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# What can we learn from high-frequency appliance-level energy metering? Results from a field experiment

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## HIGHLIGHTS

- Hourly electricity usage was collected from 124 comparable apartments for 24 months.
- Households overestimate lighting use by 75% and underestimate HVAC usage by 29%.
- Households using the same appliances show substantial variations in electricity use.
- Plug load accounts for the largest share of electricity use at all hours of the day.
- Savings of 11% were achieved by replacing old refrigerators.

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## ABSTRACT

This study uses high-frequency appliance-level electricity consumption data for 124 apartments over 24 months to provide a better understanding of appliance-level electricity consumption behavior. We conduct our analysis in a standardized set of apartments with similar appliances, which allows us to identify behavioral differences in electricity use. The Results show that households' estimations of appliance-level consumption are inaccurate and that they overestimate lighting use by 75% and underestimate plug-load use by 29%. We find that similar households using the same major appliances exhibit substantial variation in appliance-level electricity consumption. For example, households in the 75th percentile of HVAC usage use over four times as much electricity as a user in the 25th percentile. Additionally, we show that behavior accounts for 25–58% of this variation. Lastly, we find that replacing the existing refrigerator with a more energy-efficient model leads to overall energy savings of approximately 11%. This is equivalent to results from behavioral interventions targeting all appliances but might not be as cost effective. Our findings have important implications for behavior-based energy conservation policies.



## 1. Introduction

### 1.1. Background

Electricity generation accounts for over 40% of the carbon dioxide emitted by the United States, with residential and commercial buildings collectively accounting for over two-thirds of total U.S. energy consumption (EIA, 2014; EPA, 2013). Recent studies estimate that behavioral changes can reduce residential energy consumption by about 7.4% (Delmas et al., 2013). Providing more detailed feedback to consumers about their energy usage at the appliance level can potentially encourage such behavioral changes (Ehrhardt-Martinez et al., 2010; Fischer, 2008; Neenan et al., 2009). However, currently, the majority of residents in the United States and around the world do not receive such feedback. Consumers' electricity bills report total consumption, rather than consumption by each appliance, and do not provide information about which appliances offer the consumer the highest potential for energy savings. Kempton and Layne (1994) analogize a household's electricity bill to getting a grocery-shopping receipt each month without knowing how much each good contributed to the total. The planned deployment of more than 65 million digital electricity meters by 2015 (Edison Foundation, 2012) will allow

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utilities to provide a wealth of new information to more than half of the nation's electricity accounts, unlocking new conservation potential (Armel et al., 2013). While this new information could help consumers make better decisions about their appliance use, little is known about energy consumption patterns by appliance and the behavioral component of appliance energy use.

In this paper, high-frequency appliance-level electricity consumption data was collected from 124 apartments over 24 months to answer the following questions: Are consumers cognizant of their electricity usage across different appliances? Are there important differences in the use of the same appliances across households and what is the behavioral component of appliance energy use? Which individual appliances are contributing to peak demand usage? How do the savings from installing new appliances compare with the savings from behavioral changes? The answers to these questions have important implications for the design of more effective policies to encourage energy conservation behavior.

### 1.2. Related work

There is a growing interest in reducing energy consumption and the associated greenhouse gas emissions in every sector of the economy. According to the International Energy Agency, the continuing demand for newer appliances with improved functionality and more power is leading to an increase in electricity consumption even though appliances are becoming more energy efficient.[1] This increase in energy consumption warrants a detailed understanding of the residential sector's consumption characteristics to prepare for and help guide the sector's energy consumption.

Studies of the effect of different types of energy feedback on energy savings indicate that information on real-time appliance-level energy consumption data has the potential to empower consumers to effectively manage their household energy consumption and encourage conservation (Delmas and Lessem, 2014; Ehrhardt-Martinez et al., 2010; Neenan et al., 2009).

The current study goes beyond previous work analyzing appliance-level consumption in five ways. First, scholars have argued that households are unaware of how much electricity is used by specific appliances and the potential for energy savings from each appliance (Attari et al., 2010). However, so far, the evidence presented is mostly based on surveys and expert recommendations – not on observed household electricity usage. This study compares each household's actual electricity usage with the estimated usage they stated at the beginning of the study. This allows us to precisely evaluate households' knowledge of energy use for each appliance.

Second, studies that have shown variation in usage across households focus on total usage or on usage in a particular subset of appliances. For example, Lutzenhiser (1993) notes that even in energy consumption studies that use nearly identical units, electricity usage can vary as much as 200–300% but did not differentiate among appliances. Other appliance studies include the research by Wood and Newborough (2003), who focused mainly on cooking appliances, Coleman et al. (2012), Rosen and Meier (1999, 2000), and Rosen et al. (2001), who focused on entertainment appliances, and Isaacs et al. (2010), who studied space heating. In contrast, our study includes a broad set of appliances and end uses that are found in most homes. We also use a study site that consists of apartments with little variation in design and identical major appliances, something that most previous studies were unable to provide (Parker, 2003; Pratt et al., 1993). Additionally, since all the apartments are in the same complex, our results are not affected by variations in weather (Hart and de Dear, 2004).

Third, recent studies by de Almeida et al. (2011) and Saldanha and Beausoleil-Morrison (2012) highlight the growing share of non-HVAC sources in electricity consumption. However, neither study was conducted in the United States and both had other shortcomings: de Almeida et al. (2011) had a small sample size and Saldanha and Beausoleil-Morrison (2012) used a non-standard set of appliances across countries. Using a large sample size with a common set of appliances across households, this study assesses lighting and plug load usage during peak demand hours and compares electricity usages for appliances throughout the day.

Fourth, previous studies have attempted to estimate the variation in appliance usage across household types (Bladh and Krantz, 2008; Pratt et al., 1993); however, they were unable to do this for a standardized set of major appliances. The study site used here allows an identical set of major appliances to be compared across households in apartments with little variation in design. Finally, this is the first study that uses real-world observations to estimate energy savings from the installation of a new appliance; previous research relied on simulation techniques to estimate energy savings (de Almeida et al., 2011).

## 2. Methods

### 2.1. Field site

The field experiment site, University Village, is an apartment complex for graduate student families. It comprises two sites with 1102 one-, two-, and three-bedroom rental apartment units. Of these, 124 apartments were occupied by residents who agreed to participate in our experiment, also known as the ENGAGE project, and were equipped with an electricity metering system that allows electricity usage to be recorded in real time. During the study period, some participants moved out of the apartment complex and the new occupants of their apartments agreed to participate in the ENGAGE study. This led to a sample of 137 unique households. Each apartment is equipped with heating and cooling systems and a full kitchen including a refrigerator, microwave, stove, dishwasher, and garbage disposal. Except for variations in size and floor plan, apartments are standardized with the same major appliances and amenities.[2] This consistency ensures that variation in electricity usage results from household behaviors and lifestyles, not differences in apartment or appliance features. Furthermore, circuits in University Village are fairly standardized with only minor variations which allowed for a hardware installation kit that would accommodate all of the circuit breaker panels without any hardware reconfiguration.

The electricity usage in the ENGAGE sample is comparable to similar households across California based on information from a nationally representative survey of the share of household electricity usage by appliance. Electricity usage for the current sample was compared with data from the 2009 Residential Energy Consumption Survey (RECS) administered by the United States Energy Information Administration (EIA). To ensure that the comparisons are meaningful, the RECS data was reduced to a subset of households that were similar to households in this study.[3] Since the

[1] https://www.iea.org/Textbase/npsum/Gigawatts2009SUM.pdf. Accessed October 29, 2014.

[2] University Village apartments are rented with the following appliances: refrigerator, dishwasher, lights, microwave, and heating and cooling. We could not control for additional appliances installed by the participants. These could include appliances such as toasters, rice cookers, fans, space heaters, humidifiers/dehumidifiers, etc. Variations in these types of appliances will lead to differences in the other kitchen and plug load categories across households.

[3] The sample includes California households that lived in apartment complexes with more than five units, are renters, have a bachelor's degree or higher, have two

**Table 1**
Shares of total electricity usage.

| ENGAGE | | | RECS | | | |
|---|---|---|---|---|---|---|
| Variable | Mean | S.D | Variable | Mean | S.D | *p*-Value |
| Heating/cooling | 18.14 | 10.90 | Heating/cooling | 18.83 | 16.08 | 0.61 |
| Refrigerator | 24.93 | 10.50 | Refrigerator | 18.25 | 7.26 | 0.00 |
| Lighting | 14.45 | 9.43 | All other[a] | 62.91 | 14.92 | 0.00 |
| Plug load | 30.90 | 12.90 | | | | |
| Dishwasher | 2.72 | 2.28 | | | | |
| Other kitchen | 8.86 | 6.76 | | | | |

*Notes*: The average share for each appliance in the ENGAGE sample was calculated by finding the daily share of electricity for each appliance for each household in the sample. These daily shares were then averaged for each household providing a total of 137 averages for each end use. The shares for the RECS dataset are based on the frequency weighted totals that were provided in the 2009 RECS dataset for the subset of respondents that are described in footnote 3.

[a] This category is compared to the sum of lighting, plug load, dishwasher, and other kitchen in the ENGAGE dataset.

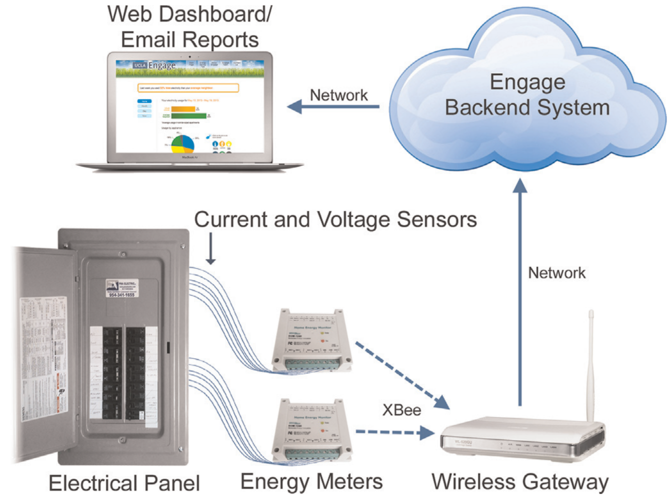


**Fig. 1.** Engage system.

RECS does not provide the same level of granularity as the data collected here, only heating and cooling, refrigerator, and "all other" categories can be compared. The average shares of electricity for each appliance in the sample and the corresponding share based on the RECS data are shown in Table 1. In the ENGAGE sample, heating and cooling accounts for 18.14% of total electricity usage and the refrigerator accounts for 24.93%. According to the RECS data, California residents use 18.83% of total electricity for heating and cooling and 18.25% for the refrigerator. A *t*-test shows that the ENGAGE sample is similar to the RECS sample of California households with respect to the share of electricity used by HVAC. A *t*-test rejects the hypothesis that the ENGAGE sample is similar to the RECS sample of California households with respect to the refrigerator and "other" categories. While the shares of electricity between these two samples are statistically different, the differences are quite small (6–7 percentage points).

To compare the total monthly electricity usage of the ENGAGE sample to a larger California population, we used data from the California Energy Commission Residential Appliance Saturation Study (RASS) that estimated energy consumption for 27 electricity end uses in 2009.[4] According to this survey, the average California household living in a multi-family apartment complex with more than five units consumes 309 kWh of electricity per month. The average household in the current sample uses 230 kWh per month, about 25% less than the California average. This lower consumption is not surprising since the University Village apartment units were built more recently (1994) than most California units.

The electricity usage of the ENGAGE sample of 137 volunteer households was compared to the rest of University Village to see how representative the self-selected sample is of the larger apartment community. Since there is a concern that households who agreed to participate in the energy study are systematically different than those who did not agree to participate, we compared the electricity usage for those participating in the study with all of the other households at the study site using data from the outdoor electricity meters. The average daily usage for the self-selected units is 7.90 kWh and the daily average for the rest of University Village is 8.71 kWh. A *t*-test for the difference in averages for the study sample compared to the rest of the households fails to reject the hypothesis that the averages are the same with a *p*-value of 0.18. This shows that the study sample is similar with respect to electricity usage to other households at the experimental site who chose not to participate in the study.[5]

### *2.2. System design and dashboard*

Since the original metering system at University Village did not provide detailed information about electricity usage, an end-to-end system architecture was designed to measure real-time, appliance-level data and provide feedback to households. Appliance-level electricity usage was measured at the circuit breaker panel in each apartment, through which power is fed to various loads. By measuring the current and voltage on each circuit, it was possible to compute energy consumption for each circuit (lights, HVAC, plug load, lighting, dishwasher, refrigerator, other kitchen).[6] These measurements were made using a commercial energy metering device that was installed inside the electrical panel. The meter transmitted data wirelessly to a gateway device, located elsewhere inside the apartment, which performed further data processing and then transmitted the data to the ENGAGE server. The elements of the ENGAGE energy metering system are displayed in Fig. 1 and described next.

#### *2.2.1. Electrical system*

University Village uses a 208/120 V 3-phase electrical service. Each apartment receives two legs of this system, which will be referred to as phase A and phase B. Each apartment at University Village has its own electrical panel through which power is routed to various loads. Many of these loads are powered by dedicated circuits. For example, recessed lights in the kitchen and bathrooms are powered by dedicated lighting circuits. Thus, it is convenient to measure electricity consumption from an electrical panel and with high granularity. However, all wall outlets for the apartments are fed by one or two circuits so it is not possible to isolate power consumption for plug-in devices.

(*footnote continued*)
to five occupants living in the apartment, and are in apartments that range from 595 to 1035 square feet.

[4] Website: http://www.energy.ca.gov/appliances/rass/. Accessed May 30, 2014.

[5] Detailed electricity usage and apartment and household characteristics could not be collected from those that did not participate in the experiment. Because of this limitation, we are unable to make detailed comparisons between the self-selected sample and the rest of University Village.

[6] Plug load included all appliance plugged into the wall such as TV, computer, etc. Other kitchen included microwave, sink garbage disposal, and appliances plugged in the kitchen such as toaster or rice cooker.

Electrical circuits in University Village are fairly standardized with only minor variations. For example, the heating and cooling system is usually powered by four circuits but sometimes three circuits, the refrigerator and microwave are always each on dedicated circuits, etc. This allowed us to design and install a hardware installation kit that would accommodate all of the circuit breaker panels without any hardware reconfiguration. Although circuit types were fairly consistent (since refrigerator, HVAC, dishwasher, etc. were standard across apartments), there was a lack of consistency in circuit configurations. For example, the refrigerator might be the first circuit on phase A in one apartment while it might be the fifth circuit on phase B in a different apartment. It was therefore necessary to record each circuit's configuration and store it in the database for use in appliance load calculations. Data processing is described in the Appendix.

### 2.2.2. Hardware

The hardware consists of energy meters for measuring energy consumption and a wireless gateway for data transfer to our backend system. We used a commercial energy metering device which provides sensor inputs for measuring up to seven circuits individually. Two meters were used to fully instrument the electrical panel because the buildings use a two-phase electrical service and the meters are designed only for single-phase measurement. The energy meter uses personal area network (PAN) radios (called XBee radios) to enable wireless communication between the energy meters and the gateway. The gateway is an Asus 520-gU wireless router which was modified to interface with an XBee radio on its serial port for communicating with the energy meters. The gateway uses a customized OpenWRT operating system with library support for features like USB flash memory and time-based job scheduling utilities. Additional software modules were developed to enable data processing and data transfer, as well as to support remote device management.

### 2.2.3. Software

On the gateway, a software program (known as a daemon) was developed to manage reading and local processing of the meter data as well as uploading data to the server. The program is executed via a boot script to enable automatic recovery in the event of a hard reset. A status program is also executed periodically using a job scheduling utility to ensure that the daemon process is running. If a fault is detected, the status check program issues a kill signal or the process may be killed forcefully, after which the daemon is restarted. The daemon is also responsible for ensuring reliable upload in the event of a network failure, server processing delay, or server crash.

Due to the distributed and remote nature of energy monitoring, software for the gateways and server was designed to facilitate system management. Data reliability is critical given the time and cost of deployment and it is necessary to detect failures and respond as quickly as possible. Since the gateways are installed as clients on the residents' own routers and sit behind a network address translation (NAT) wall, they are not directly accessible. To circumvent this limitation, a virtual private network (VPN) was set up to allow remote access to the gateways from the ENGAGE server. Like the processing daemon, a VPN client on the gateway is executed using a boot script and a status check script ensures that the VPN connection is maintained.

Using the VPN, the server may be programmed to perform any number of status checks remotely. As with any software development, bugs can be discovered even after release; the gateway software was no different. A script was developed to use the VPN IP addresses of the gateways to remotely check the version of the processing daemon and update to the latest version if a MD5 checksum mismatch was detected.

System status could also be determined by analyzing the data upload history and an administrative dashboard was developed to provide these analytics. This included a summary of hourly sample counts for each apartment as well as VPN IP address and all hardware ID numbers to facilitate debugging and repair. These administrative tools were essential for effective system management given the size of the deployment.

### 2.2.4. Dashboard

Information feedback was implemented using individualized web dashboards and weekly email reports. The dashboard was designed to inform the residents about various aspects of their energy consumption using different graphical elements and provided them tips on how to reduce their energy consumption. Weekly summaries of total energy usage and appliance-level energy breakdowns with comparison to a reference group were provided. Daily total energy for the past four weeks, hourly total energy for the past day, and real-time total power consumption were also provided. This information is structured hierarchically such that the weekly summary is the top-level information and the other information is easily accessible for users who wish to drill down and learn more. Each graphical element also provides some level of interactivity so that users can get more details if they wish. The weekly email report provides the same weekly summary as the dashboard and also serves as a reminder to the residents about their participation in the study and about accessing the dashboard.

## 2.3. Data

Hourly electricity usage data was collected from January 1, 2012 to December 31, 2013 from 124 apartments that accounts for 137 unique households.[7] Energy data for each monitored end use was recorded along with basic demographic information so that differences in usage caused by variation in household characteristics could be accounted for. Summary statistics for each monitored end use and demographics are shown in Table 2. The average head of household is 31 years old, approximately 36% of households have children, and 9% of the households had someone who was a member of an environmental organization. The average apartment is 863 square feet, 61% of the apartments have two bedrooms, 75% of the apartments are on the second or third floor, and about 57% face south.[8] The average household used 7.58 kWh of electricity per day with the majority of this coming from HVAC (1.77 kWh), plug load (2.42 kWh), and the refrigerator (1.43 kWh). The data shows that a user in the 75th percentile uses nearly twice as much electricity as a user in the 25th percentile. Variation in each end use is discussed in the next section.

[7] This time period was chosen so that there would be a sufficient amount of time to determine each household's electricity consumption behavior and also to allow for variation in temperature that will affect how a household uses particular appliances. While this paper does not discuss the results from the information strategies that were used in the ENGAGE project, it is important to mention that during this time period some participants were part of a treatment that did lead to changes in their electricity usage. Results from the time period used in this study were compared to those that use data that was collected before any treatments were used and no significant differences were found. Because of turnover in the apartments, two full years of data were not collected for everyone who participated in the study.

[8] To avoid problems with multicollinearity, the number of bedrooms is not included in the regressions that follow. All one-bedroom apartments are 595 square feet and all 3 bedrooms are 1035 square feet.

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**Table 2**
Summary statistics for electricity usage and household characteristics.

| Variable | Mean | Std. Dev. | Min | Max | 25th | 75th |
|---|---|---|---|---|---|---|
| *Average daily electricity usage* | | | | | | |
| Total | 7.58 | 5.80 | 0 | 91.96 | 4.98 | 9.11 |
| Heating/cooling | 1.77 | 2.91 | 0 | 29.97 | 0.61 | 2.54 |
| Lighting | 1.10 | 1.67 | 0 | 31.18 | 0.53 | 1.24 |
| Plug load | 2.42 | 3.48 | 0 | 82.59 | 1.20 | 2.68 |
| Refrigerator | 1.43 | 0.76 | 0 | 4.79 | 1.12 | 1.88 |
| Dishwasher | 0.20 | 0.30 | 0 | 2.57 | 0.07 | 0.24 |
| Other kitchen | 0.66 | 1.03 | 0 | 22.66 | 0.30 | 0.77 |
| *Apartment characteristics & demographics* | | | | | | |
| Age | 31.09 | 4.28 | 20 | 47 | | |
| Has children | 0.36 | 0.48 | 0 | 1 | | |
| Total occupants | 2.47 | 0.80 | 2 | 6 | | |
| Member of NGO | 0.09 | 0.28 | 0 | 1 | | |
| SquFt | 862.77 | 103.44 | 595 | 1035 | | |
| Two bedrooms | 0.61 | 0.49 | 0 | 1 | | |
| Second floor | 0.36 | 0.48 | 0 | 1 | | |
| Third floor | 0.39 | 0.49 | 0 | 1 | | |
| South facing | 0.57 | 0.50 | 0 | 1 | | |

*Notes*: Average electricity usage is for all households for the entire two years data was collected. Demographic data is for the 137 households that are included in the sample.

**Table 3**
Comparison of actual and predicted shares of electricity usage.

| Category | Estimated | Actual | Correct | Correlation | $R^2$ |
|---|---|---|---|---|---|
| Heating/cooling | 26.72 | 18.14 | 6 | 0.39 | 0.152 |
| Plug load | 48.03 | 67.42 | 2 | 0.03 | 0.001 |
| Lighting | 25.25 | 14.45 | 6 | −0.01 | 0.000 |

*Notes*: The actual shares are slightly different than the shares in Table 1 because not all participants responded to the question concerning their estimated electricity usage. Of the 137 households in the sample, 132 responded to this question. A correct guess means the household's estimated share electricity consumption fell within the 95% confidence interval based on their actual shares of electricity consumption. The $R^2$ value is from a regression of the actual share of electricity on the predicted share that was stated in the survey administered at the beginning of the study.

## 3. Results

### 3.1. Predicted vs. actual electricity usage

Households need to know how much electricity is being used for specific end uses in order to take effective steps toward reducing their electricity usage (Fischer, 2008). To test this knowledge, we compared each household's own electricity usage estimate with their actual measured appliance usage for three major categories. Each household's estimate was reveled through a survey conducted at the beginning of the study. The question on the survey asked, "What percentage of your apartment's electricity usage do you anticipate coming from the following sources?" The three sources listed were overhead lighting, heating and cooling, and items plugged into electric outlets (TV, laptop, refrigerator, etc.). For each household in the sample, the daily share of electricity used for each of these three categories was calculated using their actual electricity usage. These values were then averaged and a 95% confidence interval was constructed for each household. If the estimated share fell within the 95% confidence interval, the household was credited for correctly estimating the share of electricity in that category. The actual versus predicted electricity usage is summarized in Table 3 and shows that very few households correctly estimated appliance usage. Of the 132 households in the sample that completed this question, only six correctly estimated the share of HVAC, six correctly estimated the share of lighting, and two correctly estimated the share of electricity used by items plugged into electrical outlets. More importantly, no household estimated more than one category correctly.

Columns 2 and 3 of Table 3 show that the typical household overestimated the share of electricity used by lighting and HVAC and underestimated the share used by plug-in devices. The fifth column of Table 3 shows the correlation between the actual and estimated shares for each category. For lighting and plug load, estimated and actual electricity usage are uncorrelated ($p$-values of 0.94 and 0.72, respectively). For HVAC, there is a positive and statistically significant correlation between actual and predicted usage even though the observed values are much different than each household predicted. This result, which is consistent with Attari et al. (2010), reinforces the point that households are unaware of the distribution of electricity usage across these common categories.

### 3.2. Variation in usage by appliance

We were able to assess differences in electricity usage by appliance due to differences in behavior across households because all the major appliances at the study site are standardized (i.e., each apartment has the same appliances) and the characteristics of each apartment are known. Indeed, household characteristics such as work schedules and environmental consciousness could influence how much electricity is consumed for specific appliances. The distribution of average daily electricity usage for each of the 137 households in the sample for each metered end use is shown in Fig. 2. The data reveals important differences in usage by appliance. Interestingly, the distribution for refrigerator usage is approximately normal while all of the other end uses are positively skewed. The lower skewness in refrigerator electricity usage can be explained by the fact that once the refrigerator is plugged in, there are few behavioral actions a household can take that will lead to drastic changes in electricity usage (Ueno et al., 2006; Wood and Newborough, 2003). Each of the other end uses depends heavily on the household's behavior (how often they are home, how many children are in the apartment, etc.) and can reflect preferences for each end use. The last two columns of Table 2 compared the 25th and 75th percentiles for each appliance and reported large differences. To understand whether such large variations in energy usage were primarily driven by the differences in household characteristics, we examined the sample of households that live in two-bedroom apartments and have children. While the results are not shown here, they are very similar with differences in electricity usage from 200% to 300% still found for dishwasher and heating and cooling, respectively. These large differences are discussed next.

Results from three separate regressions that determine the driving factors behind the large differences in electricity usage are shown in Table 4. The first specification attempts to explain the variation in electricity usage using only observable apartment characteristics. As shown in Table 4a, observable characteristics explain only 6–16% of the variation in electricity usage across households. The next specification provided in Table 4b adds observable household demographics but these do not add explanatory power with little change to the $R^2$. This suggests that the main drivers in variation in electricity usage across households are unobservable apartment and household characteristics. To test this hypothesis, the last specification, provided in Table 4c, includes household fixed effects to control for unobservable time-invariant apartment and household characteristics. In this specification, the unobservable apartment and household characteristics explain an additional 25–58% of the variation in electricity usage across households. The largest increase are for lighting and dishwasher usage; two end uses that have a large behavioral component. These results highlight the importance of accounting for

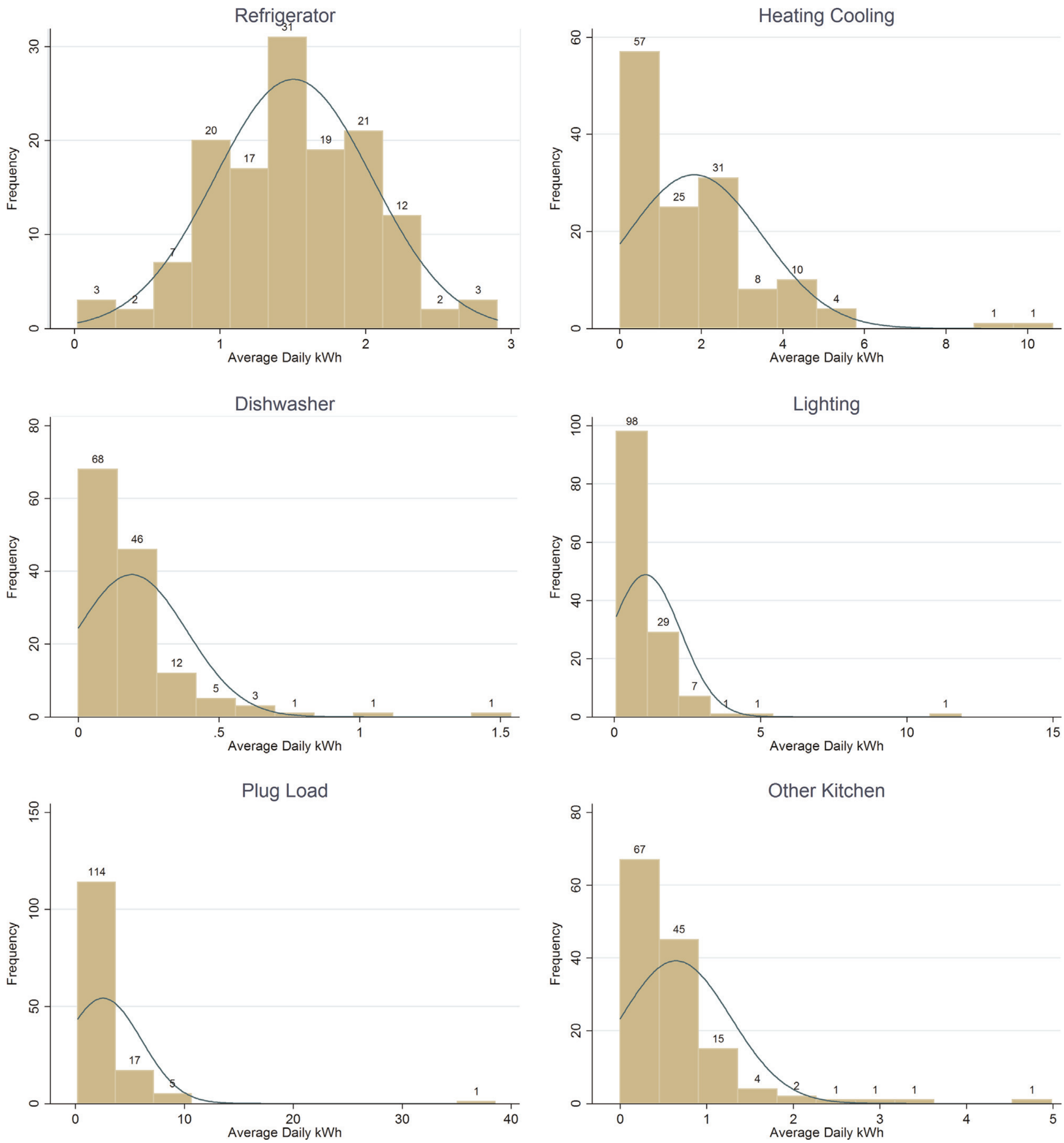


**Fig. 2.** Distributions of daily average electricity usage.

behavioral differences when comparing electricity usage across households in similar housing units.

### 3.3. Time- and appliance-specific usage

Knowing how much electricity is being used for each end use is important, but time-specific usage is also critical for utilities designing grid management systems. The data generated in this study allows for the determination of peak demand hours to identify which appliances are the largest contributors to peak usage. Variations in electricity usage and temperature by season are presented in Fig. 3. As expected, electricity usage varies throughout the day with household's schedule, and usage varies by season due to changes in the weather (Hart and de Dear, 2004). Total electricity usage is consistent in the early morning hours across the four seasons with noticeable differences after 10 a.m. for the winter and summer months. This is largely driven by increased HVAC usage in the summer months after 10 a.m.[9]

Total electricity usage peaks around 9 a.m. and 9 p.m. and is at its lowest around 6 a.m. and 6 p.m. in every season.[10] The shares of

[9] Each of the other end uses were plotted by season and showed little variation. Plug load was slightly higher in the winter, which may indicate that residents were using space heaters instead of HVAC for heating.

[10] These peak times are slightly different than those reported for similar areas in California in Herter et al. (2007) which show electricity usage peaking around 8:00 a.m. and 9:00 p.m. and at its minimums around 5 a.m. and 3 p.m. These small differences in critical times are likely due to the schedules of graduate students

**Table 4a**
Regression results for total and appliance specific electricity usage observable apartment characteristics.

| Variables | (1) Total (sum) | (2) HVAC | (3) Lighting | (4) Plug load | (5) Fridge | (6) Dishwasher | (7) Kitchen |
|---|---|---|---|---|---|---|---|
| SquFt | 0.00993*** | 0.00250** | 0.00287* | 0.00332 | 0.000316 | 0.000240* | 0.000687 |
| | (0.00328) | (0.000997) | (0.00162) | (0.00221) | (0.000332) | (0.000134) | (0.000566) |
| Second floor | 0.186 | 0.491 | −0.601 | 0.234 | 0.102 | −0.0420 | 0.00204 |
| | (0.906) | (0.330) | (0.517) | (0.442) | (0.124) | (0.0389) | (0.124) |
| Third floor | 0.662 | 0.339 | −0.617 | 0.499 | 0.215* | 0.0163 | 0.209 |
| | (0.840) | (0.288) | (0.453) | (0.463) | (0.124) | (0.0614) | (0.190) |
| South facing | −0.448 | −0.196 | 0.330 | −0.323 | −0.00898 | −0.101* | −0.149 |
| | (0.660) | (0.265) | (0.277) | (0.362) | (0.0913) | (0.0517) | (0.166) |
| Average daily temperature | 0.0413*** | 0.0346*** | −0.000744 | −0.00466 | 0.0105*** | 0.000248 | 0.00129 |
| | (0.0135) | (0.0106) | (0.00262) | (0.00595) | (0.000978) | (0.000397) | (0.00146) |
| Constant | −3.125 | −2.848** | −1.071 | 0.266 | 0.523* | 0.0489 | −0.0442 |
| | (3.269) | (1.226) | (1.188) | (2.367) | (0.301) | (0.124) | (0.520) |
| Observations | 49,162 | 49,162 | 49,162 | 49,162 | 49,162 | 49,162 | 49,162 |
| $R^2$ | 0.059 | 0.107 | 0.066 | 0.027 | 0.160 | 0.050 | 0.023 |
| Year–month dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: Regressions use household level daily electricity consumption collected from January 1, 2012 to December 31, 2013.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

**Table 4b**
Regression results for total and appliance specific electricity usage observable apartment and household characteristics.

| Variables | (1) Total (sum) | (2) HVAC | (3) Lighting | (4) Plug load | (5) Fridge | (6) Dishwasher | (7) Kitchen |
|---|---|---|---|---|---|---|---|
| SquFt | 0.0102*** | 0.00274*** | 0.00321* | 0.00338 | 0.000313 | 0.000122 | 0.000483 |
| | (0.00333) | (0.00102) | (0.00187) | (0.00226) | (0.000357) | (0.000137) | (0.000535) |
| Second floor | 0.168 | 0.475 | −0.644 | 0.235 | 0.105 | −0.0281 | 0.0241 |
| | (0.925) | (0.339) | (0.528) | (0.450) | (0.124) | (0.0381) | (0.133) |
| Third floor | 0.618 | 0.392 | −0.617 | 0.470 | 0.201 | 0.000210 | 0.173 |
| | (0.827) | (0.296) | (0.457) | (0.483) | (0.124) | (0.0517) | (0.163) |
| South facing | −0.476 | −0.207 | 0.308 | −0.331 | −0.0110 | −0.0952* | −0.140 |
| | (0.661) | (0.267) | (0.259) | (0.368) | (0.0907) | (0.0492) | (0.164) |
| Has children | −0.343 | 0.149 | −0.242 | −0.145 | −0.0546 | −0.000913 | −0.0486 |
| | (0.657) | (0.300) | (0.247) | (0.343) | (0.0904) | (0.0467) | (0.159) |
| Age | −0.0117 | −0.0363 | −0.0164 | 0.00204 | 0.00334 | 0.0116* | 0.0239 |
| | (0.0737) | (0.0385) | (0.0235) | (0.0359) | (0.0111) | (0.00603) | (0.0175) |
| Member of NGO | −0.481 | −0.445** | 0.367 | −0.265 | −0.104 | −0.0496 | 0.0162 |
| | (1.205) | (0.212) | (0.625) | (0.509) | (0.153) | (0.0422) | (0.162) |
| Average daily temperature | 0.0411*** | 0.0345*** | −0.000743 | −0.00476 | 0.0105*** | 0.000238 | 0.00129 |
| | (0.0136) | (0.0106) | (0.00274) | (0.00596) | (0.000977) | (0.000397) | (0.00142) |
| Constant | −2.813 | −1.948 | −0.771 | 0.248 | 0.458 | −0.208 | −0.592 |
| | (3.708) | (1.511) | (0.941) | (2.356) | (0.362) | (0.201) | (0.683) |
| Observations | 49,162 | 49,162 | 49,162 | 49,162 | 49,162 | 49,162 | 49,162 |
| $R^2$ | 0.060 | 0.111 | 0.077 | 0.028 | 0.162 | 0.077 | 0.031 |
| Year–month dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: Regressions use household level daily electricity consumption collected from January 1, 2012 to December 31, 2013.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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**Table 4c**
Regression results for total and appliance specific electricity usage household fixed effects.

| Variables | (1) Total (sum) | (2) HVAC | (3) Lighting | (4) Plug load | (5) Fridge | (6) Dishwasher | (7) Kitchen |
|---|---|---|---|---|---|---|---|
| Average daily temperature | 0.0366$^{***}$ | 0.0330$^{***}$ | −0.00123 | −0.00737 | 0.0104$^{***}$ | 0.000281 | 0.00153 |
| | (0.0134) | (0.0105) | (0.00269) | (0.00580) | (0.000921) | (0.000439) | (0.00175) |
| Constant | 0.986 | −1.263$^{*}$ | 0.358$^{**}$ | 1.352$^{*}$ | 0.164$^{**}$ | 0.0742$^{***}$ | 0.301$^{***}$ |
| | (1.107) | (0.718) | (0.145) | (0.714) | (0.0748) | (0.0262) | (0.0925) |
| Observations | 49,162 | 49,162 | 49,162 | 49,162 | 49,162 | 49,162 | 49,162 |
| $R^2$ | 0.455 | 0.357 | 0.660 | 0.460 | 0.539 | 0.527 | 0.502 |
| Year–month dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: Regressions use household level daily electricity consumption collected from January 1, 2012 to December 31, 2013.

$^{*}$ $p < 0.1$.
$^{**}$ $p < 0.05$.
$^{***}$ $p < 0.01$.

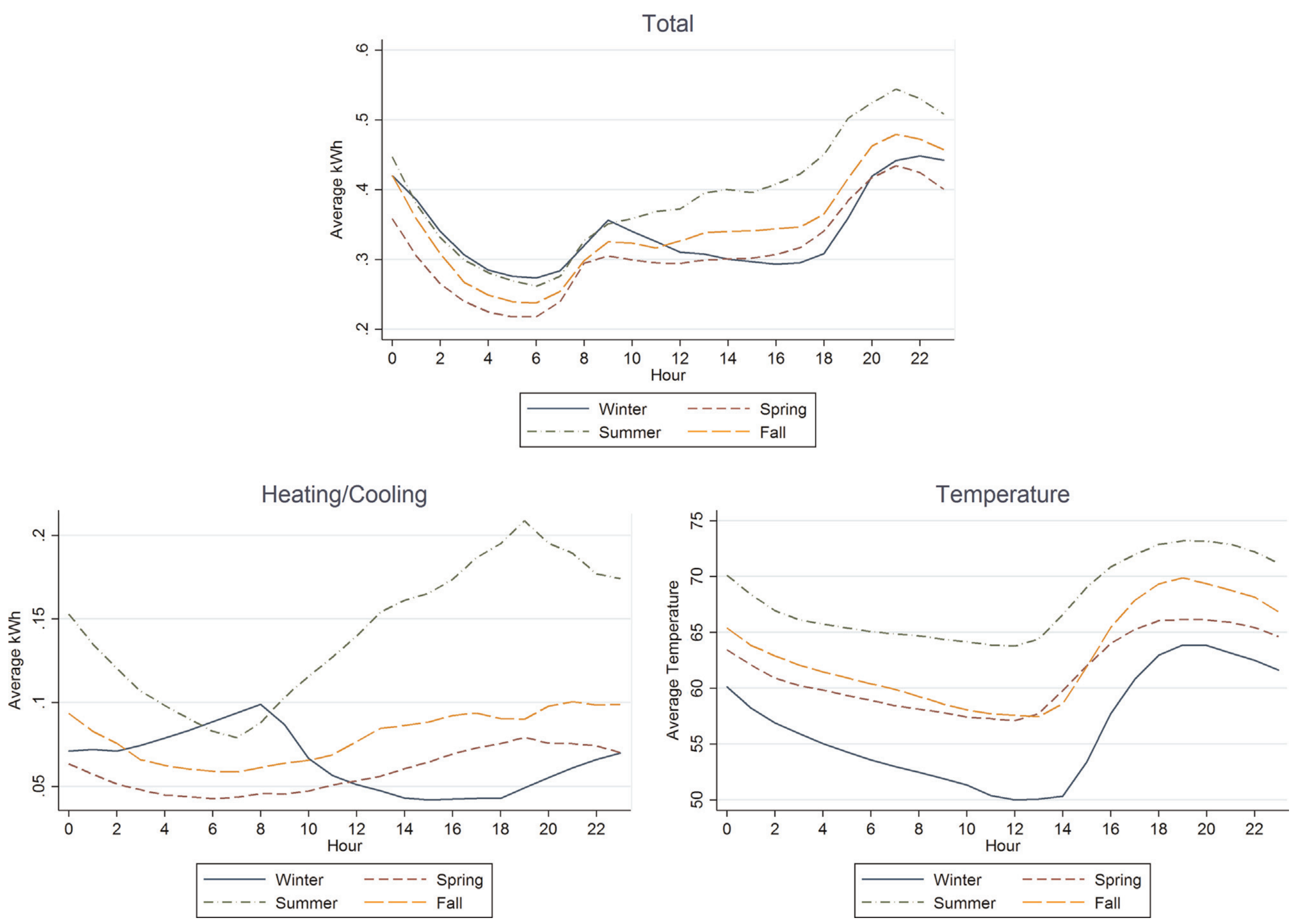


**Fig. 3.** Average hourly electricity usage and temperature by season.

total electricity usage for each appliance are shown in Fig. 4. During peak demand (9 p.m.), the average household uses 0.47 kWh of electricity with 31% coming from plug load, 21% coming from HVAC, and 19% coming from lighting. This is consistent with the results in de Almeida et al. (2011) and Saldanha and Beausoleil-Morrison (2012) that show the importance of non-HVAC loads during peak demand hours. While not unusual, the significant share of electricity consumed by lighting during peak demand hours reinforces the importance of the public utilities' efforts to promote energy-efficient lighting as a means to achieve conservation goals.[11] It is important to note that these trends may vary substantially in climates within California that are not as moderate as Los Angeles.

(*footnote continued*)
which might differ slightly than those of the rest of the population. The Los Angeles Department of Water and Power defines peak hours as 1–5 p.m. for customers on time of use pricing.

[11] http://www.ladwpnews.com/go/doc/1475/264244/LADWP-GIVES-AWAY-2-MILLION-COMPACT-FLUORESCENT-LIGHT-BULBS-TO-RESIDENTIAL-CUSTOMERS. Accessed September 5, 2014.

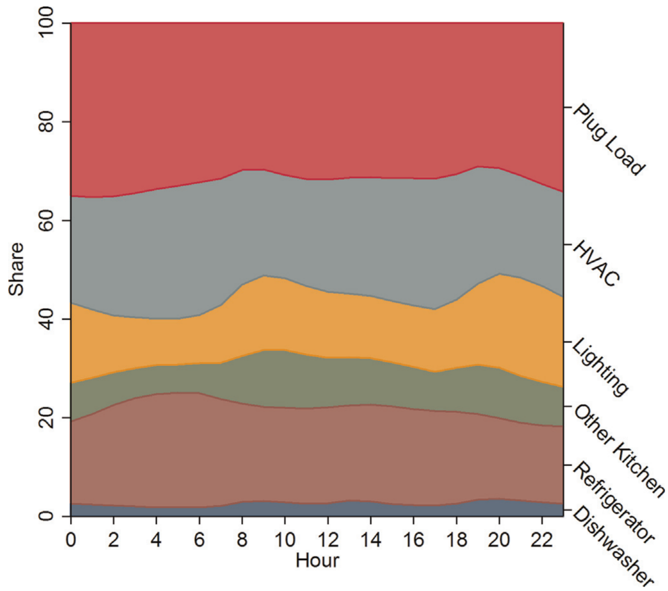


**Fig. 4.** Hourly appliance share of total electricity consumption.

### 3.4. *Savings from new refrigerators*

Households can conserve energy by making behavioral changes that lead to reductions or by upgrading old appliances with newer, more energy efficient models. Between April 15 and May 10, 2013 University Village installed new refrigerators in units where the current refrigerator was more than ten years old. This allowed us to measure the savings that result from installing a new major appliance and to compare those savings to those achieved using behavioral interventions. Of the 124 apartments that are included in the sample, 90 received a new refrigerator. The savings resulting from the installation of a new refrigerator were estimated using observed changes in electricity usage, an improvement over previous studies that use simulation techniques (de Almeida et al., 2011). The distribution of electricity usage for the new and old refrigerators using all of the daily energy usage data collected in 2013 is shown in Fig. 5a. This time period was chosen to make the pre- and post-installation time periods comparable. As expected, the new refrigerators use less electricity than the old refrigerators and have a smaller variance in electricity usage.

In Fig. 5b, the daily refrigerator energy usage before and after the installation of the new refrigerator on April 15, 2013 is plotted to illustrate the savings resulting from the installation of this new appliance for one particular apartment. It shows a significant decrease in electricity usage after the installation of the new refrigerator along with a decrease in variance. Summary statistics for the daily kWh usage for the new and old refrigerators are shown in Table 5. The average usage for the old refrigerators is 1.35 kWh per day compared to 0.82 kWh per day for the new refrigerator. In both cases, the observed average is below the estimated usage shown on the U.S. Energy Star energy guide label; the new refrigerators use 78.0% of the estimated usage on the label compared to 71.0% for the old refrigerators.

Since the graph in Fig. 5b is based on only one apartment, the energy savings could be over- or understated. In Table 6, we present the results of several regressions estimating the impact of the installation of new refrigerators after controlling for household and apartment characteristics. Column 1 includes housing and household factors and also includes month–day fixed effects to capture any time invariant factors, such as average daily temperature, that could be correlated with daily refrigerator usage. In this specification, the installation of a new refrigerator leads to an average decrease of 0.43 kWh per day (12.9 kWh per month). Column 2 includes month fixed effects so that average daily temperature can also be included and shows a reduction of 0.44 kWh per day (13.2 kWh per month). This is similar to the raw difference in means show in Table 5, but slightly less than the estimated reduction based on the energy guide labels.

One concern when estimating the savings from the installation of a new refrigerator is that the allocation of the new refrigerators is not random. To address this concern, column 3 of Table 6 includes household fixed effects to control for any time-invariant apartment and household characteristics. The results suggest that using observable household and apartment characteristics to estimate the savings from the installation of a new refrigerator understates the actual savings. The estimate in column 3 suggest that the installation leads to a 0.84 kWh per day (25.2 kWh per month) reduction in electricity usage, and this effect is estimated more precisely than the specifications that use observable characteristics as controls.

While 25.2 kWh per month corresponds to an 11% decrease in total electricity use based on the average participant's electricity consumption, this is equal to a savings of only $65 a year.[12] Because research has described the potential for energy conservation from behavioral intervention (Stern, 1992), it is important to compare such savings to those that have been found in behavioral experiments. The savings from a new refrigerator are slightly larger than the 7.4% average reduction in electricity consumption found in Delmas et al.'s (2013) meta-analysis of 156 studies that use information strategies to achieve energy conservation. These savings are, however, much larger than the 2% savings reported in Delmas et al. (2013) for the highest quality studies that include a control group as well as weather and demographics controls such as Allcott (2011).

## 4. Discussion

Armel et al. (2013) discuss the benefits of disaggregated electricity usage for consumers, policy makers, and public utilities. Our study illustrates these benefits by taking advantage of a state-of-the-art field experiment that monitors appliance-specific electricity usage in real time. We address four important areas that consumers, policy makers, and public utilities can incorporate to promote energy conservation. First, we found that households are generally not aware of how much each electricity end use contributes to their overall electricity consumption. This finding is consistent with Attari et al. (2010) who estimate consumer awareness of electricity consumption using an online survey. By comparing estimated appliance-level energy use to actual measured values, we confirm that household electricity usage differs greatly from their perception. We find that the average household in our sample overestimated the electricity used by lighting by 75%, while they underestimated the share of electricity used by plug-in devices by 29%. This could cause them to direct their conservation efforts towards lighting when they would be more effective if targeted at plug load usage. This finding leads to the conclusion that if households perceive one category of appliances to be more or less important than they actually are their conservation efforts may be misguided.

The data also reveals that plug load accounts for the largest share of electricity consumption at all hours of the day, a result consistent with the RECS survey. During peak demand hours, HVAC and lighting are the second and third largest sources of electricity consumption, respectively. While most public utilities

[12] This is using an average electricity price of 21.5 cents based on data from the Bureau of Labor Statistics. Website: http://www.bls.gov/ro9/cpilosa_energy.htm. Accessed May 30, 2014.

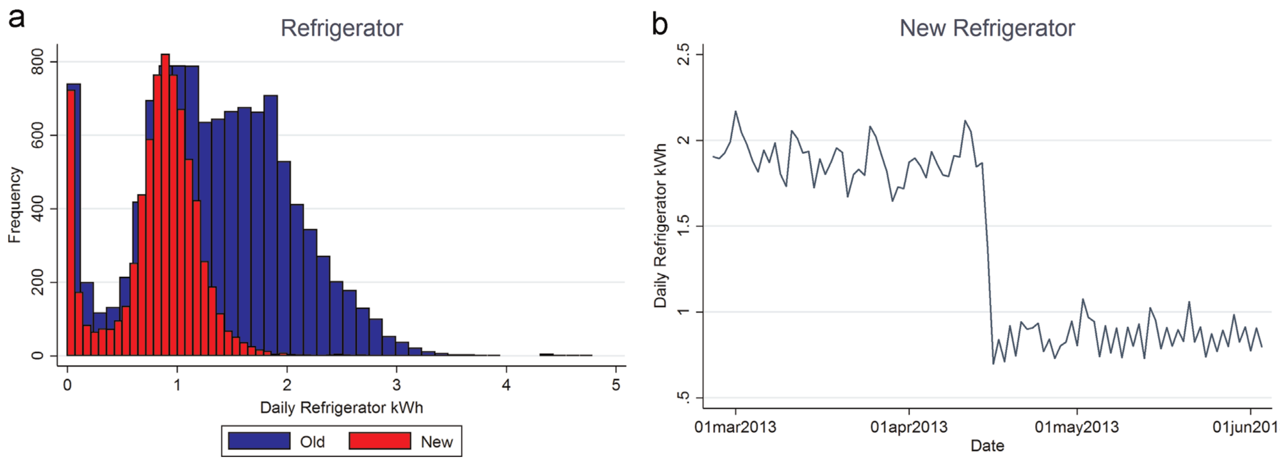


**Fig. 5.** (a) Distribution of electricity usage for old and new refrigerators. (b) Reduction in electricity usage with new refrigerator.

**Table 5**
Daily summary statistics for new and old refrigerators.

| Appliance | *N* | Mean (kWh) | Predicted USAGE (kWh)[a] | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| New refrigerator[b] | 7452 | 0.82 | 1.05 | 0.39 | 0 | 2.72 |
| Old refrigerator[b] | 11,155 | 1.35 | 1.91 | 0.69 | 0 | 4.79 |

[a] Estimated daily kWh usage is based on the energy guide label.
[b] The old refrigerators are General Electric model # TBX18SAXERWW. The new refrigerators are General Electric model # GTH18GBDWW.

focus on reducing HVAC loads through their demand response programs, the results presented here suggest that plug load should also be considered when developing programs to reduce peak demand electricity usage, and that the public utilities focus on energy efficient lighting should continue.

Next, the data shows that in this sample there is a significant amount of variation in electricity usage across households. The differences in usage can be attributed to differences in behavior and household composition since all of the major appliances are the same, there are only minor variations in design for the apartments, and the temperature is the same for everyone in the sample. In Table 2, we show that households in the 75th percentile of HVAC usage use over four times as much electricity as a user in the 25th percentile. Since HVAC usage depends heavily on a household's preference and behavior, large differences are expected. For the refrigerator, an appliance whose usage depends very little on behavior, much smaller differences are found. The regression results presented in Table 4 support this hypothesis. Regressions that explain the variation in electricity consumption across households using observable household and apartment characteristics perform poorly when compared to a specification that controls for time-invariant observable and unobservable household and apartment characteristics. The distributions in Fig. 2 show that for most appliances electricity usage is highly skewed with the average user consuming much more electricity than the median user. While those who are in the right tail of the distribution in our sample could benefit from installing energy efficient appliances and lighting, the typical resident in this study would see little benefit from purchasing these items. For example, if the average household in this study invested in new appliances and achieved a 15% reduction in overall electricity usage, they would only save approximately $7.44 per month.[13]

Lastly, the energy savings that were realized after the installation of new refrigerators were estimated. As expected, after the installations took place there was an immediate decrease in the mean and variance in electricity used by the new refrigerators. Holding weather, housing, and household characteristics constant, the installation led to a decrease of approximately 0.44 kWh per day. When unobservable time-invariant household and apartment characteristic were held constant to account for behavioral differences and the possibility that refrigerators were not randomly assigned, the estimates show a 0.84 kWh per day (11% overall) decrease in daily electricity usage. At a price of 21.5 cents per kWh, this leads to a savings of $5.42 per month for the average user in this study. This result makes the point that ignoring differences in how consumers use different appliances can lead to biased estimates of the energy savings that can be gained from the installation of a new major appliance.

Our study is not without limitations. First, the experimental site was located at an apartment complex for graduate students and their families. Even though the sample was similar to the rest of California in terms of electricity usage, the participants are more educated than the typical California household. However, this characteristic indicates that the results are conservative. Indeed, if an educated population does not know much about appliance-level usage, it is unlikely that the rest of the population knows more. Second, for households that are away from their apartment during academic holidays, electricity usage for those households will appear much lower than normal. Third, due to technical limitations and user error, some electricity measurements were missing or recorded with some error. This implies that some of the outliers in Fig. 2 might be due to technical issues and not above-average electricity usage. Since each circuit panel was inspected, these errors are thought to be minimal. Finally, since the Los Angeles climate is more moderate than that of the rest of the United States, these results may not hold in other parts of the country where heating and cooling usage is more common. Future work should address these questions in areas with climates that are not as moderate as in Southern California.

## 5. Conclusions and policy implications

This paper presented results from a state-of-the-art electricity field experiment that provided participants with high-resolution, highly granular electricity consumption information. The data from this experiment was used to answer important questions that previous research could not answer due to technological and data

[13] A new refrigerator similar to the ones installed at University Village costs around $750 and generated an overall energy savings of 11%.

**Table 6**
Regression results estimating the impact of new refrigerators on daily energy use.

| Variables | (1) Refrigerator | (2) Refrigerator | (3) Refrigerator |
|---|---|---|---|
| New refrigerator installed[a] | −0.429*** (0.113) | −0.441*** (0.109) | −0.837*** (0.0866) |
| SquFt | 0.000421 (0.000406) | 0.000420 (0.000402) | |
| Second floor | 0.0624 (0.139) | 0.0636 (0.139) | |
| Third floor | 0.159 (0.138) | 0.162 (0.137) | |
| South facing | −0.111 (0.0973) | −0.110 (0.0972) | |
| Member of NGO | −0.259 (0.182) | −0.264 (0.179) | |
| Has children | −0.138 (0.0981) | −0.140 (0.0976) | |
| Age | 0.00530 (0.0109) | 0.00555 (0.0108) | |
| Average daily temperature | | 0.00992*** (0.00144) | 0.00964*** (0.00127) |
| Constant | 0.781* (0.418) | 0.224 (0.435) | 0.368*** (0.0808) |
| Observations | 18,607 | 18,607 | 18,607 |
| $R^2$ | 0.269 | 0.242 | 0.660 |
| Old fridge mean | 1.345 | 1.345 | 1.345 |
| Time effects | Month–day | Month | Month |
| Clustered SE | Yes | Yes | Yes |
| Household fixed effects | No | No | Yes |

[a]There are 7452 observations for the new refrigerators and 11,155 observations for the old refrigerators.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

limitations. First, the data shows that households are unaware of how much electricity is being used by three major categories of appliances and end uses. The results show that households overestimate lighting use by 75% and underestimate plug-load by 29%.

Second, the data also reveals that there is a significant amount of variation in appliance-level electricity usage for a standardized set of major appliances in a setting where the housing units have minor variations in design. In this setting, unobservable apartment and household behavior account for 25–58% of the variation in appliance-level electricity consumption. Lastly, the savings from installing a new refrigerator were estimated. The savings were equivalent to an 11% decrease in electricity usage for the average household; however, the monetary savings only amount to approximately $65 per year. Since the monthly monetary savings that results from appliance specific reductions can be quite small for households that are low users of electricity, there needs to be a careful cost–benefit analysis of policies that encourage investment in new major appliances.

Our results have important implications for energy conservation policies. First, we find that differences in electricity usage are mostly driven by differences in behavior rather than apartment or household characteristics. This indicates that policies should focus on understanding how to influence energy conservation behavior. Providing tailored information about energy use seems to be particularly important in this respect since most households are ignorant of the energy used by their appliances. Second, because the behavioral component of electricity consumption varies by appliance, appliance level information policies need to target appliances with the largest behavioral component. For example, this study showed that HVAC is the appliance with the most potential for energy savings from changes in behavior. In our sample that includes households that live in the same size apartment with the same number of people, we find that households in the 75th percentile use more than four times the amount electricity from HVAC as compared to households in the 25th percentile. There is much less potential for energy conservation through behavioral change for refrigerators, which account for 19% of total electricity usage in this sample. In such cases, technological solutions might be preferable. Our research confirms the increasing share of plug load in electricity consumption as key contributors to the power demand. This indicates that plug load should be a priority target especially for peak demand usage policies.

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## Appendix. Data processing

Data from the meters consist of energy measurements in units of watt-seconds for each of seven channels. The meters record energy using monotonically increasing counters which function much like the dials on analog utility meters. These counters increase monotonically until a maximum byte value is reached and then start over at 0. Data packets are transmitted wirelessly to the gateway at 1 Hz. A custom Python daemon running on the gateway receives and parses the packets, preprocesses the data, and then uploads measurements to the gateway along with identifiers.

With 4 bytes per channel, 7 channels per meter along with timestamp and identifiers, 2 meters per apartment, and 124 apartments recruited in the study, the system would generate almost 300 GB per year. To reduce the amount of data stored, the data is down sampled by the gateway at 1/30 Hz (1 sample every 30 s). The incoming data packets are monitored constantly and at the end of the 30 s window the total energy per channel is computed as the difference of the energy from the first and last packets received. This energy is divided by time (nominally 30 s) to produce power measurements. $P_{m_i, c_j}(t) = (E_{m_i, c_j}(t) - E_{m_i, c_j}(t-T))/T$.

The gateway then uploads the power measurements to a database on an ENGAGE server via a POST handler. Once every hour, a software script processes the new power data into hourly energy measurements as follows. Let $A = \{a_1, a_2, \ldots, a_M\}$ be the set of apartments. For each apartment $a \in A$, there are a set of meters $M_a = \{m_1, m_2, \ldots, m_N\}$. For each meter $m$, there are a set of measurement channels $C_m = \{c_1, c_2, \ldots, c_Q\}$. The meters used support 7 channels and as such the number of meters $N$ was limited to two as this is sufficient to instrument each circuit in the electrical panel. For each apartment $a \in A$, the power for channel $i$ on meter $j$ is given by $P^a_{m_j, c_i}$.

Next, a set of appliance loads $L = \{l_1, l_2, \ldots, l_R\}$ were defined corresponding to the categories "plug load," "lighting," "HVAC," "refrigerator," "dishwasher," and "other kitchen." The power for each load $l \in L$ in apartment $a$ is given by $P_l^a = f_l^a(P_{m,c}^a)$ for each $m \in M_a$ and each $c \in C_{m,}$ where $f_1^a$ is some known function based on the circuit configuration of a particular apartment. For example, in apartment 305, the HVAC circuits may comprise channels 3 and 4 on meter 1 and channels 5 and 6 on meter 2 so the HVAC power function would be $f_{HVAC}^{305}(P_{m,c}^{305}) = P_{1,3}^{305} + P_{1,4}^{305} + P_{2,5}^{305} + P_{2,6}^{305}$. Each of these load power functions is defined and stored in the database. Conveniently, circuit configurations were not completely unique for each apartment and most used a few "templates." Nonetheless, a great deal of effort was needed to collect the configuration information and still resulted in some errors which required rechecking.

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