Overcoming the Data Scarcity Challenge for Energy Efficiency Planning in Resource Constrained Environments

Abstract

Forecasts of electricity demand suggest that most growth will occur in the global south. Furthermore, it is expected that seven out of ten people will be living in cities by 2050. Energy efficiency will have to play a crucial role in meeting basic needs, while balancing a global carbon budget and the changing consumption patterns of a growing global middle class. Designing and implementing energy efficiency strategies necessitates high-resolution data at multiple levels, but local stakeholders often lack the resources to build high-quality data infrastructure. We propose a mixed-methods approach combining machine learning for predicting appliance ownership, appliance-level trace data, results from field-level pilot projects, and combining disparate data sources (e.g., census, surveys and distributed sensor data) through Bayesian updating to characterize the magnitude and uncertainty of appliance characteristics. We implement our approach with data from Nicaragua, and demonstrate high-accuracy (3% error) at predicting appliance ownership through a decision tree framework, and provide posterior distributions for some of most energy consuming appliances in households and small-businesses. Our methodology allows us to construct a marginal cost of saved energy curve (MCSE), characterizing both the magnitude and uncertainty of a variety of energy efficiency strategies. Applying machine learning and Bayesian inference techniques to combinations of seemingly disparate data streams provides a cost-effective approach to better understand the energy efficiency gap, and better determine the feasibility and uncertainty of different implementation strategies.

1. Introduction

Elucidating demand is a crucial element for designing and implementing short- and long-term energy efficiency strategies. Developing estimates on what energy efficiency goals should be and what the 'energy efficiency gap' is (1), however, remains a contested topic in the literature. Some estimates suggest that nearly two-thirds of the economic potential of energy efficiency remains unfulfilled, that 70% of global energy use exists outside of existing efficiency performance requirements, and that the untapped efficiency resource represents approximately 40% of the green house abatement potential that can be realized below a cost of $US 80 per metric ton of tCO_2e (2–4). Other analysis suggests that these estimates are overstated by traditional analysis (e.g., engineering estimates and empirical estimates of returns observed to investments) that fail to incorporate physical, risk and opportunity costs, costs to project participants, and other unobserved factors that can reduce the effectiveness of energy efficiency interventions (e.g., behavioral aspects) (5). Thus, the literature arguing whether or not there is an energy efficiency gap, and how large it is, falls into three broad categories including market failures, behavioral explanations, and modeling flaws (6).

The energy efficiency gap is broadly defined as the perceived slow rate of diffusion and adoption of energy efficient products and practices (7). Some studies view market failures (e.g., energy pricing, uninternalized externalities, information asymmetries) as a central element explaining the slow diffusion and adoption of energy efficient solutions (5–7). Others, view systematic behavioral biases as the central element affecting user economic decision making, hindering the realization of technical potential estimates calculated through engineering estimates (7–9). When estimating the efficiency gap, there are a set of competing and complementary methods. Engineering estimates arrive at the technical potential, but usually overstate net benefits if they do not account for hidden user costs (e.g., time investments, sunk costs, risk and uncertainty), heterogeneity of preferences and users, and long-term reductions in quality of service, among others (7). Similarly, if engineering estimates do not incorporate behavioral aspects, diffusion strategies might lead to unintended consequences, such as the rebound effect (7, 10). Acknowledgement of modeling and measurement flaws has been one of the most recent additions in attempting to explain the energy efficiency gap (6). These flaws include the lack of context with regards to appliance and product characteristics and attributes, and with regards to modeling it includes a failure to incorporate heterogeneity in costs and benefits across users, use of inappropriate discount rates, uncertainty, irreversibility and option value (6). Behavioral characteristics that explain the existence of a gap, and describe why it may be difficult to reduce it, include theories on non-standard preferences (11), loss aversion (12–14), non-standard beliefs (15), bounded rationality, and non-standard decision making (6, 7, 9, 16). Because there is a wide range of methodologies through which many of these hypotheses are tested, the literature has yet to arrive at a consensus regarding the existence and size of the efficiency gap.

Strategies to reduce the efficiency gap as it relates to practices and products, include user information feedback mechanisms and energy efficiency standards. Examples of user information mechanisms include energy audits, improved appliance product labeling (e.g., Energy Star), displaying lifetime energy costs, cueing social norms, gamifying, and a suite of energy information products (e.g., energy monitors, apps, SMS) to engage users in actions that can help them achieve reductions in energy consumption (7, 17–22). Energy efficiency standards are generally implemented as policies requiring new appliances to meet certain requirements and energy efficiency levels before they can be offered to users (7). While using standards as the sole mechanism for advancing energy efficiency has been often criticized in the literature (e.g., technical potential over-estimates, neglect of welfare effects and heterogeneity of preferences and users), they are often favored as policy instruments as they appear to be relatively straightforward to implement and enforce (7). As the example of LEDs and other efficient lighting in the U.S. may suggest, efficiency standards have a large role to play in achieving energy efficiency goals (23).

Key to designing, planning and implementing these strategies is data. However, in many contexts, and especially in resource constrained environments, data is scarce. Detailed appliance ownership surveys are performed decades apart, no surveys on user perceptions related to energy consumption and energy efficiency strategies are performed, there are no regularly updated market analyses of the appliances available for purchase (in stores as well as second-hand markets), and no baseline estimates of household and small business characteristics that affect energy consumption (e.g., building envelope, temperature, household size). While the previous descriptions only provide static snapshots of the state of an appliance or energy consumption marketplace, time series data that can depict usage patterns, behavior, and the efficiency of appliances is practically non-existent. Most low, low-middle income countries do not have smart meters, or provide access to 15-minute interval data to study consumption. This lack of data obfuscates the process through which planning for which cities and countries can achieve their energy efficiency goals. For example, is the efficiency gap in a country due to a lack of appliance standards, or due to lack of financing to enable ownership of efficient appliances? Do users buy appliances from stores or second-hand markets? What is the energy consumption profile of appliances in the field, and which appliances consume the bulk of total energy? What strategies are users already implementing to save energy, and how can they be fostered? How can product design adapt to existing local energy saving customs and practices?

Here, we argue that sampling data from different sources (e.g., census, health and social demographic, surveys and sensor data) is a critical component for evaluating the energy efficiency gap - informing energy efficiency policy, designing effective standards, and discovering opportunities for behavioral and technical energy efficiency interventions. We focus our case study in Managua, Nicaragua, as it exemplifies many resource constrained environments (e.g., communities that might exist in relative income, infrastructural, or institutional scarcity) in the global south, where most of the growth in electricity demand is expected to occur (24). Similarly, the approach we take here can be used to understand the efficiency gap in low, low-middle income neighborhoods of relatively richer countries. Continuously collecting data, we argue, is central to understanding the market failures, behavioral characteristics, and modeling flaws that fail to capture and help in the diffusion of energy efficient products and technologies. Because the data that is collected for any technical analysis (e.g., engineering or user-focused modeling) will be an important driver of results (and informing policy), these data (and results) must also characterize their inherent uncertainty or sampling bias (if any). Countries like Nicaragua have little data on existing and future appliance stocks, and thus, reliable estimates must be developed combining Census and household level surveys. Second hand market analysis to understand the state and penetration of efficient appliances should also supplement available web data with second hand market data to avoid sampling bias (large retailers with websites might only cater to the middle, and upper-middle class which is relatively small in some countries), should collect field random samples and build data sets with sensor networks to understand the current state of appliances, and when possible, capture time series of usage to understand behavior. A strong complement to these data would be interviews and surveys related to usage practices, and belief systems with regards to energy efficiency.

We bring together several disparate streams of data to make predictions of appliance ownership throughout the country, use web and second-hand market data to perform a market analysis, and use data from sensor networks to validate market data and understand usage behavior. We implement machine learning algorithms to predict appliance ownership throughout Nicaragua, and Bayesian updating to characterize the magnitude and uncertainty of appliance characteristics in Nicaragua. As wealth, appliance efficiency and affordability, and social demographics change in time, it is important to recurrently update data streams to understand the diffusion, adoption and usage characteristics of energy efficient technology to meet short- and long-term demand reduction goals.

2. Materials and Methods

We use a mixed-methods approach that combines data and analytical methods at multiple timescales. First, we describe the macro-level census data that is used for predicting appliance ownership across the country, as well as the web- and market-level data that is collected to create the prior-distributions for Bayesian inference. Afterwards, we explain how these data is used with appliance-level trace data to create posterior distributions of energy consumption of different appliances throughout the country. Our methods include the use of Random Forests to predict appliance ownership, and Bayesian Inference to create posterior distributions of energy consumption by appliance. The sections below explain our approach in detail.

2.1 Data Sources

We use three principal sources of socioeconomic data for this analysis: official macro-level data streams, web crawlers and ground-level market analysis, and sensor data. At the macro-level (country-level), the first, is a combination of Nicaragua's 2011 Demographic Household Survey (DHS) and the Nicaraguan 2005 Census.

DHS data includes a statistically representative sample of 19,918 unique households, and 135 towns. DHS data collects detailed household characteristics including wall, floor, and roof type, sanitation characteristics, access to basic services (water, sanitation, and modern energy services), and education levels, among many other things. In addition, DHS also includes information regarding the ownership of electrical appliances including radios, televisions, cell phones, and refrigerators among others. The 2005 Nicaraguan census is a higher-spatial resolution data set, as it includes over 1 million households throughout the country (1,116,540), but collects less details about each individual household. The data includes household level characteristics albeit at a lower resolution than the DHS. For example, the census includes data regarding the *quality* (a binary variable) of access to basic services such as water, sanitation, and the *quality* of living conditions (e.g., walls, roof, and floor types), but doesn't include the service access types (for example, local vs. community water wells, or, electrification via PV systems vs. grid extension). Because neither the DHS nor the Nicaragua Census data contain geospatial data, a Python script written using a Google API was used to obtain town coordinates (lat-long). Only two thirds of the census data were able to be geo-spatially located, because the town names couldn't be found via the API.

To aggregate the DHS and Nicaraguan census data, socio-demographic data from each DHS household was transformed into a format equivalent to that of the Census. For example, if 'water access' was specified in DHS as coming from a river or stream, lake or lagoon, or a water hole, it would be considered of poor quality (binary value: 1). Next, the households DHS 'weights' were used to expand the size of the data set within its sampling area (a house's weight suggests the number of similar households that are *likely* to be found within a sampling area). Because DHS is household-level data and the Census is town-level data, the latter was disaggregated into households. For each region (state) within the DHS all possible household socio-demographic characteristic combinations were identified and associated with a probability. Then, by using town socio-demographic characteristics totals, and the associated probabilities of all unique combinations, each town was disaggregated into distinct households. Figure X and X depicts some elements of these dat

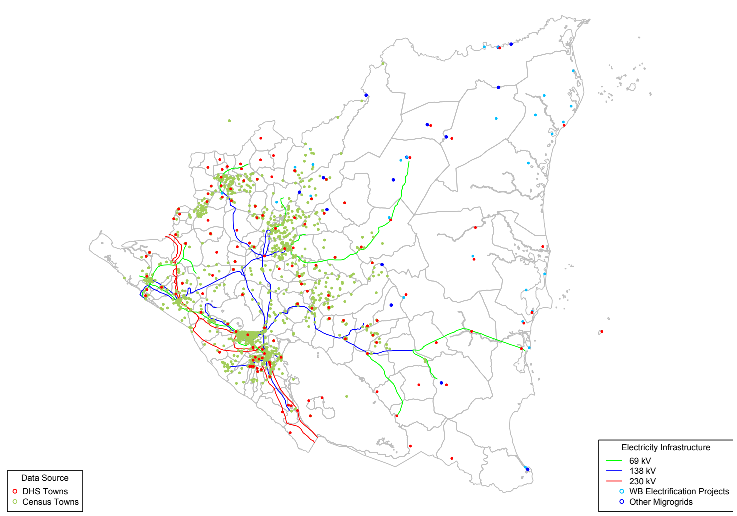

Figure 1. DHS and Census town locations [X.A] and [X.B] features used in this analysis.

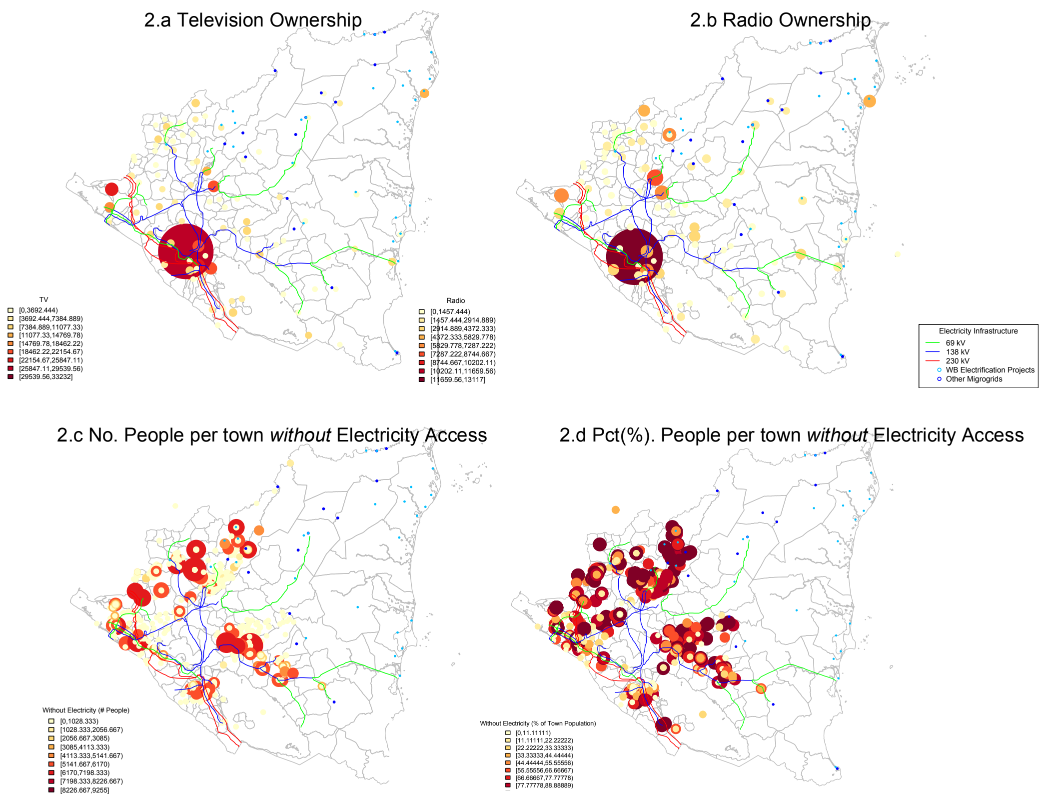

Figure 2. Spatial diversity of appliance ownership [2.a and 2.b] and lack of electricity access [2.b number of people, 2.c percent of people in town]. Note: 2.a and 2.b depict the representative number of households that own a particular appliance within a certain sampling region.

Our appliance market analysis was a combination of web-crawlers and ground-level market analysis (25). Energy consumptions from these data were merely used to create the prior distributions in our analysis, as it would later be updated via the trace level data obtained through sensors in the posterior distribution. We collected web and ground-level market data related to brand, dimensions, wattage, and prices for plug loads such as televisions, fans, and washing machines. For refrigerators and freezers we collected wattage, volume, and labeled expected monthly energy consumption, when applicable. For refrigerators and freezers for which there was no wattage data available, we used cubic size, refrigerator or freezer type, and age, in combination with the fridge energy calculator available at the Energy Star website to determine approximate monthly energy consumption values (26). Because web-crawlers used on stores that are ready-available online can provide a skewed distribution geared towards the urban middle- and upper-middle class, we complement these data with an on-the-ground market survey. We surveyed two of the most popular second-hand markets in Managua, where it is most common for households to purchase used appliances. In total, we collected market data for 227 appliances including televisions (35), washing machines (42), refrigerators and freezers (116) and fans (34).

Sensor data is gathered from two pilot projects in Managua that were evaluating the potential for flexible demand and behavioral energy efficiency in households and small businesses throughout the city (27). Households and small businesses participating in our pilot projects (105) were randomly selected from a random sample of over 700 households and small businesses throughout the city. This random sample was created from low, low-middle income neighborhoods of similar social and economic demographics such as overcrowding, access to basic services, housing quality, education level, economic dependency and incidence of poverty. From the flexible demand project, we use field-data from 30 refrigerators and freezers that was collected throughout over a year of baseline and implementation. Data was collected through a FlexBox sensor gateway (27) that aggregated disparate data streams including ambient temperature, inside temperature of refrigerators and freezers, total household energy consumption, refrigerator-level energy consumption, and refrigerator door openings. The high-resolution (minute-level) refrigerator-level energy consumption data reflects the variability and impact of seasonal consumption (e.g., summer vs winter) as well as intra-day hourly variability, when aggregated. The second and most recent behavioral energy efficiency project provided plug-load level data for refrigerators and freezers, fans, televisions, washing machines, and cellphones for 75 households and small businesses. For these data, we recorded the labeled wattage, dimensions (e.g., screen size for television, cubic size for refrigerators), approximate age, as well as 30 minutes of energy consumption per household or business. When measuring energy consumption at each house we could use from one to five ZOOZ Z-wave plug load monitoring devices to measure the contribution of each appliance to the household total.

Data Source	Units	Socio-Demographic Characteristics	Appliance Data	Resolution
Demographic and Health Survey (DHS) 2011	19,918 unique households, and 135 towns	wall-type, roof-type, floor-type, household type, primary energy source (type), primary electricity source (type), primary energy source (type), ownership type, sanitation access (type), state.	radio, sound system, television, refrigerator, microwave, iron, fan, AC, sewing machine, DVD, washing machine, video gams, cable TV, internet, cellphone	Household level variable type (e.g., wall-type)
Census 2005	1,116,540 households	Binary variables (1 - adequate, 0 - inadequate): walll quality, roof quality, floor quality, household quality, electricity access (1 - access, 0 - no access), water quality, sanitation quality, household	-	Town level aggregates
Web and on-the-ground appliance market survey	227 appliances	-	Dimensions (e.g., screen size, volume), wattage, monthly energy consumption estimates, price: refrigerators/freezers, televisions, fans, washing machines, cell phones	Appliance level
Sensor data	105 appliances	-	Minute-by-minute power and energy consumption: refrigerators/freezers, televisions, fans, washing machines, cell phones	Appliance level

Table 1. Data: Macro-level aggregates, market analysis, and sensor data.

2.2 Analytical Framework

To predict future ownership of electrical appliances for households currently without them, but with the possibility and conditions to access them in the future, we use socio-demographic similarities and a decision tree framework. To build credible distributions of existing appliances in the country, and their energy use, we use market analysis, survey and sensor data, combined with Bayesian updating.

We use the extended (un-weighted) DHS data to train our decision tree. The goal is to create a model that accurately predicts ownership of each electrical appliance separately, by using decision rules inferred from social-demographic characteristics. A random forest gradient boost algorithm then iterates over all possible combinations of social demographic characteristics, and hyperparameters, seeking to identify the optimal combination that minimizes the training error for each electrical appliance (radio, sound systems, television, refrigerators, microwaves, irons, fans, ACs, sewing machines, DVDs, video game consoles, internet, and cellphones). To improve the decision tree algorithm, we explored the maximum depth hyperparameter of the tree. For individual trees, we found that it was best to expand all nodes completely. However, for the ensemble methods described below, we found that the maximum depth hyperparameter played an important role in minimizing the error of predictions. In addition to an individual decision tree, we tested boosting ensemble methods, including Gradient Boosted Regression Trees (GBRT) and Random Forests. In contrast to averaged ensemble methods, boosting methods build base estimators sequentially with the goal of minimizing the bias of the combined estimator. The GBRT, for example, is an additive model of the form:

$$F(x) = \gamma_0 f_0(x) + \gamma_1 f_1(x) + \gamma_2 f_2(x) = \sum_{i-1}^{M} \gamma_i f_i(x)$$

Here the final GBRT classifier (F) is the sum of several decision tree classifiers (f_i). The model is additive at each sequential boosting stage, such that:

$$F_i(x) = F_{i-1}(x) + \gamma_i f_i(x)$$

where $f_i\ (x)$ is chosen to minimize the loss function. For the GBRT algorithm, we optimized three hyperparameters, namely the number of boosting stages to perform, the learning rate that sets the contribution of each tree, and the maximum depth of individual estimators that limits the nodes in each individual decision tree. The hyperparameters were optimized by training with the full DHS dataset for each of the predicted output variables. For most of these variables, the optimal depth, which depends on the interaction of input variables, was equal to 6 nodes. There was a trade-off between the number of boosting stages and contribution of each tree, with an optimal of 100 and 1 for boosting states to perform and learning rate, respectively.

To build reliable distributions from disparate appliance level data streams we perform summary descriptive statistics, and use Bayesian updating to construct posterior distributions for each appliance characterizing their magnitude and uncertainty. We use Bayesian updating as an example of a methodology that can be used to improve (or update) prior knowledge to produce posterior probability estimates. We use web-market data as our prior (a log-normal distribution), and build the posterior probability estimates using data from second-hand markets and sensors. R functions including JAGS and CODA are used to construct the posterior distribution for each appliance's characteristics (28, 29). Because our data is well described by log-normal distributions we implement Markov Chain Monte Carlo chains on log-normal data, and then transform the estimated parameters to obtain mean and uncertainty estimates for *y* as opposed to *log(y)* (y being appliance characteristics)(30). We perform a posterior predictive check on our data, and obtain distributions for the mode, mean and standard deviation of both *y* and *log(y)*. We argue that using Bayes is appropriate to arrive at a better understanding of our baseline appliance characteristics, as using static data is not sufficient to understand the true distribution (and parameters) of that data. Bayes, in this case, allows us to arrive at parameter estimates and characterizations of uncertainty that are crucial for determining energy efficiency strategies.

3. Results and Discussion

3.1 Appliance Ownership Prediction

The variables (electrical appliances) where ownership could be predicted with the smallest error in the training set were AC systems (1.6%), video game consoles (5.5%), internet access (5.9%), and television sets (10.3%). Table 2 provides a summary of results and the optimal predictors for each electrical appliance in the training set. AC, video games, and internet access are likely to be the appliances with the most accurate predictions because they are only owned by a small and very particular niche of social-demographics relevant to middle-high, and high-income households in Nicaragua (their characteristics are very specific and easy to predict). The rest of the appliances ranging from televisions to radios have a high likelihood of being owned across a spectrum of social-demographics, and thus, the prediction error is higher in the training set. Radios, for example, are very likely to be found in every household (80%) and thus have a much higher prediction error (31). The ownership of radios ranges from the highest to the lowest income bracket, and across all combinations of social demographics. Because our macro-level data aggregates are from 2005 (Census) and 2011 (DHS), they don't fully capture the rapid and evolving dynamics that have come to play with regards to appliance ownership. For example, in 2011, cellphone ownership in Nicaragua had only reached 70% of the population, but by 2014 there were already 1.5 cellphones per person (more cellphones than people in the country)(32, 33). Although this doesn't suggest that cellphones are equally distributed across social demographics, it does suggest that in recent years there are some important technology evolution dynamics that are not captured by historical data – and thus, our analysis. If there were more recent data available, we would expect the training error to be equally low (or lower) for cellphones as it is for radios.

Variable	% Error	Predicting Vars
AC	1.6	0, 1, 2, 3, 7, 8, 9, 10, 11
Video games	5.4	0, 1, 2, 3, 7, 8, 9, 10, 11
Internet Access	5.9	0, 1, 2, 3, 7, 8, 9, 10, 11
Television	10.3	0, 1, 2, 3, 7, 8, 9, 10, 11
Sewing Machine	12.5	0, 1, 2, 3, 7, 8, 9, 10, 11
Microwave	15.8	0, 1, 2, 3, 7, 8, 9, 10, 11
Iron	16.6	0, 1, 2, 3,7, 8, 9, 10, 11
Cellphone	18.6	0, 1, 2, 3, 7, 8, 9, 11
Fan	20.0	0, 1, 2, 3, 7, 8, 9, 10, 11
Cable TV	20.3	0, 1, 2, 3, 7, 8, 9, 10, 11
Refrigerator	20.5	0, 1, 2, 4, 7, 8, 9, 10, 11
Sound system	27.2	0, 1, 2, 3, 7, 8, 9, 10, 11
DVD	29.4	0, 1, 2, 3, 8, 9, 10, 11
Radio	31.0	0, 1, 2, 3, 7, 8, 9, 10, 11

Variable Code: [1] 0: Water quality, 1: roof quality, 2: floor quality, 3: household quality, 7: water access qualit, 8:household ownership, 9:sanitation access quality, 9: firewood as primary cooking fuel

Table 2. Accuracy of Predicting Different Appliances in the Training Set

After training our decision tree classifier on each appliance using the full DHS extended data set, we predict appliance ownership based on social demographic similarity. We use each individually trained appliance model to predict appliance ownership for all towns (and households) in the country for which we have data. Our prediction results make intuitive sense. Cellphones, televisions, and irons are predicted to be the appliances with the greatest diffusion based on social-demographic similarity. In the literature, cellphones and televisions, and other affordable connectivity related appliances, have been documented to be the most coveted appliances pre- and post-electrification (34–36). Furthermore, the growth of cellphones and televisions has been significantly documented in Nicaragua's media since 2005 and 2011 (when we have the latest available data). In the absence of official data, web media from Nicaragua suggests that there are now more cellphones than people in the country, and that the growth in the ownership of televisions increases year after year (32, 33, 37, 38).

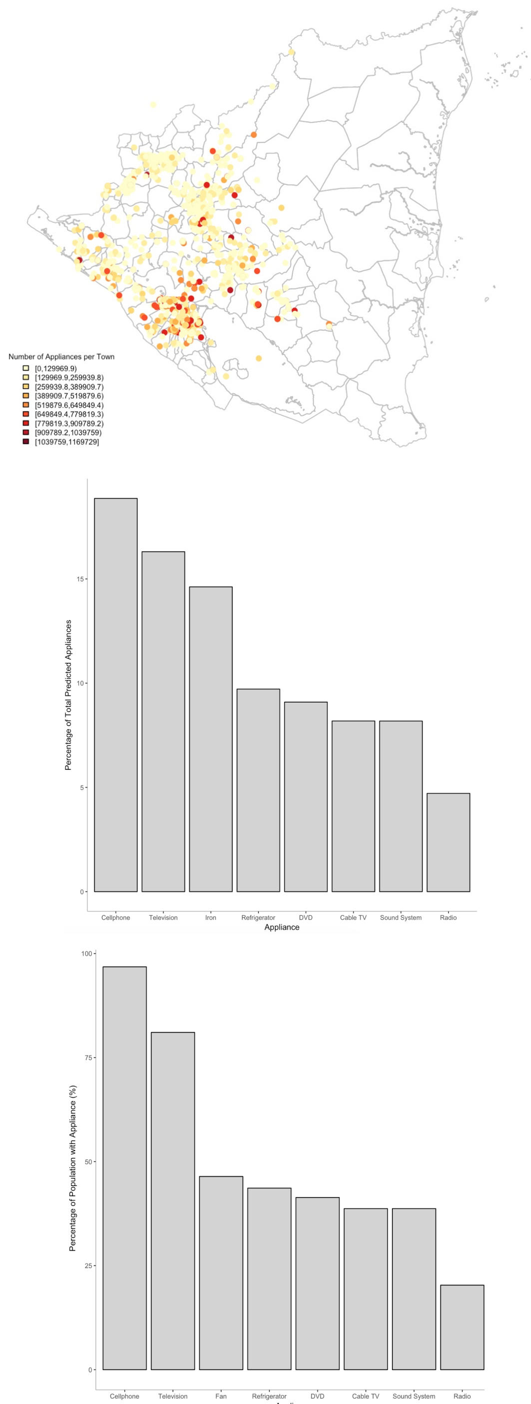

Figure 3. Test Set Predictions: Spatial distribution of prediction on sample towns, percentage market share by appliance, and percentage population reach. Because neither the DHS nor the Census contain geospatial data, a Python script written using a Google API was used to obtain town coordinates (lat-long). Only two thirds of the census data were able to be geo-spatially located.

We explore the distribution of predicted appliances in two different ways, one determines the market share of each appliance with respect to the total (% market share), and the other determines the distribution of appliances with respect to population (% population with ownership of specific appliances). Cellphones, televisions and irons capture the largest appliance market shares with 20%, 16% and 15% respectively (over 51% of the total appliance market), followed by refrigerators, cable TV and sound systems, and radios. Similarly, our prediction using social-demographics suggests that if communities without electricity were to be electrified, the most ubiquitous loads would be cellphones (97% population reach) and televisions (81%). Following relatively behind are fans (46% population reach), refrigerators (43%), DVDs (40%), Cable TV modems (38%), sound systems (38%), and radios (20%). Based on the training data, we should expect to see a much higher distribution of radios, but the relatively higher prediction error associated with them produces a relatively lower number. Our results make intuitive sense and are aligned with small sample market analysis performed by newspapers in Managua, and our own field data.

To validate our predictions, we compare our estimates to the latest 2016 national survey of households in Nicaragua (39). Unfortunately, there are only five coincident appliances available for comparison between the 2005 Census, 2011 DHS data, and the 2016 Household level surveys: cellphones, televisions, refrigerators, access to Cable TV (antennas and modems), and AC ownership. Our most accurate predictions for total appliance ownership are for AC (prediction: 0.5% vs. actual: 1%), cable TV (prediction 38.7% vs. actual: 35.4%), and refrigerators (prediction: 43.6% vs. actual: 38.2%), with an average error of 3%. Cellphones (prediction: 96.8% vs. actual: 86.5%), and televisions (prediction: 81.1%vs. actual: 68.5%), have an average error of 11%. Data for computers, internet modems, plasma TV, and washing machines were not able to be verified either because the data was not available in the 2005 Census and 2011 DHS data, or because the data was not available in the 2016 household survey. Although we have a relatively low prediction error of 7%, these comparisons are not fully accurate. When performing appliance predictions using social demographics, the underlying assumption is that the spectrum of social demographics is maintained as households become electrified. Thus, we consistently over predict appliance ownership as Nicaragua hasn't reached full electrification (85%), with 15% of the population remaining without electricity access. If Nicaragua were to be fully electrified while maintaining a similar spectrum of social-demographics we would expect our predictions to be even closer to ground-truth. However, in reality, and as electrification, wealth, social-demographics, and the efficiency of appliances co-evolve, the affordability and access to appliances significantly changes.

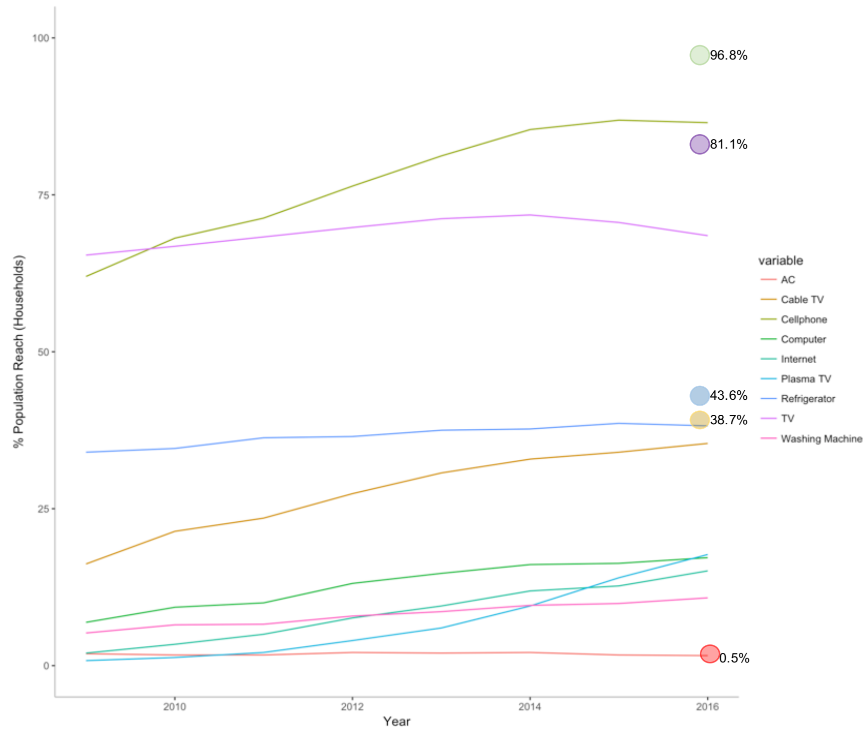

Figure 4. Ownership of Appliances over Time vs. Prediction Accuracy: Air conditioners, Cable TV (antennas and modems), refrigerators, televisions and cellphones. Lines depict actual data, circles depict predictions.

3.2 Appliance and Usage Characteristics

Using web and second-hand market data, data from appliance stickers and labels, and real-time power consumption measurements from randomly selected households and businesses (televisions, fans, washing machines, refrigerators, and cellphones), we compare wattage and energy consumption distributions for some of the most popular and more energy consuming appliances in the country. Data collected from households and small businesses regarding fans, televisions, and washing machines suggest that these appliances consume less power than the median rated consumption values through our market analysis and survey data. For example, on-mode power consumption of fans was 55 Watts, compared to the 61 Watts median value found on the appliance labels, and the 64 Watts found through our market research. Televisions consumed an average of 62 Watts (on-mode power consumption), compared to the 65 Watts found on the appliance labels, and the 85 Watts calculated through market research. Washing machines consumed an average of 354 Watts, compared to the 510 and 530 Watts found on appliance labels and through market research respectively. The large difference in power consumption televisions values between our field-data and the market suggests that there is more availability of larger screens, and relatively inefficient television models in markets than what the households and small businesses in our sample currently have. For washing machines, the difference in values is likely due to measurement, as our data collection snap shot was likely taken at a washing-cycle of relatively low power consumption.

The comparison with the greatest difference was from refrigerator energy consumption values. For this comparison, we used energy consumption values (kWh/month) from market research and refrigerator labels when available, or used cubic size, refrigerator type and age, and the Energy Star website to calculate monthly energy consumption (26). For real-time measurements of monthly energy consumption we used data from the implementation of a FlexBox, which monitored real time parameters in Nicaragua (27). The results suggest that the appliances surveyed in the field (dimensions) consumed 40% more energy than the appliances available in the market (43.2 kWh/month vs 31.6 kWh/month respectively). However, when using actual usage data as a comparison, we found that field refrigerators consumed 70% more energy than what is currently available in the Nicaraguan market (70 kwh/month).

The power and energy consumption values collected through measurement, and gathered from web and field market research suggest the existence of an appliance-level efficiency gap. For example, 15-24 inch efficient televisions range in consumption from to 14 to 63 Watts (0.06-0.11 W/in^2)(40), suggesting that televisions in our sample are at the upper end of the spectrum. There exist even more energy efficient televisions that are twice the size (50 inches, 35 Watts, 0.014 W/in^2), but are not affordable ($US 900)(41). We did not find literature summarizing the most energy efficient floor fans, but web research suggests that some of the most efficient fans range from 40 Watts to 60 Watts, suggesting both that fans in our sample were also at the upper end of the efficiency spectrum (42, 43). Similarly, when we compare the washing machines encountered in the field (on the ground and market research) with Energy Star washing machines, we find that washing machines in Nicaragua consume from 40% to 1.08 more per year (using the same set of assumptions for calculating annual energy consumption as specified by Energy Star)(44). When comparing refrigerators and freezers to the latest and most efficient refrigerators available through Energy Star (CITE), we find that refrigerators in our sample consume between 36% and 1.21 more energy per year than the median value available from Energy Star (45).

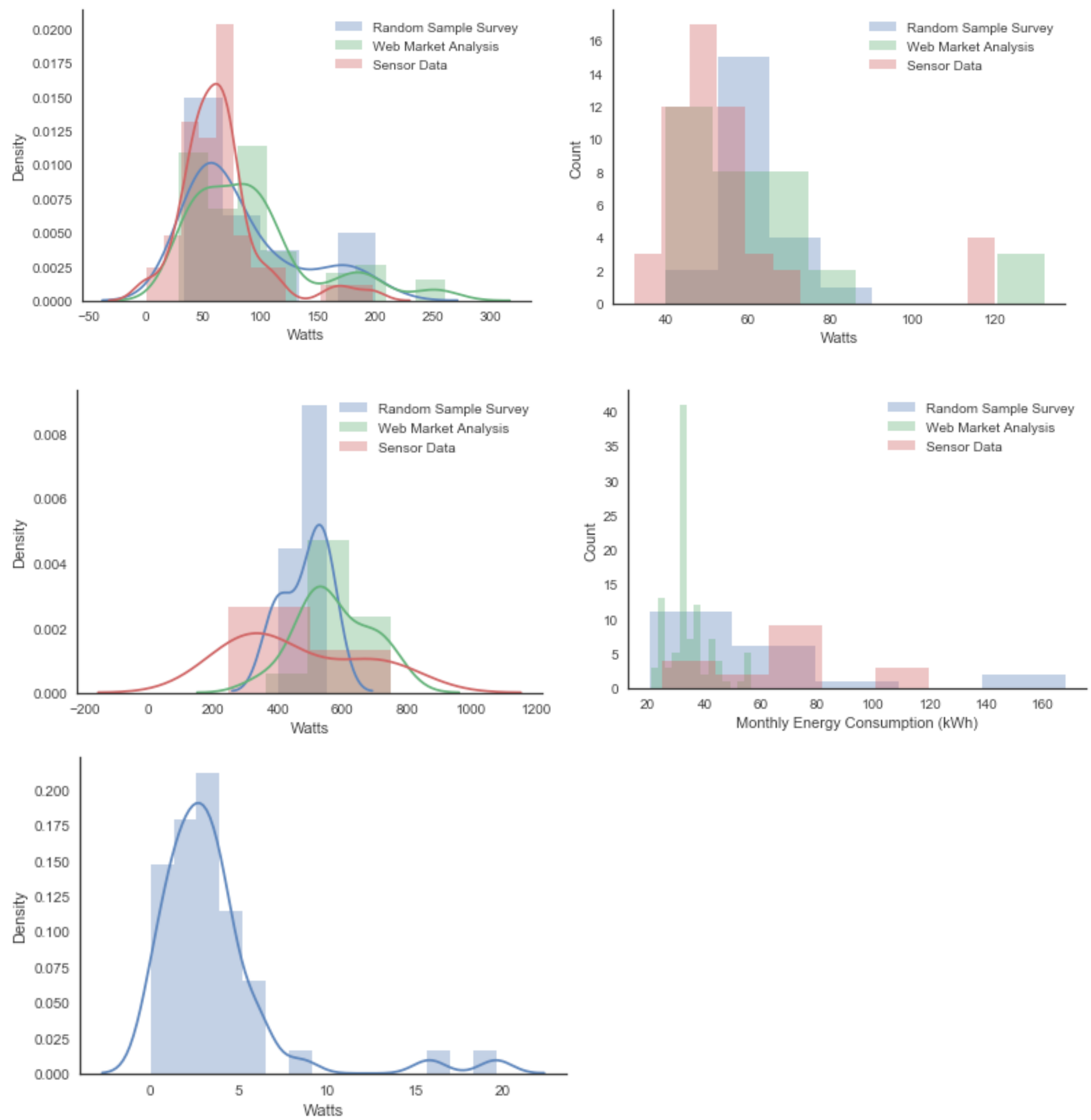

Figure 5. Distributions of Common Household and Small Business Appliances: Densities of televisions and washing machines, and Cellphones [A,C,E], and histograms of fans (Watts), and monthly energy consumption of refrigerators (kWh/month) [B,D]. Distribution depicted depends on data availability and quality of visual representation. All comparisons incorporating real-time data use maximum on-mode power consumption values, as these values are what is widely used in market analysis and appliance labels.

While collecting disparate streams of data may be useful for simple technical comparisons, they provide little information about usage. For example, the engineering calculations used to estimate monthly energy consumption for refrigerators and freezers provided an underestimate close to 30%. While volume, refrigerator type, and age can give an approximation to energy consumption, there are confounding elements that may affect the energy consumption of appliances (e.g., usage behavior, appliance physical condition, and efficiency). For example, in Nicaragua, 70% of users surveyed in another study suggested that users turn their refrigerator or freezer at different times of the day in an attempt to save energy (27), and the physical condition of many of these refrigerators and freezers would often be in a poor state. Door gaskets could be completely missing or broken, the inside metal or plastic insulation would be missing or corroded, thermostats would be set at their highest cooling level, leaky coolants would be present without any previous diagnosis, and in some cases, compressors would have been swapped two or three times. Furthermore, best practices on fridge maintenance such as wall spacing, cooling of food before storing it, and placing lids on all storage containers were not part of local user behavior. Other work in Nicaragua has found the usage efficiency of refrigerators to vary significantly throughout the day, leaving them particularly vulnerable to hot weather (27).

To understand the contribution of all appliances to the household or business level consumption we measured power and energy trace of each unit's major appliances at the same time. At each household or business, we collected three hours' worth of total household and appliance level data. Figure X (below) depicts the distribution of each appliance's contribution to total household- or business-level consumption. On average, and during the three-hour interval in which we collected data, refrigerators consumed between 35% to 95% of total energy consumption (median: 58%) when all other appliances were turned on, followed by washing machines 34%, televisions 14%, fans 12%, and cellphones 1.5% ('other' appliances had a median energy consumption of 23%). Although these data provide further insight into the actual energy use of these appliances, it is still not fully representative of actual usage. A more rigorous approach would be to have a week's worth of fully labeled appliance data in order to capture weekly temporal variability, usage patterns, and the contribution of each appliance to the monthly total. While user surveys and appliance labels could be complementary used to arrive at these numbers, confounding data issues related to actual behavior and physical condition of appliances would create a large difference between engineering estimates and ground-truth.

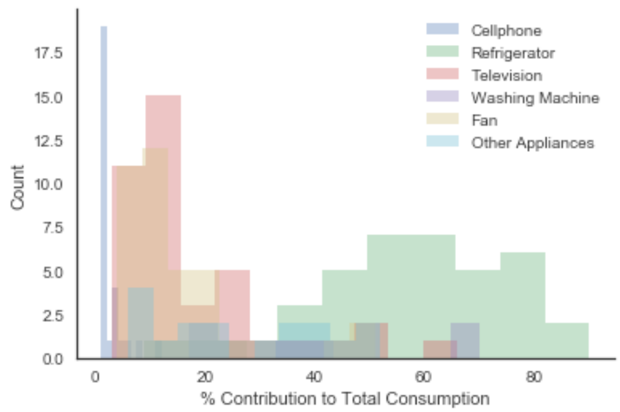

Figure 6. Contribution of Different Appliances to Total Household and Small Business Energy Consumption: Results from 3-hour interval measurements of 75 households and small-businesses in Managua, Nicaragua. Refrigerators consume between 35% to 95% of total energy consumption when all other appliances were turned on.

3.3 Posterior Distributions of Appliance Characteristics

We use Bayesian updating to construct posterior distributions for appliance characteristics (Watts and energy consumption, when appropriate) for fans, televisions, washing machines, and refrigerators. Web-market data is used as a prior for each appliance and we build posterior probability estimates using data from second-hand markets and sensors. MCMC is implemented on log-normal data, and the estimated parameters are transformed to obtain mean and uncertainty estimates for *y* as opposed to *log(y)* (y being appliance characteristics). For fans, the most likely estimate is 59 Watts, 3 Watts lower than what is found through web-market analysis. The distribution of the most likely values is narrowed from 56.3 – 71.7 Watts in the prior, to 55.9 – 62.1 Watts in the posterior. The most likely Wattage value in the prior (62.9 Watts) does not fall within the 95% high density interval (HDI) of the posterior. For televisions, the most likely estimate is 81 Watts, 9 Watts lower than in the prior distribution (web-market analysis). Similarly, the distribution of the most likely values is reduced from 80.3 – 107 watts in the prior, to 74.7 – 89.6 in the posterior, and like the fans, the most likely value in the prior (92.2 Watts) does not fall within the most likely values of the posterior. In the posterior distribution, the most likely value was 61 Watts lower than in the prior (530 vs. 591 Watts respectively), with a similar distribution width of likely values in the prior and posterior distributions. Out of the four appliances, energy consumption estimates were the only to have been provided an underestimate by the web-market analysis. In the prior distribution, the most likely value of energy consumption was 33.9 kWh/month, with a HDI of 32.5 and 35.4 kWh/month, and in the posterior distribution the most likely value was 40.7 kWh/month with a distribution of likely values ranging from 37.9 to 43.7 kWh/month. The most likely value in the prior distribution, obtained through web-market analysis did not fall within the HDI of the posterior distribution.

When comparing the parameters and distributions obtained through Bayesian updating, to some of the most energy efficient appliances in the market we find that our estimates are towards the higher end of the energy consumption spectrum. Fans and televisions in the Nicaraguan market are at the high-end of energy consumption with respect to the most efficient appliances currently available. Similarly, washing machines and refrigerators consume between 35% and 110% and 30% and 125% more energy than the most efficient appliances available, respectively (26, 41–45).

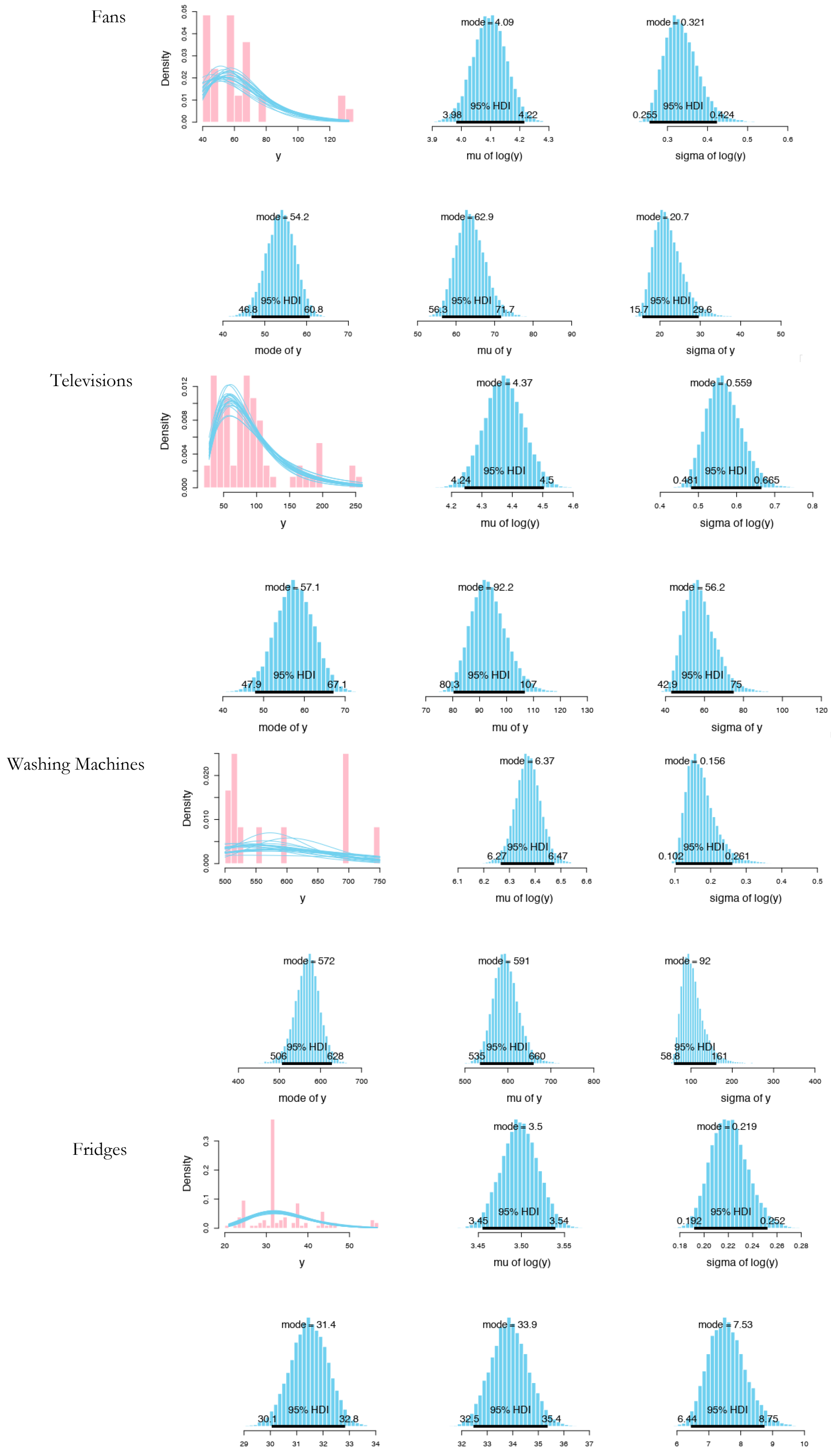

Figure 7. Appliance Characteristics for Prior Distributions

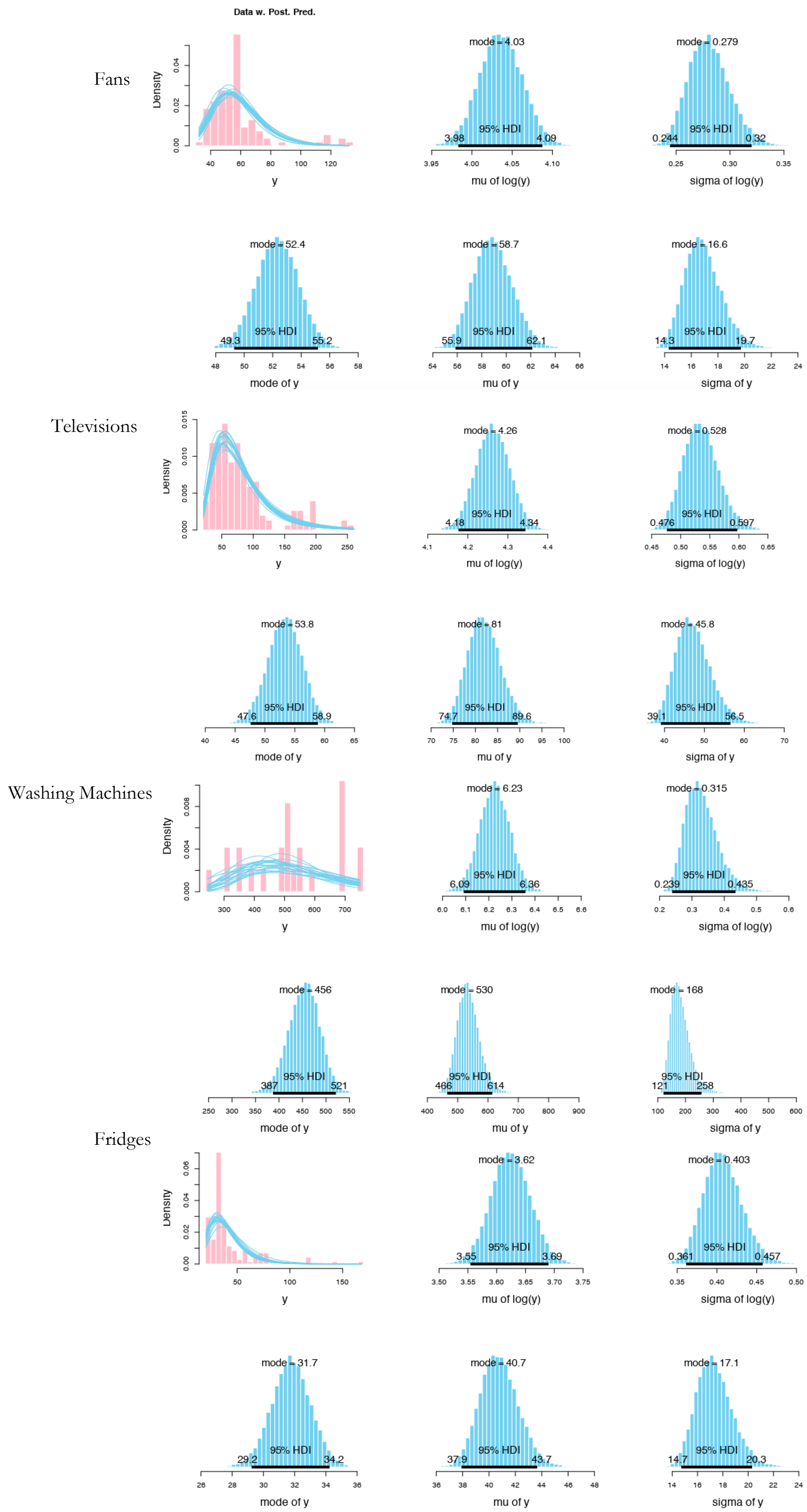

Figure 8. Appliance Characteristics for Posterior Distributions

3.4 Roofing Material: Lumens and Temperature in Housing and Small Businesses

Throughout our surveys, we also collected brightness data inside the households and small businesses that we visited. Low, low-income neighborhoods are the vast majority of population in Managua and their roofs are usually made from laminated roof, with some of them having Skylights (mean Lumens: 88, median: 65). The median value for roofs with skylights had more visible light (68 Lumens) compared to laminated roofs without skylights (62 Lumens). All these values are significantly lower than the potential available light that they could receive with alternative and appropriate roofing materials. Despite Nicaragua being a tropical country, with significant natural visible light available, the great majority of households and businesses would turn lights on in the middle of the day to perform tasks, hold meetings, host family and engage in business practices. On average, our surveys suggested that households would turn their lights on for at least 2 hours during times of the day with ample available natural light. This is an energy efficiency issue, as it is relatively straightforward and affordable to swap laminated sheets for sheets with skylights (or install them from the outset). Furthermore, cost-effective innovations such as the solar bottle lamp claim that they can provide the Lumens equivalent of a 50 Watt non-LED light bulb (750 Lumens) – significantly more than what households and small businesses currently have available (Figure 9)

With regards to heat and roofing materials, data from a previous implementation of flexible demand and behavioral energy efficiency in Managua found that households and small businesses directly experienced ambient temperatures throughout the day (27). Many of them, in fact, experienced 2°C warmer inside temperatures than the ambient data collected by an outside weather station during the hottest parts of the day (the laminated roof, working as an urban oven) (Figure 9). These warm temperatures not only affect comfort and health of households and small businesses, but they also increased the energy consumption of cooling loads between 20% and 40% during the warmest times of the day (peak usage and small business sales also occurred during the warmest times of the day). Poor roofing materials could present a critical problem for city-wide energy efficiency programs, as warm temperatures in households and small businesses could reduce the benefits of energy efficient appliance swap programs, increasing the use of electric lights during the day, as well as the use of fans and other cooling appliances for comfort.

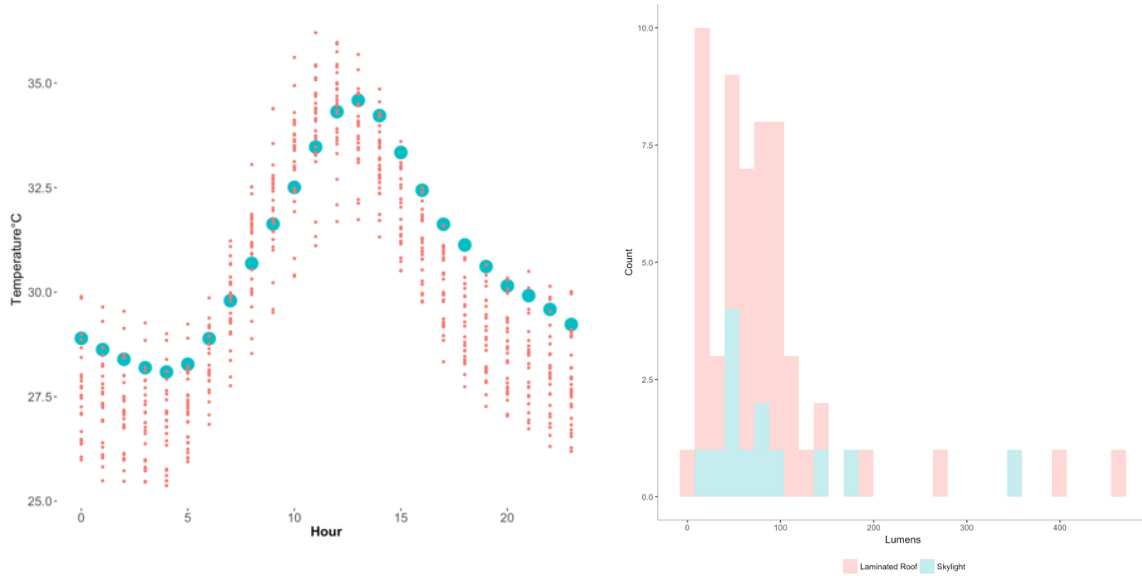

Figure 9. [A] Room temperature of household and small businesses (red) vs. ambient weather station data (blue), and [B] Distribution of Lumens inside households and small businesses with laminated roofs, and laminated roofs with skylights in Managua, Nicaragua.

3.4 Conclusion: Using Micro-Data for Energy Efficiency Planning

Together, these data allows us to build a marginal cost of saved energy curve (MCSE), which can help evaluate the magnitude and uncertainty of different energy saving strategies, as well as the energy savings per dollar spent pursuing the strategy. On average, pursuing all these strategies could lead to over 1000 kwh saved per year (if all actions were implemented), with varying rates of success and uncertainty across households and small businesses. As a baseline, we consider the energy and cost savings from swapping a 40 Watt incandescent light bulb for a 10 Watt LED bulb, implemented in three rooms of a household or business (with the lights being turned on for an average of five hours a day). Energy efficiency strategy scenarios are then compared against the baseline including swapping old for new more energy efficient appliances (televisions, fans, washing machines, and refrigerators), installing solar water bottles or large skylights, insulating roof materials and behavioral energy efficiency interventions. The results suggest that some of the most cost-effective interventions include behavioral energy efficiency and allowing for more indoor light, while behavioral energy efficiency, insulating roofs and an efficient refrigerator result in the technical savings. A shortcoming, is that our calculations are only engineering estimates, with only the behavioral energy efficiency estimates coming from a real-world pilot (24). Ideally MCSE curves should be constructed using real world pilots instead of engineering estimates.

The uncertainty estimates for appliances come from posterior distributions, for roof materials they come from the estimated induced energy reduction that cool ambient temperature would have on the energy consumption of appliances and comfort (e.g., use of fans), and on the baseline assumptions of current energy consumption and efficiency strategies.

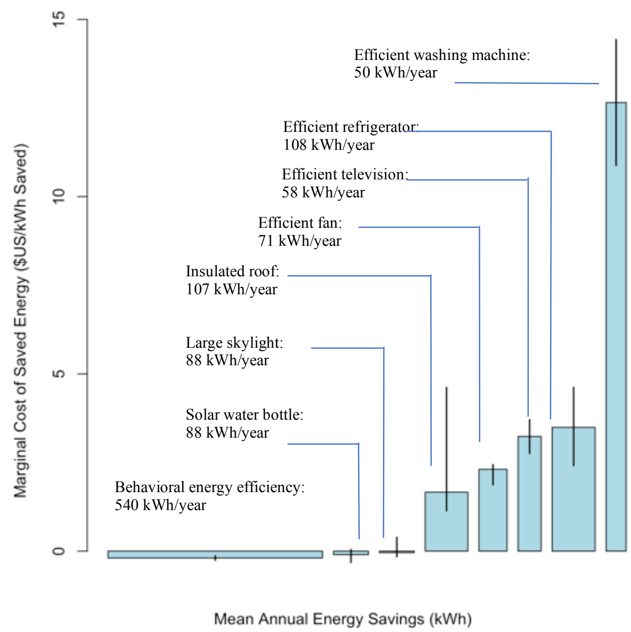

Figure 10. Marginal Cost of Saved Energy Curve for Households and Small-Businesses. Baseline assumptions include watching television three hours a day (every day of the year), using a fan ten hours a day for half of the year, using an efficient washing machine two hours a week (every week of the year), lights being turned on for two hours a day during time with plenty of available daylight.

An element that is missing from this analysis is the complexity and affordability of each of these interventions. While the marginal cost of saved energy provides some information about the cost-effectiveness of an intervention, there are several hidden costs that are no included in this analysis. For example, in Nicaragua, there are several barriers that would need to be removed for users to have access to new appliances including bank accounts and credit history, letters of recommendation from three colleagues or peers, 5-8% interest on two-year financing, and no help in removing old appliances from a household or small business. From surveys and field pilots of behavioral energy efficiency, all these barriers prevent many households and business to acquire new appliances although they would be willing to invest in long term efficiency strategies. There are no mechanisms from the government or entrepreneurs to remove these barriers.

We argue that a reason why it is hard to establish the existence and the size of an efficiency gap in resource constrained environments is because there is little bottom-up data collected that can help elucidate bottle necks for the implementation of successful strategies. Table 3 depicts some of the data that could be useful for the implementation and success of long term strategies. Each of these data complement each other, and it would be hard for them to reach full technical potential without knowledge of different components in the table below. For example, a market survey of appliances in country can tell you the availability of energy efficient appliances but doesn't tell you whether or not they are actually in people's houses and how they are used. Complementing market data with appliance ownership, as it is done here, provides more reliable data on the penetration of energy efficient appliances. Furthermore, even if analysts or planners had market data, appliance ownership and actual metered energy consumption data, little would be known about the efficiency of these appliances without sensor data (e.g., cooling loads), or any existing user behavioral energy saving practices. Behavioral energy efficiency, and hidden opportunities such as cool roofs and skylights are not obvious strategies but can have significant benefits in populations that are eager to pursue savings, and where retrofits could be cost-effective.

Without these data, we argue that it will be difficult to design and implement energy efficiency strategies that could lead to the necessary reductions in electricity demand for the decarbonization of the electricity sector. Because countries and cities with resource constrained environments have a multitude of pressing issues that need to be addressed, developing context-specific energy efficiency strategies is crucial to their long-term success. Collecting ubiquitous bottom-up data, and using appropriate analytical tools to determine the size and uncertainty of different implementation strategies is crucial for cost-effective investments and context-relevant interventions.

Data	Ideal Data Collection Mechanism	Methodology if Data not Available	Analysis/Insights
Appliance ownership by socio-economic status, race, religion and other relevant demographics	Updated national household and small business survey on appliance ownership and social demographics	1) Census, 2) Demographic and Health Care Surveys, 3) Critical Random Sampling (appliance and social demographic surveys). Machine learning to predict appliance ownership.	Penetration of efficient appliances, efficiency gap
Market survey of appliances in-country	National inventory of appliances available for sale (disaggregated by retailer types, second-hand markets)	Web-crawlers and 2nd hand market analysis from representative retailers and markets throughout the country	Availability of efficient appliances, efficiency gap
Actual in-field energy use of appliances	Utility provided 'data snapshots' of smart meter data and appliance-level energy consumption profiles by region and social demographics	Random sample of household and appliance-level energy consumption profiles by region and social demographics (off-the-shelf sensors and metering devices)	Actual energy consumption profiles, actual min, mean, and max power consumption values
Efficiency of cooling loads	Utility provided appliance-level parameters for calculating energy efficiency.	Random sample of appliances with distributed ambient and temperature sensors, and energy consumption.	Example: Internal and ambiente temperatures can be used inside a refrigerator to calculate the amount of energy that is required at different times of the day. Sensors and infrared imagery also provide information of gaps in insulation inside refrigerators, and rooms for air conditioners.
User behavior	Utility or government provided (1) surveys on the perception and adoption of energy efficiency strategies (e.g., disposable income, affordability of appliances), (2) time-series smart-meter and appliance level data for a representative population to elucidate consumption behaviors	Random sample of (1) surveys on the perception and adoption of energy efficiency strategies, (2) time-series smart-meter and appliance level data for a representative population to elucidate consumption behaviors	(1) Insights into existing user practices (e.g., unplugging refrigerator to save energy), (2) relative usage of different appliances ('priority' appliances),
User budget management	Household and/or small-business budgement management (e.g., income, costs, disposable income) by socio-economic status, race, religion and other relevant demographics	Random sample of surveys regarding budgement management (e.g., income, costs, disposable income) and affordability of accessing new appliances, financial barriers to obtain new appliances (incuding transportation)	Efficiency gap as it relates to financing new appliances and their affordability
Hidden opportunities	-	Random sample of (1) sensor data collecting room ambient temperature, energy consumption, and load level data provides hidden insights into the efficiency gap, (2) surveys of household characteristics (e.g., roof type, wall type, number of windows)	Insights into overlooked energy efficiency strategies (e.g., cool roofs, natural light)

Table 3. Useful Data in Determining the Existence, Magnitude and Strategies to Address the Efficiency Gap in Resource Constrained Environments

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