding research with human subjects, participation was strictly voluntary and no personally identifiable information (PII) was collected or shared. We conducted an enrollment survey to capture basic apartment demographics and occupancy characteristics for the community at-large, including households who opted in and those who opted out of the study. We recruited many more willing participants than there were active equipment allotments. Among the 1,102 households at University Village, 226 households volunteered to participate and another 88 households in our entry survey chose not to participate. This equals a participation rate of 20%. We randomly selected 118 participating households from these 226 volunteers. The participating households in our experiment represent 10.7% of the population at University Village. Household assignment into treatment and control groups was then randomized.

While households could at any point withdraw their consent to participate, no households dropped from the study for the entire duration of the experiment.

We tested for potential differences between the population of households at our field site and our sample of volunteer participants. We compared the monthly electricity meter readings of the entire population of University Village to those of our participants as well as other characteristics such as the size of the apartment, the number of occupants, the apartment floor and the location of the apartment in the complex. As shown in Table S2, there are no significant differences between participating and non-participating households. This analysis is based on electricity meter readings for 12 months prior to the start of the experiment.

Empirical Strategy. We modeled the household behavioral outcomes as a time series of electricity consumption before and after the start of information treatments. Our general empirical strategy consists of panel regressions of total and appliance-level electricity loads on a series of treatment group indicators and important statistical controls, namely, household and occupancy characteristics, a proxy for household environmental leaning and seasonal variables including weather and time trends. Table S7 lists descriptive statistics for all variables in this study. To estimate the treatment effects on the study population, we use an analytical approach by difference-in-differences (DD). We define "treatment" to mean weekly updating informational messages about household energy use defined previously. Treatments are exhaustive and mutually exclusive, meaning each household receives only one randomly assigned treatment. Once assigned, there is no crossover between treatments. A control group is also monitored alongside the treatment groups, but receives no information other than their standard utility bill.

Identification. In keeping with our identification strategy, we define treatment dummies denoting treatment *group* and event *time* status. Let $\widehat{T}_i$ be the binary *treatment group indicator*, equal to 1 if household is a member of treated group *i*, and 0 otherwise. Let P be the binary *post-treatment indicator*, equal to 1 after the start of information treatments (i.e., post-treatment period), and 0 during the baseline period (i.e., pre-treatment period). Let $\mathbb{E}[\cdot]$ denote the expectations operator. The behavioral response function y_j for household *j* is allowed to be heterogeneous at the household level. Conditioning on observables, we define the average treatment effect on the treated (ATET) as:

$$\tau^{DID} \equiv \left[\mathbb{E}[y_j \mid X, \widehat{T}_i = 1, P = 1] - \mathbb{E}[y_j \mid X, \widehat{T}_i = 0, P = 1] \right] \text{ (post-treatment period)}$$

$$- \left[\mathbb{E}[y_j \mid X, \widehat{T}_i = 1, P = 0] - \mathbb{E}[y_j \mid X, \widehat{T}_i = 0, P = 0] \right] \text{ (pre-treatment period)} \quad (1.1)$$

Treatment is identified when the group-time interaction $\{(\widehat{T}_i = 1) \times (P = 1)\}$ equals 1 over all feasible treatments $\{i = 1, 2\}$ (i.e., monetary savings or health). The ATET in Equation 1.1 is the population average difference in the *control group* $\widehat{T}_i = 0$ before and after treatment minus the population average difference in the *treated group* $\widehat{T}_i = 1$ before and after treatment. We condition on household level covariates, X. Any common unobservable characteristics are also captured in the control group.

Dependent Variable. Our dependent variable and behavioral response measure is the total kilowatt-hour (kWh) electric power consumption. A kilowatt-hour (kWh) is the most common unit of electricity used by electric utilities in commercial and residential billing. We aggregate real-time electricity measurements into hourly observations. Our total kWh signal for each household is further decomposed into one of six major appliance categories. By direct measurement, the appliance-level kWh consumption categories are: (i) lighting, (ii) heating and cooling, (iii) plug load, (iv) refrigerator, (v) dishwasher, and (vi) other kitchen (including the microwave and kitchen outlets). These six appliance categories make up the complete circuit breaker distribution for all electricity uses in the household. We note that this level of granularity in kWh measurement is unique to our installed metering technology and wireless sensor network. We normalize our dependent variable by dividing by the average post-treatment control group consumption, and multiplying by 100, allowing us to interpret our regression coefficients directly as percentages versus control group. We do not use logs as monotonic transformations of the hourly kWh measurements since appliance-level electricity loads in the range $[0, \mathrm{R}^{+})$ can frequently be equal or close to zero, for example, when the dishwasher or other appliance is off. For other examples of this normalization approach with electricity metering data, see (1). The distribution of dependent variables is shown in Table S3.

Independent Variables. The variables of interest are the treatment group indicators, observable household characteristics, and seasonal controls including weather and time trends. *Household occupancy* includes the number of adults (ranging from 0 to 3), and number of children (ranging from 0 to 4). *Apartment size* indicates the number of bedrooms in the unit, ranging from 1 to 3 bedrooms. *Building floor* captures apartment elevation, ranging from 1 to 3, where 1st floor indicates ground level. *Floor plan* captures differences in apartment layout, measured in nominal square footage. Because political leaning or ideology can significantly impact energy use attitudes and behaviors (2-4), we include statistical controls for household environmentalist ideology to account for the fact that greener participating households might have more proclivities toward conservation. To this end, *member environmental organization* is a proxy variable which captures a fixed measure of household environmentalist ideology or orientation. It is equal to 1 if the head of household reports being an active member of an environmental non-governmental organization (NGO), and 0 otherwise.

Seasonality and Time Trends. Electricity demand (in kWh per unit time) exhibits seasonal fluctuations and serial correlation that depends on outside factors such as time of day or weather. Modeling electricity loads with high time-resolution data requires special consideration of seasonality and time-varying characteristics on consumption, most notably, the effects of outside temperatures on hourly energy demand. Even with the milder climate in Los Angeles, heating and cooling hours capture significant seasonal variation on electricity consumption. We calculate heating and cooling degree hours, using quality-controlled local weather data from the Santa Monica Municipal Airport weather station, as maintained by the National Climatic Data Center (NCDC). Outside dry bulb temperatures were recorded hourly at the Santa Monica Municipal Airport weather station, located less than 1 mile from the study site. Archival access was provided by the National Oceanic and Atmospheric Administration (NOAA's) Quality Controlled Local Climatological Data (QCLCD), which contains hourly, daily and monthly summaries of outside weather conditions for the specific station. Mean degree-hours are a fundamental measure in building energy management that expresses the magnitude of expected heating or cooling load at a given location. Degree-hours capture seasonal heating or cooling requirements at a finer resolution than degree-days, making our hourly kWh observations compatible with outside weather variation. The weather vector is $\mathbf{\Psi}_t = [\Psi_t^H, \Psi_t^C]$ where:

$$\Psi_t^H = \max\left\{0,\ \sum_{h=1}^{24}\left(\theta_b - \theta_{out}\right)\right\} \quad \text{heating degree hours}$$

$$\Psi_t^C = \max\left\{0,\ \sum_{h=1}^{24}\left(\theta_{out} - \theta_b\right)\right\} \quad \text{cooling degree hours} \tag{1.2}$$

As shown in Equation 1.2, the larger the indoor heating or cooling requirement, the larger the distance between the measured mean hourly outside temperature θ_{out} and a given base temperature θ_b. By U.S. convention, the indoor base temperature θ_b is defined as 65˚F (18.3˚C) (5). When outside temperatures rise above the given indoor base temperature, cooling degree hours are strictly positive and heating degree hours are zero. Conversely, when outside temperatures fall below the base temperature, heating degree hours are strictly positive and cooling degree hours are zero. In this way, differential effects of heating and cooling load on electricity consumption are decomposed in a meaningful way over a 24-hour period. By rigorously specifying heating and cooling degree hours, we mitigate issues of seasonality and serial correlation in the disturbances of the regression model and address some methodological limitations previously identified in the literature (6).

Econometric Model. The basic econometric specification for household *j*, in treatment group *i*, at time *t*, is

$$E_{jit} = \alpha P_i + \tau(P_i \cdot T_i) + \mathbf{H}_j + \mathbf{\Psi}_t + \gamma_t + c + \varepsilon_{jt} \tag{1.3}$$

The dependent variable, E_{jit}, represents hourly panel observations of total and appliance-level electricity loads. Our main coefficient of interest, $\hat{\tau}$, indicates the *average treatment effect on the treated* and the coefficient $\hat{\alpha}$ indicates the *post-treatment on the population*. $\mathbf{H}_j$ is the vector of household covariates and Ψ_t is the weather vector. We include degree hours of the study period and day of the week time dummies to control for common time trends. Time dummies offer a convenient and robust control for community-wide effects. The regression constant is denoted by *c* and the residual error is captured in ε_{jt}. We mitigate the effects of serial correlation—a common source of estimation bias in difference-in-differences models (7) by fully specifying important seasonal weather variables on consumption and clustering the standard errors at the household level. Our standard errors are satisfactory due to a number of important design considerations. First, we have very high-resolution measurement, down to individual appliances, in which both make and model of all appliances have been standardized across the community. This provides for more precise behavioral estimates than are otherwise available in comparable studies with monthly residential billing data. Second, we control for the impact of seasonality and time-varying characteristics on consumption by use of degree hours, which offers a finer resolution controls for weather variability than typical approaches that use heating and cooling degree-days, or that have no weather controls at all (6). In addition to seasonal degree-hours, we also specify time dummies to capture common time trends (or cycles) in the data and any calendar shocks on consumption. We estimate treatment effects in Equation 1.3 conservatively by difference-in-differences using the standard feasible generalized least squares estimator (FGLS), $\hat{\beta}_{GLS} = (\mathbf{X}\hat{\Omega}^{-1}\mathbf{X})^{-1}\mathbf{X}'\hat{\Omega}^{-1}\mathbf{y}$ (8). We note that GLS panel estimation is feasible because the panel's time dimension is larger than the cross-sectional dimension of N households, a characteristic of our high time-resolution data set. In the next section, we also present alternative results and show robustness checks using OLS.

Baseline Characteristics. Table S10 shows descriptive statistics for both treated and control households during the 6-month baseline period. As shown in Table S10, the covariates and electricity consumption are reasonably balanced between treated and control households. In particular, the average electricity consumption is statistically indistinguishable between groups along with other important household fixed effects. The last column in Table S10 shows the results of a regression testing for significant differences between groups. As given by the F-test p-value of 0.2485, we reject a hypothesis of imbalance between groups. One exception is the variable representing membership of an environmental organization, which is significant at the 10 percent level. We note that households who report membership in an environmental organization represent a very minor share (~8%) of households in the study. In separate results, we computed the effect of belonging to an environmental organization as a proxy for green behavior. These results show no significant interaction with either treatment (results available from the authors upon request). This indicates that environmentalist households are not driving the study's main results.

Robustness checks. Table S11 shows the ATE specifications using OLS. Table S11 lists results of standard protocols with robust standard errors clustered at the household level, starting with a simple comparison between treatment and control groups and subsequently adding covariates. Column I shows a simple comparison between treatment and control groups in the post-period, without adjustment for the covariates. We obtain a -9.9% point estimate of the treatment effect in the health treatment group, and no significant conservation result in the cost savings group. We then add covariates to reduce standard errors. Specifications II to V present the estimates with covariates, which are robust to different configurations of fixed effects and controls. In Column V in Table S11, we include heating and cooling degree hours in addition to hourly fixed effects. As described above, degree hours capture both the magnitude and direction of heating and cooling loads on electricity consumption due to outside weather variation. We note that our use of degree-hour bins instead of hourly dummies leads to more conservative estimates of the treatment effects -8.2% treatment effect (Table S11, column V) versus -9.8% (Table S11, column IV). Here we confirm why usage of rigorous degree hours might be preferable to usage of time dummies alone.

We carefully considered the impact of a large effective sample size for this case given a fixed N and large T dimension across households. The issue of autocorrelation, cross-sectional correlation and finding appropriate controls has been in the household energy consumption literature for some time (9). As robustness checks on our estimates, we considered both a range of sampling intervals and clustering options in order to distinguish statistically trivial from substantively important treatment effects. First, we compared results based on different frequencies. Second, we evaluated some of the pitfalls of panel data analysis identified in Bertrand, Duflo, and Mullainathan (7), particularly autocorrelation variance estimation. Third, we implemented multi-way clustering as described by Cameron, Gelbach and Miller (10) and Thompson (11) to account for dependence in both group and time dimensions.

In order to check for the potential effects of large sample size on our estimates, Table S12 shows OLS estimates at various sampling frequencies. To do this, we re-sampled our electricity time series at monthly, weekly, daily, hourly, minute, and 30-second intervals. As expected, our clustered standard errors decrease as the sampling frequency increases, and we show that our ATE estimates are robust even at the lower-frequency sampling rate. While the precision of our estimates is improved by our panel's time dimension, we do not rely on high T to demonstrate statistical significance. As such, we differentiate statistically trivial from substantively important effects, particularly for the health group in which the ATE estimates range from 8-11%. We report the most conservative ATE estimates in this study.

Comments on External Validity. Our sample population consists of Los Angeles Department of Water and Power (LADWP) customers who pay their electricity bills. They are a California multi-family renter population with typical housing characteristics and demographics (age, income, household composition, per capita electricity usage, etc.). Our population has been described as one of five recognizable U.S. lifestyle consumers: young urban families –new baby, new car, smaller unit, newer appliances, fast food, frozen food, travel for commuting, shopping and visiting (12). Importantly, our participants are part of the information generation of consumers who regularly use Internet-based devices in their consumption habits.

Here we compare the housing characteristics of our multi-family renter community with broader populations. For example, 42.1% of housing units in Los Angeles County and 30.9% of housing units in California are in multi-unit housing structures, making the multi-unit housing communities meaningful to study (U.S. Census, 2014). More generally, there are 28.1 million multi-family housing units in the United States (Residential Energy Consumption Survey 2013, 2009 data) and 24.3 million of these housing units are renter occupied. According to data from the American Community Survey 2013, 52.7% of American housing units are renter-occupied. Among these renter-occupied households nationally, the average number of occupants was 2.84 persons, which falls very close to the average occupancy of 2.42 persons in our sample at University Village. We also note that 90% of all multi-family housing units in the United States are 1-, 2- and 3-bedroom units (Residential Energy Consumption Survey 2009), with the most common type being 2-bedrooms (there are 12.7 million 2-bedroom units in the U.S.). In our sample at University Village, all multi-family apartments are 1-,2- and 3-bedroom units, with 2-bedroom units being the most common type (N=101 households, 86% of all units in the study). In terms of square footage, the average size of multi-family homes in the U.S. (with 5 or more units) is 811 sq. ft. (Residential Energy Consumption Survey 2009). In our sample, the average sq. footage of multi-family homes at University Village is 835 (ranges from 595-1035 sq. ft.).

In terms of sample demographics, we also compared the age range of our sample participants to a broader population. For example, the median age in our sample of participants (heads of household) is 31 (ranges from 22 to 47); while the median age in California is 35.2 and in the U.S. is 37.2 (U.S. Census 2010). We note that persons aged 18 to 44, who are the most common age span of our sample participants, make up 38.7% of the entire population in California (14.4 MM people), and 36.5% of the U.S. population (112.8 MM people) based on Census data. In terms of their educational attainment status, our participants at University Village are more highly educated than the general U.S. population, having all received a bachelors degree or higher. We note however, that this is still a population of interest. Persons with a bachelor's degree or higher (age 25+) represent about 1/3 of the population: 29.5% of the population in Los Angeles county, 30.5% of the population in California and 31.7% of the population in the U.S. as a whole (U.S. Census 2010).

Our sample population is also a fast growing demographic in the. Between 2003 and 2013, there has been a 28% increase in the population of males seeking advanced degrees and 52.2% increase in females seeking advanced degrees. Thus, while educational attainment status represents about 1/3 of the population in the U.S., our sample participants who are seeking advanced degrees, are also a growing demographic.

Our final demographic variable we consider is family income. Because income disclosure was voluntary, we had very few respondents (N=46, or 38% of population) who provided family income information. Among those participants who chose to disclose the information: the median annual household income for University Village participants is $50,000 to $74,000 (ranging from under 25,000 to 100,000 or more). By comparison, the median household income in the U.S. was $51,017 in 2012 (US Census 2014), which places our sample participants in the middle range of income in the U.S. Because our self-reported income data is a biased sample due to nonresponse, we report the average household income for the two nearest Census block groups. The average income for University Village block group 1 is $51,182 (U.S. Census 2010) and the average income for University Village block group 2 is $61,467 (U.S. Census 2010), which also places our sample in the mid-range of earners in the U.S.

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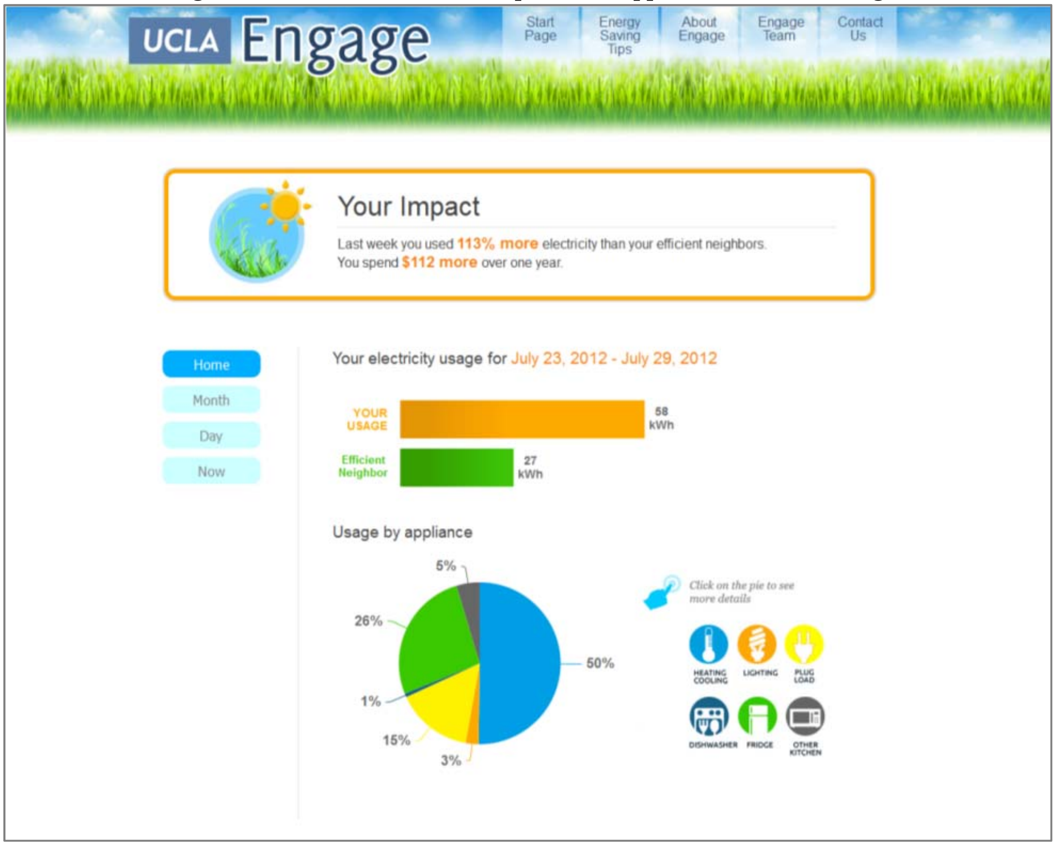
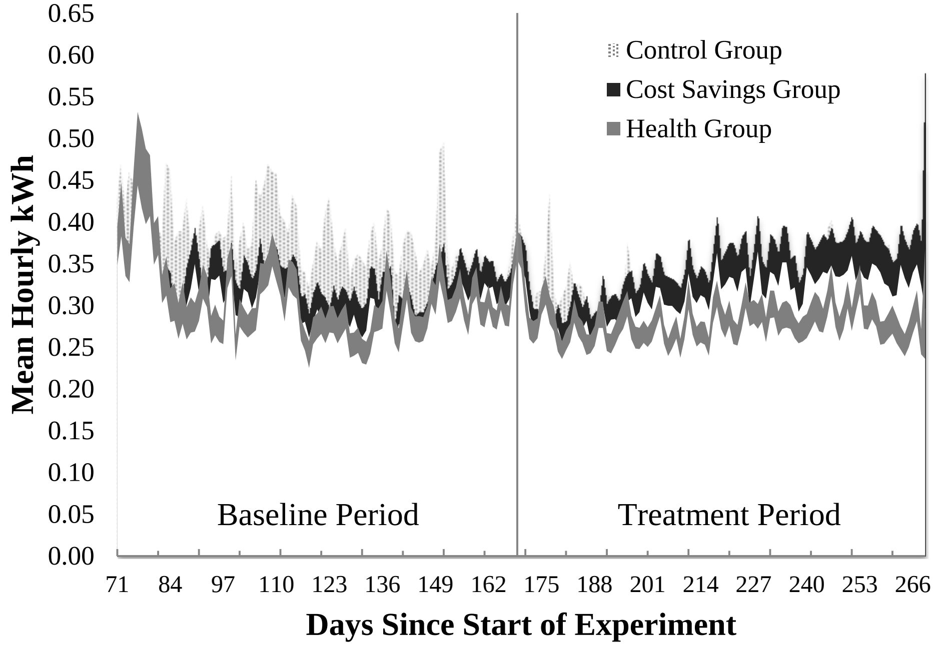
Fig. S1. Website Information Graphic with Appliance-Level Metering



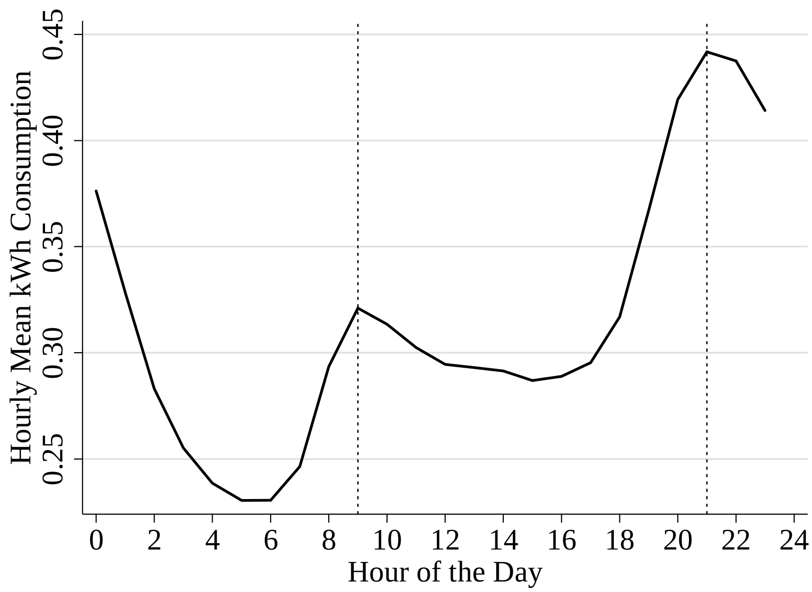
The weekly treatment message is highlighted in the rectangular box. Appliance-level feedback is shown as an interactive pie chart with clickable elements. Historical consumption information, including real-time feedback, is also accessible from the left pane of the website.

Fig. S2. Time Series of kWh Consumption by Group



During the baseline period, the mean hourly consumption is overlapping for all three groups. After treatment begins, the mean hourly consumption diverges for all three groups. Treatment effects are identified by difference-in-differences using a before-after-control-impact design.

Fig. S3. University Village Daily Load Profile



Peak daily consumption for the community occurs at 9:00am and 9:00pm

Table S1. Treatment Messages

Group	Treatment Message
Monetary Savings Group	"Last week, you used 66% more/less electricity than your efficient neighbors. In one year, this will cost you (you are saving) $34 dollars extra."*
Health Group	"Last week, you used 66% more/less electricity than your efficient neighbors. You are adding/avoiding 610 pounds of air pollutants which contribute to health impacts such as childhood asthma and cancer."*
Control Group	None.

* 'Efficient neighbors' in this context means households in the top 10^{th} percentile of household weekly average kWh consumption (households with the lowest electricity use) for similar size apartments in the community.

Table S2. Comparison of Participating versus Non-Participating Households at University Village (Meter Readings Data)

	Participating Households (S.D.)	**Non-Participating Households (S.D.)**	**Difference (S.D.)**	$Y_{in} - Y_{out}$ **(S.E.)**
Electricity Consumption [§]				
Average kWh per day	8.429	8.737	0.3070	-.0004
	(15.2)	(28.7)	(32.5)	(0.0004)
kWh per square foot	0.2007	0.2043	0.0036	.0833
	(0.339)	(0.479)	(0.587)	(0.198)
kWh per person	42.53	44.72	2.18	-0.0003
	(68.5)	(108.8)	(128.6)	(0.0009)
Square Footage	859.79	868.83	9.04	-0.0001
	(106.3)	(98.54)	(144.9)	(0.0002)
Number of bedrooms	1.97	1.97	-0.003	-0.0263
	(0.379)	(0.343)	(0.511)	(0.160)
Number of bathrooms	1.60	1.65	0.05	.0143
	(0.490)	(0.474)	(0.681)	(0.040)
Number of occupants	4.03	4.01	-0.02	-0.0107
	(0.566)	(0.512)	(0.763)	(0.126)
Building Floor	2.08	2.08	0.002	-0.0308
	(0.808)	(0.786)	(1.12)	(0.021)
Location in Complex	0.543	0.596	0.053	-0.041
(1 if Sawtelle, 0 if Sepulveda)	(0.498)	(0.491)	(0.699)	(0.040)
Number of Households	118	986	1,102	1,102
Number of Observations	5,533	46,184	51,718	51,718
F-test *p*-value	-	-	-	0.669

[§] Based on 12 months of independent electricity meter readings. Coefficients for kWh per square foot and kWh per person are based on independent regressions. No significant differences are found.

Table S3. Distributions of Dependent Variables (hourly kWh measurements)

Percentiles

Percentiles	Total	Heating Cooling	Lighting	Plug Load	Refrigerator	Dishwasher	Other Kitchen
1%	0.0044	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5%	0.0824	0.0007	0.0000	0.0075	0.0050	0.0000	0.0000
10%	0.1038	0.0029	0.0000	0.0160	0.0187	0.0000	0.0000
25%	0.1442	0.0083	0.0008	0.0337	0.0446	0.0000	0.0000
50%	0.2288	0.0156	0.0160	0.0616	0.0675	0.0000	0.0041
75%	0.4017	0.0239	0.0702	0.1197	0.0894	0.0060	0.0149
90%	0.6321	0.1807	0.1351	0.2200	0.1275	0.0134	0.0742
95%	0.8236	0.3704	0.1850	0.2941	0.1455	0.0487	0.1402
99%	1.3374	0.8098	0.3091	0.6311	0.1794	0.1167	0.3857
Mean	0.3157	0.0622	0.0471	0.1105	0.0701	0.0084	0.0277
Std. Dev.	0.2746	0.1622	0.0700	0.2739	0.0402	0.0297	0.1061
Observations	490,994	490,994	490,994	490,994	490,994	490,994	490,994

Table S4. Heterogeneous Treatment Effects on Families with Children

Study Variables	(1) Total kWh	(2) Total kWh	(3) Total kWh
Experimental			
Post-Treat*Monetary Savings Group	**3.785**	**1.688**	**3.771**
	(4.391)	(5.221)	(4.391)
Post-Treat*Health Group	**-8.215****	**-8.206****	**-1.419**
	(4.120)	(4.119)	(4.862)
Post-Treat*Monetary Savings Group*Children=1 or more		**7.831**	
		(11.32)	
Post-Treat*Health Group*Children=1 or more			**-19.07****
			(8.998)
Monetary Savings Group	1.853	1.531	2.478
	(7.814)	(7.722)	(7.844)
Health Group	-1.383	-1.542	-0.844
	(8.033)	(8.022)	(8.053)
Household Characteristics			
Adults	4.003	3.705	3.400
	(8.556)	(8.419)	(8.557)
Children (1 or more)	17.91**	16.63**	21.42***
	(7.494)	(6.923)	(7.780)
Apartment Size (No. of bedrooms)	33.01*	32.44*	32.03*
	(16.95)	(16.96)	(17.06)
Floor Plan (Nominal square footage)	-0.0109	-0.00983	-0.00852
	(0.0612)	(0.0610)	(0.0613)
Building Floor	9.854***	9.732***	9.265***
	(3.400)	(3.384)	(3.426)
Ideology			
Member Environmental Organization	-7.222	-7.464	-8.908
	(9.076)	(8.937)	(8.884)
Hourly Weather Controls			
Heating Degree Hours	0.284	0.286	0.281
	(0.255)	(0.254)	(0.255)
Cooling Degree Hours	-0.811***	-0.809***	-0.813***
	(0.186)	(0.186)	(0.186)
Time Dummies			
Day-by-Week	Yes	Yes	Yes
Constant	12.94	14.59	13.83
	(33.75)	(33.45)	(33.48)
Observations	490,994	490,994	490,994
Number of Apartments	118	118	118
R^2	0.0437	0.0451	0.0454

Robust standard errors clustered at the household level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table S5. Treatment Effects by Appliance

Study Variables	(4) Heating Cooling	(5) Lighting	(6) Plug Load	(7) Refrigerator	(8) Dishwasher	(9) Other Kitchen
Experimental						
Post-Treat*Monetary Savings Group	**5.331***	**-11.46*****	**0.414**	**8.844*****	**3.260**	**0.987**
	(2.779)	(4.274)	(2.395)	(2.153)	(3.918)	(3.056)
Post-Treat*Health Group	**-2.567**	**-9.011*****	**-4.719****	**8.673*****	**-3.790**	**-1.370**
	(2.554)	(2.324)	(2.152)	(1.981)	(2.471)	(4.454)
Monetary Savings Group	3.248	-20.61	-81.42	18.37*	-16.68	-38.79
	(3.189)	(17.73)	(51.13)	(9.372)	(24.42)	(25.29)
Health Group	6.370**	-19.32	-87.15*	15.41*	-37.06*	-37.81
	(3.129)	(14.29)	(48.52)	(9.161)	(22.20)	(24.93)
Household Characteristics						
Adults	-0.839	-6.284	-2.518	16.83*	-11.89	16.16
	(3.165)	(16.27)	(18.95)	(10.13)	(14.45)	(17.74)
Children (1 or more)	3.982	0.650	-22.42	11.11*	-4.389	-1.703
	(2.909)	(14.67)	(27.07)	(6.722)	(14.02)	(14.67)
Apartment Size (No. of bedrooms)	3.792	53.26	-80.41	40.39***	28.58	39.46
	(6.700)	(43.85)	(56.84)	(14.94)	(29.88)	(28.09)
Floor Plan (Nominal square footage)	0.00887	-0.0676	0.226	-0.102*	0.00103	-0.105
	(0.0232)	(0.0958)	(0.231)	(0.0547)	(0.102)	(0.0975)
Building Floor	1.661	-8.622	-5.106	13.81***	5.492	3.162
	(1.553)	(8.345)	(22.40)	(4.016)	(8.502)	(8.908)
Ideology						
Member Environmental Organization	-6.223**	-10.97	-0.228	-3.647	-14.51	3.426
	(2.742)	(9.532)	(16.15)	(11.24)	(15.75)	(17.68)
Weather Controls						
Heating and Cooling Degree Hours	Yes	No	No	Yes	No	No
Time Dummies						
Hour-by-Day, Day-by-Week	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-10.08	128.5***	169.5	50.52*	67.38	95.00
	(12.59)	(41.70)	(141.8)	(30.67)	(53.80)	(68.10)
Observations	490,994	490,994	490,994	490,994	490,994	490,994
Number of Apartments	118	118	118	118	118	118
R^2	0.0163	0.145	0.0316	0.0964	0.0159	0.0124

Robust standard errors clustered at the household level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table S6. Treatment Effects by Time of Day

Study Variables	(10) Midnight - 3:00am	(11) 3:00-6:00am	(12) 6:00-9:00am	(13) 9:00-12:00pm	(14) 12:00-3:00pm	(15) 3:00-6:00pm	(16) 6:00-9:00pm	(17) 9:00-Midnight
Experimental								
Post-Treat*Monetary Savings Group	**-6.919**	**-0.351**	**4.434**	**1.965**	**8.999***	**15.46*****	**20.22*****	**5.346**
	(4.960)	(4.890)	(5.241)	(5.953)	(4.865)	(5.215)	(6.024)	(6.099)
Post-Treat*Health Group	**-17.51*****	**-12.01****	**-11.43***	**-10.13***	**-1.689**	**6.665**	**5.027**	**-5.725**
	(4.328)	(5.048)	(6.131)	(6.110)	(4.132)	(4.354)	(5.028)	(4.871)
Monetary Savings Group	2.845	-5.393	-2.503	2.788	2.180	0.467	2.420	5.663
	(9.320)	(8.854)	(8.023)	(9.561)	(9.127)	(9.267)	(10.12)	(10.34)
Health Group	-1.928	-0.428	5.402	-2.706	-3.751	-4.329	-3.850	-5.858
	(9.900)	(9.620)	(9.740)	(9.513)	(8.211)	(8.317)	(9.220)	(10.18)
Household Characteristics	2.845	-5.393	-2.503	2.788	2.180	0.467	2.420	5.663
Adults	3.251	-8.546	-9.369	-0.283	7.129	12.16	15.51	13.51
	(9.976)	(9.802)	(10.04)	(10.83)	(10.06)	(10.59)	(12.69)	(9.828)
Children	14.38*	10.79	15.81**	24.16***	18.79**	18.75**	21.73**	18.74*
	(7.690)	(6.931)	(6.373)	(9.312)	(9.292)	(9.383)	(10.32)	(9.836)
Apartment Size (No. of bedrooms)	28.36	28.26	38.97**	34.30	24.86	22.91	36.21	49.94**
	(19.41)	(17.44)	(16.59)	(20.93)	(20.01)	(20.36)	(22.79)	(20.15)
Floor Plan (Nominal square footage)	-0.0352	-0.0410	-0.0402	-0.00901	0.0143	0.0236	0.0222	-0.0177
	(0.0689)	(0.0605)	(0.0561)	(0.0697)	(0.0694)	(0.0727)	(0.0816)	(0.0782)
Building Floor	9.115**	6.130*	11.25***	8.551**	7.538*	8.820**	12.79***	14.81***
	(3.737)	(3.533)	(3.462)	(4.260)	(3.927)	(4.259)	(4.840)	(4.358)
Ideology								
Member Environmental Organization	-7.491	-4.355	-7.588	-4.960	-4.180	-2.367	-10.66	-15.94
	(9.676)	(9.151)	(9.098)	(10.14)	(9.862)	(11.07)	(12.95)	(10.92)
Hourly Weather Controls								
Heating Degree Hours	0.800***	1.251***	0.746***	1.258***	0.188	0.119	0.765**	0.579
	(0.290)	(0.269)	(0.269)	(0.241)	(0.219)	(0.219)	(0.356)	(0.395)
Cooling Degree Hours	2.662	-5.304***	3.932***	-0.245	-0.157	0.517**	-0.591	0.180
	(4.208)	(1.936)	(0.764)	(0.181)	(0.189)	(0.260)	(0.681)	(1.294)
Time Dummies								
Day-by-Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	48.54	49.73	25.34	9.612	-5.217	-23.34	-39.93	-2.685
	(38.41)	(36.16)	(34.22)	(38.02)	(37.89)	(41.02)	(45.58)	(41.68)
Observations	60,942	60,433	61,206	61,543	61,402	61,581	61,891	61,996
Number of Apartments	118	118	118	118	118	118	118	118
R^2	0.0404	0.0521	0.0762	0.0616	0.0558	0.0542	0.0567	0.0630

Robust standard errors clustered at the household level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table S7. Means, Standard Deviations, and Correlations

		Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Total kWh (normalized)	103.11	89.71	0.0	3489.1	1.00											
Experimental																	
(2)	Health Group	0.37	0.48	0.0	1.0	-0.06*	1.00										
(3)	Monetary Savings Group	0.38	0.49	0.0	1.0	0.02*	-0.61*	1.00									
(4)	Control Group	0.24	0.43	0.0	1.0	0.04*	-0.44*	-0.45*	1.00								
Household Characteristics																	
(5)	Number of Adults	1.93	0.29	1.0	3.0	-0.01*	-0.18*	0.12*	0.07*	1.00							
(6)	Number of Children	0.52	0.81	0.0	4.0	0.14*	-0.04*	-0.08*	0.13*	-0.10*	1.00						
(7)	Apartment Size (beds)	1.97	0.38	1.0	3.0	0.15*	-0.14*	0.04*	0.12*	-0.09*	0.30*	1.00					
(8)	Floor Plan (Nominal sq.ft.)	862.3	104.49	595	1035	0.14*	-0.14*	0.05*	0.10*	0.06*	0.20*	0.83*	1.00				
(9)	Building Floor	2.07	0.81	1.0	3.0	0.08*	0.04*	-0.13*	0.10*	0.07*	-0.05*	0.03*	0.05*	1.00			
Ideology																	
(10)	Member Env. Organization	0.09	0.28	0.0	1.0	-0.02*	0.00	0.10*	-0.11*	-0.15*	-0.01*	0.02*	-0.03*	-0.05*	1.00		
Weather Controls																	
(11)	Heating Degree Hours	7.15	5.76	0.0	26.0	0.03*	-0.01*	-0.01*	0.02*	0.00	0.00*	0.00	0.00	-0.01	-0.01	1.00	
(12)	Cooling Degree Hours	0.6	1.94	0.0	26.0	-0.02*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.39*	1.00

N = 440,059 panel observations (118 apartments)
** p <.05*

Table S8. Quantile Regression Estimates

	Quantiles				
Study Variables	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Experimental					
Post-Treat*Monetary Savings Group	**3.835*** **	**2.597*** **	**2.006*** **	**-1.031**	**4.912*** **
	(0.153)	(0.174)	(0.382)	(0.801)	(1.587)
Post-Treat*Health Group	**1.907*** **	**-0.428** **	**-5.898*** **	**-13.98*** **	**-15.52*** **
	(0.170)	(0.175)	(0.339)	(0.632)	(1.200)
Monetary Savings Group	-2.551***	-2.980***	-5.655***	-2.029***	18.34***
	(0.112)	(0.159)	(0.331)	(0.667)	(1.212)
Health Group	-3.137***	-2.574***	-5.780***	-6.069***	7.288***
	(0.174)	(0.117)	(0.268)	(0.541)	(0.978)
Household Characteristics					
Adults	-0.908***	0.622***	-5.351***	-2.349***	10.28***
	(0.174)	(0.141)	(0.563)	(0.760)	(1.598)
Children	4.465***	8.248***	20.37***	26.86***	32.90***
	(0.0942)	(0.139)	(0.256)	(0.595)	(0.920)
Apartment Size (No. of Bedrooms)	6.211***	11.92***	27.41***	40.44***	36.51***
	(0.353)	(0.289)	(0.511)	(0.941)	(1.231)
Floor Plan (Nominal square footage)	0.00368***	0.00481***	-0.0121***	-0.00597*	0.0626***
	(0.00124)	(0.000914)	(0.00166)	(0.00337)	(0.00439)
Building Floor	3.760***	4.814***	6.871***	10.16***	14.93***
	(0.0810)	(0.0748)	(0.125)	(0.226)	(0.343)
Ideology					
Member Environmental Organization	0.850***	-1.488***	-0.260	-6.505***	-23.09***
	(0.135)	(0.155)	(0.377)	(0.469)	(1.182)
Hourly Weather Controls					
Heating Degree Hours	-0.0523***	-0.0566***	-0.0626***	0.687***	1.642***
	(0.00894)	(0.00895)	(0.0196)	(0.0473)	(0.0763)
Cooling Degree Hours	-0.252***	-0.380***	-0.823***	-1.129***	-0.580***
	(0.0287)	(0.0231)	(0.0507)	(0.116)	(0.223)
Time Dummies					
Day-by-Week	Yes	Yes	Yes	Yes	Yes
Constant	13.65***	9.360***	28.95***	31.59***	-4.360
	(0.687)	(0.521)	(1.369)	(2.381)	(4.052)
Observations	490,994	490,994	490,994	490,994	490,994
Number of Apartments	118	118	118	118	118
Pseudo R-squared	.0119	.0199	.0337	.0403	.0397

Quantile treatment effects with bootstrap standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table S9. Per Capita Residential Electricity Consumption

Region	2010 Population (in thousands)	Annualized kWh	kWh per capita
United States*	308,746	$3,749,985 \times 10^6$	12,146
California*	37,254	$250,384 \times 10^6$	6,721
LADWP*	1400	8017.65×10^6	5,726
University Village	0.518	2910.782	5,619

* Source: California Energy Commission data, 2010

Table S10. Comparison of Baseline Usage Characteristics
Between Treated and Control Households

	Control Group (S.D.)	**Treatment Group 1: (S.D.)**	**Treatment Group 2: (S.D.)**	**Difference Treat 1-Control (S.D.)**	**Difference Treat 2 - Control (S.D.)**	$Y_0^T - Y_0^C$ **(S.E.)**
Average kWh usage/Day	**8.660**	**7.543**	**7.457**	**-1.118**	**-1.204**	**-0.000377**
	(7.623)	(6.485)	(6.672)	(10.01)	(10.13)	(0.00195)
Apartment Size (bedrooms)	**2.043**	**1.980**	**1.914**	**-0.063**	**-0.128**	**-0.153**
	(0.394)	(0.339)	(0.358)	(0.520)	(0.532)	(0.205)
No. of Adults	**1.968**	**1.970**	**1.847**	**0.002**	**-0.122**	**-0.105**
	(0.175)	(0.271)	(0.360)	(0.322)	(0.401)	(0.106)
No. of Children	**0.653**	**0.425**	**0.480**	**-0.227**	**-0.172**	**-0.0562**
	(0.800)	(0.874)	(0.713)	(1.184)	(1.072)	(0.0572)
Floor Plan (Square Footage)	**877.66**	**867.17**	**846.04**	**-10.49**	**-31.62**	**0.000203**
	(97.451)	(97.019)	(108.761)	(137.51)	(146.03)	(0.000674)
Building Floor	**2.163**	**1.919**	**2.103**	**-0.244**	**-0.060**	**-0.0494**
	(0.861)	(0.813)	(0.760)	(1.184)	(1.148)	(0.0501)
Member Environmental Organization	**0.024**	**0.119**	**0.082**	**0.096**	**0.058**	**0.157***
	(0.152)	(0.324)	(0.274)	(0.358)	(0.313)	(0.0835)
Number of Observations	119,609	187,684	183,701	307,293	426,902	371,385
Number of Households	33	43	42	76	75	118
F-test *p*-value						0.2485

6 month baseline period (no electricity use feedback) *** p<0.01, ** p<0.05, * p<0.1

Table S11. ATE Specifications, OLS (Hourly Sampling)

	I	II	III	IV	V
	Total kWh	Total kWh	Total kWh	Total kWh	Total kWh
Post-Treat*Cost Savings Group	**5.210**	**3.917**	**3.915**	**3.822**	**5.297**
	(5.019)	(4.966)	(4.968)	(4.972)	(4.533)
Post-Treat*Health Group	**-9.958****	**-9.694****	**-9.682****	**-9.833****	**-8.192***
	(4.656)	(4.648)	(4.647)	(4.652)	(4.306)
Treat Cost Savings	-7.302	2.801	2.797	2.902	2.238
	(8.488)	(7.303)	(7.303)	(7.298)	(7.382)
Treat Health Group	-8.469	-0.157	-0.173	-0.035	-0.795
	(8.870)	(8.085)	(8.086)	(8.090)	(8.060)
Degree-hour bins	No	No	No	No	Yes
Apartment fixed effects	No	Yes	Yes	Yes	Yes
Day x Week time dummies	No	No	Yes	Yes	Yes
Hour x Day time dummies	No	No	No	Yes	No
Observations	490,994	490,994	490,994	490,994	490,994
R^2	0.005	0.043	0.044	0.094	0.044
F-statistic	2.549	3.627	9.117	27.480	8.985
Number of households	118	118	118	118	118

Robust standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1
Sampling frequency: hourly kilowatt-hour electricity consumption.

Table S12. ATE Estimates at Various Sampling Frequencies, OLS

	I	II	III	IV	V	VI
	Monthly	Weekly	Daily	Hourly	Minute	30 sec
Post-Treat*Cost Savings Group	**5.669**	**4.111**	**3.914**	**2.962**	**2.961**	**2.972**
	(4.808)	(4.696)	(4.720)	(4.455)	(4.455)	(4.471)
Post-Treat*Health Group	**-8.673***	**-9.131****	**-9.474****	**-10.54****	**-10.54****	**-10.58****
	(4.409)	(4.376)	(4.429)	(4.177)	(4.176)	(4.191)
Treat Cost Savings	-0.314	0.4611	0.580	0.994	0.994	0.998
	(7.377)	(7.478)	(7.499)	(7.542)	(7.542)	(7.569)
Treat Health Group	-2.431	-2.186	-1.991	-1.523	-1.523	-1.529
	(7.85)	(7.859)	(7.879)	(7.864)	(7.864)	(7.892)
Apartment fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Degree-hour bins	Yes	Yes	Yes	Yes	Yes	Yes
Day by Week time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	855	3,320	21,437	490,994	26,718,555	53,437,110
R^2	0.003	0.023	0.023	0.048	0.024	0.024
F-statistic	3.176	4.319	11.30	12.93	12.93	12.93
Number of households	118	118	118	118	118	118

Robust standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1