Title
Demand-side Knowledge for Sustainable Decarbonization In Resource Constrained Environments: Applied Research at the Intersection of Behavior, Data-Mining, and Technology

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Demand-side Knowledge for Sustainable Decarbonization in Resource Constrained Environments: Applied Research at the Intersection of Behavior, Data-Mining, and Technology

By

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Professor Daniel Kammen, Chair
Professor Duncan Callaway
Professor Alexey Pozdnukhov

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Abstract

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Diego Ponce de León Barido

Doctor of Philosophy in Energy and Resources

University of California, Berkeley

Professor Daniel M. Kammen, Chair

Recent developments in behavioral science, machine learning, and information and communication technologies are fundamentally transforming the questions and methods that can be applied to sustainability science. Research in decision making is transitioning from rational expectations towards bounded rationality models, machine learning excels at prediction rather than hypothesis testing, and ubiquitous sensor networks can elucidate new insights regarding previously unobserved system dynamics. This dissertation combines these three approaches to explore demand side features and strategies for sustainable decarbonization through various case studies of global, national and urban energy systems.

Behavioral science provided a strong theoretical framework with which to frame many of the insights that I encountered through field-research and data-mining. Why and how is it that some relatively poor countries, with weaker traditional notions of institutional strength make significant progress towards decarbonization? Why do relatively wealthier countries, with supposedly stronger institutions, and with abundant renewable resources fail to make such progress? Why do low-income households fail to invest their savings from energy efficiency or long-term energy efficiency retrofits? Why would a low-income household prefer high-resolution information over cash? How can we design more effective support mechanisms for sustainability at the national and household level? Ryan and Deci's insights on intrinsic motivation (and all the subsequent work by other researchers they've inspired) (1, 2), Kahneman and Tversky's work on prospect theory, the endowment effect, and loss aversion (3–5), Thaler's insights on nudging and savings (4, 6), and Mullainathan and Shafir's work on the psychology of scarcity (7, 8), have all provided rich insights with which I address many of these questions.

This dissertation also places a strong emphasis on data mining and statistical inference. Data mining and machine learning approaches are appealing because they are theory agnostic, can deal with nonlinearities, and encourage the researcher to collect as much data as possible. While this dissertation makes no contributions to improving the accuracy of data mining and machine learning techniques, it does provide new ways of bringing data together for the purpose of sustainability science. Rather than using causal inference to explore a specific hypothesis, I organize disparate 'long and wide' data and use data mining and prediction approaches (e.g., principal component regressions, nearest neighbors, random forests) to extract the features that can best predict my dependent *y* variable. In some cases, I also use Bayesian inference to characterize the size and uncertainty of the outcomes measured in my field-work, as well as to build posterior distributions from several seemingly disparate data streams.

Bayes, philosophically, is particularly interesting as its usefulness increases as more data is collected, encouraging the researcher to continuously collect more evidence in order to test the strength and uncertainty of an initial hypothesis. A strong hypothesis would need a lot of data to be refuted, and thus, one has to collect an extraordinary amount of evidence to change a well-established norm. On the other hand, a weak hypothesis that is not backed up by data can be easily refuted. More importantly, Bayes lends itself to the evaluation of strong theories. Strong theories estimate the magnitude of parameter values and their credibility, not merely reject null values (9, 10). I use Bayes, data-mining and machine learning approaches in my work as they provide a flexible yet rigorous analytical tool box for which to extract meaning from data.

The rapid cost reduction in sensor networks suggests that in the near future they will be the bridge between behavioral science and data mining. While they have been used in manufacturing and industry for decades, they are now proving to be fundamental for research at the intersection of behavior, technology and sustainability. For example, sensors can be used to effectively monitor the efficacy and usage of cook stoves, water filters, and water delivery in field trials (11), to validate user responses in surveys and interviews against sensor data, and to evaluate whether or not a socio-technical intervention geared towards sustainability is being used appropriately. While the gold-standard for field-technology trials is randomized controlled trials (RCTs), the evaluation of an intervention is only valid if it was implemented without error; if not, what the RCT is truly evaluating is the quality of the intervention rather than the research questions themselves. Sensors allow researchers not only to monitor and troubleshoot, but also to uncover hidden insights about a system – how do rainfall and temperature affect appliance usage? What environmental factors affect the quality of the intervention? How can the technology be changed in the future to address usage issues related to environmental and behavioral factors? Similarly, information and communication technologies (ICTs) allow for a cost-effective two-way communication pathway with users: nudging, questions, complaints, AB testing, and feedback become immediately available with ICTs.

How are these three broad and overarching themes related to sustainable decarbonization? Sustainable decarbonization, here, is defined as the equitable reduction in total energy demand, accompanied by the increased adoption and use of low-carbon life styles and technologies. Equity in this context, is defined as *equal opportunity of access* to these lifestyles and technologies, while in consideration of barriers to entry (e.g., gentrification, racism, affordability, income), and the design and implementation of mechanisms to overcome them. At the global and national-level, equitable reductions in energy consumption and increase in the growth of low-carbon technologies will not occur without contextualized knowledge of local dynamics. Here, I bring together diverse data sets to provide context to local characteristics ranging from soil data, to water bodies, access to mobile finance, and the quality of governance of local institutions, among many other variables. At the city-, neighborhood-, and household-level, sustainable decarbonization will not occur, or be equitable, without fully considering users, behavior, and co-designing technology (services and systems) that work for them and their communities. In this case, we use the nexus of information and communication technology, sensors, behavior and data mining to co-design information systems that simultaneously work for the user and the energy system in which they interact.

What are resource constrained environments? Resource constrained environments, here, are defined as spaces that exist in relative social, infrastructural, economic, or environmental scarcity, and can be found anywhere. Resource constrained environments can be found in California (e.g., Richmond in Contra Costa county) where low-income and predominantly African American residents are exposed to much higher concentrations of benzene, mercury and other hazardous pollutants due to the nearby Chevron refinery (12, 13), or Memphis, New Orleans and Birmingham where low-income households spend over 10% of their income on electricity (14). They can also be found in Kenya, where it may take a lot of time and money to reach rural communities to perform needs assessments and provision of basic services. Or, Managua (Nicaragua), where low, low-middle income neighborhoods can only afford used appliances, and have a panoply of barriers to access energy efficiency and sustainable energy services. Exploring, ideating, and implementing solutions for resource constrained environments requires knowledge of history, local context and dynamics, and many aspects of top-down (e.g., institutional, political) and bottom-up (e.g., end-users, neighborhoods) behavior.

This dissertation, explores demand-side, user-centered, sustainable decarbonization in resource constrained environments at multiple scales. The first chapter presents an analysis of global demand-side features that are enabling low-carbon transitions. It synthesizes 10 global energy and development related data sets and uses methods from data mining and concepts in behavioral science to propose a new methodology for the design and evaluation of long-term energy system decarbonization support mechanisms. Considering the nation-state as a single agent with its own historical intrinsic motivations for enacting change (e.g., social progress, environmentalism, economic efficiency, supremacy and empire), intrinsic characteristics (e.g., population size, land area, quality of governance), and enabling environments (e.g., local fuel and electricity prices, supporting policies) it uses these data to extract the features that can best explain decarbonization progress. We find higher local energy prices, foreign energy import dependency and absence of a large extractive resource base (e.g., oil and gas, mining), relative high investments in renewable energy (per km^2 and capita), and early historical investments in geothermal energy and biomass for electricity to be key driving features. Policies, although widely advocated for in international frameworks, do not appear as key enabling drivers - especially in the rising south, and when misaligned with country specific motivators and intrinsic characteristics.

The second chapter explores and develops new methods in elucidating demand for the design and implementation of appropriate and sustainable energy interventions. It uses a mix of high spatial resolution data sets, surveys, sensor data, and data mining to develop new methods for elucidating rural electricity demand at the household and community level, and to help close the 'energy efficiency gap' in urban resource constrained environments. It uses an extended literature review and data at multiple scales to create a data-driven context that energy planners can use in their supply-side models. Using Kenya as an example, and with colleagues from the IBM-Africa (Nairobi) research lab, we develop what we consider to be the first reliable data-driven approach for elucidating household appliance ownership and induced household demand for electricity using a mixture of large-scale social demographic data, spatial data, and machine learning approaches. We also use data-mining and an extended literature review to explore and identify the enabling conditions under which electrification can lead to wealth via micro-enterprise creation in rural areas. The latter also presents the first analysis to evaluate the drawbacks/inaccuracies of the modern use of nightlights as a panacea for tracking wealth in unelectrified regions. Finally, and using Nicaragua as a case study, this chapter develops an extended literature review and framework on how to collect data for baseline energy efficiency estimates in resource constrained environments using a mixed methods approach combining surveys, sensors, population sampling and Bayesian updating.

The third chapter uses a field deployment pilot in Nicaragua as a case study, presenting opportunities and challenges for information and communication technologies (ICTs) and the internet of things (IOT) for demand-side flexibility and behavioral energy efficiency in resource constrained environments. We use ICTs and IOT to implement the first paired behavioral energy efficiency and flexible demand pilot in Latin America, in Nicaragua's capital city of Managua. The chapter is divided in two sections, the first introduces the design, implementation, and exploratory data analysis of a sensor gateway (the FlexBox) for enabling behavioral energy efficiency and demand side flexibility, and the second is a post-implementation evaluation using Bayesian estimation for evaluating energy reduction, participation in demand side flexibility, impacts on welfare, and behavioral economics insights. We present several novel findings related to technology implementation, development of new efficiency parameters, and behavioral insights (e.g., incentive types, pre-existing behaviors, motivations) describing the opportunities and barriers to behavioral energy efficiency and demand side flexibility in these contexts. More importantly, we show that ICTs and IOT are mature technology that can be used by low, low-middle income households and small businesses in cities like Managua to become important actors in city-wide resource conservation. We conclude by presenting opportunities for future research.

Dedicated to Martin Foley, who bifurcated my path towards a life of global friendships, learning and giving. To my parents (Samuel and Queta), whose sacrifice and hard work have given me a blessed life, and who have been unwavering by my side. Thank you.

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This research would not have been possible without the collaboration and support of friends and colleagues throughout my PhD including Jay Taneja, Douglas Fabini, Javier Rosa, Nikky Avila, Akomeno Omu, Simone Fobi Nsutezo, and Stephen Suffian. The ERG community provided a welcoming and safe space to do my research, and valuable feedback to continuously improve it. Kay Burns and Sandra Dovali always provided support, a helpful hand, and guidance when I felt that the world was being swept from under my feet. Professor Daniel M. Kammen provided unabridged optimism towards most of my research ideas (sometimes unjustified!), insightful conversations, financial support and numerous networking and professional opportunities, Professor Duncan Callaway provided financial support, detailed feedback, keen attention to detail, and a healthy counter-balance to my viewpoints, and Professors Eric Brewer and Alexey Pozdnukohv kindly provided careful and detailed advice, comments and feedback.

The country of Nicaragua, and the people I collaborated with, made possible most of this research. Living in Nicaragua opened my eyes to the fraternity of Latin Americans and our common histories and struggles, and to the honesty and persistence of most of its people. Professor Maria Virginia Moncada, David Lopez Carcache, Mario Aleman, and Odaly Molina were fundamental to this work, and patient, while we successfully implemented many relatively complex projects together.

At a personal level, I'm thankful for my ERG 2012 cohort, whose insubordinate behavior inspired me to pursue research that seemed risky, but fruitful and rich. None of this work would have been completed without the love, intelligence and multidimensional support of Katerina (and my Greek family) through anything that was thrown our way, and of course, my Mexican family, who are always present, loving, and unwaveringly encouraging.

Thank you.

Structures of Power, Equity, and Ethics in this Research

Throughout the creation of this work, there were numerous occasions when the structures of power, injustice and ethics emerged to clarify why it is difficult to scale solutions that simultaneously work for people and planet. The relationship between local decision makers and experts, the overwhelming detached nature (and some of the methods) of academic research, and the disparity in funding for research across geographies fosters inequality, and erodes the impact of applied research.

Decision making, often, occurs from a top-down approach with local decision makers and institutions collaborating with foreign experts (e.g., academics, consultants) to move an idea forward. The nature of this relationship is fraught, as the experts must remain in good favor with decision makers (e.g., to win contracts), although many times the ideas being supported might be to the disadvantage of a country, a region or a community. Other times, experts come with support from a funding agency (e.g., World Bank, IDB) and seek to influence the path of a country, or the opinion of decision makers, by applying an umbrella methodology (e.g., structural adjustment programs, optimization frameworks, results from big data) without understanding the historical, cultural and political factors of why a problem arose in the first place[1,2,3]. Umbrella methodologies are attractive, as they appear to be quick to implement, but are awash with assumptions. Take for example, forestry conservation programs that displace entire communities[3], agricultural development practices that engage in genocide[3], or large-scale energy developments (e.g., hydropower, renewables) that displace communities and empower an elite[4]. Because decision making is co-created by foreign experts and local elites, root issues are never addressed (e.g., corruption, inequality), fostering solutions with vested interests. Academia has the freedom to inform these issues, but often leaves them untouched.

These power structures were apparent as I began my research collaboration with the Nicaraguan National Engineering University. Local public universities in Nicaragua have almost no funding for research, and when a collaboration begins, local researchers are already at a disadvantage about what ideas and frameworks gain traction. Foreign researchers with more time and resources can often move faster than local colleagues, who are limited by a lack of research funds. Thus, at meetings with decision makers, it was my analysis that was presented, despite knowing less about the local context. Funding mechanisms that split research funds more equitably would help solve part of this problem, but the nature of how awards and grants are disbursed in the U.S. (e.g., overhead, bureaucracy) makes it even more difficult to create equitable collaborative partnerships. Streamlining how grants are awarded, how universities disburse funds, and bureaucratic complexities could create more fruitful research collaborations. Local partners often had to work for free for many months at a time, waiting for UC Berkeley to disburse payments. More consideration to the sacrifices that other institutions make to work with UC Berkeley should be considered to level the balance of power.

My applied research at the intersection of behavior and technology also brought to light several issues related to equity and ethics. While working directly with household and small-businesses in Nicaragua in technology implementation, and although we did our best (and somewhat succeeded) to ensure that our participants directly benefited from our projects, we failed to fully address societal gaps of poverty, chauvinism, and access to education that prevented many participants from fully benefitting from our program. A better thought-out and perhaps more lengthy co-design period could have prevented some of the evident gaps that later emerged. I take all these lessons with me as I transition out of UC Berkeley.

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Chapter 1: Inherent Characteristics, Enabling Environments and Motivations towards Long-Term Decarbonization

1.1 Introduction

This chapter presents an analysis of global demand-side features that are enabling low-carbon transitions. In the literature, there is an unspoken consensus that push supply-side mechanisms such as top-down policies, financing, and technology are the global drivers for decarbonization (15–19). Globally, and within international agreements and frameworks, this consensus is pushed across disparate regions, incomes, cultures, and levels of human development – without evidence that these blanket mechanisms are working across contexts (20). Take, for example, evidence that suggests that $50 billion in Illicit Financial Flows leave Africa every year, almost an equal amount to the official development assistance that the continent receives every year (21). Or expectations that countries like Mexico, Nigeria, and the United States, rampant with corruption and all with a large fossil fuel resource base will abide by their intended national determined contributions. This cognitive bias, arguably, has led to slow progress in global energy system decarbonization in a world with weak climate leadership, institutions, and governance. More research is needed to understand where and why decarbonization transitions are being successful.

Towards this effort, this chapter synthesizes 10 global energy and development related data sets and uses methods from data mining and concepts in behavioral science to propose a new methodology for the design and evaluation of long-term energy system decarbonization support mechanisms. We use a data mining approach to extract the features that capture the greatest amount of variance in the data and find that an analysis of enabling environments, inherent characteristics, and intrinsic motivations could provide a more comprehensive theoretical framework for evaluating long-term decarbonization. Higher local energy prices, foreign energy import dependency and absence of a large extractive resource base (e.g., oil and gas, mining), relative high investments in renewable energy (per km^2 and capita), and early historical investments in geothermal energy and biomass for electricity appear as key driving features. Policies, although widely advocated for in international frameworks, do not appear as key enabling drivers - especially in the rising south, and when misaligned with country specific motivators and intrinsic characteristics.

We present a theoretical framework – *decarbonization across the motivation spectrum* – that argues for long-term decarbonization support mechanisms to be designed at the intersection of country specific motivators, local enabling environments, and inherent characteristics. To exemplify the decarbonization motivation spectrum, we use data from the Social Progress Imperative, the Quality of Governance Initiative, the Yale Environmental Performance Index, the Global Footprint Network and the World Bank Development Indicators to create proxies for three key motivators: social progress, local sustainability, and desire for energy independence. We scale these metrics and assign a score to each country across the sum of these three motivators, and plot the score against a dependent variable measuring decarbonization progress between 1980 and 2014 (or latest data available) in enabling a low-carbon energy transition.

Our findings demonstrate that there is not one major driver of decarbonization, but rather, a multitude of factors that can contribute to transformative progress. Globally, there are many countries around the world with suitable inherent characteristics and enabling environments for kindling decarbonization that remain, however, in the path towards carbon lock-in. This, we argue, can be prevented or reversed in order to spark a new wave of decarbonization, and we suggest four new opportunities to reinvigorate global decarbonization progress (expanded in the text to follow): 1) Identifying and tapping pockets of demand-side opportunity, 2) diversifying the types of support mechanisms and motivations for energy system decarbonization, 3) diversifying the change agents that receive support for decarbonization, and 4) thinking beyond energy and increasing the acceptance of non-optimal decarbonization pathways.

1.2 Background

In global decarbonization support frameworks, there is a broad consensus that policies and goal-setting are the preferred mechanisms for enabling energy transitions (20, 22). Furthermore, these mechanisms have been historically motivated by climate change mitigation, leaving out a wide range of reasons why countries would choose to pursue energy system decarbonization. Global leaders in low-carbon energy transitions now appear across a wide range of incomes, regions, and levels of development, suggesting that there are multiple motivations, inherent characteristics, and enabling environments that can foster energy system decarbonization (Figure 1) (23–25).

Costa Rica, Nicaragua, and Kenya, are three unconventional examples of countries which have taken significant steps towards the goal of 80% electricity decarbonization by 2050. Currently, these three countries – and with disparate motivations – have some of highest proportions of electricity generation from non-hydropower renewable energy (24%, 46%, and 46% respectively) amongst low and low-middle income countries ($13,600, $4,500, and $2,800 per capita respectively), and are over-performers relative to other countries in their income group (Figure 1). Other global energy transition leaders – and over performers relative to their income group – such as Denmark, Germany, and Portugal had a negligible fraction of electricity generation from non-hydropower renewable resources when they were at a similar stage of economic development (~$7,000 GDP per capita). This trend highlights that renewable energy technologies have become increasingly affordable for countries across the entire income spectrum, and the importance of other features besides climate change mitigation policies to motivate decarbonization.

This chapter integrates a mixture of data mining methods, behavioral science theory, and historical perspectives to uncover these key features within the global low-carbon energy system transition. We shed light on components of energy transitions that are once again emerging, some that are changing, and new themes that require attention (26, 27). Supported by our analysis and data, we propose a framework for decarbonization across the motivation spectrum that can be used to guide the design of support mechanisms that are inclusive of a range of drivers and motivations, beyond solely focusing on climate change mitigation.

1.2.1 A Review of Energy System Transitions

The importance and role of first adopters varies across technologies, with evidence and the literature suggesting that they are more important for wind and solar, than for the global diffusion of geothermal and biomass due to their inherent risks related to resource development and sustainable resource management (28–30). Here, we consider 'adoption' when a country generates at least 1% of the total from a non-hydropower renewable resource. Biomass for electricity generation is a resource and technology that has seen widespread adoption for many decades, with Europe and the Americas both being first adopters, albeit with different sustainability practices. While most early adopters and countries in Europe have slowly increased or diversified their sources of biomass production together with the adoption of best practices (trees, arable crops, algae and other plans, agricultural and forest residues, effluents, sewage sludge, manures, industrial by-products, organic municipal waste, and imported biomass) (31–34), first adopters in the Americas and Africa have seen a more unstable path with half of the first adopters experiencing a significant decline in production due to a variety of factors including the cost-competitiveness of other fuels and technologies, supply-chain efficiency, unsustainable practices, climate change impacts, and in some cases violent conflict (35–40). Geothermal developments have also seen early global adoption with the notable cases of Iceland, Kenya and El Salvador. While Central American countries (El Salvador, Nicaragua, Costa Rica, and

Guatemala) have continued to increase the adoption of geothermal energy in their energy mix, countries in the Rift Valley, which has a large geothermal potential (41), have not followed Kenya's path despite the country doubling its production in 2014 (40%). All first adopters, except for the Philippines, El Salvador, and Mexico, whose production declined but are still pursuing the resource, have continued to foster and invest in further development. Still, despite the presence of these first adopters, the observed benefits to energy security and a cost-effective baseload, and nascent solutions to mitigate uncertainties and financial risks associated with drilling wells on green fields, the global geothermal resource remains largely undeveloped (42, 43).

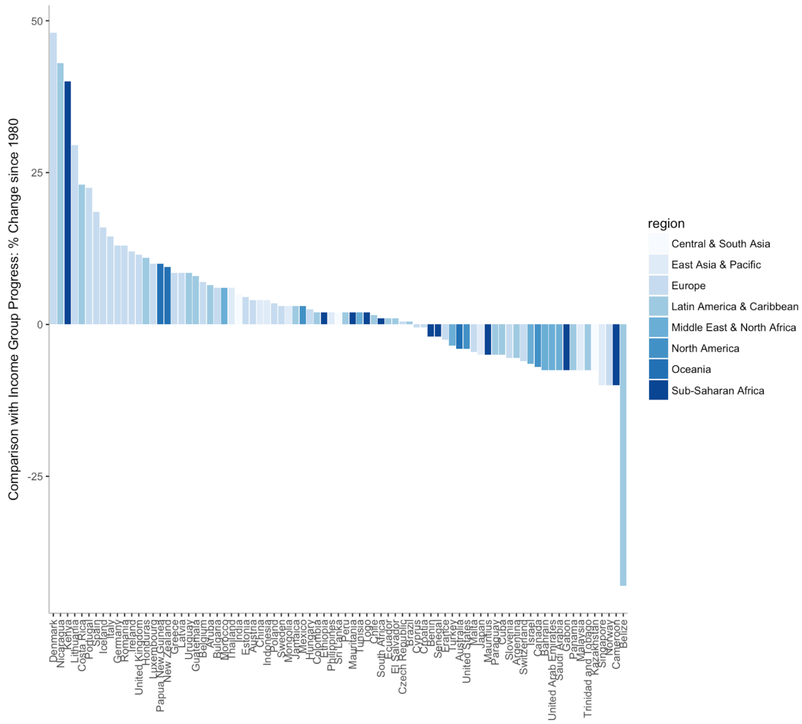


Figure 1. Over and Underperformers in Electricity System Decarbonization Progress: The y-axis depicts the difference in a country's energy system decarbonization progress and the progress of the cluster income group to which it belongs. Countries are clustered by income (low-income ≤ $10000 GDP/Capita, $US 10000< low-middle income ≤ $20000, $US 20000 <high-middle income ≤$US 45,000, and $US 45000<high-income). The median income value of each income cluster is calculated, and a relative progress score is assigned to each country by subtracting its decarbonization progress since 1980 from the median progress score of the income cluster to which it belongs.

The diffusion of wind and solar technologies have been explored extensively by the literature, with a diversity of factors being suggested as the preconditions for technological adoption including policies to support the growth of the power sector, local environmental, social, economic and political variables, support for innovation, industrial development, and technological change, learning and R&D support (and consequent reductions in investment costs), feed-in-tariffs, financial incentives and production-tax credit schemes, household social-demographics, resource potential, and spatial variability, local electricity cost, and the emergence of China and India as global players in solar and technology development, among others (29, 44–49). While many of these motivations are in line with the energy transitions literature (motivated by policies and institutions, with successful policies necessitating continuity and persistence, alignment and balance)(28), a different point of view is also offered by the wind and solar literature that views environmental groups, constituents, and civil society as key agents in an energy transition (44, 50). Finally, a new emerging literature is beginning to explore the differences in decision making around technology adoption in the rising south. This research suggests, that policy formulation is not sufficient in countries with an "institutional gap", and suggests that clear and strong financial incentives, predictability of government decision making, and streamlined permitting procedures are as important (or more) as the existence of policies (51, 52). Like the energy transitions literature suggests, the repertoire of policies for late technology adopters should be very different from those established by first adopters and early pioneers, especially if the technology carries low risk. A recognition of this central issue is key to designing mechanisms that work specifically for countries who want to simply adopt technology, and do not seek to build R&D or development of a local industry like market leaders tend to prefer. Figure 2 presents a visual representation of the diffusion of renewable energy technologies in space and time.

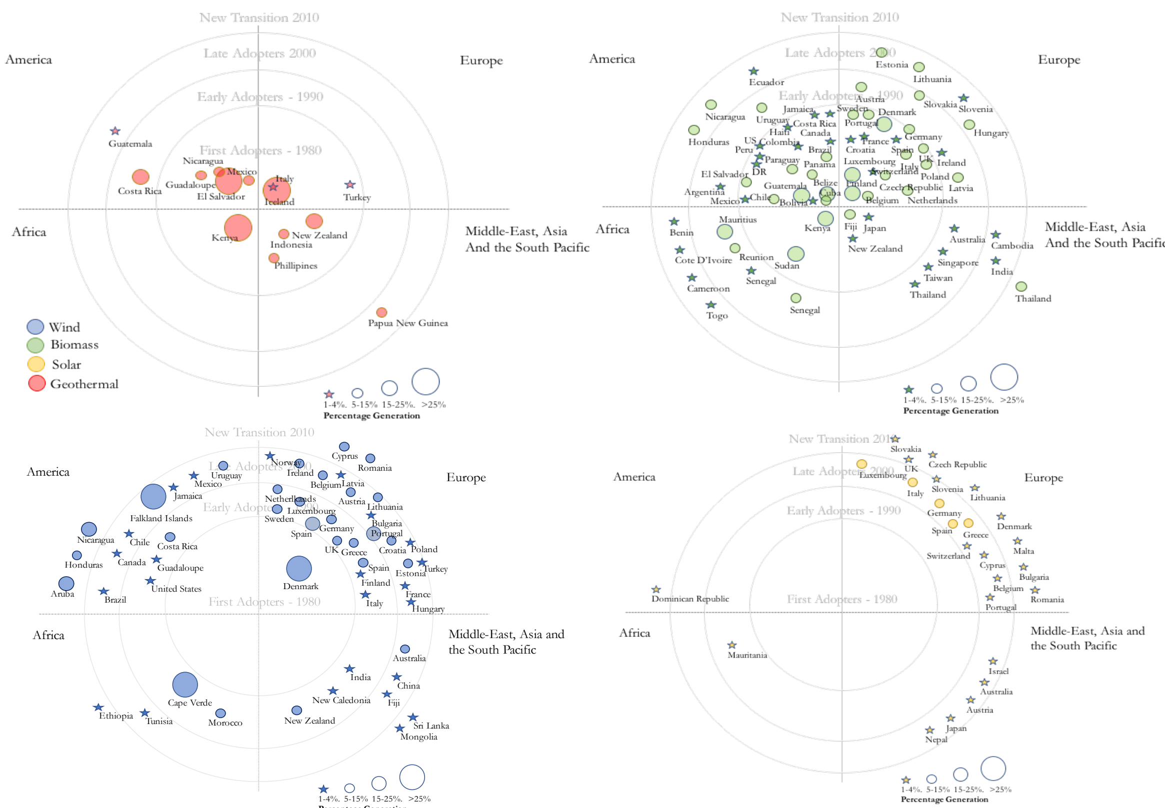


Figure 2. Global Spatiotemporal Diffusion of Non-Hydropower Renewable Energy Technologies: This figure considers the adoption of a technology to be when at least 1% of a country's total generation comes from a specific technology. It demonstrates that countries across a wide spectrum of social-demographics have historically invested in renewable energy (e.g., geothermal and biomass), with wind and solar now experiencing the latest wave of investments and development. Geothermal energy has seen very little growth in recent decades, despite its large potential.

1.2.2 Decarbonization Across a Spectrum of Policies, Institution Types and Motivations

Progress in global decarbonization is now occurring across a spectrum of political and policy enabling environments, and diverse qualities of governance and infrastructure (Figure 3). Figure 3 shows the number of pro-renewable energy policies passed since 1974 (53) against the percentage point renewable energy change between 1980 and 2014 (54) (non-hydro renewable energy as a percentage of total generation) and depicts various enabling environments: countries with great carbon responsibility and many policies making little progress (e.g., USA and China), countries passing policies yet moving slowly or even going backwards (e.g., Mexico, Canada, Indonesia, and Paraguay), countries with few policies yet transitioning rapidly (e.g., Iceland, Nicaragua, and Kenya), and clusters of countries where more policies seemingly do translate into change (e.g., Germany, Spain, Denmark, Lithuania, Ireland, and Costa Rica). Similarly, the figure also shows that countries with relatively low-scores with regards to quality of infrastructure and governance are performing equally as well, and in some cases better, than countries with traditional notions of good governance and better infrastructure.

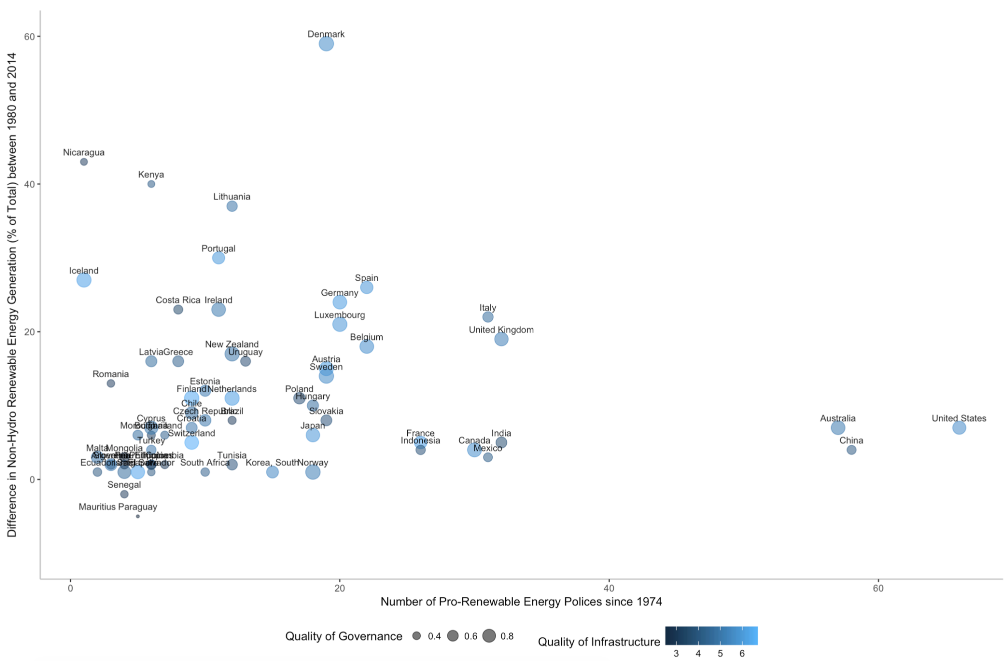


Figure 3. Policies, Quality of Governance and Infrastructure and Decarbonization Progress. Difference between total percentage generation from non-hydropower renewable resources from 1980 until 2014 in countries as a function of the number of pro-renewable energy policies passed since 1974, and Quality of Governance and Infrastructure as defined by the Quality of Governance initiative. The color of the dot represents the quality of infrastructure (such as roads, bridges and electric grids) and the size of the dot represents the quality of governance. Energy system decarbonization is occurring across a spectrum of policy environments and infrastructural and institutional characteristics.

1.3 Data

We collect data for 190 countries and territories from the World Bank Development Indicators (55), Bloomberg New Energy Finance's Climatescope (24), the Energy Information Administration (54), the Quality of Governance Initiative (56), the International Energy Agency and IRENA's joint policies and measures database for global renewable energy (53), the Global Footprint Network (57), the United Nations Human Development Indicators (58), Yale's Environmental Performance Index (59), the Social Progress Imperative data (60), and the World Energy Council (61). These data include measures and a variety of proxies for sustainability, foreign energy dependence, local resource dependence, governance and quality of institutions, renewable and climate related policies, human development, energy finance (towards renewable energy and fossil fuels), resource consumption (e.g., electricity demand, total energy demand growth rates, electricity and total energy demand rates of change), and country specific characteristics such as land size, population, population density, and gross domestic product. We clean and merge all data sets until we have a 130 country merged data set, plot and analyze correlations across variables, and perform our analysis on a subset of countries that have increased their generation from non-hydropower renewable resources by 1% or more between 1980 and 2014 (or year of latest data). This subset of the data (countries with progress equal to or greater to 1% in non-hydropower renewable energy generation between 1980 and 204) includes 76 countries across all regions and ranges of the proxies that have been described above.

1.4 Methods and Analysis

We perform a simple correlation analysis among all the variables (sample in Figure 4) to explore variables that are correlated with each other, and variables that are correlated with progress towards decarbonization. We develop this correlation analysis for the full data set (all countries ≥ 1% progress in decarbonization) and for a subset of the countries with income per capita below $US 30,000. In the full data set, the variables with the strongest correlation with decarbonization progress include local electricity prices (industrial, commercial, retail and mean electricity prices $US/MWh) and fuel prices ($US/gallon), level of energy import dependency, aid as a percentage of GDP, and ecological footprint variables. Clusters of variables that are strongly correlated with each other include intrinsic country characteristics (e.g., population, land size), and enabling environments (e.g., number of policies in support of renewable energy, local subsidies to fossil fuels and electricity prices, and total investments in renewable energy). Quality of governance variables are strongly correlated with income, and also have a higher total ecological footprint than other countries. In the lower-income data set (≤ $US 30,000) ,energy prices (electricity and fuel) and the level of energy import dependency have the strongest correlation with decarbonization progress.

After the data is cleaned and merged we implemented a k-means algorithm on the principal components that capture most of the variance in the data set. We first log-normalize skewed variables, perform a scaling methodology that is consistent with our dependent variable (on the dimensionality reduction step), implement a principal components methodology, and estimate our decarbonization progress dependent variable by using the principal components that capture most of the variance. We choose to use principal components regression (PCR) as opposed to performing a hypothesis testing driven analysis, as we attempt to extract the features that can capture most of the variability for better predicting decarbonization progress. Furthermore, we use PCR because it addresses issues related to multicollinearity in the data (highly correlated predictor variables) by implementing dimensionality reduction, removing low-variance principal components when implementing the regression step, and ensuring mutual orthogonality amongst the principal components. We use the libraries cluster, vtreat, WVplots, FactoMineR, and factoextra from the open source statistical programming language R to perform our analysis.

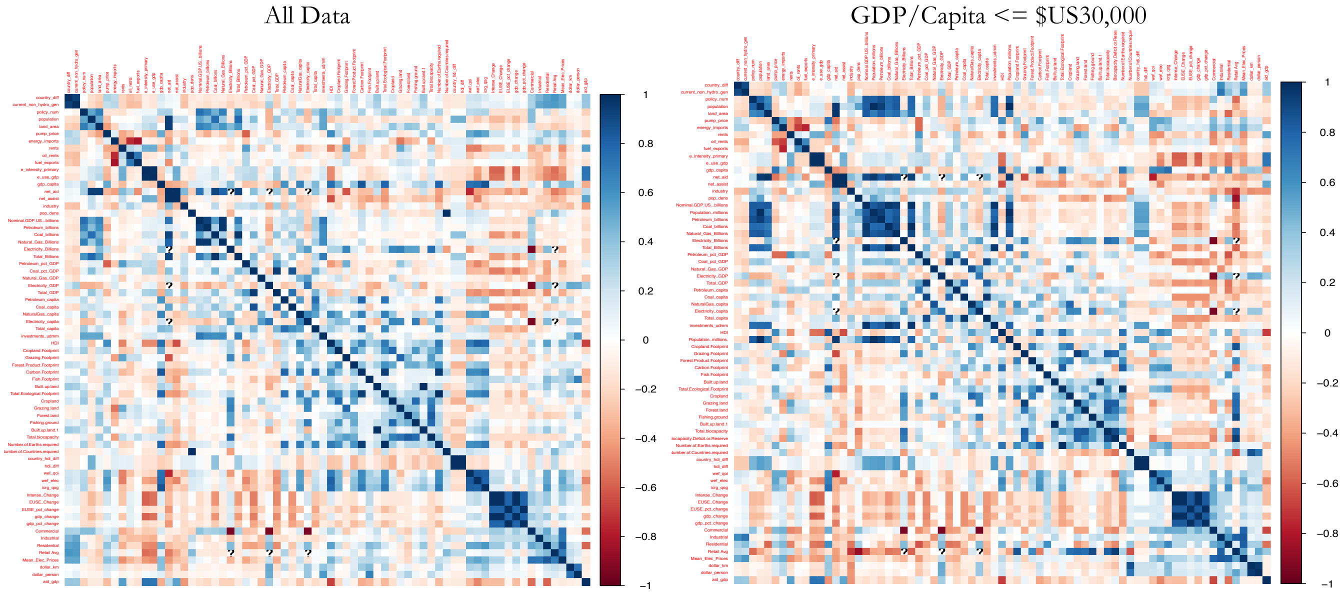


Figure 4 - Correlation Matrix (Data Subset, Full and Partial Income Data Set): Full data and countries below $30,000 per capita.

Countries Above $US 30,000: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States.

Below $US 30,000: Argentina, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Czech Republic, Ecuador, El Salvador, Estonia, Ethiopia, Greece, Hungary, India, Indonesia, Kenya, Latvia, Lithuania, Mexico, Mongolia, Morocco, Nicaragua, Peru, Philippines, Poland, Portugal, Romania, Slovenia, South Africa, Thailand, Tunisia, Turkey, Uruguay.

After significance pruning and dimensionality reduction on the World Bank Development Indicators, we implement a "y-aware" principal component analysis where the predictor variables (x) are rescaled to be in y-units (62). Improper scaling (absence of scaling, or simply performing x-specific scaling) could potentially lead to noise variables dominating the PCA loadings (direction eigenvectors that are endowed with the scale part eigenvalues). *X-scaling* (variables scaled by its own standard deviation) was avoided as it does not guarantee that all the data will be in the same coordinate system (62). By rescaling the covariates to be in y-dependent units we ensure that they all are in the same coordinate system allowing us to perform PCA on variables that are characterized by their effect on y (decarbonization progress) (62). For the figures below, we depict the implementation of PCR on the full data set (76 countries) and the subset of countries with GDP per capita below $US 30,000.

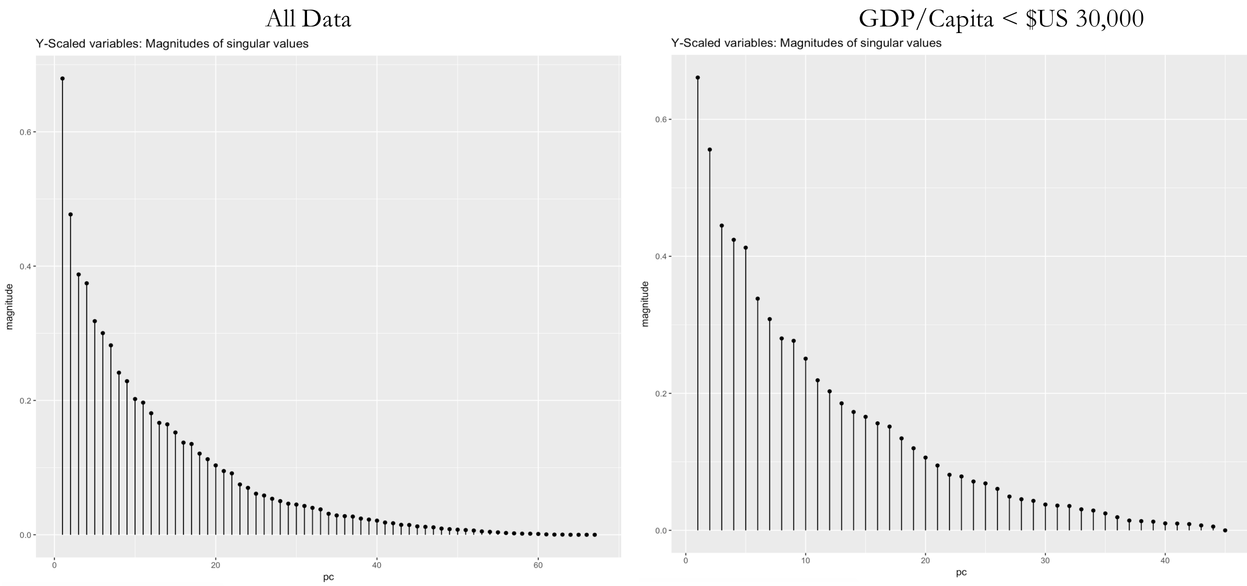


Figure 5. Magnitude of Singular Values, Principal Components

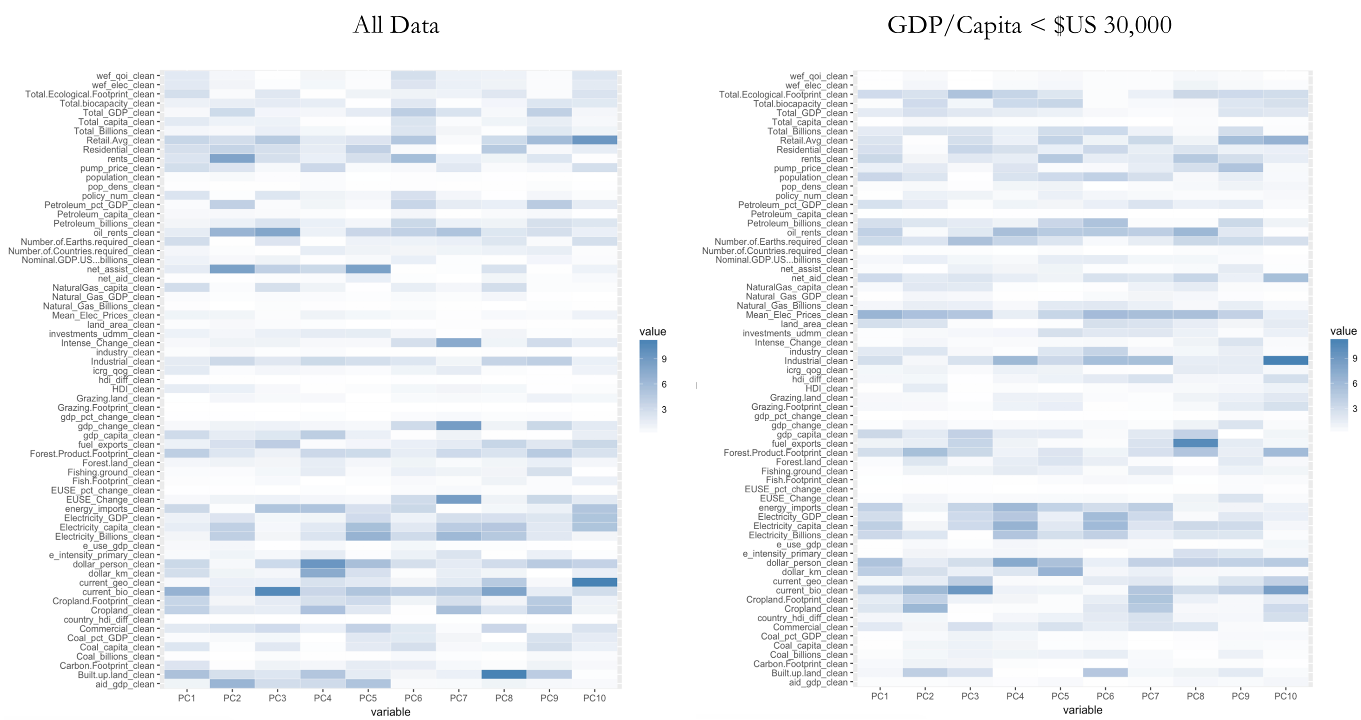


Figure 6. Cumulative Contribution of Variables to the First Ten Principal Components (sum of each principal component column is 100%)

In the full data set the first two principal components have a large portion of the signal (Figure 5, magnitude of singular values), whereas in the lower income data the first five principal components capture a similar portion of the signal. As expected, the full data set needs more principal components to fully reconstruct the data as opposed to the lower income data, which needs 20 fewer principal components. We use PCA loadings to understand the relationship and contribution of variables in our data to each principal component. PCA loadings depict the correlation between each component and the original variable, and squaring them tells us the amount of variation that each variable contributes to each component. Figure 6 depicts the cumulative contribution of each variable to each principal component (the sum of each column is 100%) with the variables that capture most of the variance varying between each data set. In the full data the variables that capture most of the variance in the first two principal components include proxies related to the quality of governance and the number of policies in favor of renewable energy, infrastructure, local electricity (\$US/MWh) and fuel prices (\$US/gallon), proxies for ecological footprint, the level of foreign energy dependence (imports), investments in renewable energy per km^2 and per capita, GDP per capita, early historical investments in (biomass and geothermal), amount of aid and financial assistance received, and level of dependence on local resource extraction.

In the subset data, local energy prices (fuel and electricity prices), financing towards renewable energy per km^2 and per capita, foreign energy dependence (imports), subsidies to and dependence on extractive industries and early historical investments in renewable energy (biomass and geothermal) play a larger role. Proxy variables for the quality of governance and policy support for renewable energy capture little to no variance for the lower income subset.

A All Data

B GDP/Capita < \$US 30,000

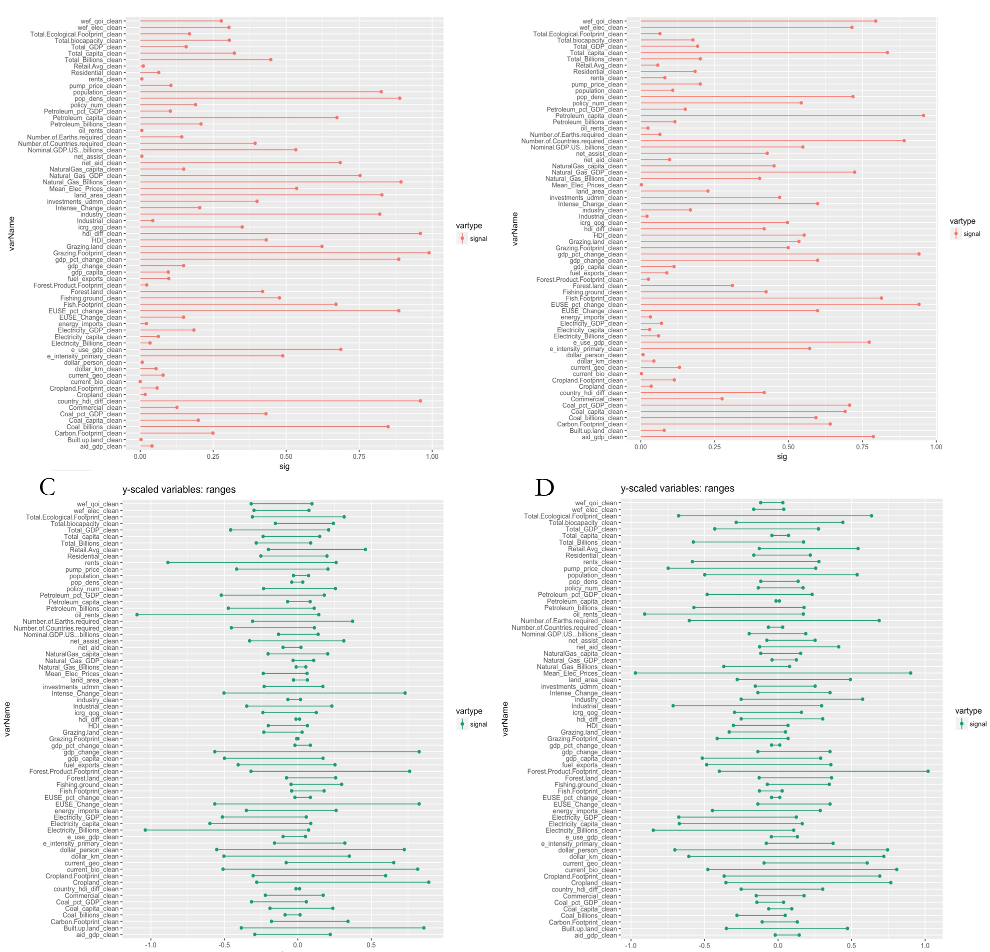


Figure 7. Variable Significance [A,B] and Scaled Variable Ranges [C,D]

Statistically significant variables also change between data sets (Figure 7A and 7B, values below 0.25). In the full data set, energy prices (fuel and electricity), resource rents (oil), aid (received net assistance), ecological footprint, foreign energy dependence (net energy imports), subsidies to fossil fuels and electricity have greater statistical significance. In the subset data, resource rents (oil), energy prices (fuel and electricity), renewable energy investments (per capita and per km^2), and early historical investments in renewable energy (biomass) have greater statistical significance. Figure 7 (panels C and D) also depict that the signal carrying and statistically significant variables have larger scaled ranges than noise variables in the data.

All Data | GDP/Capita < $US 30,000

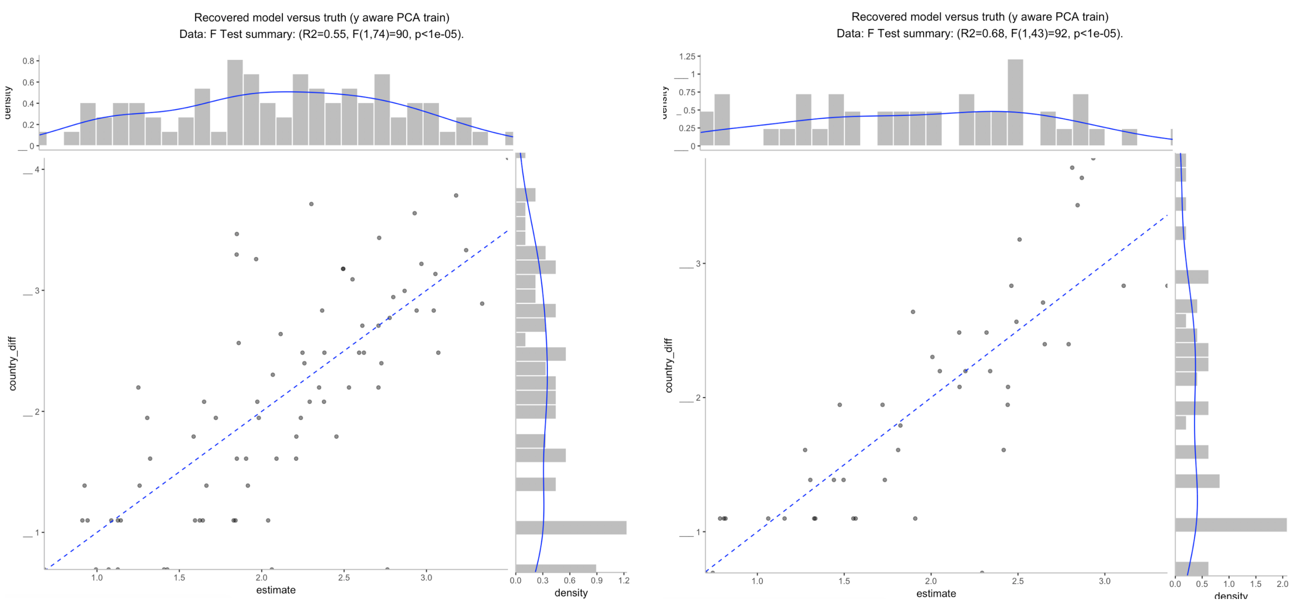


Figure 8. Actual vs Estimate for Full and Subset Data

A linear regression is fit to the first 20 principal components to estimate our dependent variable. On the full data set we are able to capture 55% of the variation with 20 variables, and are able to capture 70% of the variation with the same number of variables in the lower-income subset.
We next determine the optimal number of clusters for the top 20 principal components in each data set, and extract the countries within each cluster. Because k-means is a naïve algorithm (clustering data into k-clusters regardless of whether or not they are optimal), we first use the elbow method and silhouette scores to determine the optimal number of clusters. The elbow method performs a sensitivity analysis on a range of k-clusters, calculates the sum of squared errors (SSE) for each k-cluster, and provides a visual representation of where an additional cluster begins merely providing diminishing returns. Silhouette scores are a similarity measure of a data point to its cluster compared to other clusters, ranging from -1 to 1 (high values indicating that the data point is well matched to its cluster). Silhouette scores are calculated as the fraction of the difference between the lowest dissimilarity that any data point has to another cluster to which it is not a member (b_i), and the average dissimilarity to all data points within its assigned cluster (a_i), and the maximum value between a_i and b_i. The average silhouette scores are 0.25 and 0.13 respectively, with values closer to 1 suggesting

greater strength in the accuracy of clustering. Our analysis suggests that the first 20 principal components of the full data have three clusters and five clusters respectively (Figure 9).

Full Data Clusters (K-Means on 20 principal components, Silhouette Score: 0.25)

Cluster 1: Aruba, Cape Verde, Falkland Islands (Islas Malvinas), Faroe Islands, Iceland, Korea, South, Netherlands Antilles, New Caledonia, Taiwan, Togo
Cluster 2: Australia, Austria, Belgium, Canada, Croatia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Poland, Portugal, Singapore, Slovakia, Spain, Sweden, Switzerland, Thailand, United Kingdom, United States, Uruguay.
Cluster 3: Argentina, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Cyprus, Ecuador, El Salvador, Estonia, Ethiopia, Guatemala, Honduras, India, Indonesia, Israel, Jamaica, Kenya, Malta, Mauritania, Mexico, Mongolia, Morocco, Nicaragua, Norway, Papua New Guinea, Peru, Philippines, Romania, Slovenia, South Africa, Sri Lanka, Tunisia, Turkey.
The full data has three stable clusters with countries grouped according to land size, energy dependency, energy intensity of the economy, subsidies to fossil fuels and electricity, rates of economic growth, and clear distinctions across income and regions (despite no labels existing in the data).

Income Cluster <$US 30,000 (K-Means on 20 principal components, Silhouette Score: 0.13)

Cluster 1: Aruba
Cluster 2: Mauritania, Mongolia, Morocco, Papua New Guinea, Philippines, Thailand, Togo,Tunisia
Cluster 3: Costa Rica, El Salvador, Guatemala, Honduras, Jamaica, Kenya, Malta, Nicaragua, Sri Lanka
Cluster 4: Argentina, Brazil, China, Colombia, Ecuador, Ethiopia, India, Indonesia, Mexico, Peru, South Africa.
Cluster 5: Bulgaria, Chile, Croatia, Cyprus, Czech Republic, Estonia, Greece, Hungary, Latvia, Lithuania, Poland, Portugal, Romania, Slovenia, Turkey, Uruguay.

The lower-income clusters divide countries across intrinsic characteristics (population, land area, income per capita, population density) and enabling environments (number of policies in support of renewable energy, level of foreign energy dependency, level of domestic economic dependency on resource extraction and fossil fuel exports, subsidies to fossil fuels and electricity, level of human development, local electricity and fuel prices, and investments in renewable energy per capita and per km^2). Relative to other clusters, and on average, the cluster in this data subset that has made the most progress in decarbonization since the 1980's is neither the wealthiest, nor the one with the most policies in support for renewable energy. Cluster 3, which includes all of Central America, Jamaica, Kenya, Malta and Sri Lanka are characterized by a small land area, large energy dependency, relatively high fuel and electricity prices, low income per capita, relatively higher investments in renewable energy per capita and per km^2 and relatively historical earlier investments in biomass and geothermal energy as a large percentage of total generation relative to other countries.

The full dataset has three stable clusters, and the data subset with income per capita below $US 30,000 has five stable clusters. For the former, countries are grouped according to land size, energy dependency, energy intensity of the economy, subsidies to fossil fuels and electricity, and rates of economic growth. For the latter, a different set of variables cluster the data including inherent characteristics (population, land area, income per capita, population density, quality of governance) and enabling environments (number of policies in support of renewable energy, level of foreign energy import dependency, level of domestic economic dependency on resource extraction and fossil fuel exports, subsidies to fossil fuels and electricity, level of human development, local electricity and fuel prices, and investments in renewable energy per capita and per km^2).

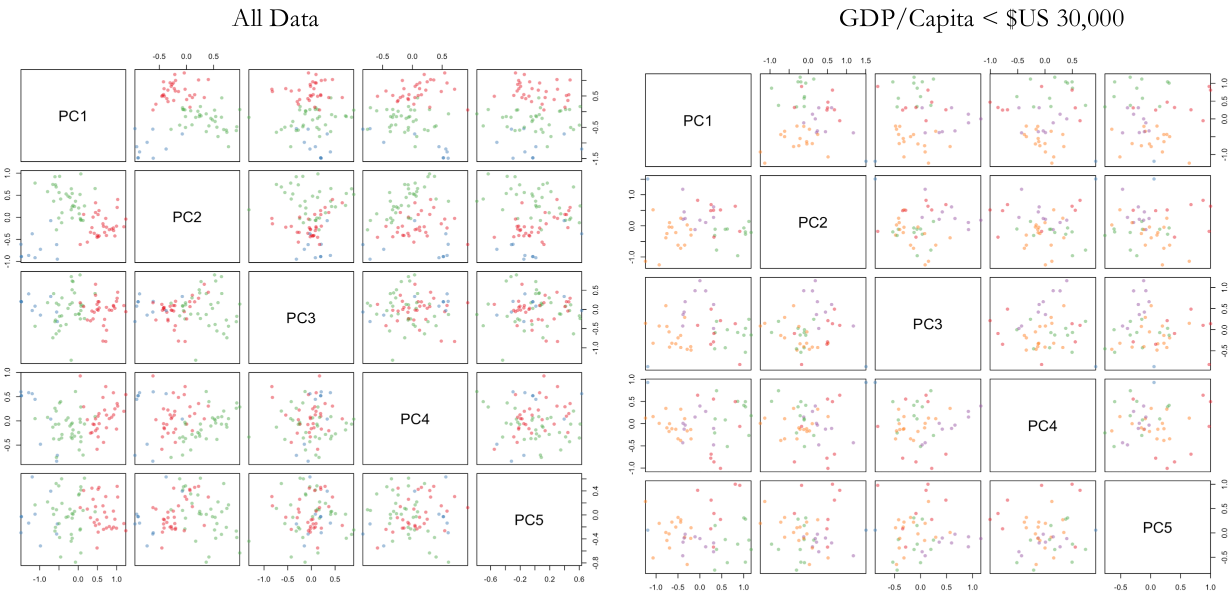


Figure 9. K-Means Clustering by Principal Components (Five first principal components)

While inherent characteristics of a country (e.g., population, size, resource availability, institutional strength, resource dependency) and its enabling environment (e.g., number of policies, energy prices) can allow decarbonization to foster, it doesn't necessarily mean that a country will make progress. Here, we argue that countries are driven by a variety of motivations to decarbonize of which social progress, sustainability, and energy independence represent but three of the myriad of other motivations that exist. For this portion of the analysis we built a social progress proxy which is constructed using the Social Progress Index from the Social Progress Imperative Network (60) and a Quality of Governance Score from The Quality of Governance Initiative (56) (0-1, with 1 being the highest score), built a Sustainability score combining the Yale Environmental Performance Index (59) and the Total Ecological Footprint(60) from the Global Footprint Network (0-1, with 1 being the highest score for sustainability), and a motivation for energy independence proxy constructed from net energy imports extracted from the World Bank Development Indicators (55). All variables are scaled between 0 and 1 and were then assigned to countries depending on their relative progress across each proxy. The maximum score across three-dimensional motivational spectrum was 3. Higher scores across the motivation spectrum indicate greater progress towards decarbonization. The three outliers: Kenya, Nicaragua, and Lithuania are all over performers relative to their region and income group across the three different proxies of the motivation spectrum.

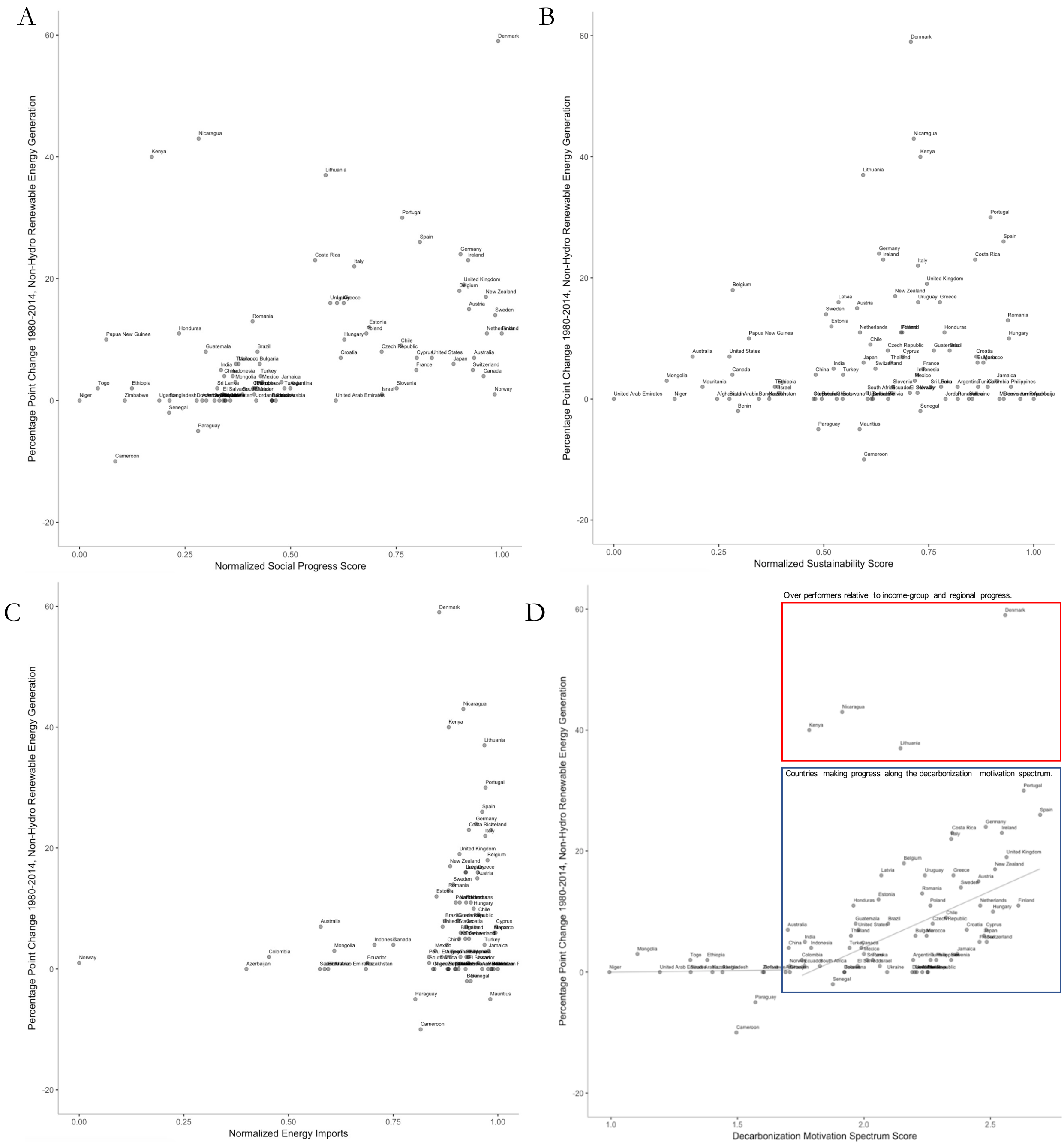


Figure 10: Components of the Decarbonization Spectrum – Proxies for Social Progress, Sustainability, and Energy Dependence

1.5 Results and Discussion

What we find from our global data comparison is that even in the absence of major climate change policy instruments, the rising south has been making rapid progress, and in fact displaying a wide range of different approaches to building the necessary enabling environments and starting conditions. Some of these motivations include energy independence and security, as well as the opportunistic profit from regional interconnections. For the case of countries such as Nicaragua (46% non-hydro renewable energy generation), Uruguay (16%), and Morocco (7%)(63, 64). Others, have stand-alone motivations, enabling environments and inherent characteristics such as Honduras (11%), which recently became the first non-island country in the world to have 10% solar capacity despite its current violent crime crisis (65, 66), Costa Rica (24%), which has a long tradition of conservation and environmental stewardship surrounding coffee and eco-tourism, and Kenya (46%), whose crippling droughts in the 1990s incentivized the country towards a power sector reform and early investments in geothermal (67). Other highlights include Brazil (10%), which, despite hydropower, oil dependency, and current political instability has one of the most progressive solar net-metering policies in the world (and one of the most progressive uses of biofuels)(68, 69), and Chile (10%), whose initial renewable energy progress has been motivated by the provision of cheap power to the power-hungry mining industry in the northern part of the country (70). Denmark, a global leader in wind energy development, did not begin its low-carbon transition through climate-related top-down policy (44, 71–75). In fact, the support of civil society to revitalize rural areas using wind energy in Denmark date back to the 1900s, but it took the energy crisis of the 1970s, grassroots opposition to nuclear energy, and community-driven wind cooperatives (76) that directly benefitted from clean energy investments to catalyze the low-carbon transition the country observes today.

For the United States, it is meaningful to consider change beyond the nation as a whole, and increasingly so as the politics of climate change become insurmountable, and cities and states continue to make much faster progress than the nation. States like Iowa, South Dakota, and Kansas produce large shares of their generation from wind energy (31%, 26%, and 24% respectively)(54), while Arizona, Hawaii, and Nevada have large amounts of installed solar energy per capita (167,137, and 123 Watts per capita, respectively) (77), and California (78), New York (79) and Hawaii (80) have adopted aggressive renewable energy goals (50% by 2030 for CA and NY, and 100% by 2045 for Hawaii). Furthermore, traditionally rural and republican-majority states like Iowa, South Dakota and Kansas have reached this progress in a pursuit of diverse motivations, and arguably more relaxed policy targets than California and New York, which are often touted as the nation's climate and renewable energy leaders.

1.5.1 Inherent Characteristics and Enabling Environments as Drivers of Global Energy System Decarbonization

Our results suggest that twenty principal components describe 60% and 70% of the variance on the full and subset data, respectively. Although we only select the principal components with the highest variance as regressors, we find that low-variance components still play a large role in accurately capturing the full variance of the data. Analyzing the contribution of each individual variable to each principal component suggests that there are several underlying enabling environments and inherent characteristics that are driving global decarbonization progress. In the full dataset, which includes all countries across levels of income, regions and levels of development, several features emerge that, consistent with the literature, are good predictors for sparking decarbonization. These features include inherent characteristics (e.g., income per capita, quality of governance, human development index, level of foreign energy import dependency, level of dependency on resource extraction, land size, and population) and enabling environments (number of policies passed to foster renewable energy, investments on renewable energy per km^2 and per capita, aid, and historical early investments in renewable energy such as biomass for electricity and geothermal). When we perform our analysis on the subset of countries with income per capita below $US 30,000, we find that local energy prices (fuel and electricity), foreign energy import dependency, investments per capita and per km^2, and historical early investments in renewable energy (such as biomass for electricity and geothermal) play a larger role in predicting decarbonization progress, whereas the weight and significance of variables describing quality of governance and policy support for renewable energy is significantly reduced.

Nation	**Motivations**	**Support Mechanisms**	**Governance Status (2015)[1]**	**Non-Hydropower Renewable Generation (2015)[2]**
Honduras	Economic Growth Social Progress(68)	Feed-in tariffs Tax credits	20th and 35th percentile.	11%, 18%
Nicaragua	Energy Independence Social Progress(69)	90% Renewable Energy Target by 2020 Feed-in Tariffs Investment incentives	21st and 19th percentile	46%, 63%
Costa Rica	Environmental Sustainability Economic Growth(70)	100% Renewable Energy Target by 2030 Feed-in Tariffs	Ranked in 67th and 75th percentile	24%, 25%
Brazil	Energy Security Opportunistic Investment Status(71)	Renewable Energy Target (30 GW by 2024) Low Interest Investments Technological mandates for bioethanol	Ranked in 48th and 41st percentile	10%, 12%
Chile	Energy Independence Economic Growth Social Progress(72)	20% Renewable Energy Target by 2025 Carbon Tax	85th and 88th percentile	10%, 13%
Uruguay	Energy Security Environmental Sustainability(73)	95% Renewable Energy Target by 2017 Feed-in Tariffs	Ranked in the 73rd and 89th percentile	16%, 35%
Kenya	Economic Growth Opportunistic Investments(74)	Renewable Energy Target (15000 MW by 2030) Feed-in Tariffs Tax credits	Ranked in the 44th and 13th percentile	46%, 48%
Morocco	Economic Growth Opportunistic Investments(75)	50% Renewable Energy Target by 2030 Investment incentives	Ranked in the 50th percentile	7%, 10%

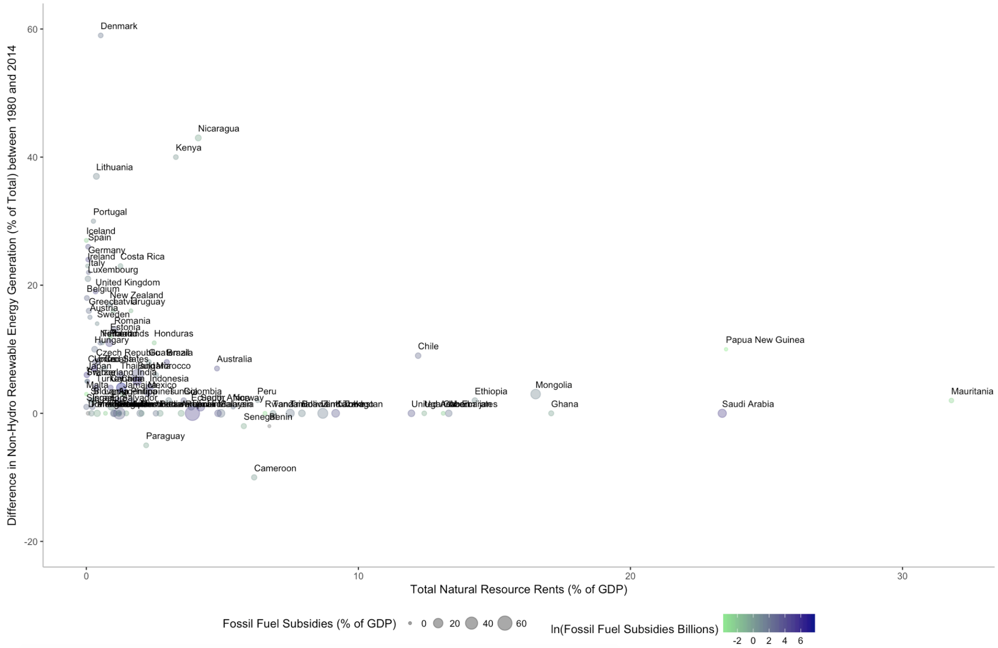
[1] *For governance score we consider or the "Government Effectiveness and Control of Corruption" indicators by the World Bank. Being part of lower governance score percentiles is indicative of weaker governance.*(55)
[2] *First percentage represents 2014 data from the International Energy Agency (latest available data), second percentage represents latest data as reported to the International Renewable Energy Agency.*(81)

Table 1. Motivations and Strategies for Energy System Decarbonization: The range of motivations for energy system decarbonization span opportunistic investments, energy security and environmental sustainability. The enabling strategies range from feed-in tariffs to tax credits across a spectrum of governance status.

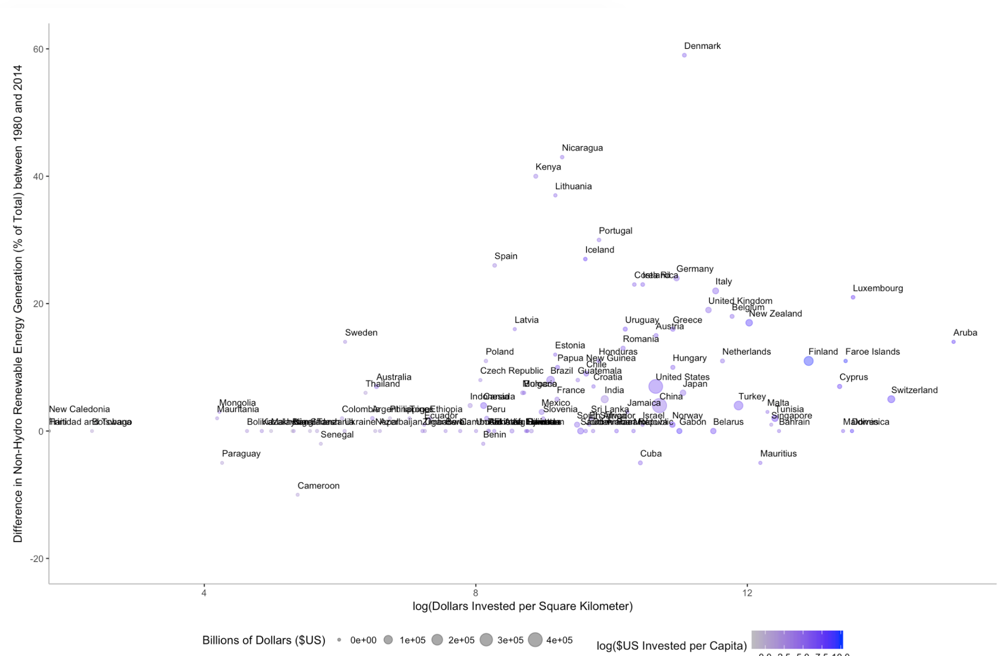
According to our analysis, there is not one key predictor of decarbonization, but rather, a multitude of factors that may contribute to transformative progress. The data and our analysis suggests that several economic- and energy-evolution dynamics are at play in these emerging low-carbon energy transitions. Figure 11 represents a visual summary of some of the core features which are extracted from the principal component analysis. Features that are negatively correlated with decarbonization progress include a large dependency on natural resource rents as a percentage of GDP, a high percentage of fuel exports as merchandise exports, and being a large net energy exporter (Figure 11A and 11C). While relatively higher energy prices (e.g., fuel, commercial, retail and spot prices), relatively high renewable energy investments per capita and per km^2, and a relatively high level of energy import dependency is associated with a faster pace of decarbonization (Figure 11B). Except for two outliers (Chile and Papua New Guinea), these data should present weariness for global decarbonization policy makers. In Chile, solar and wind farms are beginning to be used to displace fossil fuel expenditures in mining, and PNG was the first country to submit the final version of its nationally determined contributions at COP21 despite it being heavily dependent on hydrocarbon exports. Chile's mines produce the largest amount of fine copper, the second largest amount of gold, and half the world's lithium, with mining consuming approximately 85% of capacity in its northern grid (70). PNG's economy is greatly reliant on the export earnings from minerals and energy (82) extraction and thus far has only developed about 2% of its high potential for renewable energy.

Without specific measures such as feed-in tariffs, or green certificates, PNG – with large geothermal potential – has begun an attempt to shift towards the adoption of renewables in an effort to reduce local consumption of fossil fuels and increase revenue from the mineral and petroleum sectors (81–83). Other fossil fuel lock-in concerns, as they relate to countries that are major climate change drivers, are that the United States is set to become a net energy exporter within the next decade (84), China provides the largest amount of fossil fuel subsidies in the world (while almost single handedly having catalyzed the drop in PV prices)(85) and several top-ten CO_2 emitters such as Russia, Iran, and Saudi Arabia are all largely dependent on resource rents (Figure 11A). In addition to the vast existing literature on the resource curse, new literature has begun detailing how there could be an emerging wave of carbon lock-in affecting the rising south through the global renaissance of coal (86, 87). While this scenario may seem daunting, it is important to highlight that the data also suggests that there are also enabling environments, and intrinsic characteristics that present pockets of opportunity where long-term decarbonization could be enabled. Our analysis suggests that countries without a strong natural-resource-rents dependency, who are energy import dependent, with relatively high energy prices, and with relatively higher renewable energy investments per capita and per km^2, could make significant progress towards long-term decarbonization (Figure 11B and 11C).

A)


Difference in Non-Hydro Renewable Energy Generation (% of Total) between 1980 and 2014
Total Natural Resource Rents (% of GDP)
Fossil Fuel Subsidies (% of GDP)
0
20
40
60
ln(Fossil Fuel Subsidies Billions)
-2
0
2
4
6
Denmark
Nicaragua
Kenya
Lithuania
Portugal
Chile
Papua New Guinea
Mongolia
Ghana
Saudi Arabia
Mauritania
Paraguay
Cameroon

(B)


Difference in Non-Hydro Renewable Energy Generation (% of Total) between 1980 and 2014
log(Dollars Invested per Square Kilometer)
Billions of Dollars ($US)
0e+00
1e+05
2e+05
3e+05
4e+05
log($US Invested per Capita)
0.0
2.5
5.0
7.5
10.0
Denmark
Nicaragua
Kenya
Lithuania
Portugal
Luxembourg
Aruba
Switzerland
New Caledonia
Paraguay
Cameroon
Cuba
Mauritius

(C)

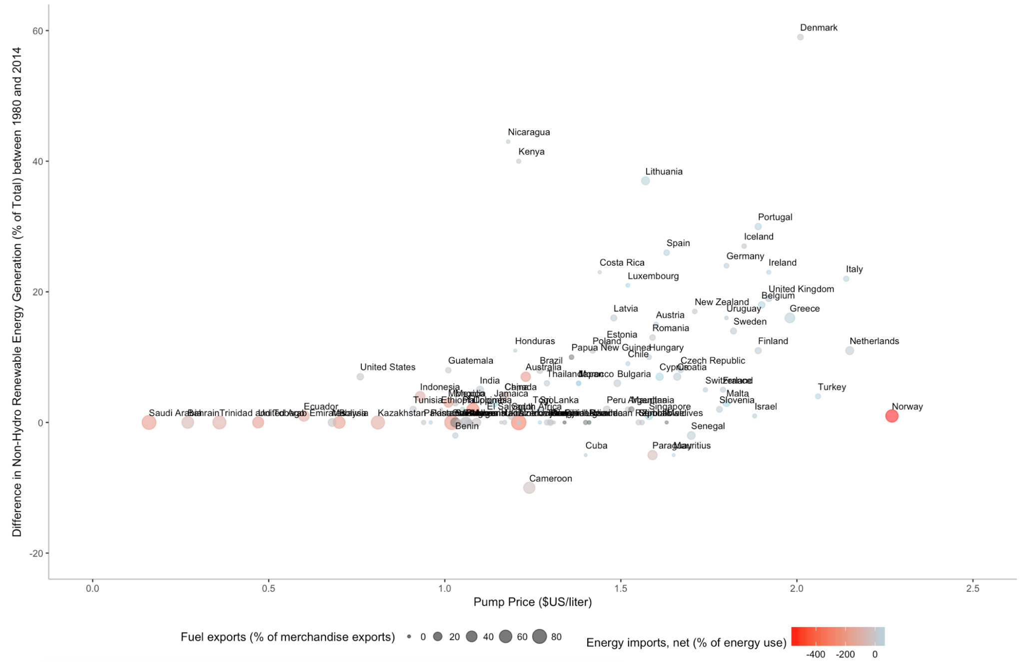


Figure 11. Data Mining Extracts: A Diversity of Key Inherent Characteristics and Enabling Environments Driving (or Hindering) Global Decarbonization. Our analysis and data suggests, that among several other features (described above), a relatively large resource rents dependency and local fossil fuel subsidies hinder decarbonization (4A), whereas relatively large investments in renewable energy (per capita and km²) (4B), a relatively larger energy import dependency, and relatively higher energy prices (gasoline pump prices and mean residential, industrial, commercial, and spot prices where available) provide a suitable environment for rapid decarbonization. Countries with positive demand side enabling environments and inherent characteristics for decarbonization could be pursued as targeted investments for the global diffusion of renewable energy technologies.

1.5.2 Motivation as a Key Driver for Long Term Decarbonization Progress

Given the historical and systemic challenges (e.g., political, institutional, technological and behavioral) of transitioning towards a low-carbon energy system (87), it is crucial to define new strategies and support mechanism to rekindle and achieve goals towards global decarbonization. Climate change mitigation is often cited as the main motivator for decarbonization, with contingent monetary rewards, global meeting invitations, and capacity-building exercises made available if countries create enabling environments to achieve those goals. There has been little discussion, however, about the creation of support mechanisms geared towards other motivations that can catalyze long-term low-carbon energy system transitions.

In recent years, behavioral research has brought to light the importance of understanding the multiple motivations that exist behind reaching climate and environment related goals, and the risks of using extrinsic motivators to facilitate long-term behavioral change. While this research has focused on the individual level, it has come to a broad consensus that a multitude of factors exist that can determine the adoption of or aversion to renewable energy technologies including appeal comparisons of monetary vs. non-monetary incentives (e.g., morals, environmental and climate change co-benefits)(88, 89), the benefits and caveats of using competitions to achieving goals (90), and the perils of framing solutions around unique political ideologies (91). For example, research in the United States has shown that, in some states, framing adoption of energy efficiency technology as an environmental beneficial solution can be detrimental to its adoption (91). A desire to understand the motivations through which individuals may adopt or fail to adopt a behavior change or a new technology ties many of these studies together, generally finding that intrinsic motivation can be one of the most effective mechanisms for inducing long-term behavioral change (88, 92–95). While this body of research has largely focused on understanding individual motivations for renewable energy or energy efficiency adoption, we argue that the same theories can be used to understand the multiple motivations that exist for a nation state to decarbonize.

Frameworks for advancing solutions to the lack of fast-paced progress in energy system decarbonization could borrow intellectually from self-determination and intrinsic motivation theory (1, 2). Generally, the theory suggests that motivation appears across a continuum of extrinsic and intrinsic processes, in which pure intrinsic motivation is guided by interest, enjoyment, and inherent satisfaction in an activity, and pure extrinsic motivation is guided by group compliance, and the presence of external rewards and punishments. Within the continuum of extrinsic motivators, ego-involvement, internal rewards and punishments, personal importance and synthesis with self all change the position where an individual might lie across the motivation continuum. The theory suggests that extrinsic motivators (e.g., monetary rewards and punishments) may often forestall intrinsic motivation and merely provide short-term change as compliance with a project, and an activity may quickly end if the incentive or reward is removed. The theory posits that truly understanding what motivates and drives individuals, and designing mechanisms that fit with their intrinsic motivation, is key for ensuring long-term behavior change.

Considering global decarbonization, we argue that it is crucial to think about a country's historical motivations when enacting change in order to design adequate support mechanisms. Local and global environmental challenges, climate mitigation, technological innovation and leadership, energy independence and national security, the creation of niche markets and new industries, economic efficiency, group compliance, and need for foreign direct investment are but a few of the motivators that may drive energy system decarbonization. The key, we argue, is that framing decarbonization under the over-arching motivation of mitigating climate change might be disadvantageous for long-term progress. Instead, pathway catalysts must be designed by first understanding the unique immediate needs and motivations of countries and working with local change agents (e.g., entrepreneurs, local vs. federal governments, cities vs. states, and universities) to design strategies that best fit their intrinsic characteristics (e.g., land size, population, quality of governance) and enabling environments (e.g., amount of investment, number of policies, resource dependency).

To exemplify the decarbonization motivation spectrum, we use data from the Social Progress Imperative, the Quality of Governance Initiative, the Yale Environmental Performance Index, the Global Footprint Network and the World Bank Development Indicators (55–57, 59, 60) to create proxies for three key motivators: social progress, local sustainability, and desire for energy independence. We scale these metrics and assign a score to each country across the sum of these three motivators, and plot the score against a dependent variable measuring decarbonization progress between 1980 and 2014 (or latest data available) in enabling a low-carbon energy transition (difference between total percentage generation from non-hydropower renewable resources between 1980 and 2014, or most recent year). We find a slope change in the trend at a motivational score of 1.75

(observed as an elbow in Figure 10D), with countries that score higher along the motivational spectrum having made greater progress towards decarbonization. There are four outliers: Kenya, Nicaragua, Denmark and Lithuania – all over-performers relative to their income groups – and with different motivations for sustained decarbonization progress. To help conceptualize the various features of decarbonization and to guide the design of supporting mechanisms, we propose a framework for a country's decarbonization pathway (Figure 10D). First, one must understand the unique motivations that could drive change in different countries, then, inherent characteristics (unchangeable, or very hard to change) and enabling environments (constantly evolving) are taken into account to design and implement support mechanisms to promote decarbonization.

1.5.3 New Hypotheses and Possible Ways Forward

Our findings demonstrate that there is not one major driver of decarbonization, but rather, a multitude of factors that can contribute to transformative progress. Globally, there are many countries with favorable combinations of inherent characteristics and enabling environments for kindling decarbonization that remain, however, in the path towards carbon lock-in. This, we argue, can be prevented and we suggest four opportunities to reinvigorate global decarbonization progress based on our findings, as follows:

1) Identify and Invest in Pockets of Demand-Side Opportunity: Our analysis suggests that there are favorable enabling environments and inherent characteristics that enable decarbonization to occur rapidly, and unfavorable conditions that slow down or thwart decarbonization progress. We argue that it is essential to identify and tap into pockets of opportunity with favorable conditions in order to spark neighbor and technology diffusion effects to occur across a diversity of regions, incomes, and levels of development. While most energy system decarbonization analyses focus on supply-side opportunities (e.g., renewable resource potential maps), we argue that it may be equally or more important to focus on country-specific demand-side drivers (adequate enabling environments and inherent characteristics) and create a diversity of mechanisms to support them.

2) Diversify the types of support mechanisms for decarbonization: While the COP21 meeting was successful due to the number of parties that submitted Intended Nationally Determined Contributions (INDCs), as well as the types of proposals that were put forward, recent analysis of the INDCs also suggests that these goals would not be sufficient to meet current global stabilization targets (58, 96). More importantly, there is an absence of support mechanisms that could tie a country's immediate needs and intrinsic motivations to the long-term decarbonization goals and strategies stated in its INDCs. For example, some countries might be motivated by political and technological leadership, while others might be more motivated by national security, energy access and economic efficiency. Designing diverse support mechanisms, such as pay by performance goals, financing country-specific intrinsic motivators, local capacity building, and technological partnerships, that are reflective of the diversity of motivations could support clusters of countries unified by similar motivations. These clusters could encourage countries to learn from each other try new ways of thinking about energy transitions, while working on their country-specific goals that in turn support progress towards decarbonization.

3) Diversify the change agents that receive support for decarbonization: In some countries, government institutions can foster top-down enabling environments for decarbonization. However, in other countries, government institutions can create roadblocks to energy system transformation. Indeed, recent research suggests that policy formulation is not sufficient in countries with an "institutional gap", and suggests that clear and strong financial incentives, predictability of government decision making, and streamlined permitting procedures are as important (or more) as goal-setting decarbonization policies (51, 52). As the energy transitions literature suggests, the repertoire of policies and institution types designed to support late technology adopters should be very different from those for first adopters and early pioneers, especially if the technology carries low risk (28). Recognizing the appropriate change agents is key to designing support mechanisms that work specifically for countries who want to simply adopt technology, and do not seek to build research and development capacity like first adopters tend to prefer. To tap these pockets of opportunity, it is crucial to identify local successful change agents and provide support mechanisms that help them achieve their goals.

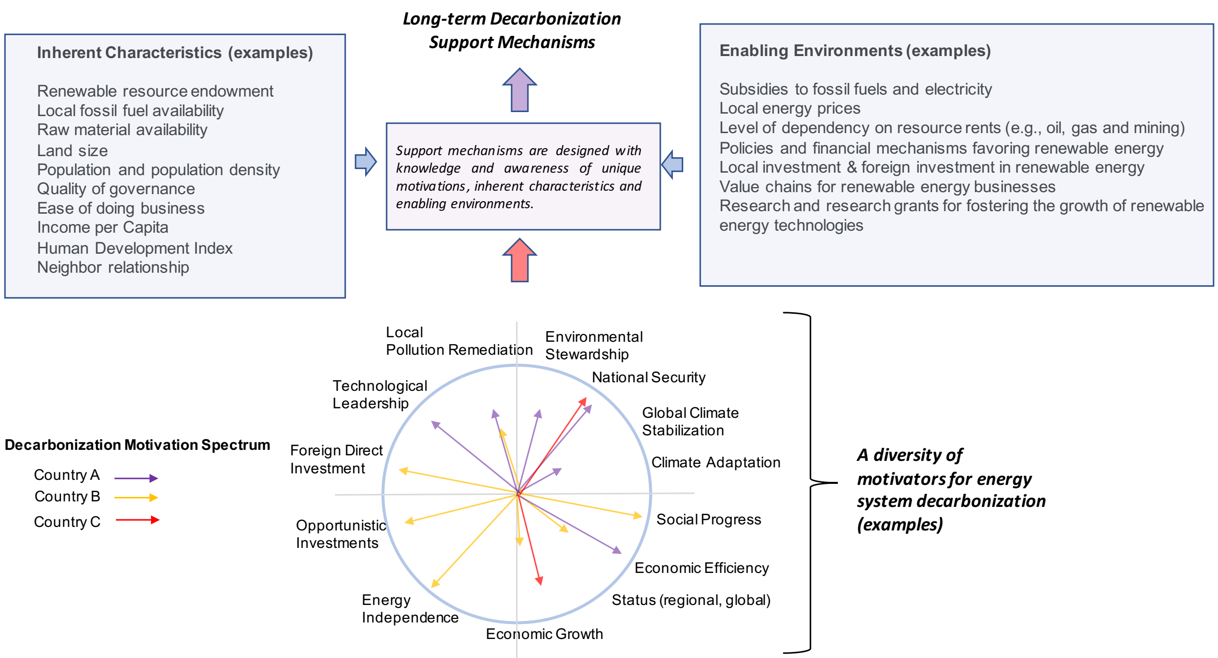


Figure 12. The Decarbonization Motivation Spectrum: The diagram illustrates how the decarbonization motivation spectrum could be used when evaluating or designing support mechanisms for long-term decarbonization. Countries are evaluated on an individual basis, analyzing their trajectories in decision making and spectrum of motivations surrounding energy planning. After identifying key motivators, country specific inherent characteristics and enabling environments are considered in the design of long-term decarbonization support mechanisms.

4) Think beyond energy and promote non-optimal pathways: While it is useful to develop and analyze optimal techno-economic decarbonization pathways, in reality, most countries have complex political, socio-economic and cultural constraints that are not accounted for in such analyses, making engineered optimal pathways unattainable. A narrow focus on techno-economic optimality could be detrimental to realizing modest progress on decarbonization. Take, for example, countries where local pollution, water scarcity and management, garbage, or deforestation pathways might be immediate pressing issues. A narrow focus on least-cost technologically optimal pathways could overplay the promise of large-scale wind and solar developments, as compared to alternative solutions including methane collecting at landfills, water use efficiency programs (that in turn save energy), or funding for inclusive and fair conservation land management practices that may in fact be better suited for the particular country.

There are many countries around the world with favorable features (inherent characteristics and enabling environments) for long-term decarbonization, but also many without. Our analysis suggests that it is crucial for change agents, policymakers, and financiers to understand the roles of intrinsic motivation, inherent characteristics and enabling environments in finding new pockets of investment for renewable energy. Our study, corroborated by recent literature (88, 89, 91, 92, 94, 95), suggests that there is a wide spectrum of these features for decarbonization ranging from sustainability, to energy independence and national security, to technological leadership and social progress (97). Designing support mechanisms that are encompassing of this wide spectrum of motivations is crucial to sparking decarbonization across incomes, regions, and levels of human development. Investing in pockets of change, first regional adopters, and harnessing positive neighbor low-carbon relationships is key for the long-term diffusion of efficient low-carbon strategies. These pockets of progress towards low-carbon energy systems, as historical energy transitions suggest, could spread their knowledge and experiences to other countries and regions that have so far been timid in stepping forward (26, 28, 98).

1.5.4 Limitations

Out of 130 candidate countries, the analysis was performed on two subsets that included 76 and 45 countries, which means that our results can only explain variability within this smaller data subset. In the future, and as countries and regions implement better data collection protocols, studies like this can be replicated on a regular basis to constantly re-evaluate the mechanisms that are being successful towards decarbonization, and under what conditions. A limitation of is this study is that it did not differentiate between all the different policy mechanisms that countries implement or design to enable decarbonization. Future work could implement a similar analysis to that performed here, but with additional policy details, in an attempt to extract the types of policies that are most effective at sparking or sustaining long-term decarbonization progress, and under what conditions.

Chapter 2: New Methods in Elucidating Demand for the Design and Implementation of Appropriate Sustainable Energy Interventions

2.1 Introduction

Predicting demand for electricity, and services, is a crucial element for designing, implementing, and managing appropriate and sustainable energy interventions (28, 98, 99). Demand projections inform planning at all levels, from traditional country-wide grid capacity expansion planning, to the provision of community energy services, including households and small businesses. Prediction resolution varies across space and time, with high-temporal resolution prediction being used to reduce grid uncertainty (e.g., seconds, minutes, hours), while lower-temporal resolution prediction (e.g., months, years) can be used for long term planning. This chapter uses a mix of high spatial resolution data sets, surveys, sensor data, and data mining methods to develop new methods for elucidating demand at the household and community level, and to help close the 'energy efficiency gap' in resource constrained environments.

Literature for elucidating demand can be divided into three general categories: survey driven studies exploring the social dynamics of demand (100–103), broad techo-economic approaches (104–108), and machine learning approaches blending large data sets and social science (109–111). The first gives highly-detailed depictions of users (e.g., behavior, preferences, trade-offs) but is usually not generalizable due to small sample sizes. The second generally assumes that appliance stocks, technological diffusion, and electricity demand are predominantly income driven, and follow western-style development paths. They ignore micro-level dynamics (e.g., household and small business specific factors), country-by-country heterogeneity (e.g., clustering all 'developing countries' together), cultural context, and within-country heterogeneity (109). The last one is a mixed methods approach blending high-resolution data-sets (e.g., census, appliance stocks, demographic and healthcare data, natural and infrastructural data) and social dynamics (e.g., affordability, wealth, race, and religion) to explore the within-country heterogeneity of demand (109).

Elucidating demand is also crucial for progress in energy efficiency, but here as well, the literature is divided. 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 (112–114). Other analysis suggests that this energy efficiency gap is overstated by traditional analysis (e.g., engineering estimates and empirical estimates of returns observed to investments) that fails 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) (115). But, what is the efficiency gap where there are no baseline data? What about places with no information on appliance stocks, behavior, or household and building envelopes? How can reliable estimates be developed for these contexts?

To our knowledge, and using Kenya as an example, this chapter presents – in collaboration with colleagues from the IBM Africa Nairobi research lab – the first reliable data-driven approach at elucidating household appliance ownership and induced household demand for electricity using a mixture of large-scale social demographic data, spatial data, and machine learning approaches (110). We also use data-mining and an extended literature review to explore and identify the enabling conditions under which electrification can lead to wealth via micro-enterprise creation in rural areas. The latter also presents the first analysis to contrast and compare the drawbacks/inaccuracies of the modern use of nightlights as a panacea for tracking wealth in unelectrified regions. Finally, and using Nicaragua as a case study, this chapter develops a framework on how to collect data for baseline energy efficiency estimates in resource constrained environments using a mixed methods approach combining surveys, sensors, population sampling and Bayesian updating.

2.2 Background: Elucidating Residential Demand

Advocates of centralized and distributed power systems are engaged in a vigorous debate over the economic, developmental, environmental, and ethical implications of the diversity of existing approaches for expanding electricity access to the un-electrified rural poor (116–118). Large, interconnected power systems capture significant economies of scale and resource efficiencies and flexible with regards to future demand growth. On the other hand, they require large upfront investments in generation and transmission that can be hard to justify in the absence of robust, accurate demand projections. Small, distributed power systems that serve individual households, villages, or towns are of increasing interest due to sustained technology and cost improvements in solar photovoltaics and other distributed generation, solid-state power conversion, and metering and management systems. If implemented properly, these nascent technologies may present a cost-effective, low-carbon approach to expanding electricity access that bypasses some of the financing, execution, and corruption challenges that can plague large energy infrastructure projects. However, poorly designed and executed build-outs of distributed power systems run the risk of locking rural populations into small quantities of high cost, low reliability electricity with little room for demand growth. In order to develop sound analyses and inform rural electrification stakeholder decision-making among various centralized and distributed approaches, accurate estimates of electricity costs and demand for electricity services are needed.

Induced demand represents the potential additional electricity consumption if reliable electricity services were made available. Quantifying this potential for demand is critical in evaluating the feasibility of a particular electrification program or business in a particular location; if there is enough demand to generate sufficient revenue to cover operational costs, an electrification business can grow to serve more and more customers or the program can be expanded to more areas. Most approaches to off-grid electricity demand estimation, as well as studies that evaluate users' ability and willingness to pay for electricity services, have traditionally used social science methods such as surveys (97, 98), field and longitudinal studies (100, 101), and stated preferences (contingent valuation, ability and willingness to pay) (121, 122). These approaches are extremely valuable as they usually provide detailed knowledge about a consumer and the intricacies of daily life in a region, village, or town. They can be used for evaluating the preference and decision making process that goes into buying and using different energy services (fuelwood or gas for cooking, kerosene or solar lamps for lighting, for example), and perhaps later be used for design of optimal tariff structures and demand-side management schemes. However, although extremely insightful about a particular place, they are time- and resource-intensive, and results are not usually generalizable. End-use methods can allow the researcher to incorporate different scenarios (behavioral dynamics, energy efficient de- vices, and income and energy transitions, for example), and data sources (census and appliance ownership data, technology characteristics, and usage patterns, among others) to make assertions about electricity consumption in different sectors and areas of village life (123). These approaches can facilitate generalization across larger spatial footprints.

2.2.1 A Review of Supply-side Technology Options for Electrification

To further contextualize the demand side, it is important to summarize supply side approaches to rural electrification. These approaches can be coarsely condensed into three categories: 1) centralized grid extension, 2) solar home systems, and 3) micro- and mini-grids. The suitability of each electrification concept depends on local geographic factors (topography, renewable resources, etc.), electricity demand, and ability to pay for electricity services. In the absence of any of these technology options, rural consumers sometimes resort to auto-motive batteries and small commercial charging services to meet their electricity needs. These modes of minimal access are not consistent with sustained human and economic development and are not considered here.

The extension of national- or regional-scale electric power systems ("centralized grids") to rural areas has traditionally been the main strategy for rural electrification. However, grid extension becomes significantly less cost-effective for sparsely settled areas with relatively low demand. Due to these fundamental factors and to the typically high cost of materials in sparse rural areas, grid extension into remote rural communities is often economically prohibitive, as budgets for electrification are constrained and utilities are unable to recoup the full costs through connection fees and revenue from electricity sales. The result is that grid extension becomes a negative profit endeavor, giving little incentive for utility companies to undertake such programs in the absence of government mandates or subsidies. Another major challenge with this approach is the relatively weak reliability of the power grid in low, low-middle income countries. In Kenya, and according to the World Bank Enterprise Survey, typical commercial consumers with grid electricity experience an average of 6.3 power outages per month, with the average outage lasting 5.6 hours (55). Outage rates and durations vary significantly across sub-Saharan Africa but are non- trivial in most nations. Low reliability significantly diminishes the value of electricity services, particularly for commercial or industrial uses and cold storage, and mitigating this problem requires costly investments in backup generation systems. On the positive side, by capturing economies of scale and efficiencies associated with large generation facilities and large interconnection footprints, the grid offers the lowest marginal costs for electricity and the greatest potential for demand growth. In 2014, Kenya's national utility, Kenya Power and Lighting Company (KPLC) was charging a fixed monthly cost of KES 120 (US$1.36) and consumption tariffs of KES 2.50/kWh (US$0.03/kWh) for the first 50 kWh, KES 13.68/kWh (US$0.16/kWh) for consumption between 50 and 1500 kWh, and KES 21.57/kWh (US$0.25/kWh) for all consumption above 1500 kWh for residential customers (124). However, there is an additional upfront connection fee of KES 75,000 (US$852), which raises the barrier to entry to beyond the means of the typical potential rural customer. In recent years, the Kenyan Rural Electrification Authority has focused its efforts on electrifying health clinics, public secondary schools, and market centers and subsequently offering subsidized connections to nearby homes and businesses (125). Despite significant progress in electrifying these public facilities, financing residential and commercial connections remains a barrier (125).

In Kenya, solar home systems are standalone solar energy kits that typically consist of a 5-100 W solar panel, a charge controller, a lead-acid battery, and a suite of DC appliances like LED lights, phone charging connections, radios, and televisions (126). The solar panel and battery are sized to provide reliable electricity to power the typical usage of the associated appliances. However, while reliability is high, the total electricity generation is small and essentially fixed over the life of the equipment, limiting demand growth with time. Additionally, these systems typically only support DC appliances, which are less widely available and are typically more expensive than their AC counterparts. M-KOPA is one of the leading solar home system companies in Kenya and Uganda, with 100,000 units sold in less than two years of commercial operation (126). Its primary product is a solar energy kit, consisting of a 5W solar panel, a charge controller, a sealed lead-acid battery, three LED lights, a hub for mobile phone charging, and a radio. M-KOPA utilizes an innovative pricing model, whereby customers pay a KES 2999 down payment (US$34) and KES 50 per day (US$0.57), paid via a mobile money platform, for one year before owning the kit outright (127). This results in electricity that is more than sixty times the cost of centralized grid electricity for every unit of energy consumed (assuming a two-year battery lifetime). However, the low-down payment cost in comparison to the high grid connection cost makes this option more accessible to potential rural consumers.

Microgrids and minigrids are small electric power systems that typically comprise one or more generation sources – such as solar panels, small wind turbines, or diesel gensets – a battery bank, a distribution network, and associated metering and management hardware (128). They are arbitrarily distinguished by their size, with microgrids here referring to systems of 1-100 kW and minigrids referring to systems larger than 100 kW. If designed and operated properly, these systems can provide high power quality and reliability – however, this requires substantial data on variability of load and renewable resources or conservative overdesign of generation and storage components. In minigrids and larger microgrids, the larger load footprint and power ratings of generation and storage may allow accommodation of sharply transient productive loads like welding and grain milling.

In Kenya, both small village-scale and large town-scale microgrid projects are being implemented by a variety of private and public entities. Access Energy is a Kenya-based microgrid design and operation company that aims to provide affordable electricity to rural populations in East Africa (129). It has installed 5 systems to serve remote communities in Western and Central Kenya. These solar PV and/or wind turbine systems are typically 1-10 kW in generation capacity and serve 10- 100 people in a village. The distribution network of these microgrids is currently limited to a 100m radius due to distribution line losses. Much like the centralized grid option, Access Energy consumers are charged a connection fee and then a consumption tariff. However, while the electricity is around KES 400/kWh (US$4.55/kWh), the connection fee is in the low thousands of KES (129). Therefore, while rural microgrid customers pay roughly twenty times more for every unit of electricity than their centralized grid counterparts, they are more easily able to afford the connection fee that allows them "first access" (130). A number of large towns in Kenya that are situated far from the national grid are served by larger-scale (130-3400 kW) minigrids built and operated by the utility, KPLC. These minigrids tend to be fully diesel, though recently some have been hybridized with small amounts of solar and wind (130).

2.3 Data: Elucidating Off-grid Residential Demand

The data sources used in this study are briefly described in Table 2. Two principal sources of socioeconomic data were utilized for this analysis. Exploring Kenya's Inequality: Pulling Apart or Pooling Together (131), a joint publication of the Society for International Development and the Kenya National Bureau of Statistics (herein, "SID-KNBS"), includes information on household-level demographics, employment, education, and poverty indicators for each ward in Kenya (wards are the smallest administrative unit, with each covering roughly 30,000 people, and numbering 1455 in Kenya). These data were derived from the 2009 Kenyan census and the 2005-2006 Kenya Integrated Household and Budget Survey. Details on the disaggregation of the data from administrative units preceding a constitutional restructuring in 2010 to the current boundaries and the sampling errors associated with these small areas are included in the report. Table 2 summarizes the types of features which are incorporated in our analysis. For brevity, a full description of the 100+ features in the dataset is omitted.

A subset of data from the 2008-2009 Kenya Demographic and Health Survey (herein,"DHS")is also utilized (132). Specifically, detailed household-level information is available from ~9000 households across ~400 sample sites nationally on electricity access and ownership of a number of electricity- related assets. These data are summarized in Table 1. The 2008-2009 survey represents the most recent information available, though a forthcoming 2014 survey can be used to update results. In addition to these socioeconomic and electricity-related data, geographic data describing the ward boundaries of Kenya were utilized for visualization purposes and to derive secondary data such as population densities. These geographic data were compiled by a private consultant from sources available on the website of the Independent Electoral and Boundaries

Commission of Kenya (133).

Data Source	Feature Types Used	Year
SID-KNBS	Water Source, Human Waste Disposal, Lighting Fuel, Cooking Fuel, Floor Material, Wall Material, Roof Material, Demographics, Employment	2009
DHS	Appliance Ownership & Electricity Access	2009
IEBC	Ward Boundaries	2012

Table 2. Data Sources

2.4 Methods and Analysis: Elucidating Residential Demand

The electricity access and asset ownership data from DHS were transformed into a format equivalent to that of the SID- KNBS socioeconomic data. That is, for each variable of interest, the transformed data is a proportion of households in each ward possessing a certain characteristic. This was accomplished by first aggregating the original binary variables (e.g. possession/non-possession of a television, access/non- access to electricity) for each household into a proportion of households at a given sample site (~400 across Kenya) that possess the relevant asset or have the relevant access. Next, the DHS sample sites were matched to their corresponding wards via their geographic coordinates. Where multiple sample sites exist within a single ward, the value for the ward was considered to the be the mean of the associated sample site values for lack of a more rigorously justifiable method. A map of Kenya's wards and the locations of the 2008 DHS sample sites (with corresponding wards highlighted) is given in Figure 13. After necessary data cleaning, 1401 wards of the original 1455 remain. This ~4% attrition is due to missing socioeconomic or geospatial data or to irreconcilable differences in place names between the datasets.

We now estimate, at a fine geographic resolution, the demand for residential electricity services (and implicitly, the ability to pay for such services) under two scenarios: (1) current levels of electricity access; and (2) expanded access to electricity services in localities which do not currently have access. The approach employed here is to develop estimates of electricity-consuming appliance ownership as a proxy for an economically sustainable level of residential electricity demand under each of these scenarios. We will refer to these proxies as current ownership and total ownership, respectively, for the current access and expanded access scenarios outlined above. Induced ownership, the additional appliance ownership one would expect when electricity is made available, is simply the difference between total ownership and current ownership (analogously, we will refer to current demand, total demand, and induced demand for electricity). To develop these proxy estimates, we employ k-nearest neighbors regression to predict detailed ownership information across a finer and wider geographic basis than the DHS using socioeconomic similarity from the SID-KNBS data.

Implicit in this approach is the assumption that localities that share socioeconomic characteristics will also have similar demand for electricity services and similar ability to pay for them. Additionally, this assumes that electricity prices are uniform across the locations where ownership observations are available (in this case, the DHS sample sites). This price uniformity will likely not be the case in a world with a diverse range of potential technologies and business models for rural electrification. We address this issue later on in the chapter.

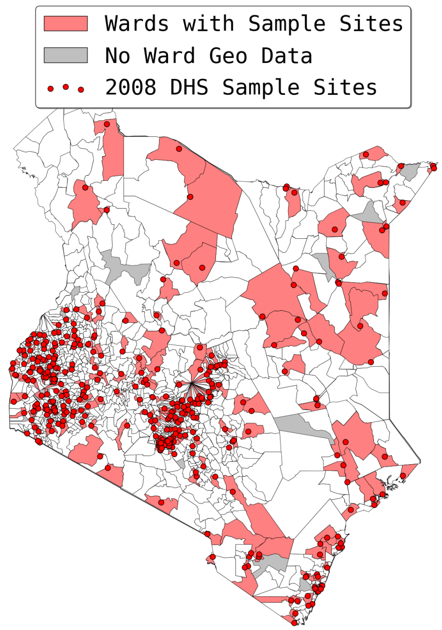


Figure 13. Kenyan Wards and 2008 DHS Sample Sites.

We choose to employ k-nearest neighbors regression for its simplicity and intuitive interpretation. Other supervised approaches, such as multivariate linear regression, were explored. The underlying structure of the data was found to be highly non-linear, and in the absence of a domain-informed rationale for more complex pre-supposed relationships between the dozens of socioeconomic characteristics and appliance ownership levels, this technique was abandoned. Similarly, k-means and hierarchical clustering techniques were explored to determine whether the wards form natural groupings by their socioeconomic characteristics. While the resulting clusters do build intuition about the socio-economics of Kenya's wards, the distributions of the data are rather continuous (rather than tightly clustered) so the validity of any hard-assignment clustering techniques is dubious. Lastly, while principal components analysis was explored, the small datasets obviated the need to compress the data for computational reasons, and domain knowledge- driven feature reduction is preferred for interpretability reasons.

In defining a similarity metric for k-nearest neighbors regression, care must be taken to include characteristics that impact the quantities of interest but not to allow regional differences that are exclusively a function of geography to skew the analysis. For example, one might expect that economic status is an important predictor of asset ownership and energy appetite and that home building materials could be an indicator of this status. However, households in one region may build with grasses or reeds where those materials are widely available, while households of similar socioeconomic status in another region may use mud and dung because of different soils and a prevalence of cattle.
To address this challenge, features in the socioeconomic dataset are aggregated into similar classes (e.g. natural building materials, improved sanitation) in an attempt to account for heterogeneity

without obscuring important differentiators that may impact energy behaviors. Wherever possible, these aggregation choices follow accepted standard definitions in the development community (131, 132, 134).

Additionally, a number of extensive properties that are dependent on the absolute size or population of a ward are transformed into intensive properties (via normalization by population, ward area, etc.) to facilitate comparison across wards of somewhat arbitrary boundaries. Lastly, redundant features (those that are repeated or not linearly independent from the others) are removed from the dataset so that they do not contribute disproportionately to the determination of socioeconomic similarity. These choices of feature aggregation are summarized in Table 3 while choices of feature reduction and normalization are omitted for brevity.

Feature Class	Aggregated Feature	Original Features
CookingFuel	Transitional	Paraffin, Charcoal
CookingFuel	Advanced	LPG, Biogas, Electricity
FloorMaterial	Finished	Tiles, Cement
LightingFuel	Kerosene or Paraffin	PressureLamp, Lantern, TinLamp, GasLamp
RoofMaterial	Natural	Makuti, Grass, Mud or Dung
RoofMaterial	Rudimentary	Corrugated Iron Sheets, Tin
RoofMaterial	Finished	Tiles, Concrete, Asbestos Sheets
WallMaterial	Rudimentary	Mud and Wood, Mud and Cement, Wood Only, Corrugated Iron Sheets, Tin
WallMaterial	Finished	Stone, Brick or Block
WasteDisposal	Unimproved Sanitation	Pit Latrine Uncovered, Bucket, Bush
WasteDisposal	Improved Sanitation	Main Sewer, Septic Tank, Cess Pool, VIP Latrine, Pit Latrine
WaterSource	Surface Water	Pond, Dam, Lake, Stream or River
WaterSource	Unimproved Sources	Unprotected Spring, Unprotected Well, Water Vendor
WaterSource	Improved Sources	Protected Spring, Protected Well, Borehole, Piped, Rainwater Collection, Jabia

Table 3. Feature Aggregation

Next, each of the features are translated by their mean value and scaled by their standard deviation so that the data take the form of z-scores. This is a common choice of feature standardization that facilitates comparison based on the underlying structure of the data rather than the absolute breadths of the feature distributions. Lastly, each of the feature classes is scaled by the number of features in the feature class (e.g. three features in the “roof material” class: natural, rudimentary, and finished). This is a design choice, and reflects the fact that no more rigorous method for determining the importance of the various data in predicting appliance ownership is known. Some efforts were undertaken to establish the predictive power of the socioeconomic data in this regard via principal components analysis and multi- variate regression, but further work is needed to establish a conclusive answer.

These choices of feature aggregation and reduction result in a 42-dimensional feature space for the socioeconomic dataset (each ward i is described by an observation vector $x_i \in R$). We define the socioeconomic distance, or dissimilarity, between two wards to be the L-1 norm (Manhattan length) of the difference between the two vectors that de- scribe the ward characteristics. With this distance metric in hand, k-nearest neighbors regression can be performed. The training set comprises the socioeconomic data for wards for which labels exist (asset ownership and electricity access data from the DHS) and the labels themselves. We refer to these wards as w_{obs} and the associated socioeconomic data and labels as X_{obs} and y_{obs} respectively (obs: observations). The test set comprises the socioeconomic data for wards where no labels are known. We refer to these wards as w_{test} and the associated socioeconomic data as X_{test}. For each ward in the test set, the label is estimated to be the average of the labels of the k_{nn} nearest neighboring wards in the training set, where 'nearest' refers to those with the least socioeconomic distance from the ward at hand.

The value of k_{nn} in the nearest neighbors regression algorithm is chosen via k-folds cross validation. In this non- exhaustive technique, the original training set is randomly partitioned into k_f subsets. One at a time, each of the k_f subsets are withheld from the training set, and the regression is performed using the withheld subset as the test set. The root mean square prediction error in accurately predicting the label values for each of these subsets is averaged and recorded. This is repeated across a range of potential k_{nn} values, and k_{nn} is chosen to the be the value that minimizes this error metric. The number of subset combinations needed for exhaustive cross-validation is intractably large, but the random partitioning in the non-exhaustive k-folds cross validation can produce inconsistent results. As a compromise between speed and accuracy, we perform this validation across a range of k_f values and a number of random seedings for the partitioning process and average the results to arrive at a consistent choice for k_{nn}. This approach is illustrated graphically in Figure 14. The error metric described above is plotted against potential values for k_{nn}. This relationship is plotted for a range of k_f values and the entire process is conducted for 20 different random seedings (hence the multiple lines for each k_f value). The average error metric across all of these k_f values and all of the random seedings is also shown. In the case presented in Figure 14, we choose $k_{nn} = 20$ to minimize this average error.

Once the data have been imported and transformed, and the features in the data have been aggregated, normalized, selected, and scaled as discussed above, k-NN regression can be directly used to ascertain an estimate for current owner- ship of the relevant electricity-consuming appliances. Specifically, the current ownership levels are predicted for the test set socioeconomic vectors X_{test} using the training set vectors

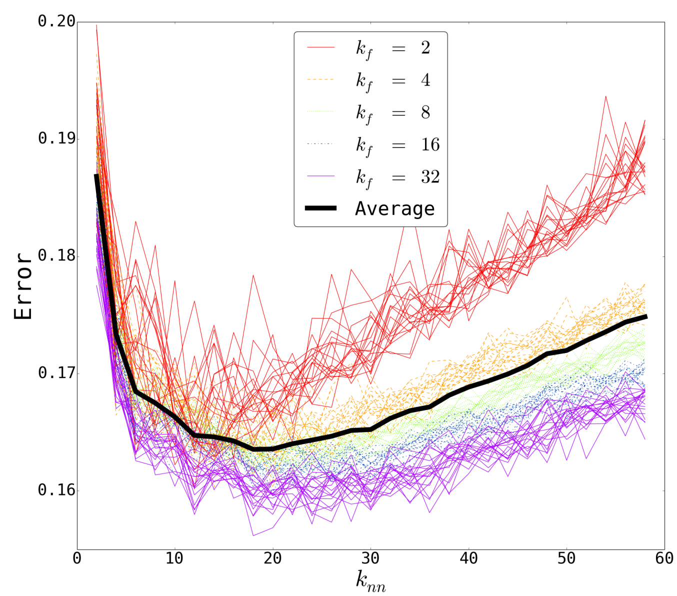


Figure 14. Example of k-folds cross validation for prediction of current television ownership (k_{nn} = 20)

and labels X_{obs} and y_{obs}. However, to produce an estimate for induced ownership, a more involved process is required. First, electricity access is predicted across w_{test} via the k-NN algorithm using w_{obs} as the training set. More specifically, the estimated electricity access $\bar{y}_{test,e}$ is predicted for the socioeconomic vectors in X_{test} using the vectors and labels X_{obs} and $_{obs,e}$. Next, combining the observed and predicted electricity access data, the wards are divided into those 'with' and 'without' electricity access as defined by a threshold proportion of households with electricity access. This threshold is chosen to be 10% in this analysis, which reflects a balance between domain knowledge considerations and limited availability of data. This threshold is reasonable despite its ostensibly low value because of the low penetration rates of actual connections that often exist in rural areas to which KPLC's distribution infrastructure extends. A higher choice of threshold value would also lead to an unacceptably small set of wards that are deemed to have electricity access for the next step in the induced ownership estimation.

Next, the original training set, w_{obs}, is partitioned into wards without electricity access, $w_{obs,no}$ and wards with electricity access, $w_{obs,yes}$. Similarly, the test set is partitioned into $w_{test,no}$ and $w_{test,yes}$. The socioeconomic data and labels are partitioned according to the same nomenclature. The sizes of each subset of the data are given in Table 3. The total ownership for wards in $w_{test,no}$ is predicted using the training set $X_{obs,yes}$, $y_{obs,yes}$. Similarly, the total ownership for wards in $w_{obs,no}$ is predicted using the same. Induced ownership is the difference between total ownership and current ownership.

	With Elec.	**No Elec.**	**Total**
Observation Set	121	211	332
Test Set	439	630	1069

Table 4. Data Partitioning Sample Sizes (Number of Wards)

The basic rationale for this approach is a slight extension of the core assumption of our methods: one would expect that a ward without electricity would have similar adoption of electrical appliances (need or desire for the services they provide and ability to pay for them) as a ward with electricity if the two closely share socioeconomic characteristics. This approach treats electricity access as an exogenous factor. If an un-electrified village were to become electrified, its socioeconomic characteristics and the ownership of electricity-consuming appliances would not change overnight. However, there would likely be some appliance adoption transient that depends on the costs (in time, money, and inconvenience) of the incumbent energy sources, the costs of electricity, public awareness, the psychology of behavior change, and other factors. The estimates made here pertain to a steady-state level of ownership, once this transient has decayed. One might suppose that in some communities, the DHS may have been conducted shortly after electrification and thus during this transient period. This phenomenon is likely rare if it exists at all, and it is ignored here.

For the purpose of illustrating the end-to-end use of our approach, we employ a rudimentary model for translating electricity-consuming appliance ownership levels into residential electricity demand. This knowledge is essential in evaluating the viability of various technology options and business models for rural electrification, whether evaluating potential tariff structures or specifying and costing equipment. Based on evidence from rural Kenyan households in the literature (135), we assume a daily energy use of 210 W h/day for a 14-inch color TV, 960 W h/day for a small refrigerator, 6 W h/day for a radio, and 6 W h/day for a mobile phone. These appliance consumption levels are translated into an average household daily electricity demand for each ward using predicted and observed appliance ownership levels.

2.5 Results and Discussion: Elucidating Residential Demand

The relationship between reported appliance ownership (television, refrigerator, radio, mobile phone, and solar panel) and electricity access from the DHS is presented in Figure 15. The raw observations are transformed as described in the previous section into a proportion of households in the ward with a given appliance or with electricity access. It should be noted that the DHS appears to define electricity access as connection to an external power system (in this case, to the KPLC distribution system), and thus, household possession of solar panels does not constitute electricity access in this dataset.

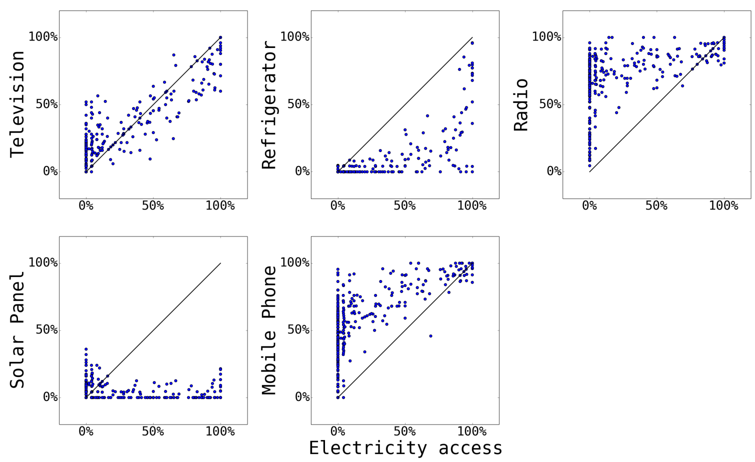


Figure 15. Observed Appliance Ownership Versus Electricity Access

These data reflect important trends about the 'appliance ladder,' which describes the order and manner in which electrified households acquire electricity-consuming appliances (106). Radio and mobile phone ownership is often in excess of electricity access, which suggests that people use batteries and charging services (for instance, from a shop in a nearby electrified town) to power these devices. Levels of refrigerator ownership are significantly below electricity access levels (except for a handful of affluent urban wards), which reflects the high capital cost of the appliance, the relatively high electricity consumption, and the high reliability of electricity service needed to make cold storage practical. Comparing the television ownership with the other appliances, one observes that TVs are more common than refrigerators, but less common than radios and mobile phones. This reflects the moderate capital cost and energy consumption and the less stringent reliability requirements as compared to cold storage. Additionally, ownership levels exceeding electricity access suggest that televisions are sometimes powered by batteries or perhaps larger solar/battery systems, and it suggests a strong desire for television viewing (given the high cost or inconvenience of these approaches to powering TVs).

The insights from the solar panel ownership data are less clear, as the technology and costs of solar photovoltaic systems have changed significantly in the years since the survey was conducted. However, recalling the narrow DHS definition of electricity access, one observes that the highest solar panel ownership occurs in wards with little to no electricity access. The presence of non-zero ownership in wards with some electricity access suggests either fuel-stacking (where households utilize multiple energy sources to enhance reliability or to navigate fluctuating prices, as for kerosene or charcoal) or it suggests a social effect in electricity usage: households that may not be able to afford a connection to the utility nevertheless become aware of electricity and its uses and acquire solar panels for low energy applications (LED lighting, radio/mobile phone charging).

Predicted and observed electricity access are given in Figure 16. For wards with DHS data, the observed access is shown, while for wards without data (136), the predicted access is shown. The Kenyan electricity transmission network down to 33kV (136) and the locations of most minigrids (130) are overlaid. Sources indicate that most minigrids predate the 2008 DHS, though the exact commissioning dates are not available. Wards with significant predicted electricity access are mostly in proximity to the transmission network (the 11kV distribution network is not shown, but its extent outwards from the transmission backbone is limited by loss or voltage drop considerations) or to known minigrids. A few border towns appear to be connected to neighboring power systems in Ethiopia and Tanzania (Moyale, Taveta, Oloitokitok).

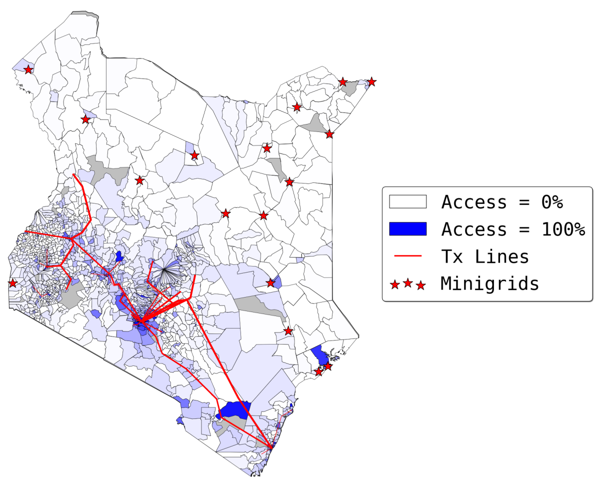


Figure 16. Electricity Access

The observed and predicted current ownership levels are plotted for each ward in Figure 17. For wards with DHS data, the observed ownership is shown, while for wards without, the predicted ownership is shown. Mobile phone and radio ownership is widespread, though noticeably higher in the western and central regions, parts of the southern Rift Valley, and the cities and large towns of the coast and northern regions. Refrigerator ownership is low overall and concentrated in urban areas. Television ownership is moderate and follows a similar regional distribution as mobile phones and radios. All of these appliances show higher concentrations in the large towns and small cities of the north and coast than the surrounding rural areas. Most of these locations, which include Wajir, Garissa, Marsabit, Lodwar, Mandera, and others, are sites of minigrids that provide traditional electricity services despite their distance from Kenya's national grid (130, 137). Solar panel ownership is limited, and concentrated in rural parts of western and central Kenya.

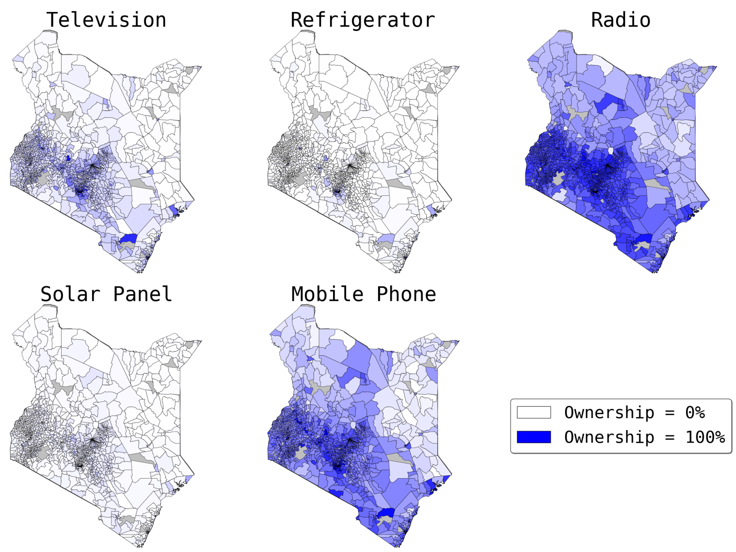


Figure 17. Current Ownership

A number of large-area wards that are fairly sparsely populated appear to be outliers due to high ownership and access levels compared to their similarly sparse neighboring wards. Closer investigation reveals that these wards have towns of significant size, and the population is in fact relatively urban and concentrated in one part of the ward. These locations include Nyahururu, which sits at a major node in the electricity transmission system, Voi, a major town on the road, rail, and electricity transmission corridor between Nairobi and Mombasa, and parts of Lamu, a tourist destination and site of a KenGen-owned minigrid.

Total ownership is shown in Figure 18. For wards with electricity access levels already above the threshold value, current ownership is equivalent to total ownership and is shown here. For all other wards, the model-predicted value of total ownership is shown. Despite differences in absolute ownership level, appliances share a high degree of homogeneity in predictions across wards. As one would expect significant socioeconomic differences to result in a broader distribution of predicted ownership levels, these results call into question the validity of the analysis, a topic we explore below. To explore the validity of induced ownership predictions, we examine the relative socioeconomic distance to the nearest neighbors with and without electricity access. One would expect that for a ward without electricity (the wards of concern here, $w_{test,no}$ and $w_{obs,no}$) the distance to the nearest wards of any kind should be less than that to the nearest wards with electricity. However, unless the latter distance is vastly greater than the former, the estimation of total ownership is likely reasonable. Conversely, a much greater distance to electrified wards would indicate that the pre- diction based on electrified wards is so inaccurate relative to prediction based on all wards that the results are not of practical value.

Figure 19 presents one possible validation metric. On the left-hand side, each dot represents one ward. The value on the x-axis is the average 'fractional distance' to a given ward's k-nearest neighbors of any kind, while the value on the y-axis is the average 'fractional distance' to the ward's k-nearest neighbors with electricity. Fractional distance d_f is defined as $d_f(d) = (d - d_{min}) / (d_{max} - d_{min})$ where d_{max} is the distance from the ward to its furthest neighbor and d_{min} is the distance to its closest neighbor. Here we observe that as expected, distance to nearest neighbors with electricity is always further than distance to nearest neighbors of any kind for this set of wards that does not have electricity.

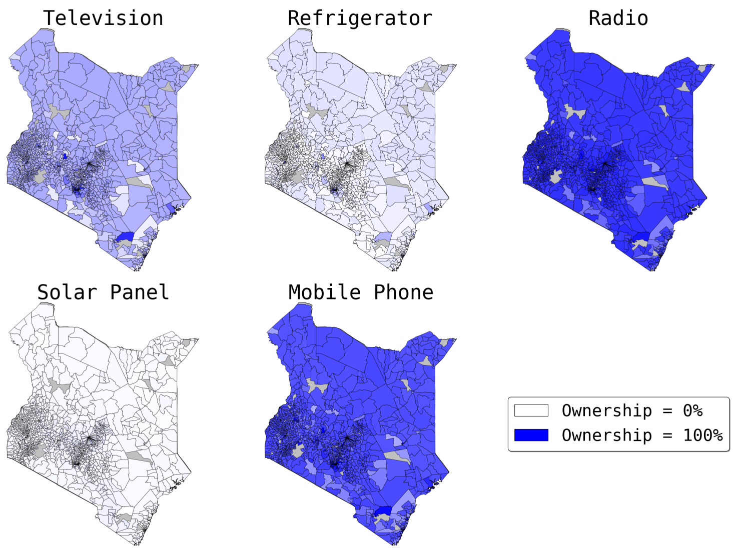


Figure 18. Total (Current + Induced) Ownership

The ratio of the latter distance to the former, which should be an indication of the validity of the induced demand approach for this dataset, ranges from roughly 1.2:1 to 4.6:1. The right-hand side of Figure 19 presents the ratio of these distances for each relevant ward in geographic form. We observe that wards in the former central province and along the infrastructure-rich Nairobi-Mombasa corridor often have the lowest values because of the abundance of nearby electrified wards with which they have significant socioeconomic similarity (this similarity is not explicitly demonstrated here for brevity, but visualization of the various socioeconomic parameters and clustering analysis confirms this assertion).

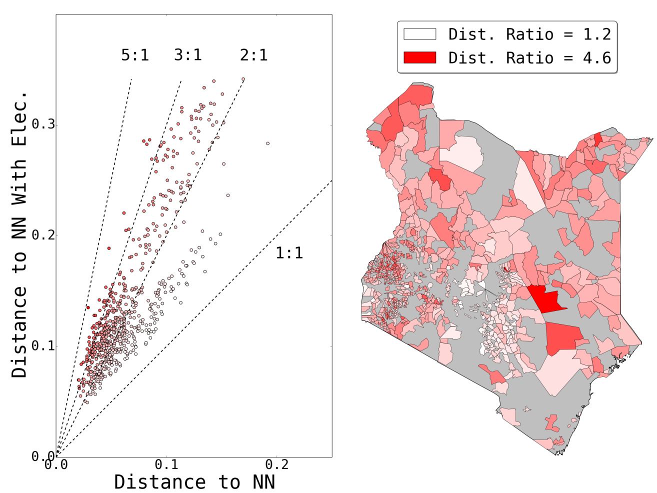


Figure 19. Validation of Total Demand Estimation Methodology

Further investigation that is omitted here for brevity indicates that a paucity of appliance ownership data for electrified wards in certain regions is the root cause of the homogeneity of induced demand predictions (even aggregating features to control for heterogeneity of poverty, the socioeconomic characteristics are quite regional, reflecting significant geographic patterns in incomes and access to improved water and sanitation). For rural areas of much of the coast and northern regions and for rural areas far from the cities in the western and Rift Valley regions, there are so few similar wards with electricity access that the prediction from k- nearest regression is overwhelmed by electrified wards that are in fact rather dissimilar. This is because the values of k_{nn} determined via cross validation are quite high relative to the total number of electrified wards to learn from (these values are given in Table 5). The current simple cross validation approach presents an objective and repeatable approach to choosing the tunable parameter k_{nn}, but a more nuanced approach could potentially yield better results from the same limited input data. It should be noted that while this does not appear to be a conceptual limitation of our induced ownership estimation method, it is a practical limitation. Data for other countries with low rural electrification may be similarly lacking. In the case of Kenya specifically, model performance should improve with use of the forthcoming 2014 DHS because there has been significant progress in rural electrification in the intervening years.

Predict	**Current**	**Induced**	**Induced**
From	All Obs.	Obs. with Elec.	Obs. with Elec.
For	All Test	Test no Elec.	Obs. no Elec.
Television	20	22	18
Refrigerator	14	12	14
Radio	18	24	26
Solar Panel	34	12	12
Mobile Phone	18	22	28
Electricity	12	n/a	n/a

Table 5. k_{nn} values determined by cross-validation

Despite the challenges discussed above, we present the ownership predictions in another form in Figure 20 to illustrate the interpretation of results produced via this method. For each ward without electricity, total ownership is plotted against current ownership (observed or predicted, depending on the ward). The high, tight distributions for mobile phones and radios in total ownership suggest that regardless of the current, unelectrified ownership level, these appliances would be adopted broadly and that their adoption is nearly independent of socioeconomic factors. The conclusions regarding television ownership are nearly the same except for the lower average ownership level. The modest total ownership in the refrigerator data (a bit wider in absolute terms, much wider in relative terms) and its concentration on the low current ownership end reflects the near non-existence of residential cold storage in unelectrified wards, and limited ownership in similar electrified areas (likely rural and relatively poor). Lastly, the most marked trend in the solar panel results is lower ownership levels in the electrified case – this derives from the definition of electricity access as a grid connection in the DHS.

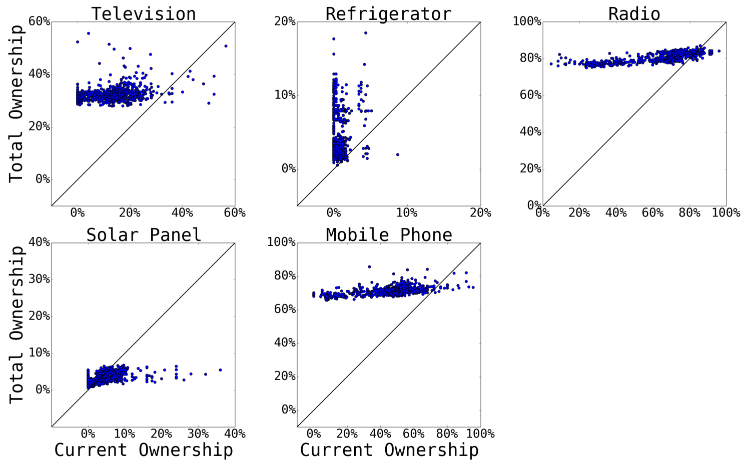


Figure 20. Current & Total Ownership

Translating the current and total ownership levels into estimates of residential electricity demand yields the results in Figure 21. Due to the significant difference in ownership levels between urban and rural wards (and corresponding difference in demand estimates), currently electrified wards are omitted to maximize the range of demand levels that can be expressed on a linear color scale. As noted above, the estimates of induced demand for certain regions are likely of limited accuracy. Nevertheless, this demonstrates the end- to-end methodology of our data-driven approach to electricity demand prediction. The implicit assumption in this supervised learning process that electricity prices are uniform presents another challenge. When evaluating potential technology options and business models for sustainable and scalable rural electrification, prices are likely to markedly vary for different strategies. One possible way to address this challenge is to transform the ownership level estimates into a total household budget for the services these appliances provide. By coupling this budget with data on the ownership costs of these various appliances and with domain-knowledge about the appliance ladder, these owner- ship estimates (derived under one price assumption) can be transformed into ownership estimates under arbitrary electricity rate scenarios.

This work represents a step towards understanding the potential for novel technologies and strategies to enable rural electrification. We have used an approach that draws from socioeconomic, demographic, geospatial, and domain- relevant data to build a model of induced residential demand for electricity in Kenya. This model helps to address an important gap: understanding future demand for electricity is essential for evaluating the wide range of technologies and business models in this space. Continuing in this direction, we recognize that there is much more to the problem of understanding future electric demand. We aim to use a similar approach to understand the potential for growth in electricity demand for commercial purposes by analyzing specific industries and business types that emerge in these communities as electricity becomes available. Further, we aim to build a tool for various public and private entities to employ our model to make business, funding, and policy decisions. With refinement, we believe that this type of approach may be relevant in other domains as well, such as water and waste management, and in other countries beyond Kenya.

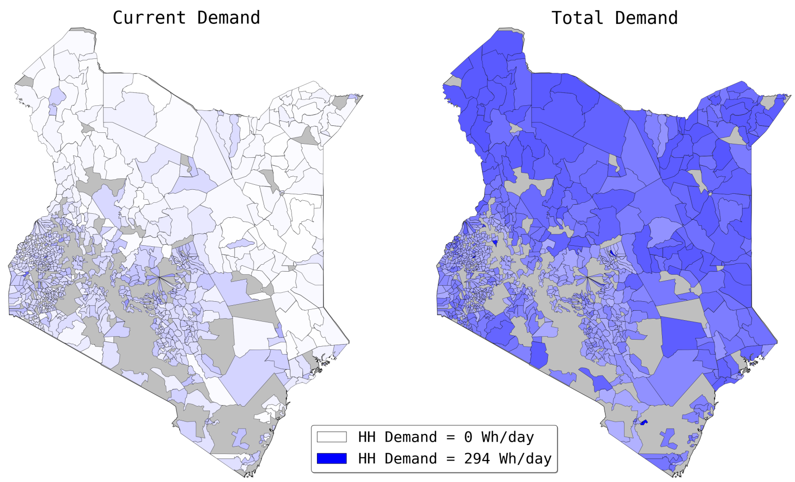


Figure 21. Household Demand Estimation (Currently Un-Electrified Wards)

2.6 Background: Potential for Micro-Enterprise Wealth-Creation Post Electrification

Most of the literature that investigates off-grid energy demand primarily focuses on the household. This focus has had a positive impact on the development of novel electrification strategies through which many households in East Africa, and many other regions across the world, have received access to modern electricity services including pico power, solar home systems, and microgrids. Any single one of these strategies, however, is not a panacea for the problem of rural electrification as their long-term sustainability ultimately depends on the intertwined relationship between demand and supply, their fate in the context of their transitional nature, and the heretofore inexorable extension of the centralized grid. While the household has predominantly been a topic of interest for researchers, evidence from Kenya suggests that within rural communities, households could represent only 30% of total electricity consumption, with institutions (schools, health care centers, and NGOs, for example) and micro-enterprises (retail and repair shops, agricultural processing, and hotels, among other services) representing the remaining 23% and 46% respectively (138). Anecdotal evidence from microgrid developers, and personal communication with solar entrepreneurs has also shown that community-level demand-side concerns (estimating electricity demand potential and persistence accurately, and management) are some of the most immediate and pressing issues affecting the long-term business sustainability of off-grid solutions. In particular, and despite the widespread notion that electricity access can in and of itself ignite entrepreneurship potential (and in turn, increase electricity demand), there is very little research that explores the complementary infrastructure that can ignite that potential. Below we briefly summarize demand- and supply-side methodologies for off-grid electrification, as well as provide brief introduction to the literature that explores the electricity-entrepreneurship nexus with a particular focus on Kenya.

Traditional approaches to off-grid electricity demand estimation, as well as those that evaluate users' ability and willingness to pay for electricity services, have traditionally used social science methods such as surveys (119, 120), field and longitudinal studies (100, 101), and stated preferences (contingent valuation, ability and willingness to pay) (121, 122). These approaches are extremely valuable as they usually provide detailed knowledge about a consumer and the intricacies of daily life in a region, village, or town. They can be used for evaluating the preference and decision making process that goes into buying and using different energy services (e.g., fuel wood or gas for cooking, kerosene or solar maps for lighting, for example), and perhaps later be used for better designing tariff structures, or demand side management schemes, among other things. However, although extremely insightful about a particular place, they are also time-consuming, and results are usually not generalizable.

Demand-side methodologies have also shed light into rural off- grid energy transitions at the household and village level, finding them to be better explained by 'energy stacking' or 'energy webs' (where households use different energy sources for the same or multiple purposes) rather than linear transitions (139–141). In South Africa, research regarding appliance ownership and grid-electricity access and demand also demonstrated that ownership of electric appliances did not necessarily mean that they were used, or that if they were used, that they were powered by the grid (or in other places, by solar home systems)(101, 102). Take, for example, households that might buy appliances for their symbolic value in a mere attempt to conceal poverty, or on the other hand, the widespread use and preference of dry-cell batteries for powering radios (101, 102).

Finally, 'end-use' approaches are less often used, but under the right assumptions, can be very useful for estimating a village or town's electricity demand. This methodology allows the researcher to incorporate different scenarios (behavioral dynamics, energy-efficient devices, and income and energy transitions, for example), and data sources (census and appliance ownership data, technology characteristics, and usage patterns, among others) to make assertions about electricity consumption in different economics sectors and areas of village life (household level, agricultural, and small commercial) (110, 123). Worth noting is that although many of these provide household and village estimates of appliance ownership and electricity demand, there has been little thought given to the topic of demand persistence, or long-term electricity demand potential. For many businesses and electricity providers in the energy access space, understanding long-term demand potential is crucial to ensuring growth in revenue and financial sustainability.

Several studies have explored optimal supply-side approaches to electricity access in Kenya (142–144). Many of these include using spatial least-cost optimization models to determine whether grid electrification (and expansion) or off-grid alternatives (solar PV and diesel mini-grids) are more suitable to the particular demand characteristics of rural Kenya (142, 143). Results from a one-scenario analysis (using fixed costs and electricity demand levels, varying penetration levels) of grid vs. off-grid alternatives in Kenya found that under most demand and geographic conditions, extension of the national grid would be less costly than off-grid options (142). On the other hand, similar analyses that implemented several scenarios (high grid electricity costs, high PV efficiency, high demand, high/low diesel prices) have found that electrification strategies vary depending on the specific sub-local characteristics of a region (143). For example, grid extension was found to be only suitable for grid cells featuring high demand and population density, whereas off-grid alternatives were more suitable for the often scattered populations of rural Kenya (143). Recent work pushes back on several of these studies, suggesting that electricity access remain elusive not only in off-grid areas, but "under-grid" areas as well (121, 125, 145). These studies demonstrate that even in "ideal settings" with high population density and extensive grid coverage, electrification rates (and possibly the benefits for electrification) for rural households and businesses remain very low, suggesting that investments in grid infrastructure in some places in Kenya have not translated to equally high rates of rural electrification, primarily because of the relative high cost for households and businesses to obtain a new connection (121, 125, 145). Perhaps a reason why an '*optimal*' electrification strategy has remained elusive is due to the relatively little importance that electricity demand estimation has received in these analyses. Although these studies do take into account important proxies for electricity demand such as other household expenditures, education, poverty, population density and urban vs. rural differences, they often fail to mention or incorporate energy transition theories, complementary infrastructure (presence of roads and trade centers for example), and consumption preferences. In Kenya in particular it has been shown that the main driver of household rural electrification is not desire for electricity per se, but the desire for connective appliances (TVs, radios, and more recently cellphones) (98, 100, 141).

Although outdated, Kenya's only survey (1999) on the country's diversity of small- and micro-enterprises provides valuable insight into the relationship between electricity access and entrepreneurship (138). The survey highlights the great sectorial diversity of small (between 10 and 50 employees) and micro- enterprises (up to 10 employees) in rural areas, including trade (65%, predominantly agricultural), manufacturing (15%), services (12%), bars/hotels/restaurants (6%), and construction (2%). Of these, traders represented the largest population using electrified machines (51%), followed by manufacturers (20%), and services (29%). At the time, rural micro-entrepreneurs reported that poor roads, access to markets, and lack of credit (access to finance) were some of their most severe constraints, with electricity not representing a major barrier, although only 33% of them had access to it. Similar results were found in South Africa (146, 147), where absence of electricity only ranked 34th out of 46 possible business problems in a micro-enterprise survey. In 2003, The World Bank published a large literature review and survey of productive uses of electricity in rural areas (148), and yet, it is not clear if off-grid entrepreneurs, and top-down energy planners incorporate this information into their decision making Kenya's Lighting Africa 2008 assessment of off-grid rural small- and micro-enterprises also highlights the plethora of concerns faced by businesses (149). It finds a predominantly agricultural population primarily concerned with improving their facilities (55%), with only a few (11%) thinking of electricity access as a top priority (149). Within this subset, however, there is a clear understanding of the co-benefits of access, and how its use could be reflected in increased productivity and sales (149).

More recent research in Kenya highlights the complexity of the electricity-entrepreneurship nexus; elucidating that access is a necessary but not sufficient condition for the creation and development of rural micro-enterprises (119). A 2006 study in the small town of Mpeketoni showed that access to electricity (availability and quality) significantly increased productivity per worker (quantity and quality of products) and revenues for micro-enterprises, as well as enabled mechanized agricultural processing and its co-benefits (increased sales, revenues, and trade) to flourish. However, the same article points out that electricity's catalyzing characteristics would not have been enabled without natural capital, markets, road infrastructure and facilities for social amenities (schools, polytechnics, and communication services); all which were developed prior to, or in parallel, with electricity access (119). In combination, these surveys (138, 146, 147, 149) and case studies (119, 150, 151) underscore the powerful synergy that exists between electricity access, human capital, and complementary infrastructure (schools, roads, and financial services, for example). With Kenya's population still being predominantly rural (>75%), and off-grid electricity remaining limited (electricity access < 20%), local dynamics and infrastructural synergies are crucial for understanding the viability of electricity access solutions.

Earlier studies in South Africa and India presented ample analysis and evidence to the range of social benefits (increased labor participation, time allocation for fuel collection, poverty reduction, and children's schooling), that can be derived from new connections and electricity access, but often ignored the conditions in which electricity access led to those outcomes (103, 152). However, more recent work in India and Kenya has begun casting doubt on the often-assumed causal link between electricity access and human development (153, 154). Work in India has compared nightlights data before and after the country's massive rural electrification program (2001 vs. 2011) with census data (demographics, occupational status, asset ownership, school enrollments and village level improvements) and found no evidence of human development outcomes improving over time (153). The work in Kenya suggests that mass rural electrification through grid extension could have limited social welfare improvements, with electrification costs being at least four times higher than the ability and willingness to pay of households for new connections, and with consumer surplus appearing lower than total costs (154). Although intriguing and suggesting alternative hypotheses, neither of these articles explore the conditions in which willingness to pay for electricity might be higher or lower, nor the diversity of conditions under which electricity can lead to improvements in human development, or the amount of time that must pass for electrification to have its greatest impact towards improving social well-being and human development outcomes. We demonstrate in the following sections, what we consider are important data elements that need to be included in analysis of the benefits of electricity access. The same data and approach can be used by top town energy access planners and off-grid entrepreneurs to find new regions in which their services are likely to be impactful, profitable, and long lasting.

2.7 Data: Potential for Micro-Enterprise Wealth-Creation Post Electrification

A summary of the data used in this study is available in Table 6. Nationwide geo-spatial data for rivers (current), small and large- scale irrigation projects (historical and planned), crop diversity (average number of crops grown; 1997) and intensity (percent land under cultivation; 1997) were collected from the World Resources Institute (WRI), the International Livestock Research Institute (ILRI), and Kenya's National Irrigation Board (155–157). We also use an agro-ecological potential score which is a composite index of moisture availability classification, rainfall (mm), average annual potential evaporation (mm), vegetation, potential for plant growth assuming that soil conditions are not limiting, and risk of failure of an adapted maize crop (158, 159). The agro-ecological potential score is ranked from one (high potential: humid forest with high potential for plant growth and extremely low risk of failure of an adapted maize crop) to six (low potential: arid to very arid regions, bushland or desert scrub, with low potential for plant growth an and high failure for maize crops). As most rural populations are predominantly employed in agriculture, natural capital is crucial for their livelihood, a stable cash flow, and for providing the basis for agricultural processing activities. The combination of access to fertile soils and water is reflected in greater agricultural productivity, and year-round irrigation access (as opposed to rain fed agriculture) can translate into a more stable cash flow throughout the year.

Methods for measuring infrastructural capital include a wide diversity of variables mostly concerning distance to services and neighboring communities. Nationwide data for existing schools, health care centers, and trade centers throughout the country (electrified vs. non-electrified) were obtained from Kenya's Rural Electrification Authority (2014) (160), and geo-spatial data for major towns, 1st and 2nd tier roads, and transmission infrastructure were obtained from the WRI and ILRI. Population density estimates were calculated using the highest resolution administrative unit for which data are available in Kenya (ward) for population and ward area (km^2) from the Society for International Development and the Kenya National Bureau of Statistics (herein, "SID-KNBS"). Data for spatial location of transmission lines, solar vendor shops and micro-grid locations were obtained for Kenya's Rural Electrification Authority, M-KOPA, Sun Transfer, SteamaCo, Powerhive, and the German Federal Ministry for Cooperation and Development. We include proxies for infrastructural capital because the literature suggests that social connectivity and education play a large role in unlocking the productive uses of electrification (141), and proximity to roads, major towns and trade centers allows for more vibrant local economies. Anecdotally, population density is one of the few variables that is used by access entrepreneurs to identify off grid target communities. We used the location of all Equity Bank and MPESA agents throughout the country (2014) as proxies for access to finance. Equity Bank is a financial services provider based in Nairobi with branches and an agent network that span almost everywhere in the country, and M-PESA is a mobile- phone based money transfer and micro-financing service that is ubiquitous throughout Kenya. Users of M-PESA can deposit money into an account referenced to their phone SIM card, send balances using SMS to other users, and redeem cash deposits from M-PESA agents throughout the country. Equity Bank and M-PESA are distributed extensively throughout the country and provide both mobile money and, increasingly, loans (M-Shwari) to a wide diversity of populations, with 80% of Kenya's adult population being actively engaged with mobile money. Recent research from Kenya suggests that over the last decade M-PESA has increased per-capita consumption levels and lifted 194,000 households, or 2% of Kenyan households, out of poverty (161).

Data source	Feature types used	Units[a]	Year
Kenya's Rural Electrification Authority World Resources Institute	Number of schools, trade centers and healthcare centers per ward	Number/1000 people	2014
	Major rivers	km	–
	Agricultural development—average crop diversity	Number of crops/km^2	1997
	Agricultural development—crop intensity	Agricultural land/km^2	
Kenya's National Irrigation Board	Small- and large-scale irrigation schemes	Number/ward	2010
Joint Research Center European Soil Data Center, FAO Soil Database	Soil quality and agro-ecological potential zones	Agro-ecological zone score (I–VII)	1980, 2008
International Livestock Research Institute	Major towns	km	–
	1st and 2nd tier roads	km	–
	Grid access	km	2004
Society for International Development and the Kenya National Bureau of Statistics	Population density	People/km^2	2009
Equity Bank	Number of agent branches throughout the country	Number/1000 people	2014
Safaricom	Number of agent branches throughout the country	Number/1000 people	2014
Solar and Microgrid Entrepreneurs	Solar agent or microgrid location	Number/ward	2014
World Bank and Defense Meteorological Satellite Program (DMSP)	Nightlights by county	GDP per capita ($US 2005)	2015
Operational Linescan System (OLS)			

[a]Distance is measured from ward center to the closest geometry-type feature (polygon line or point)

Table 6. Data Sources: Potential for Micro-Enterprise Wealth-Creation Post Electrification

2.8 Methods and Analysis: Potential for Micro-Enterprise Wealth-Creation Post-Electrification

Our approach seeks to elucidate areas of high potential for micro-enterprise development in Kenya by using different proxy-variables for natural and infrastructural capital. We consider areas of high NC and IC to potentially have a high degree of electricity demand persistence, and thus could suggest a road map to guide off-grid entrepreneurs. The data suggests that natural capital is the foundation of wealth in rural Kenya, as access to it enables infrastructural capital to flourish. On the other hand, access to high quality infrastructure also allows communities and villages to increase the benefits they could derive from natural capital. Furthermore, and as the literature suggests, electricity access can under the right conditions act as a catalyst for off-grid communities to thrive. Below we describe the natural and infrastructural capital datasets used in our analysis, and provide a description of our exploratory spatial analysis and the development of an index that measures Micro- Enterprise Development potential (MED).

In our analysis, all geo-spatial calculations are performed with respect to the center of each of our highest resolution administrative units (wards). For polygon lines (rivers, 1st and 2nd tier roads, and transmission lines), distance (km) is calculated from the center of a ward to the closest point in a line. Distance (km) from ward center to the closest major town (a 'geo-point') is also calculated, whereas for other 'geo-points', such as irrigation projects, we sum the total number of projects per ward. M-PESA and Equity Bank agents throughout the country are treated as geo-points and we sum their presence (agent branches/1000 people) by ward. Similarly, we also add the total number of schools, trade centers, and health care centers by ward (electrified vs. unelectrified; number/1000 people). We perform a geo-spatial merge using our ward and crop intensity and diversity geo-referenced data, resulting in a metric for ward-level agricultural potential. Finally, each variable is normalized between 0 and 1 using feature scaling, using the maximum and minimum of each value, and then summing across values. The result is a non-weighted micro- enterprise potential index ranging from 0 to 7.

The equations below explicitly describe the creation of the MED index. NC and IC data (described above) are first scaled between 1 and 0, and aggregated by ward. It is important to perform feature scaling (1-) as many of the variables have different units (e.g., people/km^2, km, and unit counts) that would make a comparison (and aggregation) among them inaccurate. As a result of summing IC and IC by ward, the MED index provides a spatial representation of the potential for rural electrification to create wealth throughout Kenya. Because there is no ground-truth rural wealth data that we can use to compare against the MED index, we do not assign weights to different variables within it. We provide a discussion of the benefits and limitations of the MED index data and of our approach in the results and discussion section.

(1) NC_{Ward} = Distance to water bodies + access to irrigation infrastructure + crop intensity + crop diversity + agro-ecological potential *[each variable is scaled 1-0]*
(2) IC_{Ward} = Access to schools + access to healthcare + access to trade centers/markets + access to major towns + access to roads + access to traditional electricity infrastructure (grid) + population density *[each variable is scaled 1-0]*
(3) MED_{Ward} = NC + IC *[sum of all variables scaled between 1-0]*

We explicitly compare the MED index between areas of high and low agro-ecological potential, and the MED index (and the natural and infrastructural capital) between wards with and without off-grid projects in areas across Kenya that do not have presence of electrified facilities (as for provided by the Kenya Rural Electricity Authority). We hypothesize that the MED index will score highly for places in Kenya that have already taken advantage of their natural and infrastructural capital, as well as for places that have yet to be fully developed. Thus, the MED index serves both as a tool to understand how development has occurred in a particular region or country (rich in natural and infrastructural capital), as well as a tool to map potential for wealth creation if more and better infrastructure were available (places with high natural capital but little infrastructural capital).

2.9 Results and Discussion: Potential for Micro-Enterprise Wealth-Creation Post-Electrification

2.9.1 Spatial relationship between natural and infrastructural capital

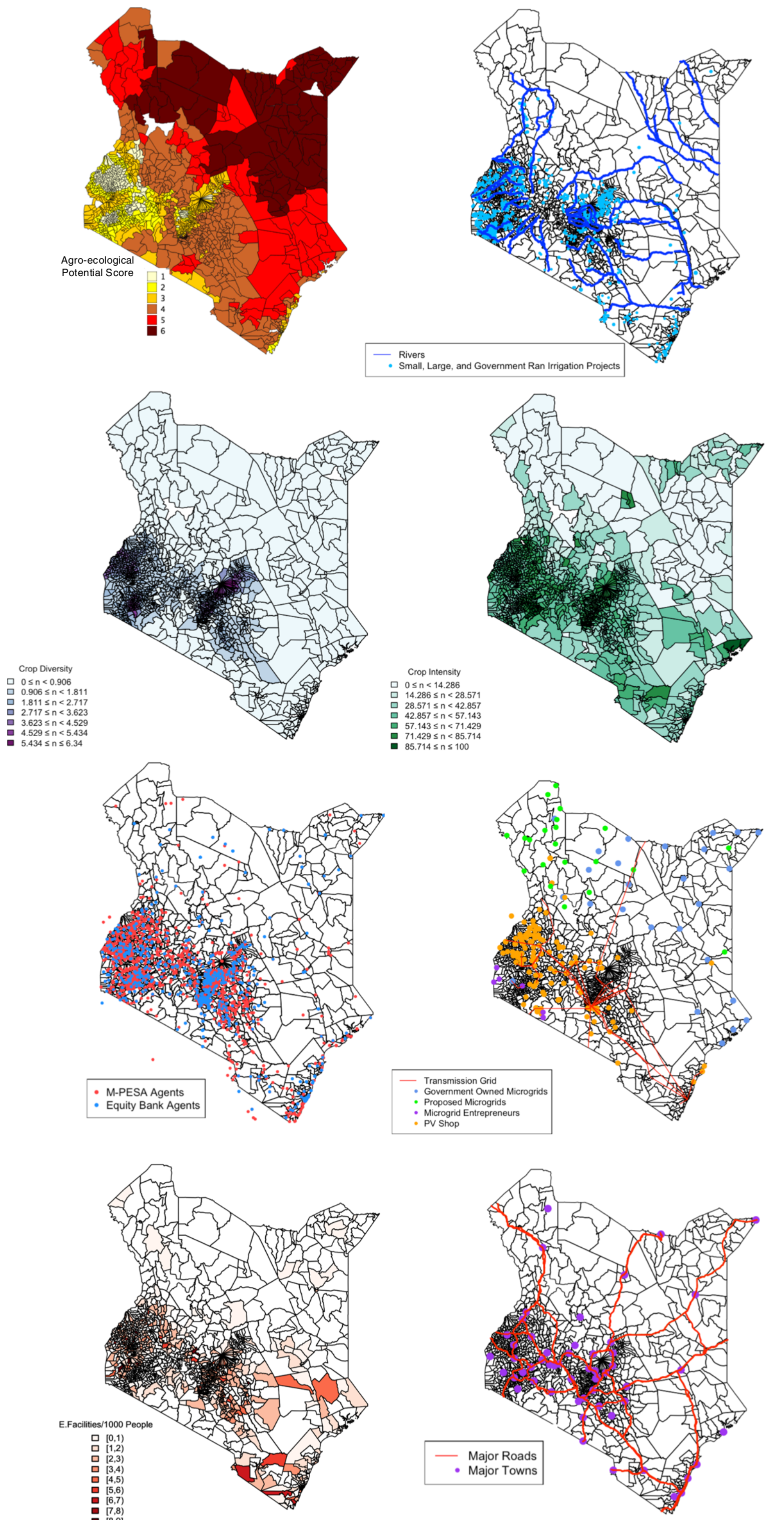


Figure 22: Natural and Infrastructural capital in Kenya (by Wards). Natural Capital includes: [A] Small and large irrigation projects as well as major rivers, [B] crop diversity, [C] crop Intensity, and [D] agro-ecological potential, among several other variables. Infrastructural capital includes [E] finance (M-Pesa and Equity Bank locations), [F] electrification infrastructure, [G] electrified facilities per 1000 people, and [H] major roads and towns, among several other variables.

Natural capital and infrastructural capital are well paired in Kenya, and one follows the other. The regions with highest agro-ecological potential also have some of the greatest crop diversity and intensity, and natural and infrastructural capital investments, making the land more productive, and in turn, more populated. High agro-ecological potential, if paired with year-round water availability (proximity to irrigation projects and rivers), may lead to increased crop diversity and intensity, which may lead to the creation of towns and the build up of infrastructural capital including trade centers, roads, electrification infrastructure and electrified facilities, and schools. This is visually explicit both from the subset of maps depicted to the right, and the data. On average, the regions with highest agro-ecological potential (composite agro-ecological index 1-4) have more natural capital infrastructure (four times more crop diversity, 35% more land dedicated to agriculture, six times more irrigation projects), and infrastructural capital (twice the number of schools, clinic, and trade centers per thousand people, and four times the number of *electrified* schools, clinics, and trade centers per thousand people, and twice the number financial branch agents per thousand people) than areas in Kenya with low agro-ecological potential (composite agro-ecological index 5- 6).

2.9.2 Electrification infrastructure, natural and infrastructural capital and the MED index

Although our off-grid projects database does not contain all off-grid electrification projects across the country, we are still able to compare the MED index of wards with available off-grid projects against the MED index of wards without off-grid projects. We define wards with off-grid projects as those that contain the presence of government, entrepreneur, proposed micro-grids, or the presence of solar home system branches. On the other hand, we define wards without projects as those without the presence of electrified facilities (as provided by the Kenya Rural Electricity Authority). On average, wards with off-grid electrification projects (government, entrepreneur and proposed microgrids, and solar home system branches) are located in areas of medium-high and medium-low agro- ecological potential (mean: 3.2, stddev: 1.7), with average crop intensity (47% of land dedicated to agriculture, on average) and average crop diversity (2 crops, on average), and on average, are 4 km further away from rivers, and with double the number of irrigation projects than other wards in our data.

In terms of infrastructural capital, off-grid wards have a slightly lower number of schools, health care clinics and trade centers facilities (8 per thousand people vs 11 per thousand people on average), a similar number of financial branches or agents per thousand people than the country average, and are almost twice as far away from major roads, towns, and transmission grid lines than other wards in our data. These results are not striking, as we have observed that the regions with higher natural capital to be more tightly correlated with higher investments in infrastructural capital. Consequently, off-grid electrification projects pursue opportunities in perhaps more remote regions (Figure 22). The average MED index of wards with presence of off-grid projects is 4 (out of 7), against the average MED countrywide index of 5.

While these insights are not striking, we do find marked differences in natural and infrastructural capital between wards where entrepreneur-driven solar home system branches and entrepreneur microgrids operate versus wards where government-owned and government-proposed microgrid projects have settled (Figure 23 and Figure 24). On average, entrepreneur ran electrification projects (microgrids and solar access) have higher natural and infrastructural capital than government microgrids and proposed microgrid greenfield projects.

On average, wards with entrepreneur operated off-grid electrification projects are located in

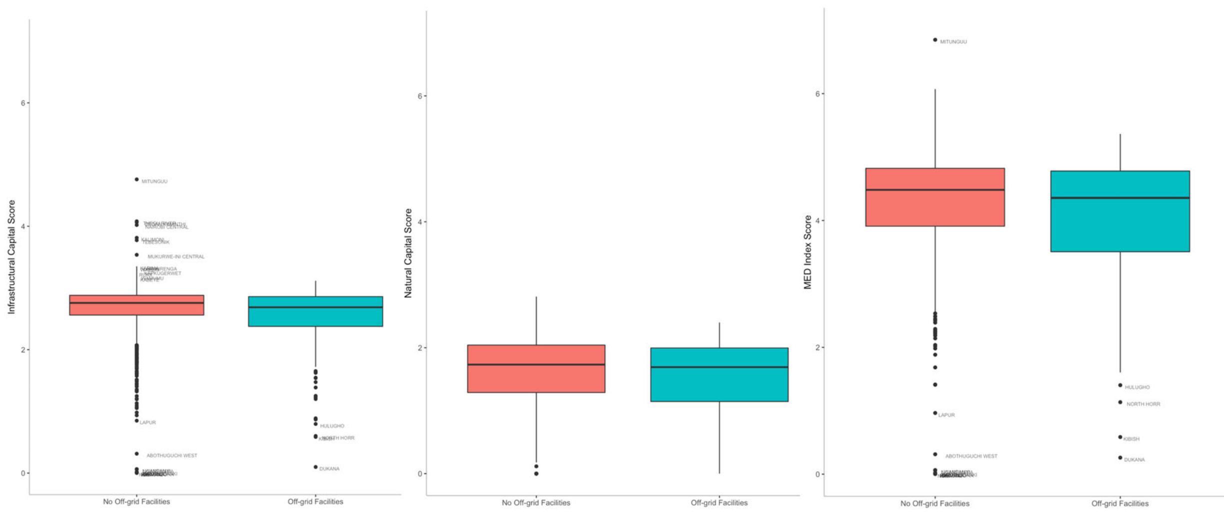


Figure 23: Natural and Infrastructural Capital Score, and MED Index Score Comparison between Wards with and without Off-grid facilities

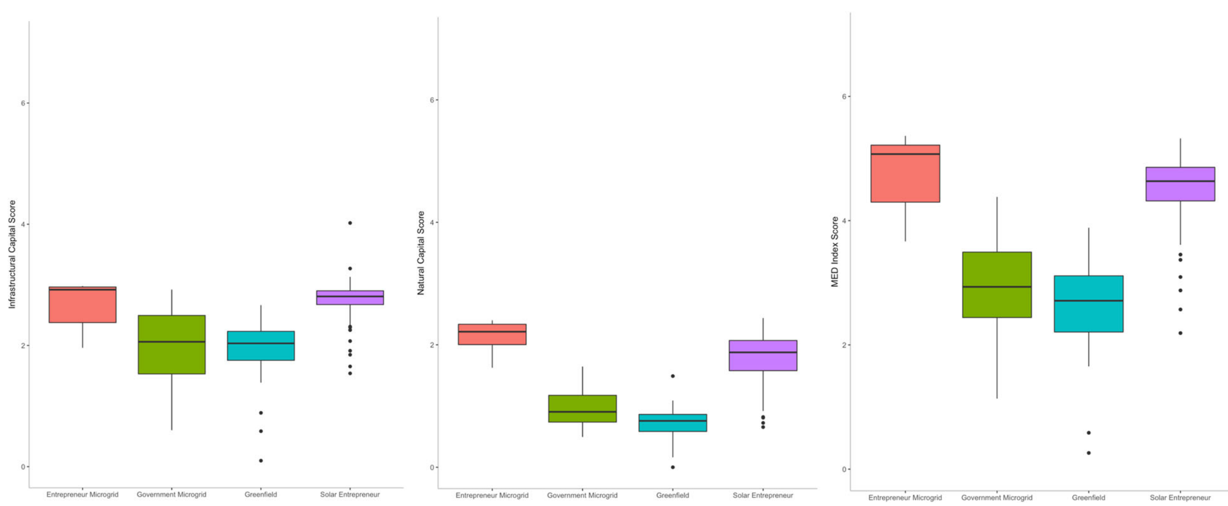


Figure 24: Natural and Infrastructural Capital Score, and MED Index Score Comparison between Off-grid electrification projects (entrepreneur vs. government electrification projects).

areas of high to medium- high agro-ecological potential (mean: 2.7, stddev: 1.3), with high crop intensity (55% of land dedicated to agriculture) and average crop diversity (2 crops), and on average, are 7 km closer to rivers, and with double the number of irrigation projects than wards with government operated off-grid projects. Wards with entrepreneur operated off-grid electrification projects also have a slightly higher number of schools, health care clinics and trade centers facilities (8 per thousand people vs 11 per thousand people), a higher number of electrified schools, clinics and trade center (4 per thousand people vs 7 per thousand people), and a higher number of financial branches or agents per thousand people than the country average (5 per thousand people vs 3 per thousand people, respectively). Entrepreneur electrification projects are equally as far away from major roads and towns, but further away from major transmission lines than wards with government operated off-grid projects. The MED index of wards with entrepreneur operated off-grid electrification projects is the same as the country countrywide index of 5. These data and analysis suggests that entrepreneurs are currently targeting regions, wards and communities with relatively high prospects of wealth creation and sustained electrification.

2.9.3 Comparing a nightlights GDP per capita proxy and wealth creation potential

We compare the MED index scores to a GDP per capita County metric ($US 2005) developed using nightlights by the World Bank in 2015 (Figure 25 A and B) (162). The GDP per capita metric for Kenya uses nightlights as a proxy for economic activity, and assumes that consumption and investment activities in the evening or night require lighting. Nightlights are often used to estimate economic activity at levels that are not usually captured in national accounts, including subnational administrative units such as provinces, districts, counties, cities (162).

Although useful when no other data is available, using nightlights alone can lead to underestimates of economic activity, particularly in countries (and counties) that heavily rely on agriculture (including subsistence agriculture), herding, and other economic activity that predominantly occurs during the day. In countries like Kenya (including wards and counties), nightlights may not appropriately capture economic activities like livestock herding, farming, subsistence farming, and fishing. Yet, this proxy for GDP per capita was one of the few available to validate and provide a qualitative and quantitative comparison to our MED index.

To compare the ward-level MED index with the country-level GDP per capita nightlights proxy by the World Bank we took the MED index average of all wards within each County and scaled the scores between 0 and 1 using their minimum and maximum values. Similarly, the GDP per capita nightlights value was normalized between 0 and 1 using their minimum and maximum values. The MED index has a higher degree of correlation with the areas of Kenya with high, middle-high, and very low income, than with areas middle-low income. Within the first group, the MED index correlates well with the nightlights proxy for GDP per capita in central Kenya, the southeastern coast, and the southeastern border with Tanzania. Within the first group the MED index provides over estimates for counties like Murang'a, Tharaka-Nithi, and Kirinyaga, while providing underestimates for Kajiado and Kwale counties. The latter provide useful insights into data that could make the MED index more accurate. Kajiado County's most important economic activities include livestock rearing and tourism, with the popular Amboseli National Park being located there. Similarly, Kwale County's most important economic activities include beach tourism, fisheries and trade, with the first two being important omissions in our data set. Future work should include the diversity of local natural beauty and the health of fisheries and reefs to the importance of natural capital in a country. The natural capital wealth of the Murang'a, Tharaka- Nithi, and Kirinyaga counties is reflected in the regional growth of cash crops such as coffee and tea, and yet, the difference between the MED index and GDP per capita proxy suggests a large gap between potential and realized wealth.

2.9.4 Evaluating discrepancies between rural wealth proxy variables

There are several reasons why the MED index noticeably provides an overestimate for many counties in the left-middle and upper-left corner of Figure 25-B. First, the data in the MED index are suggestive of the potential of a ward (and aggregated to counties) to derive socio-economic benefits from natural and infrastructural capital, and thus, it will necessarily attribute higher scores in regions that have high potential, but where infrastructural capital and wealth creation has yet to develop. Other reasons include the fact that the MED index has not been adjusted for climate stress factors (recurrence of droughts), population stress on available resources (deforestation, soil and land degradation, prevalence of unsustainable practices in agricultural expansion, unsustainable fishing practices, and over dependence on wood fuels), the quality of roads and services (not only a wards proximity to them), the health of local water bodies (pollution affecting lakes and fisheries), the local effects of climate change (drought, warming water bodies, and more variable precipitation), and the quality of local institutional governance, as corruption can be crippling to local economies. Recent research has also provided evidence to suggest that ethnic favoritism in Kenya can play a significant disadvantageous role in local development. Between 1963 and 2011, districts sharing the Kenyan president's ethnicity received twice as much expenditure on roads and five times the length of paved roads (163). Furthermore, the comparison with the nightlights GDP per capita proxy is difficult, as the latter is likely an underestimate for the economic activity in many of these counties.

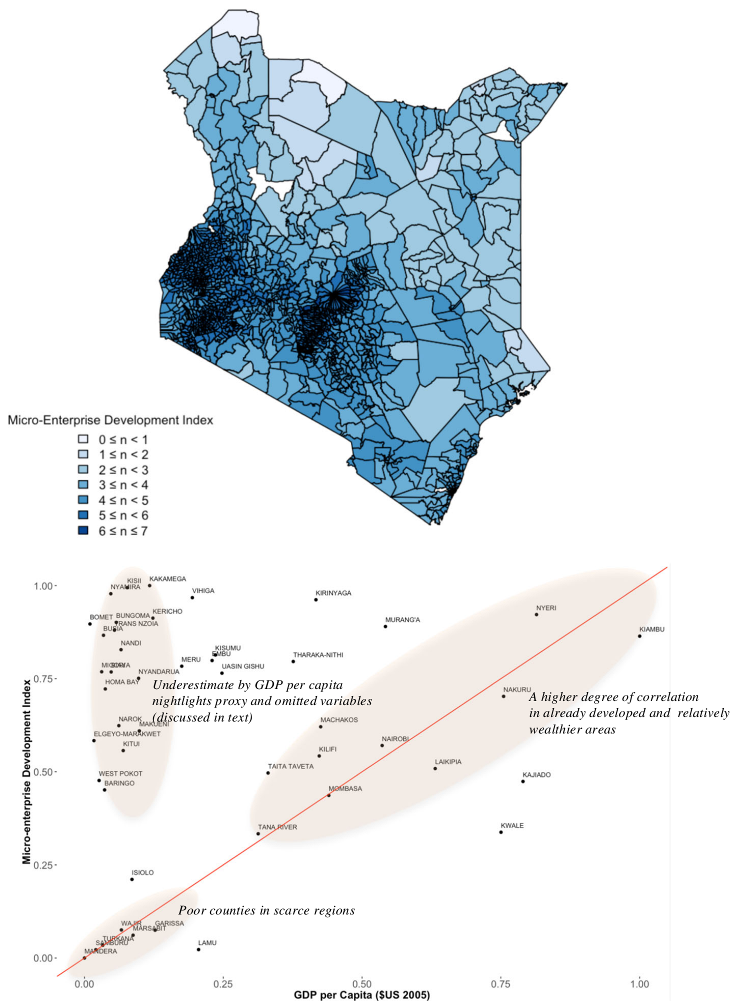


Figure 25: Micro-Enterprise Development Index [A] and Correlation with GDP per Capita nightlights proxy by County [B]: The MED index correlates well with the middle, and high-middle income regions of the country, as well as the poorest counties in the country. The MED index provides an overestimate for low-middle income counties (discussed below).

The MED index in very-low income counties is also well correlated with the GDP per capita proxy except for an underestimate in Lamu, which has a vibrant fishing and tourism industry (and thus the MED index providing an underestimate), and an overestimate for Isiolo. Isiolo is an interesting case as it is located in central Kenya and has become an important part of Kenya's economic development plan for 2030, despite it not being highly ranked in our MED index.

The MED index provides several other overestimates for counties such as Homa Bay, Nyandarua, Meru, Kisumu and Bomet. Homa Bay's most important economic activities include fishing and agriculture (including both staple and cash crops), agricultural processing in sugar cane factories, and lake tourism. Despite the presence of strong natural capital (fertile soils, water availability, and high crop diversity and intensity) and infrastructural capital, Homa Bay receives low GDP per capita estimates from the nightlights proxy, with a recent survey in Kenya putting Homa Bay in ninth position of the most corrupt counties in the country [40]. Nyandarua, Meru, Kisumu and Bomet also receive high MED index values in areas that grow both staple and cash crops, and have some industry and agricultural processing, but still receive low GDP per capita estimates from the nightlights proxy. Here, the dynamics are diverse and complex. Nyandarua County lacks a good road network and adequate distribution of electricity and water, Meru has high natural capital with fertile soils and water resources but most of the population is engaged in subsistence farming, and Bomet has favorable climatic conditions, fertile soil and water availability with tea farming and dairy production as favored economic activities, yet according to surveys, it is also the sixth most corrupt County in Kenya (164). Kisumu County's privileged location next to Lake Victoria provides both water resources and fertile soils. Some have denominated it as the next economic hub of East Africa, but Lake Victoria's pollution levels, increasing water temperature due to climate change, overfishing and unsustainable (and illegal) fishing practices have devastated fisheries (Chinese fish now have to be imported to meet local demand) (165).

Nyamira, Kisii and Kakamega Counties provide the most startling comparisons as the MED index is one of the highest, and yet, the counties are poor according to the nightlights GDP per capita proxy. Nyamira and Kisii are highly agricultural productive neighboring counties (cash crops like tea and coffee, as well as staple crops), with fertile soils and water availability, but with little access to quality roads that provide access to markets, year-round irrigation, and reliable electric power that can allow for the flourishing of other industries in agricultural processing (166). Furthermore, tea and coffee co- operatives in both counties are heavily burdened by debt, and the counties rank as the second and third most corrupt counties in the country (164, 166). Kakamega County stands alone in its contrasts, as in 2014 it was named the poorest County in the country, but has one of the highest MED index scores (167). The County has similarly favorable agro-ecological potential and climatic conditions as Kisii and Nyamira, but its predominant agricultural activity is sugarcane. Once a booming industry, the sugarcane industry in Kakamega is now unsustainable due to small land holdings, low-yields, little efficiency in sugar production, and debt (168). Moreover, farmers find themselves with minimal benefits from commercial sugarcane production after continuous laboring in the industry (169). Cane farmers in Kakamega experience various deductions that reduce the benefit from their labor which includes high costs of transportation, harvesting, supervision, out growers' services, levies, land preparations, and input advances costs (169).

The agreements and differences in the information portrayed by the nightlights GDP per capita proxy and the MED index is informative towards the current local use of resources (agreeing on areas that have already been extensively developed, and where there is poverty and very little natural and infrastructural potential), and provides indication of areas where the gap between realized and achieved potential is large, as well as highlighting areas with merely unrealized potential. The data shows that the combination of many of the MED elements and electricity can lead to socially beneficial outcomes, and highlights once again, that electricity access is a necessary but not sufficient condition for development. Like our previous discussion suggests, a County may have optimal natural and infrastructural capital requirements but can remain poor due to poor governance and corruption, poor cash crop selection, unsustainable agricultural and fishing practices, as well as debt. While electricity access entrepreneurs cannot take on all these issues simultaneously, they can certainly incorporate practices that can lead to a sustainable business and socially beneficial outcomes. These could include partnering with organizations that work with farmers on financial management and accounting, cost-effective and sustainable farming practices and crop selection, and climate resilience, among others. Furthermore, the development of infrastructural capital is crucial with access to markets as well as availability of communications and financial services being extremely important factors.

We have developed an understanding of the enabling environments of entrepreneur vs. government run off-grid electrification projects, explore the role that NC and IC can play in determining wealth creation post-electrification, and attempt to develop a micro-enterprise development (MED) index that could be used to guide top-down energy planners and off-grid energy access entrepreneurs in Kenya. We gather data and use variables that are considered in the literature to provide appropriate conditions under which electrification can lead to long-term socially beneficial outcomes including access to roads, markets, schools, communications, and finance, as well as the natural capital that enables infrastructural capital to be transformative. The maps and data of Kenya show that natural and infrastructural capital are tied to each other, with their quality and health being essential to ensure the long term beneficial outcomes of electrification.

Our results are confirmed by evidence and literature from Kenya and South Africa, which suggest that a panoply of infrastructural capital is essential for the success of rural enterprises. Poor roads, poorly maintained infrastructure, and lack of access to markets and financing have been historically burdening constraints for wealth creation in rural Kenya (146–149). Without complementary infrastructure, access to electricity becomes once again a necessary but not sufficient condition for development. If, however, electricity services are provided while taking into complementary infrastructure it could make the long-term financial sustainability goals of rural electrification more achievable. Like our discussion suggests, electricity may allow certain industries in agricultural processing to flourish, and may allow fishing markets to buy refrigerators for cold storage, but unsustainable farming practices may deplete the soil, and unsustainable fishing practices, pollution, and warming water bodies may havoc fisheries. Thus, this analysis also suggests that rural electrification projects could significantly benefit from developing best practices in environmental sustainability. Because in Kenya rural wealth creation is derived from the interaction of natural and infrastructural capita, a drop or erosion in the quality of local ecosystems (e.g., quality of water and soil) could significantly affect local sustainability and human development. This is evidenced in our discussion, which highlights several regions in Kenya where environmental degradation has significantly affected livelihoods and the health of the local economy.

Natural and infrastructural capital may provide appropriate conditions for wealth creation, but ensuring the long-term benefits of electrification could depend on developing sustainable practices and good governance around the industries that may flourish post-electrification. While the MED index highlights regions in a country where electrification could be most transformative, our discussion also suggests that there are many elements that are missing from our analysis. The health of fisheries, water body health (e.g., pollution, temperature, pH), climate stress factors (recurrence of droughts), local choice of cash and staple crops, population stress on available resources (deforestation, soil and land degradation, prevalence of unsustainable practices in agricultural expansion, unsustainable fishing practices, and over dependence on wood fuels), the quality of roads and services (not only proximity to them), and the quality of institutional governance are but a few of the factors that can determine the long-term beneficial outcomes of electrification. Another missing data element from our analysis is ethnic favoritism, which in Kenya has shown to play a crucial role in development (161).

Top-down energy planners, researchers, and off-grid energy access entrepreneurs could use these data and analysis in a variety of ways. Planning agencies and off-grid access entrepreneurs can use these data and methodology (while keeping in mind the limitations detailed above) as input in supply side models of rural electrification. The use of these demand-side data and methodology could allow for the development of supply side scenario modeling at different levels of electricity demand, thus changing the strategies that are available for electrification. Furthermore, while the use of this methodology is obvious for planning rural electrification it also highlights infrastructural gaps throughout the country. Using these data to create awareness about infrastructural gaps (e.g., access to roads, schools, markets and major towns) in Kenya (and elsewhere) is crucial to realizing the full benefits of electrification. Developing collaborative and interdisciplinary planning and research teams that touch on the various elements of NC and IC is crucial for developing sustainable long-term electrification strategies.

Practitioners, on the other hand, could use results from this analysis to find areas with large untapped potential for electrification, and are encouraged to develop transformative alliances with NGOs, institutions, and other enterprises that provide sustainable solutions around natural and infrastructural capital. For example, off grid-access entrepreneurs could develop alliances with sustainable agro-processing industries for local staple foods, sustainable farming practices, and ensure access to irrigation and financial services. Our analysis and literature suggests that these elements are key for wealth creation in rural areas.

Our analysis and map suggest that there are many areas in Kenya with large untapped potential, and off- grid-entrepreneurs could find themselves well equipped to take advantage of this opportunity if they develop the locally appropriate transformative alliances. Knowing that electricity in and of itself cannot be fully transformational, developing alliances with groups that support sustainable farming and fishing practices, cost-effective transportation, co-ops and market access, and financial services could play a large role in ensuring the long-term socially beneficial outcomes that electricity access promises to provide.

2.10 Background: Overcoming the Data Scarcity Challenge for Energy Efficiency Planning in Resource Constrained Environment

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 (170), 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 (112–114). 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) (115). 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 (171).

The energy efficiency gap is broadly defined as the perceived slow rate of diffusion and adoption of energy efficient products and practices (172). 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 (115, 171, 172). 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 (172–174). 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 (172). Similarly, if engineering estimates do not incorporate behavioral aspects, diffusion strategies might lead to unintended consequences, such as the rebound effect (172, 175). Acknowledgement of modeling and measurement flaws has been one of the most recent additions in attempting to explain the energy efficiency gap (171). 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 (171). 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 (176), loss aversion (177, 3, 4), non-standard beliefs (178), bounded rationality, and non-standard decision making (171, 172, 174, 179). 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 (172, 180–185). 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 (172). 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 (172). 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 (186).

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 (187). 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.

2.10.1 Data

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

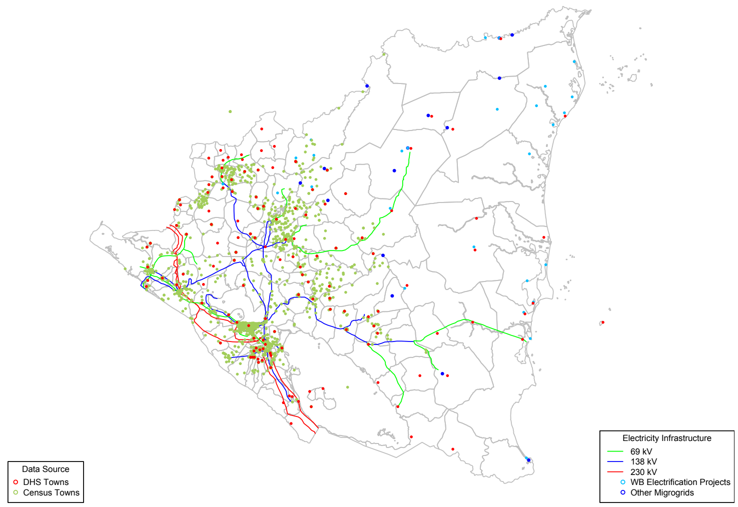


Figure 26. DHS and Census town locations [26.A] and [26.B] features used in this analysis.

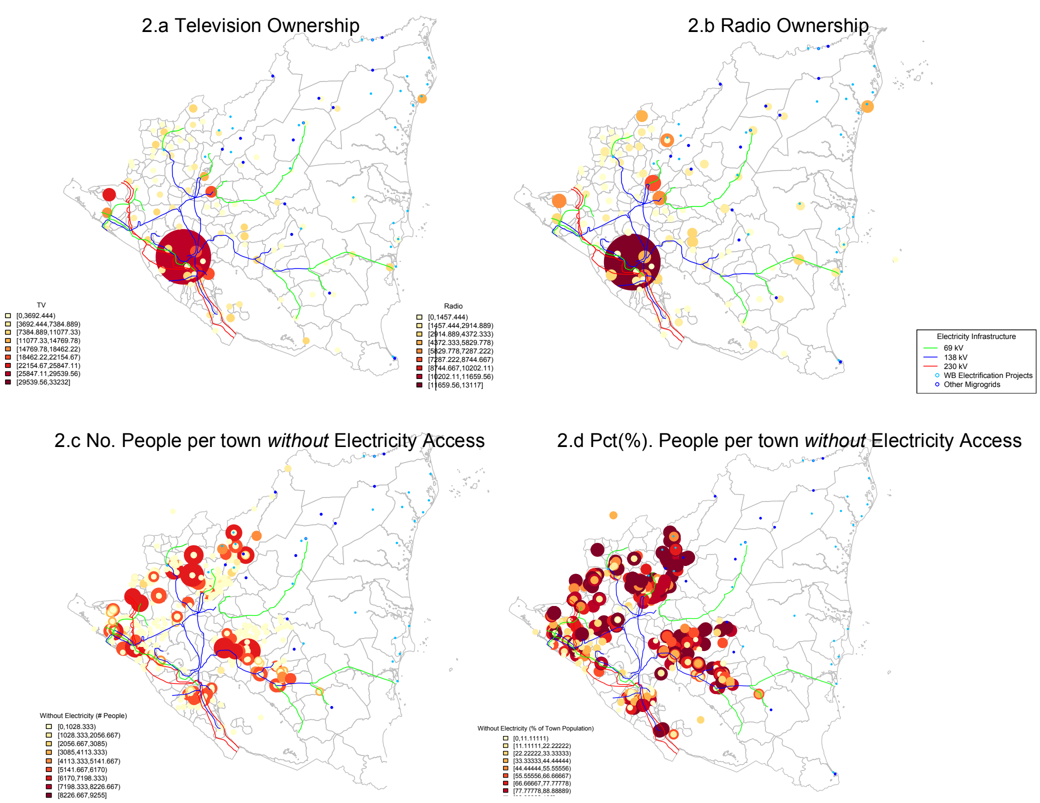


Figure 27. Spatial diversity of appliance ownership [27.a and 27.b] and lack of electricity access [27.b number of people, 27.c percent of people in town]. Note: 27.a and 27.b depict the representative number of households that own a particular appliance within a certain sampling region.

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 26 and 27 depicts some elements of these data.

Our appliance market analysis was a combination of web-crawlers and ground-level market analysis (188). 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 (189). 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 (190). 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 (190) 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. Table 7 summarizes these data.

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, 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	Appliance level
Sensor data	105 appliances	-	Minute-by-minute power and energy consumption: refrigerators/freezers, televisions, fans, washing machines, cell	Appliance level

Table 7. Data: Macro-level aggregates, market analysis, and sensor data.

2.10.2 Methods and Analytical Framework

To predict the '*hypothetical*' ownership of electrical appliances for households without electricity in off-grid Nicaragua, 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 (191, 192). 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)(193). 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.

2.10.3 Results and Discussion

2.10.3.1 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 8 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 (194). 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)(195, 196). 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 8. 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 (141, 119, 118). 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 (195–198). Figure 28 summarizes some of these results.

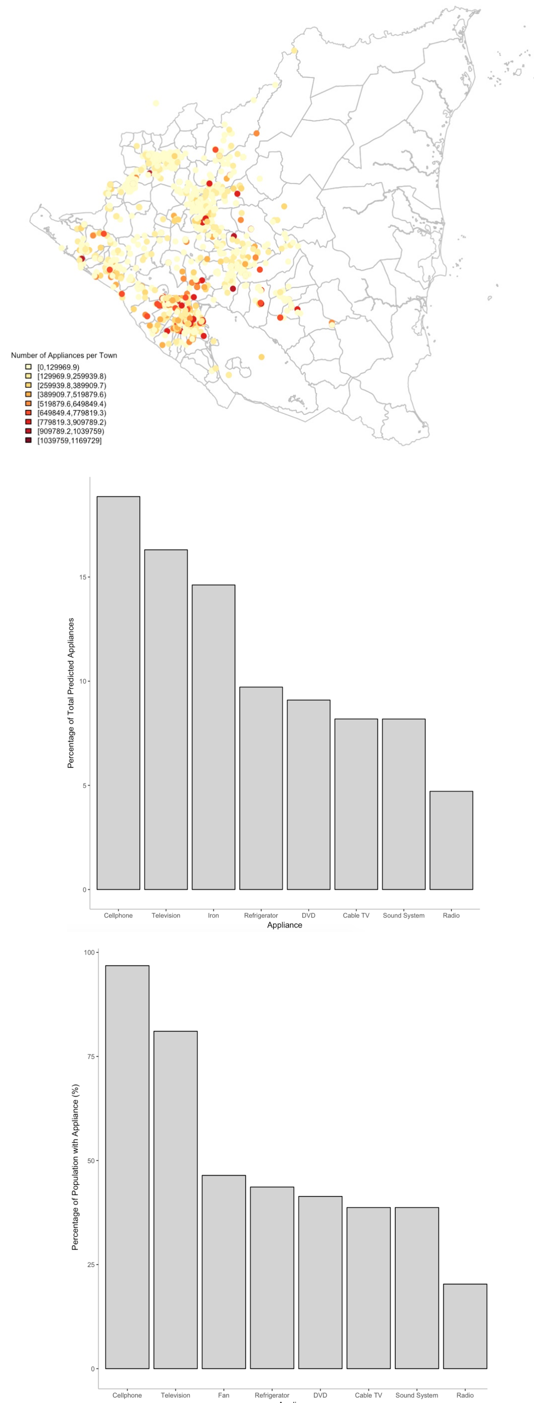


Figure 28. Test Set Predictions: Spatial distribution of prediction on sample towns, percentage market share by appliance, and percentage population reach. Because neither the DHS nor the Census contain geospatial data, a Python script written using a Google API was used to obtain town coordinates (lat-long). 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.

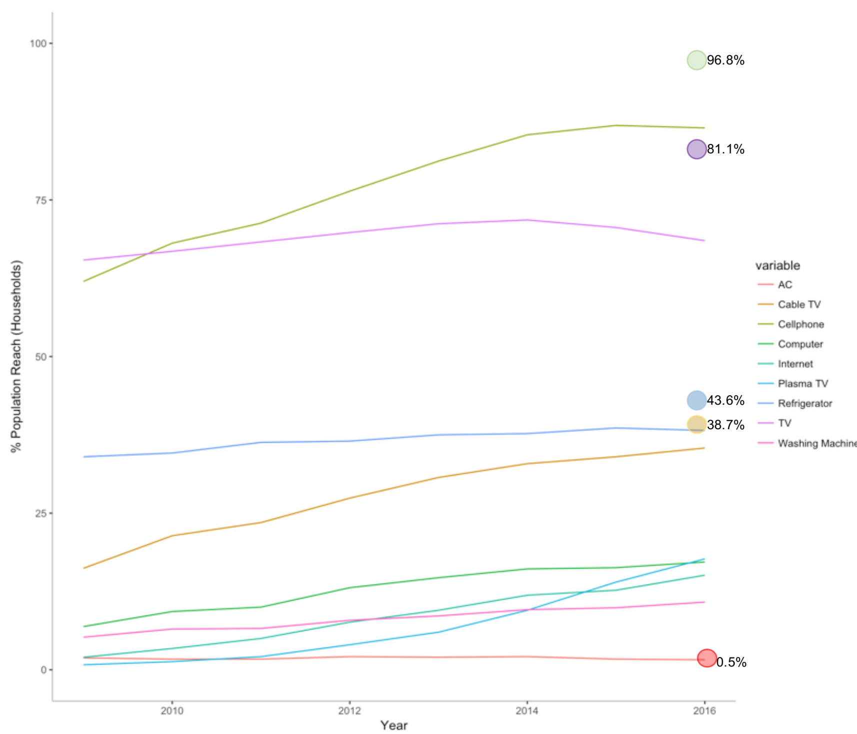


Figure 29. Ownership of Appliances over Time vs. Prediction Accuracy: Air conditioners, Cable TV (antennas and modems), refrigerators, televisions and cellphones.

To validate our predictions, we compare our estimates to the latest 2016 national survey of households in Nicaragua (199). 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 29 summarizes some of these results.

2.10.3.2 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 (189). For real-time measurements of monthly energy consumption we used data from the implementation of a FlexBox, which monitored real time parameters in Nicaragua (190). 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)(200), suggesting that televisions in our sample are at the upper end of the spectrum. There exist even more energy efficient televisions (50 inches, 35 Watts, 0.014 W/in^2), but these are not affordable ($US 900)(201). 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 (202, 203). 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)(204). 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 (205). Figure 30 summarizes these data.

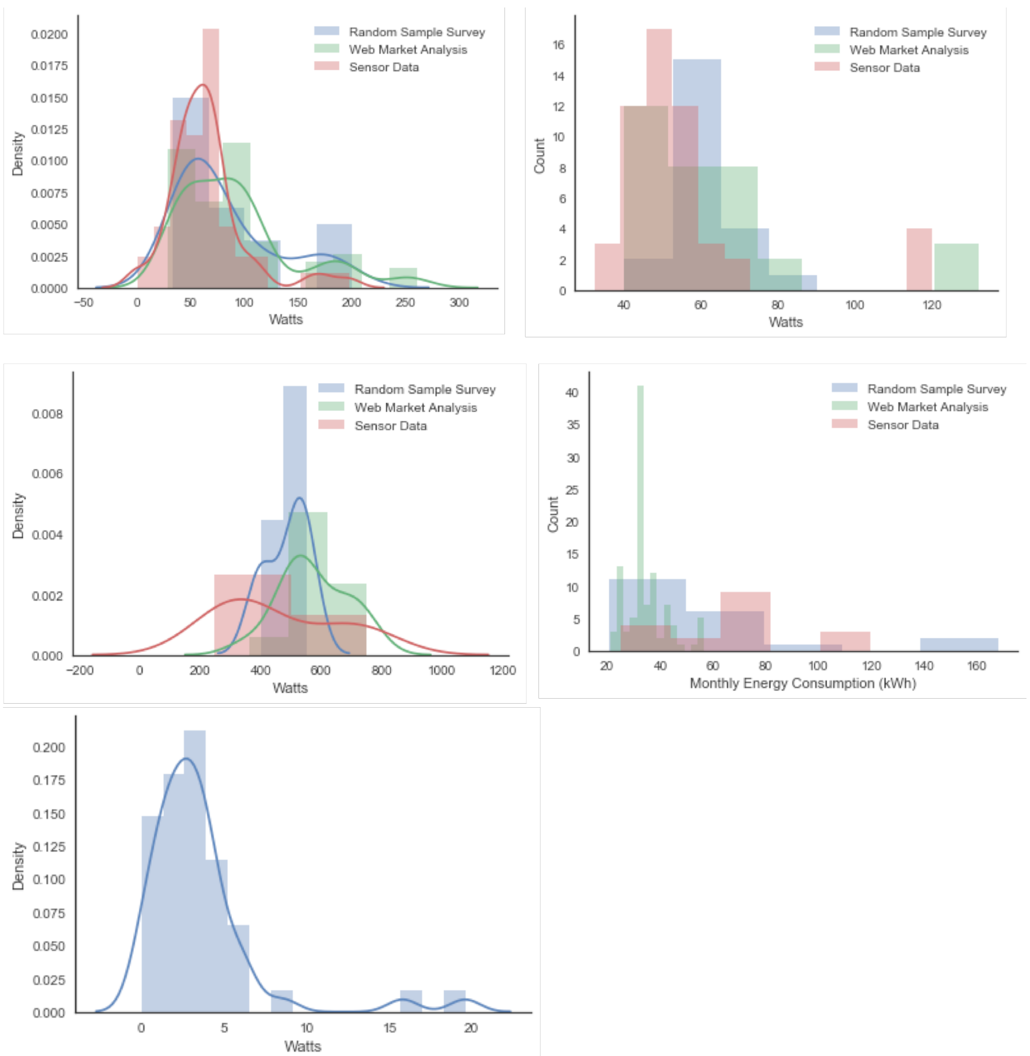


Figure 30. Distributions of Common Household and Small Business Appliances: Densities of televisions and washing machines, and Cellphones [A,C,E], and histograms of fans (Watts), and monthly energy consumption of refrigerators (kWh/month) [B,D]. Distribution depicted depends on data availability and quality of visual representation.

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 (190), 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 (190).

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 31 (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.

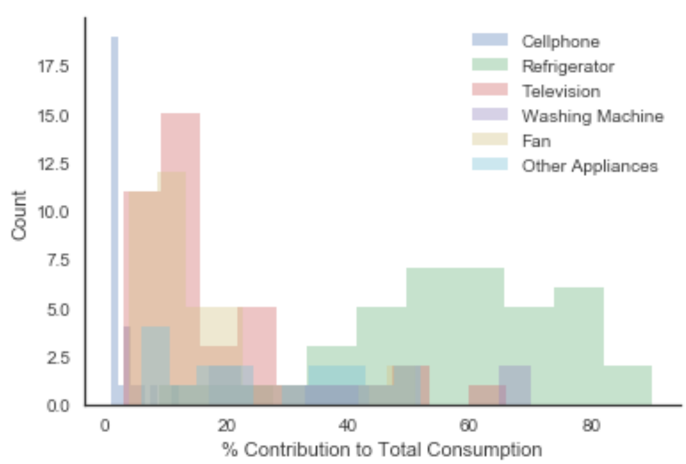


Figure 31. Contribution of Different Appliances to Total Household and Small Business Energy Consumption: Results from 3-hour interval measurements of 75 households and small-businesses in Managua, Nicaragua. Refrigerators consume between 35% to 95% of total energy consumption when all other appliances were turned on.

2.10.3.3 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 (189, 201–205).

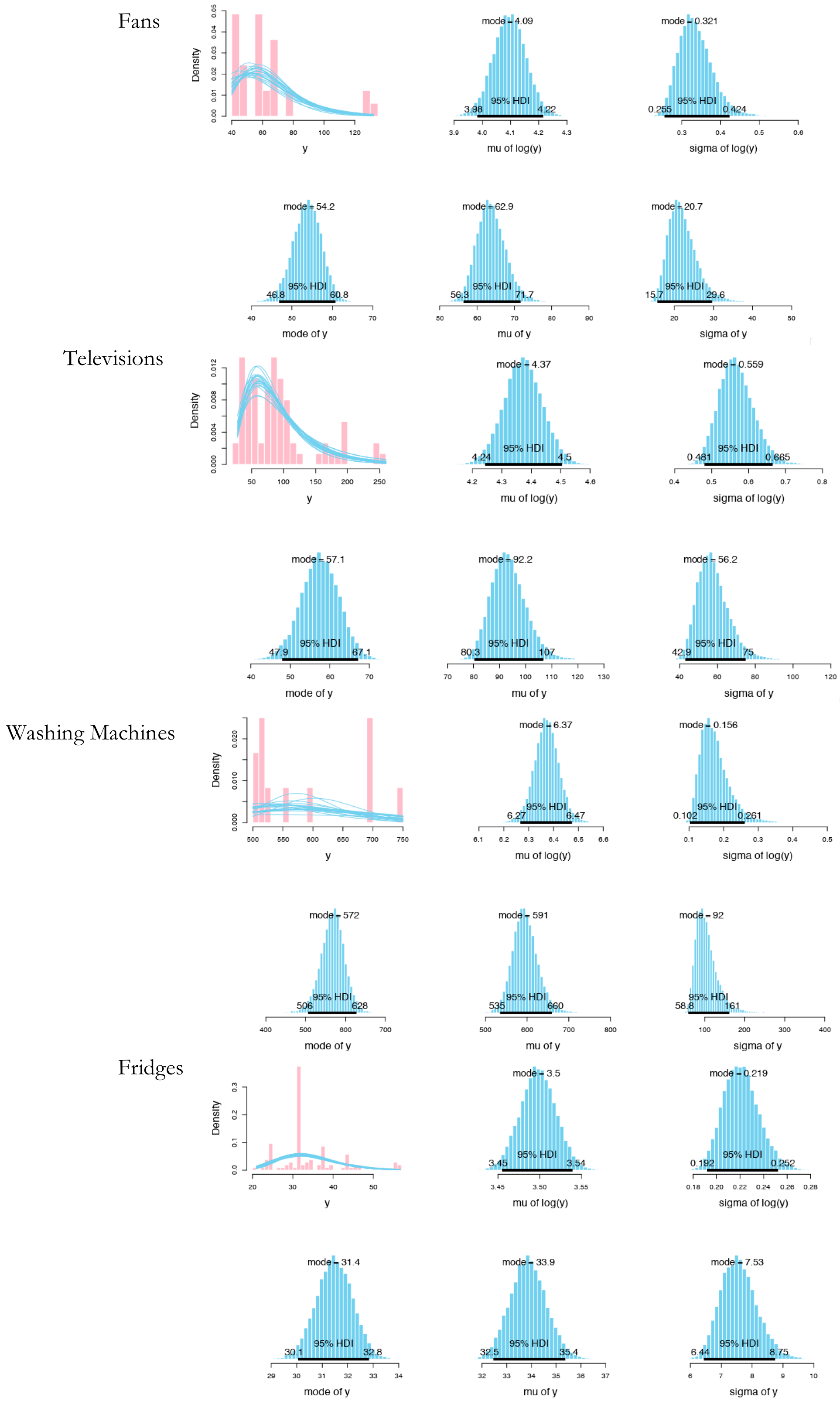


Figure 32. Appliance Characteristics for Prior Distributions

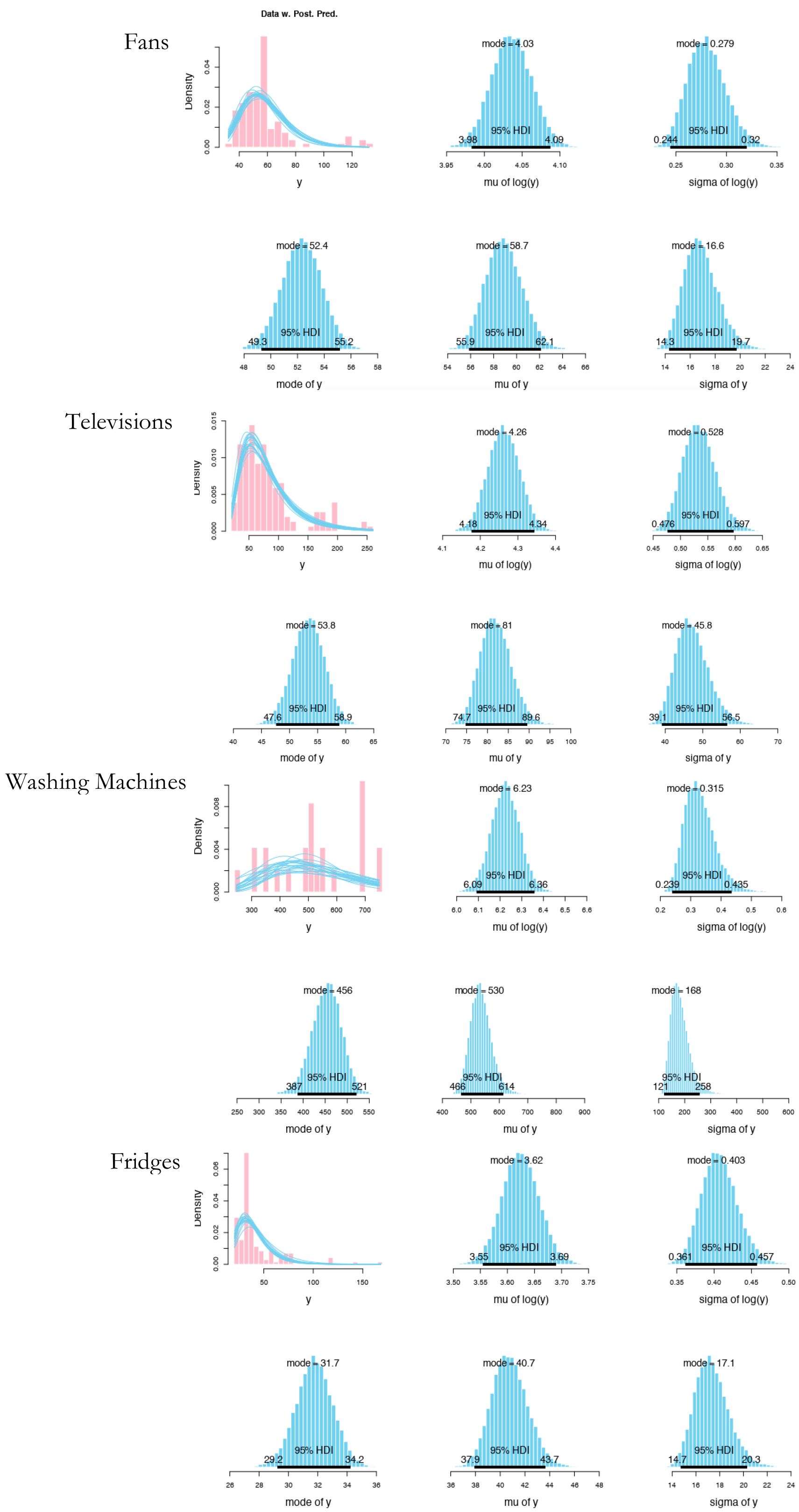


Figure 33. Appliance Characteristics for Posterior Distributions

2.10.3.3 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.

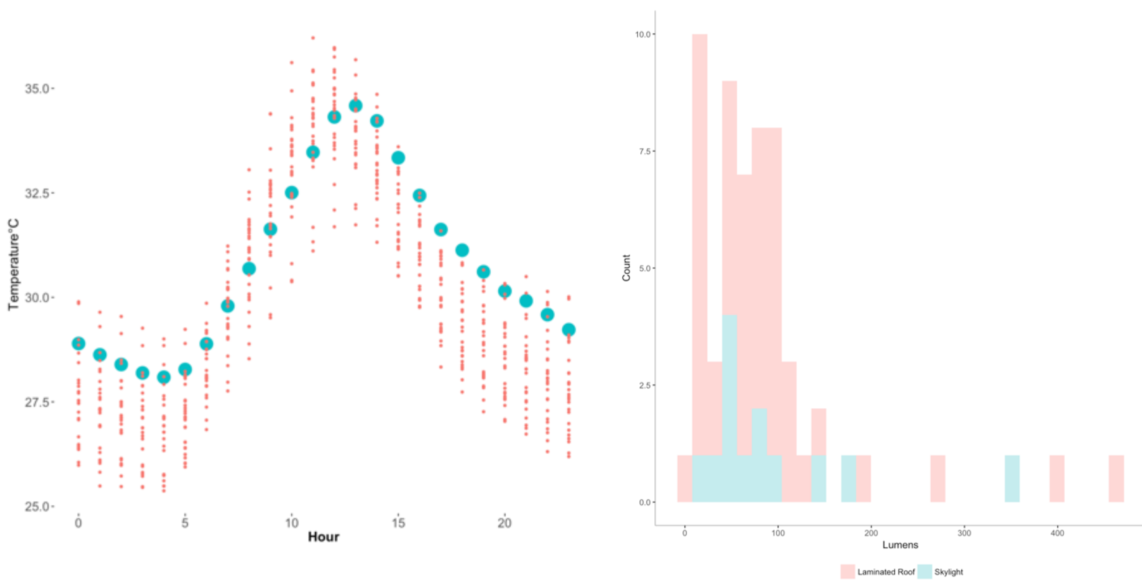


Figure 34. Temperature and Available Light Data: [A] Room temperature of household and small businesses (red) vs. ambient weather station data (blue), and [B] Distribution of Lumens inside households and small businesses with laminated roofs, and laminated roofs with skylights in Managua, Nicaragua.

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 (190). 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). 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.

2.10.3.4 Opportunities for Bottom-Up Data and the Energy Efficiency Gap

Together, these data allow us to determine the impact that various energy efficiency strategies could have, on average, on households and small businesses in Nicaragua. For this, we build a marginal cost of saved energy curve (MCSE) which allows us to see the magnitude and uncertainty of different energy saving strategies, as well as the energy savings per dollar spent pursuing the strategy (Figure 35). 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 (187). 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.

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 9 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.

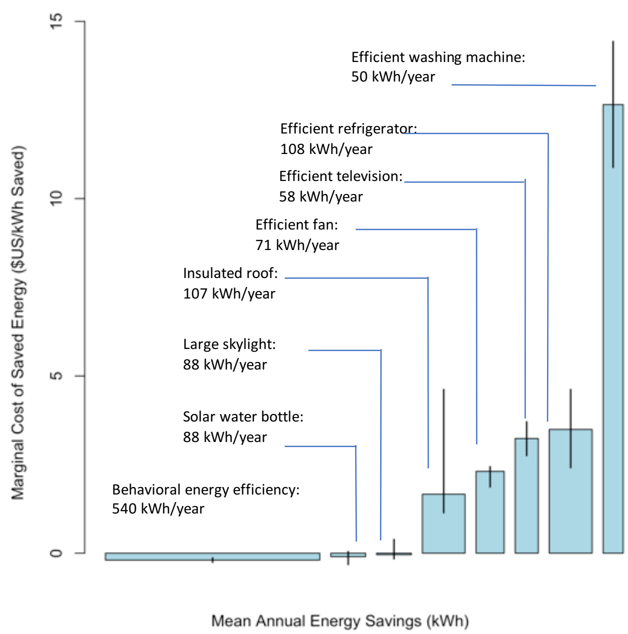


Figure 35. Marginal Cost of Saved Energy Curve for Households and Small-Businesses. Baseline assumptions include watching television three hours a day (every day of the year), using a fan ten hours a day for half of the year, using an efficient washing machine two hours a week (every week of the year), lights being turned on for two hours a day during time with plenty of available daylight.

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 (Table 9).

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 (dissagregated 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., dispossable incom, 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),
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 9. Useful Data in Determining the Existence, Magnitude and Strategies to Address the Efficiency Gap in Resource Constrained Environments

Chapter 3:

Design and Implementation of Demand-Side Information and Communication Technology and the Internet of Things for Inclusive Decarbonization

3.1 Introduction

Future growth in urbanization will mainly occur in cities of the rising south. UN Habitat reports that in the past decade, the urban population in emerging economies grew on average 1.2 million people *per week* (206). By 2050, it is expected that seven out of ten people will be living in cities (206, 207). An accompanying technology to urbanization, the use of cellphones and smartphones has seen unprecedented growth in recent decades. Currently there are more active mobile connections (7.8 billion SIM connections and 4.8 billion unique mobile subscribers) than people in the world (7.4 billion), with penetration rates being large even in low-income economies (89 subscriptions per 100 people) (208, 209). Similarly, the Internet of Things – an agglomeration of sensors and actuators connected by networks to computing systems – has been rapidly growing with a maximum potential market of $US 11 trillion by 2025 (210). With most energy demand, urbanization and connectivity growth in the coming decades occurring in low and lower-middle income countries, it is crucial to understand how technology will work in these diverse contexts, how it will blend with behavior, culture and context, understand its challenges, and highlight opportunities, to users and urban services (207, 211, 212).

Using a field deployment pilot in Nicaragua as a case study, this chapter is focused on opportunities for information and communication technologies (ICTs) and the internet of things (IOT) in resource constrained environments. We use ICTs and IOT to implement the first paired behavioral energy efficiency and flexible demand pilot in Latin America. This chapter is divided in two sections, the first introduces the design, implementation, and exploratory data analysis of a sensor gateway (the FlexBox) for enabling behavioral energy efficiency and demand side flexibility, and the second is a post-evaluation Bayesian estimation analysis evaluating energy reduction, participation in demand side flexibility, impacts on welfare, and behavioral economics insights. We present several novel findings related to technology implementation, development of new efficiency parameters, and behavioral insights (e.g., incentive types, pre-existing behaviors, motivations) describing the opportunities and barriers to behavioral energy efficiency and demand side flexibility, and a first estimate of the value of information for users in resource constrained environments. We demonstrate that ICTs and IOT are mature technology that can be used by low, low-middle income households and small businesses in cities like Managua to enable them as important actors in city-wide resource conservation.

With regards to demand-side flexibility, we find evidence to challenge traditional theoretical assumptions about the behavior of thermostatically controlled loads (e.g. coefficient of performance, duty cycle, temperature set points and dead band width), finding that user behavior and the efficiency of TCLs significantly affects resource availability and the large-scale potential for demand response (DR) – features that are largely ignored in the literature. We suggest that there should be two efficiency parameters that should be considered in DR – the coefficient of performance, and the efficiency performance index. Concepts in behavioral economics (e.g., the psychology of scarcity, prospect theory and the endowment effect)(3–5, 7) are used to explain some of the challenges encountered in the field, and how these could potentially hinder the growth and success of future energy efficiency and flexible demand pilots. To our knowledge, this is the first paired behavioral energy efficiency and flexible demand implementation in Latin America, and the first to explain the observed field results related to behavioral energy efficiency using concepts from the psychology of scarcity.

The FlexBox, the approach and system used to engage field participants and flexible ubiquitous loads, and the findings from our willingness to pay study, can be used to inform future ICT/IOT deployments and the development of new and inclusive systems for participatory low-carbon urban environments.

3.2 Background: Approaches to Demand-Side Flexibility – Theory, Technology and Applications

The penetration of uncertain and variable renewable energy is now occurring across many regions, incomes, and levels of development. In the immediate future, countries such as Uruguay are expected to produce 35% of their generation from wind energy alone (2016), Kenya expects 300 MW of wind to come online in 2016, Thailand will develop 3 gigawatts (GW) of rooftop and village based solar projects (2021), and Africa's Clean Energy Corridor should significantly increase the penetration of renewable energy in the continent (187, 213). In Central America, Costa Rica has produced up to 100% of its generation from renewable resources (~25% without large hydropower), and Nicaragua produces ~40% of its total generation from non-large hydropower renewable resources. Indeed, some research suggests that between 2015 and 2040 approximately $US12.2 trillion will be invested in global power generation, with two thirds of the total being dedicated to renewable energy, and with the great majority (78%) of this investment occurring in emerging economies (214).

Similarly to future trends in power generation, future growth in urbanization will also mainly occur in cities of the rising south. UN Habitat reports that in the past decade, the urban population in emerging economies grew on average 1.2 million people *per week*, with Asia adding 0.8 million new urban dwellers every week, followed by Africa (0.23 million/week), and Latin American and the Caribbean (0.15 million/week) (206). It is expected that seven out of ten people will be living in cities by 2050 (206, 207). Similarly, the growth in the use of cellphones and smartphones is also unprecedented. Currently there are more active mobile connections (7.8 billion SIM connections and 4.8 billion unique mobile subscribers) than people in the world (7.4 billion), with penetration rates being large even in low-income economies (89 subscriptions per 100 people) (208, 209). Although currently low, the number of 3G/4G users is expected to double by 2020 (2.5 billion users) (215). With most renewable energy, urbanization and connectivity growth in the coming decades occurring in low and lower-middle income countries, it is becoming increasingly important to understand how to harvest information from resource constrained environments (RCEs) to provide value both to users and urban services (for example, energy, water, transportation, and banking) (207, 211, 212).

Attention towards the actuation of TCLs has grown as the penetration of intermittent renewable energy increases with innovations being made in theoretical frameworks, controlled environment pilot tests, development of new technologies, and field deployments (216–218). In this section, we review theoretical approaches to demand side grid flexibility, also known as demand response, review existing solutions to the actuation of thermostatically controlled loads to provide power grid services, and briefly discuss field deployments available in the literature.

DR is related to the "end-use", with electric loads (and users) reducing or shifting their usage in a given time period in response to a price signal, financial incentive, environmental condition or reliability signal (219). Electric loads exist under three broad categories: *(1)* inflexible/on-demand (lights, television sets, radios, desktop computers), *(2)* deferrable (washers, dryers, dishwashers), *(3)* and flexible (HVAC, EVs, refrigerators, water heaters) (217). Smart flexible energy loads (TCLs) contain enough local energy to run for an extended period of time, and an intelligent controller can engage with them via direct load control (DLC) to manage energy reserves without significantly inhibiting operation (220). Furthermore, TCLs can be controlled for the purpose of curtailment, substitution, storage, and/or load shifting (221). The theoretical approach to demand response has motivated a wide body of work that seeks to show that large aggregations of TCLs can be used both to bid into grid related ancillary service markets for profit as well as to maintain reliable power system operations (216, 222–225). Detailed end-use models explore associated uncertainties in aggregating TCLs, algorithmic bidding approaches toggle load switch controllers for managing wind forecast error and reducing external balancing penalties, and control and differential equation approaches for modeling the effect of broadcasting signals for TCL set point adjustments (216, 221, 226, 227). In general, room temperature, inside temperature (of a room, or inside a refrigerator, for example), power consumption, and TCL characteristics (resistance, capacitance, and wall thickness, for example) are all used for the design of a smart controller (224). Although complex and highly detailed, many of these models make simplifying assumptions that could significantly affect model choice and development including the possibility of heterogeneity across micro-climates in urban areas, insulation of houses (or buildings) where TCLs reside, load efficiency, the size (and varying thermal mass) of TCLs, and random user behavioral patterns that can drive TCL cycling. Furthermore, data acquisition devices (sensors and power meters, for example) and communications platforms and protocols are discussed abstractly, with most of the effort being directed towards the development of theoretical frameworks to further enable greater grid flexibility.

There exists a panoply of solutions for networking sensors and plug load devices in higher-income countries, but the literature is scant regarding how sensing infrastructure will grow and be networked in countries with low internet access, and spotty communication networks. In countries with high internet penetration, the monitoring of loads can be done through Wi-Fi enabled large smart home appliances, plug- level monitors (individually installed and programmed, often with proprietary communication protocols), and non-intrusive load monitoring (NILM) (228, 229). NILM is an alternative to ubiquitous plug level monitoring, only requiring one energy meter to monitor whole house energy consumption, and signal processing for load disaggregation, but to date, this remains mostly a research effort (229–236).

Communication protocols for energy reporting and control of devices are primarily designed for local area networks (LAN) (e.g. stacks such as Zigbee or Z-Wave), and APIs, such as OpenADR and GreenButton which are intended for use over the internet (228, 229). Zigbee's Smart Energy Profile enables low-power device monitoring using 802.15.4 radios and links that support IPv6 through an HTTP interface, and OpenADR 2.0b and GreenButton Connect are XML standards for energy data exchanges between utilities, consumers, and third-party service providers (228, 229). Differently from Zigbee and IETF 6LowWPAN (which use IEEE 802.15.4) Z-Wave uses a proprietary low-latency transmission communications protocol that uses small data packets at 100kbit/s, operating through a source-routed mesh network that helps the device avoid obstacles and radio dead spots in a multipath environment. Zigbee and Z-Wave differ from OpenADR and GreenButton in that the latter were designed for high- bandwidth network connections and large files sizes, making them less useful for low-power local area networks (228, 229). Z-wave uses a source-routed mesh network architecture. In addition, Bluetooth (communicating over IEEE 802.15.1) can be used for short-range applications to replace cables for computer peripherals such as mice, keyboards, and printers, but to date has few applications for monitoring and control of electric loads (236–238).

In California, Radio Broadcast Data Systems (RBDS) have been recommended as the statewide DR broadcasting signaling standard, and it has been shown that RBDS can be used to broadcast one-way demand response messages with near 100 percent probability using merely just one FM station (239–241). RBDS use a 57 kilohertz subcarrier to transmit over 1 kbts, with data being transmitted in groups of four blocks (26 bits each) (239, 240). All available FM channels (frequencies) within proximity can be used to broadcast signals, with the probability of message reception being dependent on signal strength and the number of message repeats (239). Since DR applications only add one to two percent of total average transmission station capacity to a channel, FM station contract costs for RBDS are relatively low (hundreds of dollars per month) (239). A downside, however, is the one-way nature of the FM broadcast.

While there have been a variety of approaches that have been shown to be effective in simulation there are two principal questions that have largely remained unaddressed: *1)* how well do algorithms and loads behave in practice? and *2)* what is the actual size of the resource that is available for demand response in a region or country? Research pilots have investigated the potential of *deferrable* and *flexible* loads to provide grid-flexibility using loads as virtual power plants and exploring opportunities for users to experience energy savings through real time pricing. These pilots have instrumented as few as one and as many as five refrigerators to study real-time behavior of loads under DR (217, 218, 241). A few have also developed proprietary thermal-storage eutectic phase-change storage systems that can be controlled (217, 241). Some of the business scenarios explored in these pilots include: (1) the aggregation and market-auctioning of thermal storage 'virtual power plants' (controllable tool kits are *given* to businesses and households for a load aggregator to make a profit through auctioning), (2) 'smart refrigerators' independently taking advantage of real time pricing opportunities (users *buy* a controllable tool kit to take advantage of real time pricing), and (3) incentives for supply following loads.

In California, some research pilots have suggested that a 'thermal storage refrigerator' controlled through a load aggregation framework could have great value and a relatively fast five-year payback period, while others have found that Californian households would only benefit from buying 'controllable tool kits' if real time prices were slightly higher than what they currently are(217, 241). Taneja *et al* (2013) found that household savings in California would be negligible due to the amount of energy required to freeze and control an actionable phase change material, and Taneja *et al* (2013) and Lakshmanan *et al* (2014) both find that the amount of savings experienced by a household depends substantially on the pricing tariff. In Denmark, research pilots suggest that the "micro-payments" provided to users for participating in a load aggregation would be too low (1 to 5 euros/month) and energy cost savings would be too little (1 to seven euros/year) from buying a 'controllable toolkit'. The absence of business potential in Denmark depended heavily on rate structure and other fees that make up a large part of the electricity prices (fixed costs being a large proportion of the electricity bill, rather than variable costs), in addition to refrigerators being much smaller and efficient than Californian refrigerators, and thus, requiring a larger population to take full advantage of virtual storage plants.

Manual DR (manually changing set points, with a switch or controllers, for example), semi-automated DR (automating HVAC or other processes through the use of energy management control systems, with the remainder of a facility under 'human control'), and fully automated DR (automation of an entire facility) are the three most popular ways to implement DR research pilots and field deployments. High data granularity through metering or advanced metering infrastructure (AMI) is essential for all DR implementations to ensure project performance and end-user compliance, financial settlement, and consumer satisfaction (by providing access to data), among other things(240, 242, 243). Currently, most AMI deployments interphase with smart metering infrastructure through analog pulse or digital series outputs, as well as metering specific loads (242, 243). These data are for the most part sent back to an aggregator through existing communications infrastructure such as broadband or wifi (242, 243). With response times that can range from tens of minutes to milliseconds, DLC is an integral part of AMI kits used in pilots and research projects to ensure compliance, as it would be nearly impossible for users to act within some of the shortest time frames (238). Two-way communications have also been crucial as it allows toggling relays, sending scripts to BEMS, or attachment to a wide assortment of loads or industrial equipment (238). Network Operation Centers (NOCs), or centralized control servers, host and organize DR and are widely used in commercialized implementations for initiating automatic dispatch notifications, remote control and monitoring of customer loads and generation, and coordination technicians in the field (238).

In the United States, OpenADR is now almost always used as the communications data model of choice to *'facilitate sending and receiving DR signals from a utility or independent system operator to electric customers'* (238, 239). While the OpenADR specification certainly facilitates data exchanges across a variety of stakeholders including consumers, utilities, regional transmission organizations (RTOs), and independent system operators (ISOs), it was primarily designed for high-bandwidth networks rather than low-power local area networks, making it perhaps less useful for smaller research tailored implementations or niche markets (238). Once the system is in place, providing capacity payments, enabling meter access, facilitating accurate and transparent measurement verification procedures (establishing a baseline, for example), and encouraging aggregation are seen as industry best standards (238).

Research pilots and field deployments are an important next step in realizing the implementation of the smart grid, and future research projects will have to further investigate important aspects of DR implementations including two-way communications costs and/or challenges, and the incorporation of behavior in DR (opening and closing of doors, for example), which plays an important role in TCL cycling. Another important challenge to consider is that AMI and smart metering were not designed with DR or other ancillary services in mind. In California (PG&E), smart meter infrastructure may receive or send several signals per day, with the transmission frequency depending on its position across a mesh network, and hence, does not provide all the functionality that DR aggregators would like when ensuring high standards for project implementation. Furthermore, DLC programs have historically faced end-user challenges including customers becoming frustrated with service interruptions, and often times leaving programs if they are called on too frequently, or not offered sufficient incentives to maintain long-term project participation (243). Technology innovation in networking and DR technologies needs to consider many of these challenges.

3.3 FlexBox Design and Technology Implementation

In January 2015 we used the Open Data Kit platform to survey 230 micro-enterprises with large cooling loads in Managua. A pilot survey was tested with a small group of 20 micro-enterprises, adjustments were made, and a full implementation was performed immediately afterwards. Our surveys and conversations with micro-enterprises (MEs) with large-cooling loads (for example: butcheries, chicken shops, mom & pop shops, milk and cheese shops) attempted to assess whether a micro-level demand response implementation could be feasible in Nicaragua and touched upon different aspects of a micro-enterprise's business model: income and cost structures, energy related expenditures, daily, monthly and seasonal variations in consumption, perceptions on electric service reliability, perceptions on the quality of service provided by the utility, relationship with loads and appliances, and perceptions on income and micro-enterprise expenditures.

The three most salient results from this survey included learning about *(1) Voluntary Load Disruption:* 161 respondents (71% of sample), were already implementing a refrigerator 'energy savings strategy' by turning their refrigerator on or off at different times of the day, *(2) Perceptions on Electricity Service Reliability:* Despite 70% of the MEs experiencing frequent power outages, most were '*satisfied'* (72%) with service reliability (our data, however, registered very low voltages across the geographic spectrum, affecting the performance of certain appliances such as refrigerators), suggesting a high level of acceptance towards loads (and service) being turned off at random, and *(3) High Energy Costs and Perception of Electricity Related Expenditures:* The MEs' main cost concerns were related to high energy prices (US$ 0.33/kWh), with 60% finding their bills 'difficult to pay' (on a scale from 1-4: 'easy' to 'very difficulty to pay') (207). The objective of the system is to turn everyday TCLs (refrigerators, in this instance) into grid-tied 'batteries' that have the ability to store energy via latent heat, while still being able to perform their intended tasks. The system gathers open access high-resolution grid and weather data, as well as information from micro-level users such as micro-enterprises and homes via surveys and a wireless sensor gateway. Actionable signals and personalized and useful snippets of 'energy efficient' information are developed in the cloud and are pushed back to users, but understanding the state of an aggregated 'virtual storage plant' (as described above) for DR simulation and control is the primary task of our design and implementation.

With knowledge of previously implemented micro- level DR implementations, and taking into account characteristics and challenges particular to Nicaragua, a system was conceived that could scale across regions and levels of infrastructural development. We called this system a FlexBox. The FlexBox requires intelligence far beyond a power meter; its design must allow for the possibility of using information about household energy consumption, refrigerator energy consumption, refrigerator temperature, refrigerator usage, and room temperature to independently make decisions about turning the refrigerator on and off. Similarly, its design must also allow for the possibility of two-way communications with a load aggregator. These functionalities were not implemented in a vacuum and followed a set of design principles that fit the deployment and project context. The principles surrounding FlexBox design were guided by the needs of all the "users" including: *1) adaptability:* the team of researchers (at the University of California and the Nicaraguan National Engineering University) who will need to develop DR control laws, sensor configurations and management, and data collection and transmission functionalities, *2) modularity:* simple maintenance being performed by a local enumerator without formal training in electronics meant that the system components could be put together and apart with ease, and *3) user needs and acceptance:* the home or business owners must accept the technology, and at a later stage, receive information about household and load consumption. The second set of design principles came from our motivational research questions. A compromise had to be found between the availability of low- cost sensors and the variables of interest, including human behavior. This set of principles, while dominating the motivation of the project, is often the easiest to satisfy as it is sufficiently under the control of the researchers.

The FlexBox is designed for ubiquitous TCL and household sensing, monitoring and load control. In this section, we discuss the principles of operation, the hardware and software implementation. Our research pilot in Managua (Nicaragua) consists of thirty FlexBoxes attached to twenty freezers (micro- enterprises) and ten refrigerators (households) and a centralized server that stores data, performs analyses, and provides control signals. Each FlexBox collects fridge inside temperature, humidity, TCL energy consumption, and total household energy consumption and stores it in a local database. Data is sent over 3G to a centralized server where it is merged with time stamped open access grid and weather data. Statistical and control scripts in the server can run simulations, and when necessary, actionable DR signals can be sent to participating TCLs to either be turned off or return to their normal cycling schedules. This central server also provides web-based tools to export data for off-line analysis, user energy reports, and intuitive visualizations that allow interested parties to easily understand the state of the overall system.

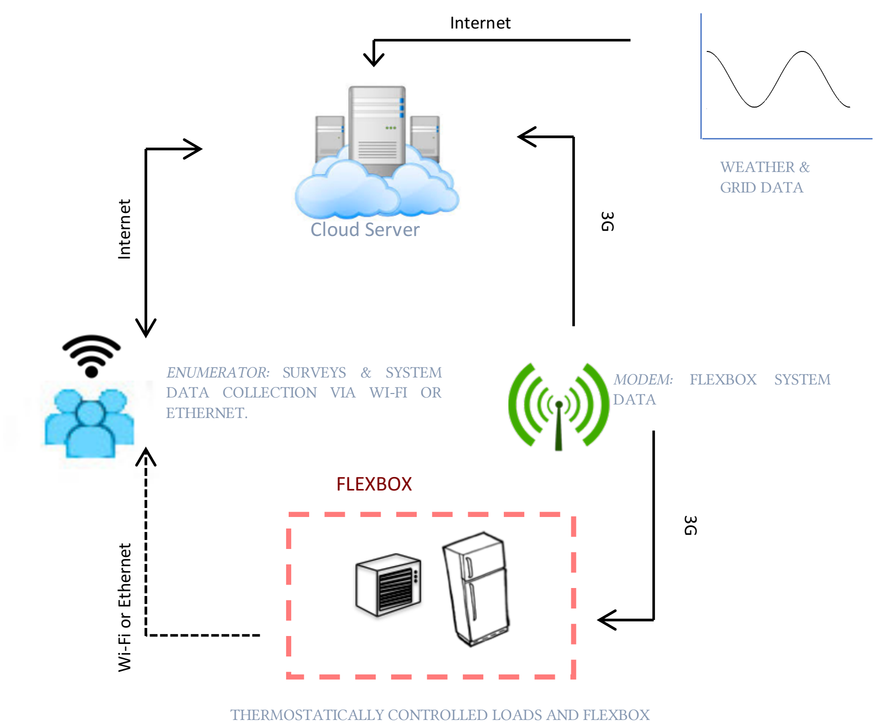


Figure 36: FlexBox System Concept: The enumerator downloads new FlexBox software and new surveys from the cloud server. The enumerator also collects data from the FlexBox via Ethernet or Wi-Fi and sends it to the cloud server. A Huawei E3531 modem opens two-way communication streams between the FlexBox and the cloud server, uploading data and downloading updated control laws. Open access grid and weather data are stored in the cloud server as well as an archive of transmitted data.

The FlexBox is comprised of several components: a Raspberry Pi 2B, a custom Sensor Gateway Board, and a variety of wired and wireless sensors. Four USB ports on the Raspberry Pi are used to add and test wireless communications peripherals for local device communications using the Z-Wave protocol, Wi-Fi, flash backup storage, and a USB Huawei E3531 3G modem. An onboard storage microSD card on the Raspberry PI 2B makes data collection much simpler. If all other avenues fail to communicate the data to our server (an enumerator collecting data via Wi-Fi, or a 3G modem streaming data to our cloud server) the card can be mounted and read using a GNU/Linux based laptop. The modem is used to stream a subset of the data to our server, to control the FlexBox, and to test the quality of the GSM network. The Ethernet port provides a fail-safe communications channel with the device.

There are 3 radios (Wi-Fi, Z-wave, and GSM) and 7 sensors used in each FlexBox (four wired and three wireless). The wired sensors (two DSB18B20 waterproof temperature sensors in the refrigerator, a DHT22 household temperature/ambient sensor, and a magnetically actuated reed switch to monitor door openings) are connected to the Raspberry Pi via the custom Sensor Gateway board via a set of RJ11 modular jacks. An mPower Ubiquiti device is used for refrigerator monitoring and control and communicates via Wi-Fi. An Aeotec Home Energy Meter monitors house power consumption (located at the electric service panel) and communicates to the FlexBox via Z-wave protocol. Several additions were made to the sensors and cables, including a small cage to surround the DS18B20s temperature sensors to minimize thermal contact conductance when inside the refrigerator as well as a thin telephone cable to extended the DS18B20s length (and allow for the refrigerator door to seal completely).

FlexBox processing and data storage is managed by the Raspberry PI 2B using the Raspbian Wheezy operating system. This platform provides a full operating system as the development environment which provides a richer feature set familiar to all researchers (UC Berkeley and UNI), which would not be the case if a simpler system were used, such as an mBed or Arduino microcontroller, which use a subset of C++. All software is implemented in Python and all data is stored in a PostgreSQL database. The Raspberry PI 2B uses the host access point daemon (hostapd) to act as a WiFi access point in order to communicate with the mPower Ubiquiti device (mPower). This access point also allows users to more easily connect to the FlexBox for diagnostics and data collection.

Values from the switch sensor are directly accessible through the GPIO ports on the Raspberry PI 2B. The refrigerator temperature and room temperature and humidity sensors appear as character devices. I2C is used to communicate with the temperature sensors and a proprietary protocol is used to communicate with the room temperature and humidity sensor. An open-source repository called python-openzwave is leveraged in order to access voltage, current, power, power factor, and energy values from the Aeotec Home Energy Meter. The python paramiko package is used to communicate with the mPower over WiFi through a secure shell (SSH) connection and collects refrigerator voltage, current, power, power factor, and energy values. In order to maintain stable connections and handle communication errors, the data collection scripts incorporate several layers of connection and process resets. First, a separate process is created for the data collection script of each sensor. This allows for independent sensor reads and stores and prevents the failure of a single sensor from interfering with the collection of other sensor values. While this system is capable of collecting data every 1-3 seconds (depending upon the sensor), the limited storage capacity of the microSD card requires a more limited collection scheme. The software stores data in the PostgreSQL database under two conditions: 1) it detects a change in the output value that is greater than a specified threshold, and 2) one minute has passed. This second condition ensures that the sensor is still functional, otherwise it would be difficult to discern between a broken sensor and a static sensor output.

The sensors that communicate over wireless protocols (mPower, Aeotec Home Energy Meter) also have an additional layer of process handling to prevent excessive data loss caused by wireless connection issues. The Z-Wave network and connection to the mPower could be very sporadic. Each hour, or if any communication error is caught, the entire system process is restarted. The mPower has an additional timeout for resetting the wireless network on the Raspberry Pi. If it cannot connect to the mPower, the wireless network is reset. After four retries, the Pi stops attempting to connect and waits for the process to be killed in the subsequent hour. This limit was imposed to allow for users to access the Raspberry Pi's WiFi network even when the mPower is not functioning without having the script constantly resetting the connection. The Python Flask microframework is used to set up a web server on the Raspberry Pi. A web page on this server allows users to easily see the last several data points that were entered into the database from each sensor. This allows for quick diagnostics by the enumerator when first entering a household. Other configuration properties include setting a static IP address for the mPower, hard-coding the temperature sensor ids, and assigning unique hostnames to each FlexBox. These configurations add stability, reduce the possibility for error during system resets, and allow for easy identification and tracking when analyzing multiple households simultaneously.

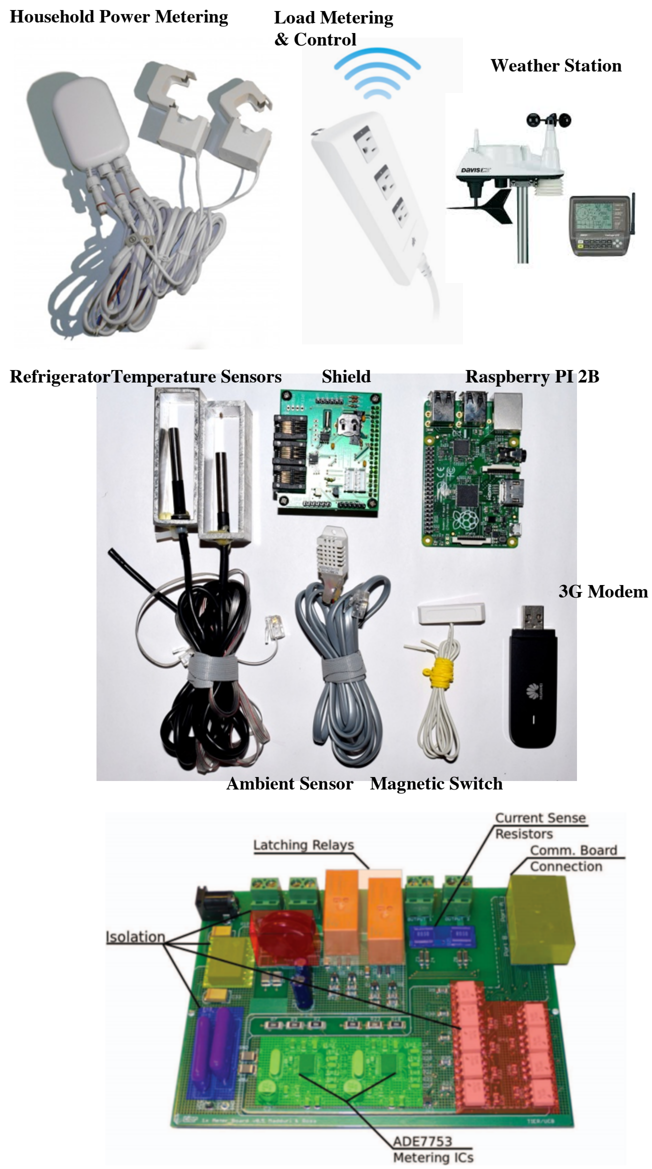


Figure 37 FlexBox Wireless Sensor Gateway Components.

Regarding communications, our approach seeks to evaluate two different network measurements: latency, and bandwidth. Latency represents the time interval in milliseconds between stimulation and response (how long it takes for data to get from one place to another), with bandwidth (bits per second) representing how much data can move across the network at a given time. Network latency is evaluated through pinging: every 30 seconds, 6 pings are sent which do a round trip to and from the server (FlexBox to clould server to Flexbox). Bandwidth is measured every 2 hours by opening a transmission control protocol (TCP) connection with the cloud server and streaming 3 megabits of randomly generated numbers from the FlexBox (to prevent compression by the network which would inflate our perceived bandwidth). Every four hours one row of data (sensor and meter readings) is sent to the cloud server to update system parameters.

3.4 Exploratory Data Analysis of Field and Sensor Data

In the summer of 2015 twenty micro-enterprises and ten households in different parts of Managua with similar social- demographic characteristics were selected at random from a sample of 230 micro-enterprises and households to receive a FlexBox. Five Huawei E3531 modems were installed to test network latency and bandwidth. This section presents an exploratory data analysis of the data collected to date, including TCL thermal parameter estimation and efficiencies, a brief communications network analysis, a cost breakdown, and a summary of field implementation challenges and opportunities that have been presented to date.

Normalized micro-level energy consumption (mean and/or median) can be clustered into 5 different *daily load shapes* (hourly data). The five different clustered *daily load shapes* (k-shape) include (1) those that have their highest consumption in the middle of the day, (2) those with two peaks occurring in the middle of the day and in the evening, (3) those whose consumption increases consistently throughout the day, (4) those with only high consumption in the morning and at night, and (5) those that have scattered consumption throughout the day, but with the highest consumption being in the middle of the day. On average, households and micro-enterprises consume more energy on weekends versus weekends (mean: 16% greater energy consumption, median: 28% greater energy consumption using median).

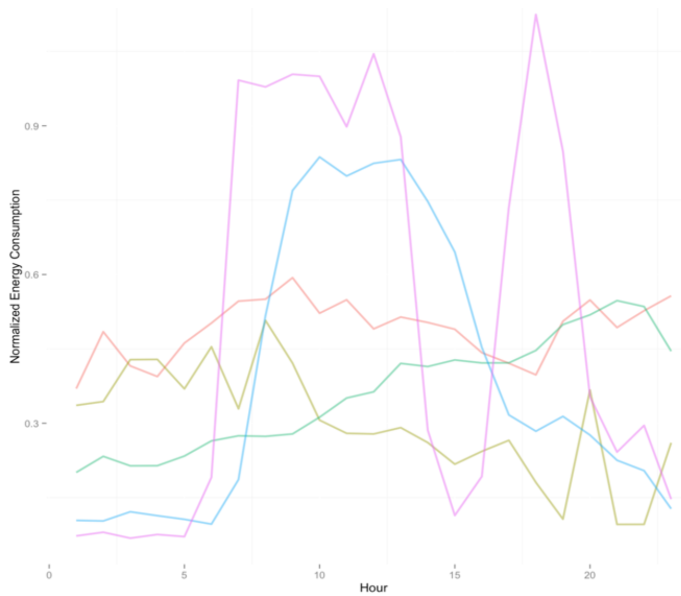


Figure 38: Load Shapes: Five different load shapes were identified when clustering load shapes by hourly mean or median. The pink load shape is the load shape that most resembles Nicaragua's characteristic daily demand load shape.

Correlating time of day with hourly room temperatures (°C), fridge inside temperatures (°C), refrigerator energy consumption (Wh), and household energy consumption (Wh) allowed us to see that there is both a room temperature and time dependence (with varying correlation strength) across our cluster (Figure 39). We observe a very weak negative relationship between inside refrigerator temperature and room temperature (Pearson r=-.06, N=16,000, p<.001), a moderate positive relationship between fridge energy consumption and room temperature (Spearman non-parametric r=-.43, N=10,000, p<.001), a moderate positive relationship between household energy consumption and room temperature (Spearman non- parametric r=-.45, N=16,000, p<.001), and a very weak relationship between room temperature and door openings (Spearman non-parametric r=-.16, N=16,000, p<.001).

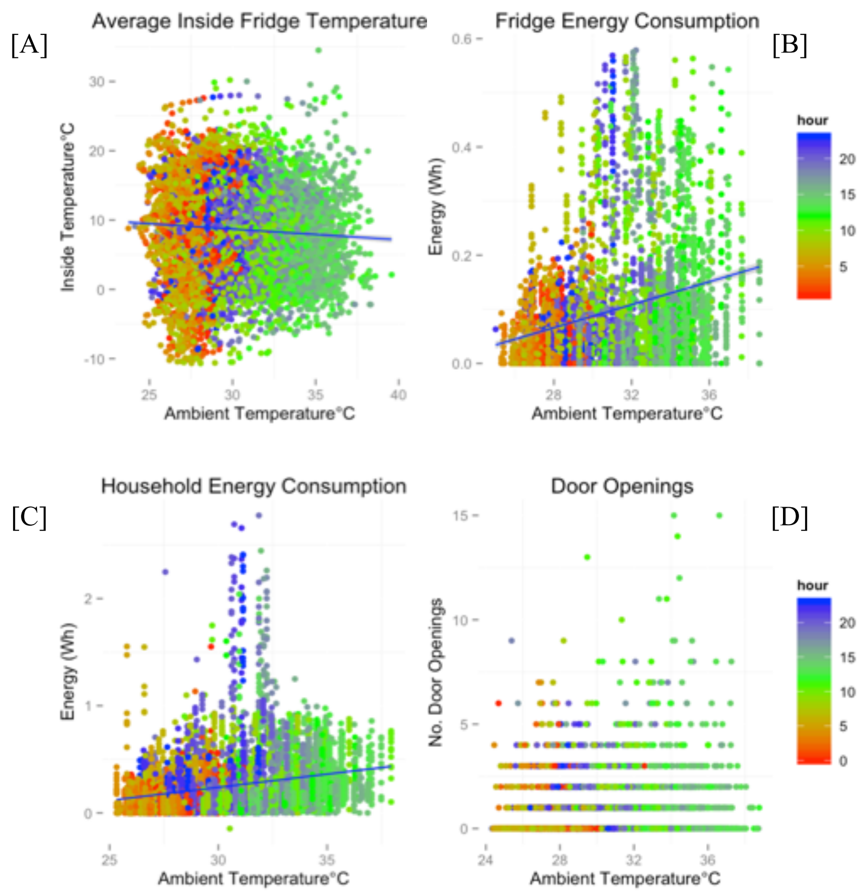


Figure 39: Controlled System Pilot Data Stream: Room ambient temperature plotted [A] fridge inside temperature, [B] fridge energy consumption, [C] household energy consumption, and [D] door openings. While the cluster only depicts weak to moderate correlations between room ambient temperature and other data streams, individual units experience stronger correlations between room ambient temperature and all other sensor data.

While these relationships may be relatively weak across the cluster, we observe great within cluster variability when exploring these relationships (Figure 39). For example, Figure 39 depicts that 8 and 3 units experience moderate ($0.4 \leq r < 0.6$; p<.001) and strong ($0.6 \leq r < 0.8$; p<.001) moderate (p<.001) and strong (p<.001) correlations between room temperature and house energy consumption respectively, and while the correlation between fridge energy consumption and room temperature is positive, this relationship is only found to be moderate and strong in a few households (2 and 1 units respectively; p<.001).

The spread in the strength of correlation between ambient room temperature and fridge inside temperature and fridge energy consumption suggests that there is a panoply of user behaviors that are driving the system (Figure 40). For example, some units might unplug their fridge when room ambient temperature is very high, whereas others might leave their appliance 'on', with the fridge using more energy to preserve (or reduce its internal temperature) during that time.

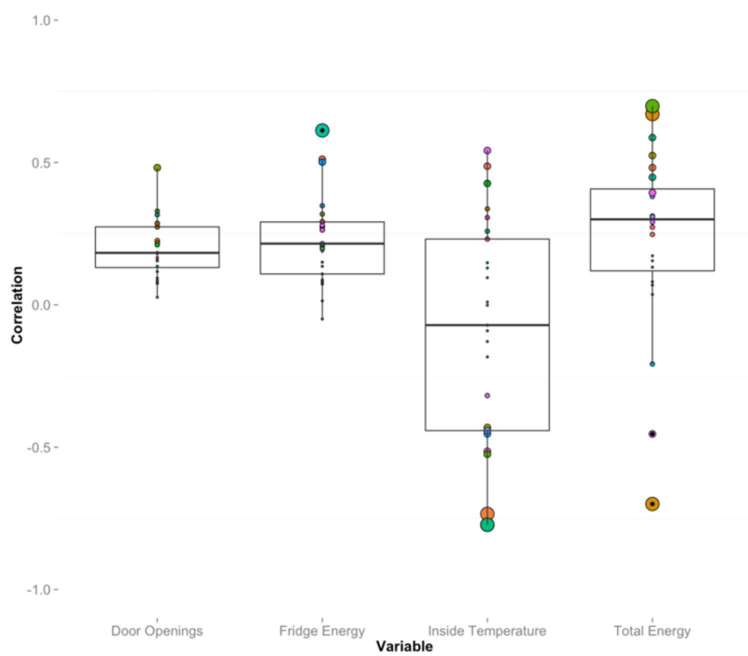


Figure 40: Correlation between Room Temperature and FlexBox Sensor Data: The figure depicts the strength of the correlation between room temperature and all other sensor readings (door openings, fridge energy consumption, fridge inside temperature, and total household energy consumption) for all units. *The size of a point represents the strength of the correlation and the color depicts a visual identifier for a specific unit (household or micro-enterprise).* While the cluster data (all units) in Figure 40 depicts only weak to moderate correlations, individual units experience stronger correlations between room ambient temperature and all other sensor data.

Similarly a strong positive correlation between fridge inside temperature and room ambient temperature could suggest that users unplug their fridge during the hottest parts of the day, and a negative strong correlation could suggest that these are the times of the day when users actually 'plug' their refrigerator (and consequently, the time of the day during which the refrigerator uses most of its energy). The correlation between total household energy consumption and room ambient temperature suggests that while there are a few households that increase their consumption at higher temperatures, there are also others that modify their behavior so as to reduce their consumption (for example, turn several freezers and refrigerators off). There are many more insights from these data, including the opportunity to target energy efficiency thermal insulation for refrigerators in certain units, as well as the development of detailed energy reports.

There are several key parameters for determining the technical resource potential of thermostatically controlled loads and for building more accurate control algorithms for large-scale TCL aggregations. Room temperature, fridge inside temperature (of a room, or inside a refrigerator, for example), power consumption, and TCL characteristics (resistance, capacitance, and wall thickness, for example) are all used for the design of a smart controller. It has also been suggested that large-scale TCL aggregations of virtual energy storage can be represented through both their *energy* and *power capacity* (244). To define the *energy capacity* (the maximum amount of energy that can be stored) and the *power capacity* (the full power range of an analogous storage device) several parameters are needed including: *h* (the amount of time it takes a TCL to traverse its deadband in ON mode), dead-

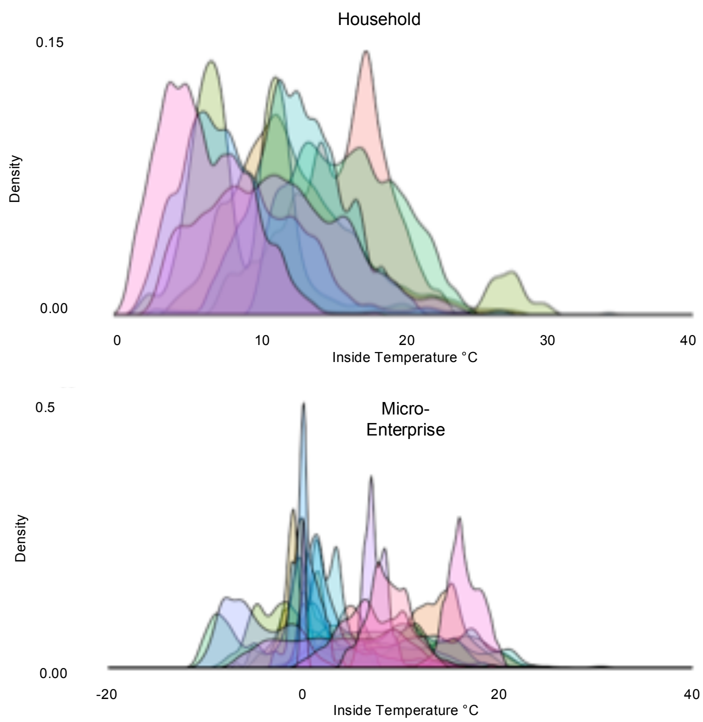


Figure 41: Internal temperature of household and micro-enterprise TCLS: The temperature range of households is similar (top), while micro-enterprise freezers display a wider temperature range, ranging from -10°C to room temperature (bottom).

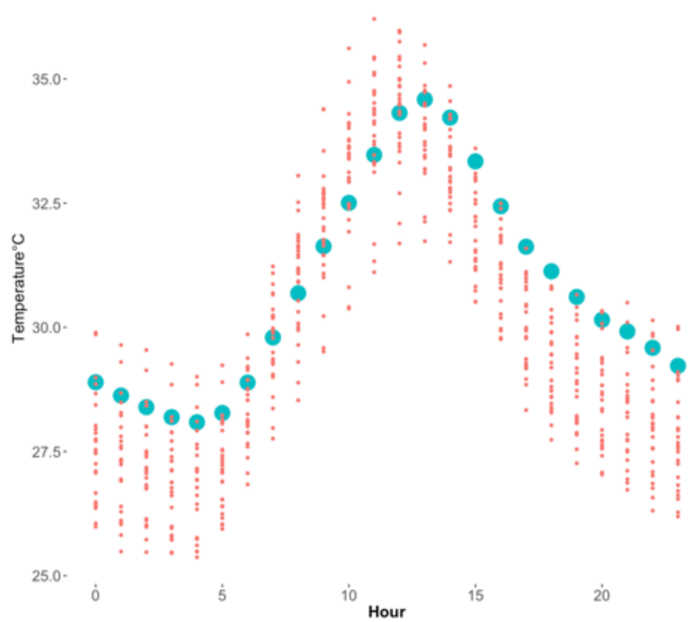


Figure 42: Room temperature of household and micro-enterprises (red) vs. ambient weather station data (blue): Houses and micro-enterprises directly experience the ambient weather station temperature on the streets of Managua. In the morning, late afternoon, evening and night, the weather station experiences higher temperatures than the households and micro- enterprises.

band width (°C), temperature set points (°C), thermal resistance (°C/kWh), thermal capacitance (kWh/°C), coefficient of performance (COP), and power consumption (kW). While TCL models in the literature allow room temperature to vary when modeling air conditioners and heat pumps, room temperature remains fixed when modeling energy and power capacity in refrigerators. Though these dynamics may vary across regions and study sites, a fixed room temperature also means that a refrigerator's duty cycle remains constant, and so do the power and energy capacities, as well as the mean annual energy consumption (244).

When comparing room temperature and humidity inside households and micro-enterprises against ambient weather station data, we found that houses and micro-enterprises directly experienced ambient temperatures, and often experienced hotter temperatures during the hottest part of the days due to the absence of reflective or insulating house materials infrastructure. During the early morning (0-6 am) all except two houses experience lower temperatures than the ambient temperature weather station, but this changes at 6 am when approximately half of the households experience higher temperatures than the weather station. While room temperature allows us to understand intra-hourly and intra day temporal variability, and temperature variability is well correlated across our weather station and all units, there was a wide spread of room temperature across all units (4°C). Poor thermal insulation could pose significant problems not only for household and city-wide energy efficiency programs, but could also significantly affect city dwellers health (245). Our data suggests that not only does room temperature vary significantly during the day, but also that the warm temperature extremes are experienced significantly by loads and people in houses and micro-enterprises.

On average, TCL consumption is greatest during the middle day when it is the hottest and when households experience the majority of their door openings. Figure 43.A depicts normalized data (0-1) for all units to compare energy usage over time throughout the study period. Manufacturer information from refrigeration units in the field labeled the temperature set points of the different freezer and refrigeration units to range between -20°C and 5°C. Field data suggests, however, that the units usually oscillated between -10°C and could reach up to 35°C (Figure 41, Table 10). This deviation could be a result of appliance losses, and behavioral components which include the opening and closing of doors and the temporary unplugging of TCLs most units engage in.

Furthermore, we find that the duty cycle (the ratio of time it takes for a refrigerator to traverse its dead-band in an on state vs. total time in compressor on and off states) fluctuates during the day. Here, field data suggests that the freezers and refrigerators spend more time in the compressor-on stage during the middle of the day (when it's hottest and when there is more activity) than other parts of the day. Evidence from these field data diverge from previous TCL modeling assumptions that suggest that the duty cycle (and energy and power capacities) is fixed throughout the day. We also compare the coefficient of performance, which was measured in an experimental setting at UC Berkeley, to an efficiency performance index, which was calculated from data. We find that while the experimental COP ranged between 0.01 and 0.03 and stayed fairly constant throughout the day (with minimal heat or behavioral disturbances), the efficiency of performance index (EPI) observed in the field ranged drastically between 0.0045 (minimum) and 18 (maximum).

While it would seem like the EPI index is consistent across field units (Fig 8), we find that the performance efficiency of the refrigerator (the amount of work required to remove heat from a cold reservoir) varies within the day. More active and hotter times of the day observe lower EPI values than other days. The rated power of these appliances ranged from 0.1 to 2.2 kW according to the manufacturer label and size; this would result in a mean annual consumption range between 280 and 6000 kWh. Our field data suggests that the actual mean annual energy consumption was 1400 kWh for the entire cluster. Findings from our field data and experiment could be used to better inform the modeling of TCLs for ancillary services as theoretical models usually assume constant duty cycles, energy and power capacities and performance efficiencies.

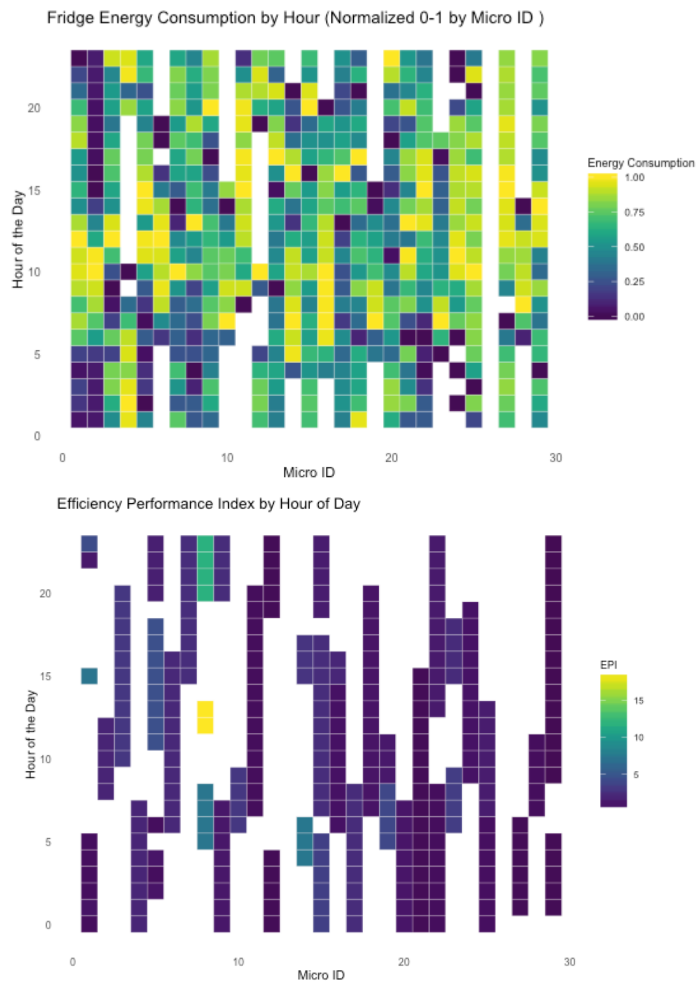


Figure 43: Normalized TCL Energy Consumption by Unit [top] and TCL Efficiency Performance Index for all Units [bottom]: [Top] We observe TCL energy consumption to be, on average, higher in the middle of the day than other parts of the day, and [Bottom] we find the efficiency performance index (the ratio between the work that is required to remove heat from a reservoir and the heat removed from a reservoir) also varies during the day, and is worst in the middle of the day when it is hottest and when the TCL experiences most activity.

3.5 Communications Exploratory Data Analysis

As part of a test for the reliability and capacity of the communications network, we installed five 3G Huawei E3531 modems in both households and micro-enterprises. Monthly 1GB data plans were purchased for each modem and two tests were written and implemented to test network latency and bandwidth. Latency refers to the base overhead of establishing and responding to a connection request. In this context, it measures the amount it takes for the FlexBox to create a data package, send it to the server, the server receiving it and the server sending it back to the FlexBox. We measured latency through pinging: every 30 seconds, 6 pings were sent from the FlexBox to the server, and then returned back to the FlexBox. With regards to DR control purposes, latency is incredibly important as we want DR control signals to travel fast through the network. Modems can take anywhere between millisecond to tens of seconds to establish a connection and send one packet of data changing what service we can reliably provide in ancillary services or spot markets.

Parameter	Units	Mean (SD: Min -- Max)
Ambient Temperature	Celsius	30 (3: 10 -- 41)
Dead-band width	Celsius	9 (4: 10 -- 35)
Temperature set point[1]	Celsius	-20 -- 5
Duty cycle	-	0.52 (0.31: 0.1 -- 0.9)
Coefficient of Performance[2]	-	0.01 -- 0.03
Efficiency performance index	-	1.8 (2.4: 0.0045 -- 18)
Power consumption[1]	kW	0.1 -- 2.2
Mean Annual Energy Consumption per TCL[1]	kWh	280 -- 6000
Actual Mean Energy Consumption per TCL	kWh	1400

Table 10: Field Data TCL Thermal Parameters

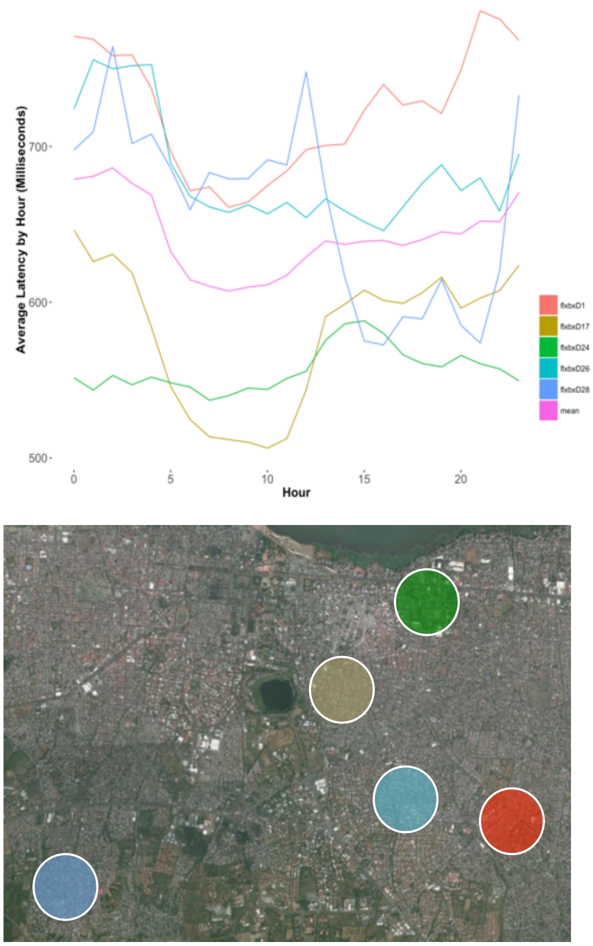
[1] From product details found in the field and from local refrigerator and freezer providers
[2] From controlled laboratory experiments. The literature suggests that the COP ranges between 1.5 and 2.5, but we did not see this in our experiment. COP is a ratio of Qc (heat removed from a cold reservoir) over Wref (the work input required to remove heat from a cold reservoir). Experimentally, we calculated the COP for a freezer and refrigerator were empty, but on the field we assumed freezers and refrigerators to be ¾ full. That is, we used the heat capacity of air and water to calculate the efficiency performance index for our field data.
[3] The rest of the data was obtained from the field.

Bandwidth refers to the speed at which data flows through the network after a connection has been established and is usually taken into account when considering bulk data transmission. We measured bandwidth by opening a transmission control protocol (TCP) connection between the FlexBox and the server and transmitting 3 megabits of randomly generated numbers. For DR control purposes, control signals are generally very small and communication time is dominated by latency, so although we measured both, latency is considered to be a more determining factor of the ancillary services that could be provided by TCLs within a particular communications network.

In our tests, and in the event that the network failed and latency and bandwidth data tests could not be sent, the tests were stored as failures in the FlexBox. Once the network was restored, data was sent to the server and analyzed to understand how many failures occurred based on how many sequence numbers were missing (as well as to calculate how much time had elapsed between successful attempts).

A

B



Approximate location of devices across Managua

Figure 44: Latency Hourly Variability: [A] Hourly average latency variability, and [B] approximate distribution of these devices across Managua. is worst in the middle of the day when it is hottest and when the TCL experiences most activity.

Each latency and bandwidth test had 6 pings, and the maximum and average values described below refer to the maximum and average value within the 6 pings that occurred within each of our tests. A non-parametric Kolmogorov-Smirnov test was used to compare the latency distributions across our five samples (for the average and maximum latency length) and found them to be all statistically significant different from each other ($p \leq 0.001$; with the null hypothesis being that the two distributions being compared are drawn from the same distribution). The mean of the average latency is 642 milliseconds (sd: 185 milliseconds) across all devices (Figure 45.A) and the mean of the maximum latency across all devices is 945 milliseconds (sd: 415 milliseconds) with the maximum latency value reaching 38,000 milliseconds. We also evaluated the average latency across all devices for every hour of the day (Figure 45.A) and found the network to be faster, on average, between 5 am and 12 pm (880 milliseconds) than other parts of the day. Distance between devices does not seem to be a determining factor of latency as devices that are relatively close together were found to be as different to each other compared to devices that were further away. The latency tests show great variability among each other and throughout the day despite the fact that they are all connected to the same network (Claro 3G), are pinging the same server, are using the same technology (Huawei E3531) and run the same software. We also analyzed network dropped packets and evaluated both the number of events (binary: 1 or 0) as well as the duration of the event (seconds: 1*seconds elapsed). Because our dropped packet events have both known average rates and are assumed to occur independently of the time since the last event, we assumed a Poisson distribution to express the probability of a dropped packet occurring within a fixed time interval. Similarly, we used an exponential distribution to describe the time between dropped packets (inter-arrival times of dropped packets in the Poisson process).

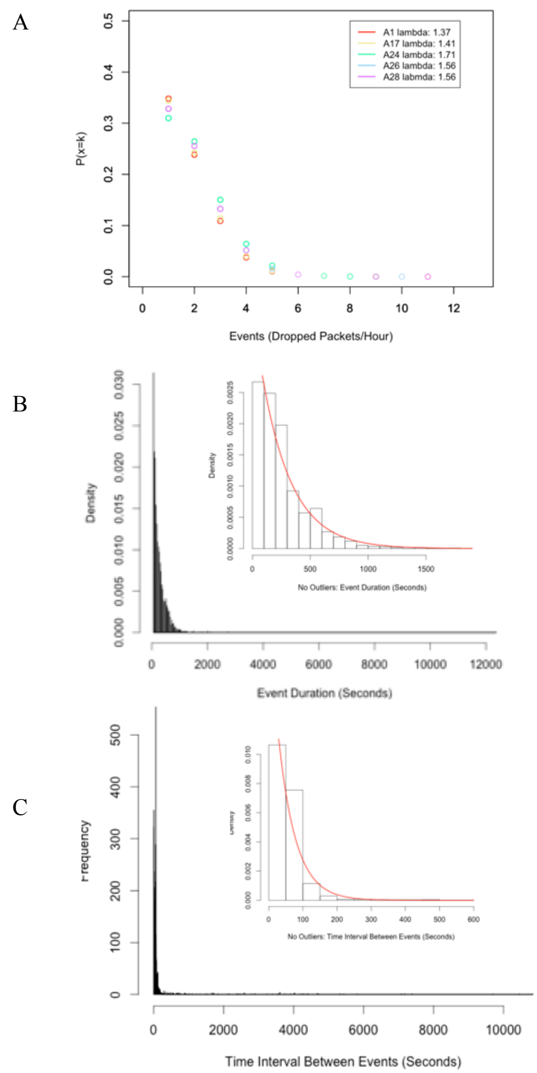


Figure 45: Poisson and Exponential Distribution Characterizing Communication Tests: Probability of number of dropped events per hour [A], distribution of event duration in seconds [B], and time interval between events [C]. Panels [B] and [C] depict the distributions without outliers and fitted with an exponential distribution (red line).

Throughout the network (Figure 44.B) each device had a different distribution for dropped packets, and therefore also a different lambda value (Figure 44.A). For all dropped packet events, the mean duration before reestablishing connection was 267 seconds (~ 5 minutes) with a 352 seconds standard deviation (min: 60 seconds, max: 206 minutes). These values are deceiving, however, because the distribution is skewed due to several extreme outliers shifting the mean to the right. Removing these outliers depicted that the duration of events follows an exponential distribution with a mean of 258 seconds (~4 minutes). Without outliers the median value is 180 seconds and the most frequent value is 60 seconds. For all dropped packet events the mean interval time between events was 106 seconds with a standard deviation of 505 seconds. Without outliers, the mean time between events is 50 seconds (median is 46 seconds) with a standard deviation of 54 seconds.

There are several findings from our system implementation that can inform how theoretical models could incorporate data from wireless sensor gateways in the future: *(1)* the use of surveys and baseline data collection could be used for more realistic assumption building before modeling begins, *(2)* while some recent work has begun to calculate the uncertainty resource potential for demand response, little attention has been placed on how user behavior increases the energy and temperature uncertainty of DR resource availability, *(3)* control algorithms are usually top-down with a load aggregator assuming user and load behavior and consumption patterns; we argue that a more holistic modeling approach could be the development of bottom-up – top-down models that incorporate behavior and appliance efficiencies in model building, *(4)* communication networks and enabling systems (such as our FlexBox) are usually discussed in the abstract, yet, the types of ancillary services that can be provided at the micro-level are conditional upon the capabilities of a specific system or technology, and *(5)* research on DR communication protocols are likely to affect not only what different services can be provided but also the design and cost-effectiveness of the enabling system itself.

The communications network' exploratory data analysis suggested that DR faces several communication challenges ahead which include a large discrepancy in the spatial quality of communications service, a high frequency of dropped packets across the network, and a high frequency in the difficulty to reestablish a connection. Future iterations of this work will involve the reduction in size of the FlexBox, the design of a system that measures temperature less intrusively, and a more inconspicuous way to measure load power consumption. In addition, future work will investigate the minimum level of grid sensing required to recover full state information from a micro-enterprise or household.

3.6 Background: Behavioral Energy Efficiency and Demand Side Flexibility

Energy efficiency has a large role to play in global long-term goals related to energy security, economic efficiency, local pollution reduction, and climate abatement (112, 246–248). While the pace of progress in energy efficiency has been satisfactory with a 2.1% compound annual reduction in primary energy intensity (the goal being -2.6% by 2030) (113, 247), and primarily led by emerging economies, numerous organizations still suggest that there is large unrealized potential for savings. 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 (112–114). Other analysis, however, suggests that this energy efficiency gap is overstated by traditional analysis (e.g., engineering estimates and empirical estimates of returns observed to investments) that fails 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) (115). Common programs such as weatherization and appliance swaps, according to some analysis, have achieved significantly smaller energy consumption reductions than anticipated(115, 175, 249).

The literature on flexible demand, largely, is pervasively dominated by theoretical and engineering analysis evaluating the mechanics, as well as the costs and benefits of large scale aggregations of flexible loads (190, 221). Theoretical analysis of flexible demand uses engineering estimates for modeling how large aggregations of thermostatically controlled loads (TCLs) can bid into grid ancillary service markets for profit, or help maintain reliable power system operations under high penetration of renewable energy (190, 221, 224, 225, 250). Other flexible demand research evaluates available sensing, actuation and control solutions for networking sensors for large aggregations of TCLs (190, 216, 217, 229, 242), and other research performs research pilots and field deployments to validate theoretical assumptions, and understand the physical engineering aspects, social dimensions, and business opportunities that can inform large-scale deployments (190, 217, 218, 241, 243, 251). While flexible demand has begun being implemented at moderate scale in commercial buildings, the residential and small business market has still been largely undeveloped. In the United States, estimates suggest that residential demand flexibility can avoid $US 9 billion per year of forecasted investment costs, and a further $US 4 billion per year in avoided annual energy production and ancillary service costs(252). In Europe, it is estimated that only 5-15% of the flexible demand potential is being utilized, and that scaling the resource could cut European peak demand by 10% or 60 GW (roughly equivalent to one-third to all European Union gas-fired power generation)(253). To our knowledge, there are no studies that have evaluated the potential for flexible demand in emerging economies; where most of the growth in global demand for electricity is expected to happen.

Crucial yet often overlooked elements in the adoption and success of energy efficiency or flexible demand programs are behavior and the participatory role of users in enabling the cost-effective deployment of new technology. Behavioral energy efficiency research has been in vogue in recent years, with a diversity of theories attempting to explain the many reasons why some programs succeed and fail, and how. Social comparisons and access to information, social cognitive theory, moralized consumer choice, political ideology, monetary incentives, and loss aversion (prospective theory), among other theories, have all been used to explain the mechanisms through which individuals (or households) chose to participate and succeed (or fail) in demand side management programs (89, 91, 180, 254–257). Similarly, these broad range of approaches have resulted in a variety of interventions and effect sizes of energy consumption reduction. A key aspect of behavioral interventions is that they are cost-effective, and if successful, can have a quick payback period for utilities, entrepreneurs and local governments. Table 11 depicts some notable papers, and summarizes their hypotheses, interventions, analyses and effect sizes.

Behavioral and user motivational aspects of flexible demand have been largely understudied. Thus far, the great majority of the literature that explores residential and small-business demand response considers users merely as consumers, or demand side resources, rather than active social agents with physical, behavioral, temporal, and budget constraints (258, 259). Within this narrow framework, it is assumed that rational individuals only respond to real-time or scheduled prices, easily adopt and use technology, and derive utility only from monetary dividends or environmental cues. Thus, flexible demand is being intellectually developed purely as regulatory and technical innovation (258, 259), rather than a tool for inclusive participatory engagement, without taking into account the diversity of barriers and drivers that have been uncovered by advances in behavioral economics. Motivation for participating in demand-side management (e.g., monetary, environmental, altruistic, community oriented) is as varied as concerns towards it (e.g., privacy, costs) (260), and more research

Author (Year)	Hypothesis and Intervention	Analysis and Control Variables:	Data	Effect Size (%)
D. Schwartz, B. Fischhoff, T. Krishnamurti, and F. Sowell (2013)	***Hawthorn Effect:*** Five weekly postcards sent to a randomly selected treatment group (N=572) simply to notify them that they were participating in a study about household electricity use (i.e., they were being observed). A control group (N=329) received nothing.	OLS with robust standard errors clustered by household: treatment vs. control dummy, intervention month, heating and cooling degree days.	Monthly electricity collected before, during, and after the experimental period for treatment and control groups.	2.7% energy reduction during study period relative to control group. No observed post-treatment effect.
H. Alcott (2011)	***Social Comparisons and Targeted Energy Efficiency Suggestions:*** A treatment group (N=306,670) received energy reports at regular intervals with a social comparison to similar households (e.g., household size, square footage, heating type) with labels describing them as "Great" "Good" or "Below Average" households, and energy efficiency tips based on historical usage patterns and demographics. A control group (N=281,776) received nothing.	(1) OLS differences-in-differences fixed effects estimator with robust standard errors: treatment vs. control dummy, post treatment indicator, month-year dummy, household fixed effects and degree days. (2) Discontinuity regression to explore if different injunctive categorizations cause large differences in treatment effects.	Monthly electricity collected before, during, and after the experimental period for treatment and control groups.	2% average treatment effect (1.4% - 3.3%). 3.3 c/kWh (1.3 - 5.4 c/kWh)
H. Boudet, N. M. Ardoin, J. Flora *et al* (2016)	***Social Cognitive Theory:*** Energy efficiency lessons delivered to 15 girl scout troops (N=159 households) with three main activites: (1) household behavior reporting/monitoring actvity, (2) rehearsing and taping behavioral change activities to be taught/performed, and 3) a pledge of behaviors to be implemented. Intervention included a parent targeted newsletter and materials to help implement energy efficiency changes (e.g., reminder stickers, power strips, and tyre pressure gauges). A control group received a simlar intervention targeted towards a food-and-transportation related behaviors.	Mixed effects linear regression (Y: Changes in reported behaviours between baseline and post-test and between baseline and post-intervention follow-up (energy savings in kWh were calculated, not measured): baseline behavior scores and baseline variable interactions.	Self-administered energy-saving behaviour surveys	49% and 29% self reported increase in residential energy-saving behaviours. 5% and 3% savings in annual energy consutmpion (estimated).
O. Asensioa, and M. A. Delmas (2015)	***Disclosure of environment and health-based externalities (moralized consumer choice):*** One treatment group (N=43) receiving environmental and health impacts of energy consumption (weekly emissions and listing of particular health consequences; e.g., childhood asthma and cancer), another treatment group (N=42) with high-resolution information about energy costs (weekly costs), and a control group (N=33).	Standard feasible generalized least squares estimator: observable household characteristics, and seasonal controls including weather (degree hours) and time trends (time dummies)	Houly energy consumption (kWh) appliance-level kWh consumption categories are: (i) lighting, (ii) heating and cooling, (iii) plug load, (iv) refrigerator, (v) dishwasher, and (v i) other kitchen.	19% and 8% average treatment effect for households with and without children receiving messages regarding environmental and health impacts. The treatment group receiving cost related information had no
D. M. Grometa, H. Kunreuthera, and R. Larrick (2013)	***Political ideology affects energy-efficiency attitudes and choices, investigating:*** (1) Participants recevied a short description of energy efficiency and answered questions about the psychological value they placed on reducing carbon emissions that harm the environment, reducing dependence on foreign oil, and reducing the financial cost of energy use to consumers (N=657), (2) Participants received $2 to purchase a light bulb (or keep the money). In one condition the bulbs had the same price ($0.50), and in the other condition, the CFL bulb was more expensive ($1.50) than the incandescent bulb ($0.50). Environmental salience was manipulated by using a "Protect the Environment" sticker or a blank sticker. Aside from the message, the stickers were identical (4 treatment groups, N=210).	Linear and logistic regressions: ideology, age, education, gender, and income	Surveys	Relating energy-efficient products to environmental concerns can negatively affect the demand for these products, specifically among persons in the United States who are more politically conservative
A. Sudarshan (2017)	**Social Comparisons and Monetary Incentives (India):** One treatment group (N=124) receiving a weekly report card with an energy comparison to other households, another treatment group (N=240) received a report card in addition to performance based monetary incentives for reducing energy consumption, and a control group (N=124).	OLS linear and log fixed effects model: treatment vs. control dummy	Cumulative consumption aggregated over two or three days to create weekly reports. This was obtained by electronically querying the meter status for all households at the same time thrice a week. Weekly electricity collected during, and after the experimental period for treatment and control groups. No baseline data collected.	7% average treatment effect during the study period. Weekly reports with performance based monetary incentives observed no detectable change in consumption.
S. Bagera and L. Mundaca (2017)	**Loss Aversion and Prospect Theory: Treatment group:** (N=11) received a smart meter that provided high resolution energy and cost information framed as "losses" (e.g., "Money lost from electricity consumption", instead of Monety saved"). A control group also received a smart meter with the same information but without framing. A second control baseline received nothing (N=3000).	Baseline to post-intervention differentces-in-differences t-test	Hourly energy consumption (kWh)	5% - 18% energy reduction for treatment group (2%-7% control) depending on analytical approach.

Table 11. Diversity of Behavioral Factors Affecting Energy Efficiency Adoption and the Effectiveness of Interventions

in varied contexts is needed to develop approaches and technologies that can reach the greatest number of people.

In this chapter we present what we believe to be the first randomized pilot of a paired behavioral energy efficiency and flexible demand intervention in low, low-middle income neighborhoods in Latin America. We find that the houses and micro-enterprises randomly assigned to the intervention (30 units) significantly reduced their energy consumption relative to themselves and to a control (30 units), and participated at length in peak shaving flexible demand events. Energy education, small business and women empowerment, as well as reducing perceived stress of energy expenditures appear as potential societal co-benefits. When given the option to choose detailed energy information over micro-payments as a reward for participation in peak events, most participants chose information over money, contradicting literature that points to monetary rewards or environmental cues as the main motivators for participating in flexible demand programs. The results from our intervention are best explained by Scarcity (7) and other concepts in behavioral economics on which we expand below.

3.7 Managua Pilot Study

Nicaragua provided an ideal enabling environment for our implementation. It is the country in the western hemisphere with one of the highest penetrations of non-hydropower renewable energy, and is also the second poorest in the region. It is a socialist country that has made large strides to improve quality of life for its population after decades of civil war and political turmoil, but still suffers from low scores on ease of doing business and relatively low infrastructural quality. At the micro-level, higher energy prices, pre-existing load-controlling behavior, a relatively high-tolerance for service interruption, and a perceived high stress due to electricity bills could make for a suitable environment for behavioral energy efficiency and flexible demand strategies. On the other hand, lack of education, little understanding of electricity bills, mistrust of the electric utility, and lack of technological literacy could present serious barriers to the success of an information and technology implementation.

3.7.1: Social Demographics, Energy Behavior, Perspectives and Concerns

We used the urban census of Managua to select neighborhoods of similar social demographics (overcrowding, access to basic services, housing quality, education level, economic dependency and poverty) where we could perform a broad multiple objective baseline to better understand the household and micro-enterprise urban energy challenge. Three enumerators walked these neighborhoods performing a baseline survey of general population characteristics and energy consumption of households and micro-enterprises. The survey collected baseline characteristics (e.g., age, education level, gender, and appliance ownership) and performed a needs assessment, gaining insight on local perspectives of climate change, energy costs and grid adequacy, the perceived usefulness of energy information, and a variety of energy management perspectives. Our surveys and interviews included 216 households and 219 micro-enterprises (e.g., butcheries, chicken shops, mom and pop shops, milk and cheese shops).

At a later stage, a random selection of 40 micro-enterprises and 20 households (treatment: 20 micro-enterprises and 10 households, control: 20 micro-enterprises and 10 households) were chosen to be part of our study from a 435 micro-enterprise and household baseline. The treatment group was told that they would receive the intervention (described below) in step wise increments throughout the length of the study period in exchange for detailed energy information and a micro-payment of $6 month. The control group would receive nothing but would participate in a baseline, midline and endline together with the treatment group. Participants (treatment and control) were told that at the end of the study they would be part of a raffle to win either a new refrigerator or freezer (or the equivalent in cash). Participants (treatment and control) agreed to share their historical energy consumption profiles ($US and kWh) for up to a year. All the randomly selected participants in both the treatment and control group agreed to participate in the program. All baseline survey participants, as well as those in the treatment and control group consented to the study, and it was approved by University of California Berkeley's Institutional Review Board and Committee for the Protection of Human Subjects (CPHS Protocol Number 2014-12-6955).

Baseline collecting for the sensor network began in July 2015 for the treatment group and lasted until January 2016. During this time period, there was no interaction with the participants except for baseline data collection from the sensor gateway (FlexBox). From January 2016 to July 2016 the treatment group began receiving paper energy reports with incremental amounts of information being added to every report. The flexible demand and real time text-messaging intervention began in July 2016 and lasted until December 2016.

The survey results elucidated many themes that allowed us to design adequate project invitation mechanisms, and later, effective information technology systems to retain our project participants. Energy, food, and access to basic services were the top three self-perceived present concerns in our sample (23%, 20%, and 12% of the sample ranking an issue as a top concern, respectively) with most members finding it very-hard (18% of sample) or hard (43% of sample4) to pay their monthly electricity bill. The combination of relatively high electricity prices (0.21 $/kWh) and low incomes thus creates a constant source of stress in these neighborhoods, with 60% of the sample checking their energy meter on a daily basis and keeping an energy calendar, or simply taking "energy notes" (energy meters are sometimes located outside houses, and other times located with other energy meters on a street corner). Furthermore, 72% of the surveyed households and micro-enterprises unplugged their refrigerator once, or at different times of the day, to reduce their energy consumption. Many of the households and MEs perform this practice on a daily basis while explicitly acknowledging that they don't know if their strategies are being successful. An additional incentive for a careful energy management approach is that a monthly consumption below 150 kWh leads, on average, to a 60% reduction in the unit cost of energy $US/month (cost of energy for 150 kWh/month vs. 300 kWh/month). For MEs, energy expenditures represent a perceived 30% of their total monthly business costs, and for households this represents 8% of their total household expenditures. On average, households and MEs overestimated their total monthly energy costs by $US 23 (median: $US 5, sd: $US 112), and underestimated their monthly consumption by 30 kWh (median: 16 kWh, sd: 110 kWh), or 10% lower than their actual energy consumption. The Nicaraguan census suggests that, on average, electricity represents only 2% of the urban household's budget.(261) We argue that the percentage in our sample is higher because it closely reflects the budget conditions of other low, lower-middle income neighborhoods in many other countries across the world, who devote a relatively larger portion of their budget towards access to basic services (e.g., energy and water) (14, 262).

Despite over half the households and micro-enterprises experiencing outages on a frequent basis (53%), only 43% found service reliability dissatisfactory, and only 16% found power quality dissatisfactory. This relatively high-tolerance for reliability issues in Nicaragua, we argue, was inherited from a recent time period when frequent rolling blackouts were a regular occurrence but also suggests another behavioral attribute that is complementary to flexible demand. With regards to the value of information, we found the sample to be divided between thinking the information provided by the utility bill to be useful (48%), and it being useless (24%) or more or less useful (42%). According to a survey performed by a local think tank, the contents of an energy bill are unclear or confusing for 70% of end users in Nicaragua. Climate change was regarded as the issue of most concern in the near future (36%), closely followed by foreign oil dependency (24%), and future increases in electricity prices (20%). Despite this concern, however, we found climate change concern to be mainly related to deforestation (20%) and pollution from cars (12%), as well as wide a variety of contributing factors to climate change ranging from religious factors to urbanization. Pollution, or emissions, from electricity generation were not mentioned as one of the local contributing factors to climate change.

In combination, we find that ubiquitous voluntary load disruption (unplugging refrigerators), relatively high perceptions on service reliability despite frequent outages, and relatively high-energy costs (and relatively high perceived energy costs) represent enabling behaviors and opportunities for flexible demand and behavioral energy efficiency. Perspectives on contributing factors to climate change and the usefulness of information allowed us to design an adequate intervention as is described below.

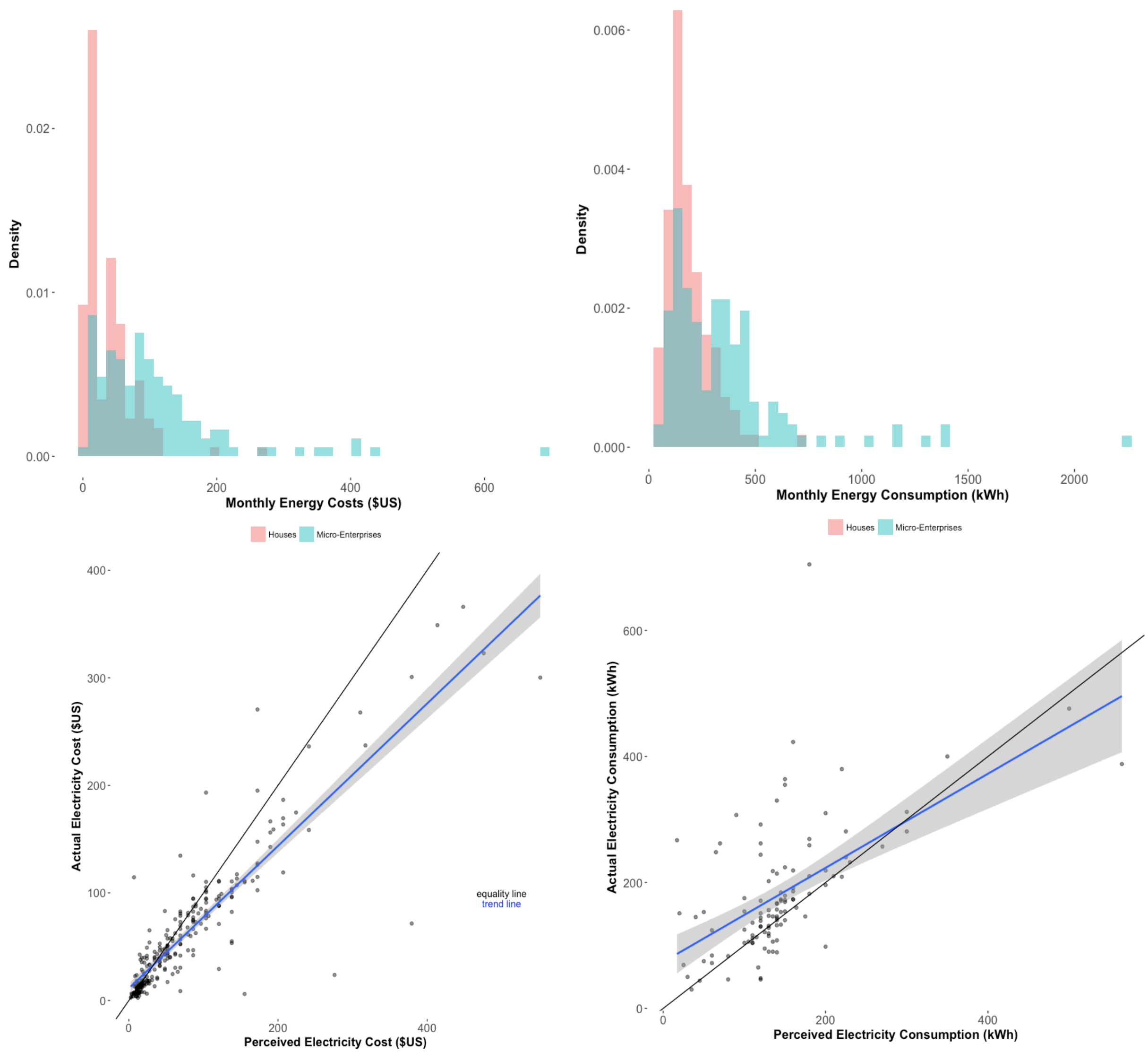


Figure 46. Distribution of Monthly Energy Costs for Households [A] and Micro-Enterprises [B], and perceived vs. actual monthly costs ($US) [C] and consumption (kWh) [D]

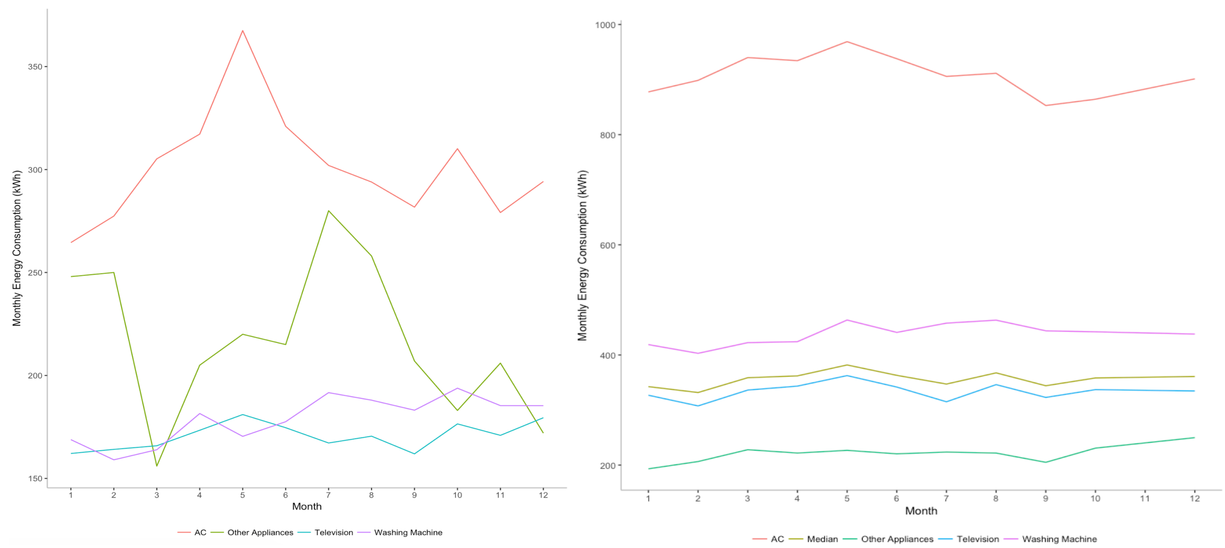


Figure 47. Baseline Monthly Energy Consumption for Households [A] and Micro-Enterprises [B]

Sample Size	
Houses	N = 219
Micro-Enterprises	N = 216
Age	47 (15)
Education	First two-years of high school
Median Monthly Energy Consumption, Energy Costs and Cost per Unit of Energy	
Houses	160 kWh/month, 30 $US/month, 0.19 $US/kWh
Micro-Enterprises	305 kWh/month, 71 $US/month, 0.23 $US/kWh
Total bill Houses vs. Micro-Enterprises [1]	22 $US/month vs. 86 $US/month
What is a problem that is currently on your mind right now?	
Energy	23%
Food	20%
Access to Basic Services	12%
Unemployment	10%
On a month-by-month basis, how difficult is it for you to pay your electricity bill?	
Very hard	18%
Hard	43%
Relatively easy	18%
How do you pay your electricity bill? (how much time do you spend, minutes) [2]	
In person at bank	44% (60 min)
In person at the utility's office	34% (60 min)
By phone	5% (15 min)
In which season do you consume more energy?	
Summer	94%
Winter	6%
Do you turn your refrigerator at some point during the day?	
Yes	72%
No	28%
What do you do to monitor your electricity consumption? (N=67) [3]	
heck the meter readings on a regular basis (calendar)	30%
Check the meter readings on a regular basis (notes)	30%
Compare bill, month-by-month	11%

[1] The total monthly bill is lower than the total monthly enery cost because the total cost is reduced if the house or micro-enterprise achieves to be below a consumption of 150 kWh/month.

[2] Could represent a proxy for technolgy know how, as it is very easy to pay with a cellphone, yet people mistrust technology or do not have bank accounts.

[3] This breakdown is only for people who responded that they closely monitored their energy consumption.

Table 12. Selection of baseline characteristics and perspectives on financial burden and future concerns.

Of the following issues which ones do you consider to be of most concern in the future? [1]	
Climate change	36% (21%, 17%)
Oil dependency	24% (31%, 28%)
Electricity prices	20% (28%, 35%)
In your opinion, what is the main cause of climate change? [2,3]	
Deforestation	20%
Pollution from cars	12%
Humanity	1%
How concerned are you about climate change? How concerned are you about a future with more extreme hot days and extreme rain days?	
Very Worried	24% (66%)
Worried	51% (26%)
Indifferent	15% (1%)
How useful is the information that is provided by the utility? [4]	
Useful	48%
Useless	24%
More or less useful	18%

[1] Houses and MEs could rank future issues in first, second, or their place in order of importance

[2] This question was only performed on people who answered "Yes, I know what climate change is" (N=132)

[3] Open answer, dozens of answer types appeared, ranging from 'punishment from god', to sunlight, greed, forest fires, and urbanization as the causes of climate change.

[4] Range went from very useful, to useless. Use of information (electric bill) ranges from making official complaints to the utility, to manage business costs, and to keep a detailed control of energy consumption (among many others)

Table 13. Baseline perspectives on information and climate change

Micro-Enterprises	
What is the biggest financial burden on your small business? [1]	
Energy	88% (5%)
Loans	5% (24%)
Employees	3% (12%)
Approximately what are your total energy costs and your total business costs? [2]	30% (12% - 48%)
Houses	
Approximately what are your total energy costs and your total household expenditures? [2]	8% (4% - 19%)

[1] Houses and MEs could rank issues in first, second, or their place in order of importance

[2] (Median 25th percentile - 75 th percentile)

Table 14. Baseline Financial and Energy Related Burden

Have electricity prices been increasing over time?	
Prices have increased	72%
Prices have stayed the same	21%
Prices have reduced	7%
Do you experience power outages?	
Yes	53%
No	47%
If yes, how often do you experience power outages?	
Once a month	60%
Once a week	30%
Everyday	7%
How satisfied are you with your service reliability?	
It's Ok	51%
Not satisfied at all	17%
Very satisfied	16%
How satisfied are you with quality of power?	
Very satisfied	50%
It's Ok	14%
Not satisfied at all	2%

[1] Only the top 1-3 results are shown per survey question

Table 15. Baseline Perspectives on Prices and Reliability

	Micro-Enterprises	Houses
Light bulbs	96%	96%
Cellular	84%	96%
Internet	30%	65%
Radio	52%	70%
Television	75%	96%
Computer	29%	57%
Refrigerator	97%	88%
Fan	63%	92%
Microwave	23%	45%
AC	9%	11%
Blender	40%	85%
Washing machine	11%	84%
Iron	*39%*	90%

Table 16. Baseline Appliance Ownership (N=435)

3.7.2 Data: Monthly Bills, Sensor Gateway and Grid-Level Open Access Data

As detailed above, the intervention was a combination of energy information (paper report and text messages) and a sensor gateway for engaging in demand side flexibility. The first paper energy report was only a comparison of each participant against energy efficient participants, average participants, and above average participants. As the project progressed we slowly increased the amount of information we provided, and would include details that the participants would ask for. Information included hourly energy consumption values (month average and historical), weekly energy consumption (month average and historical), monthly energy consumption, fridge hourly energy consumption (month average and historical), fridge weekly energy consumption (month average and historical), relationships between ambient temperature and household and fridge energy consumption and fridge door openings, and relationships between internal fridge temperature and fridge energy consumption and fridge door openings. In addition, we provided two figures every month that would show Nicaragua's demand curve and country energy generation profile by resource. These data were a combination of information gathered through the participant's monthly energy bills and information from the FlexBox sensor gateway.

For real-time energy alerts, users would text an assigned project phone number and let us know how much energy they would like to consume in their current month (e.g., "Limit for August is 320 kWh"). Our cloud server would receive the request via Twilio and would continuously send energy alerts to the user via text messages as various energy consumption thresholds were crossed (e.g., "You've consumed 10% of your total energy budget" or "Careful! You have reached 90% of your monthly energy budget!). Users could change their energy limit threshold any time. Furthermore, the text-messaging system was used to alert users one-day before a peak pricing event would occur (with length of the event and approximate time when it occur) and during the time of the event.

Each sensor gateway or FlexBox had seven sensors, which collected minute-by-minute data on all paramenters. Two DS18B20 water proof thermocouples (measuring fridge or freezer internal temperature), a DHT22 temperature and humidity sensor (monitoring room environment), a magnetically actuated reed switch (monitoring fridge door activity), and an mPower Ubiquiti device that would both monitor energy and power consumption, and control an outlet switch. An Aeotec power meter would monitor house power consumption at the electric service panel(190). Additions to the sensor gateway included a small cage to surround the DS18B20s to reduce thermal contact conductance when inside the refrigerator, and thin telephone cable to extend their length(190). Wi-Fi was used to communicate with the mPower load monitor and switch control, a Z-Wave dongle was used to communicate wirelessly with the power meter (electric panel), and we added a 3G GSM modem for remote data transmission and actuation control.

Open access data from Nicaragua's National Dispatch Center was used to monitor day ahead market prices and to send text-messages when peak pricing events would be occurring. During a peak pricing event, if a participant hadn't responded "No" to participating an event, it's FlexBox would turn the refrigerator off. During the baseline, we captured internal thermal set points at which the refrigerator would be naturally oscillating (compressor on vs. compressor off). At peak pricing events we would turn refrigerators off, but we would use the FlexBox's internal fridge and ambient temperature sensors to ensure that the internal temperature did not reach an unsafe temperature that was higher than previously recorded in our baseline for each of our participants (when participants would be plugging and unplugging their refrigerators on their own). Participants could send a text-message to stop being part of any given peak pricing event, or could simply plug their fridge on another outlet on the controllable power strip that we provided to have their fridge or refrigerator working again.

In the first few projects of baseline data collection the treatment group lost ten participants. Five participants left the study because they thought the sensor gateway was significantly increasing their consumption (despite receiving a small contribution that more than covered energy consumption of the sensor gateway at the outset), three participants had to sell their micro-enterprises to pay medical bills and debts (including debt to the electric utility), and two left the program because they said that it was not delivering on the promise of giving them high resolution information (the purpose of the baseline was to collect data without a formal intervention). The size of the control group did not change. The rest of this chapter relates to the participants that remained throughout the duration of the project.

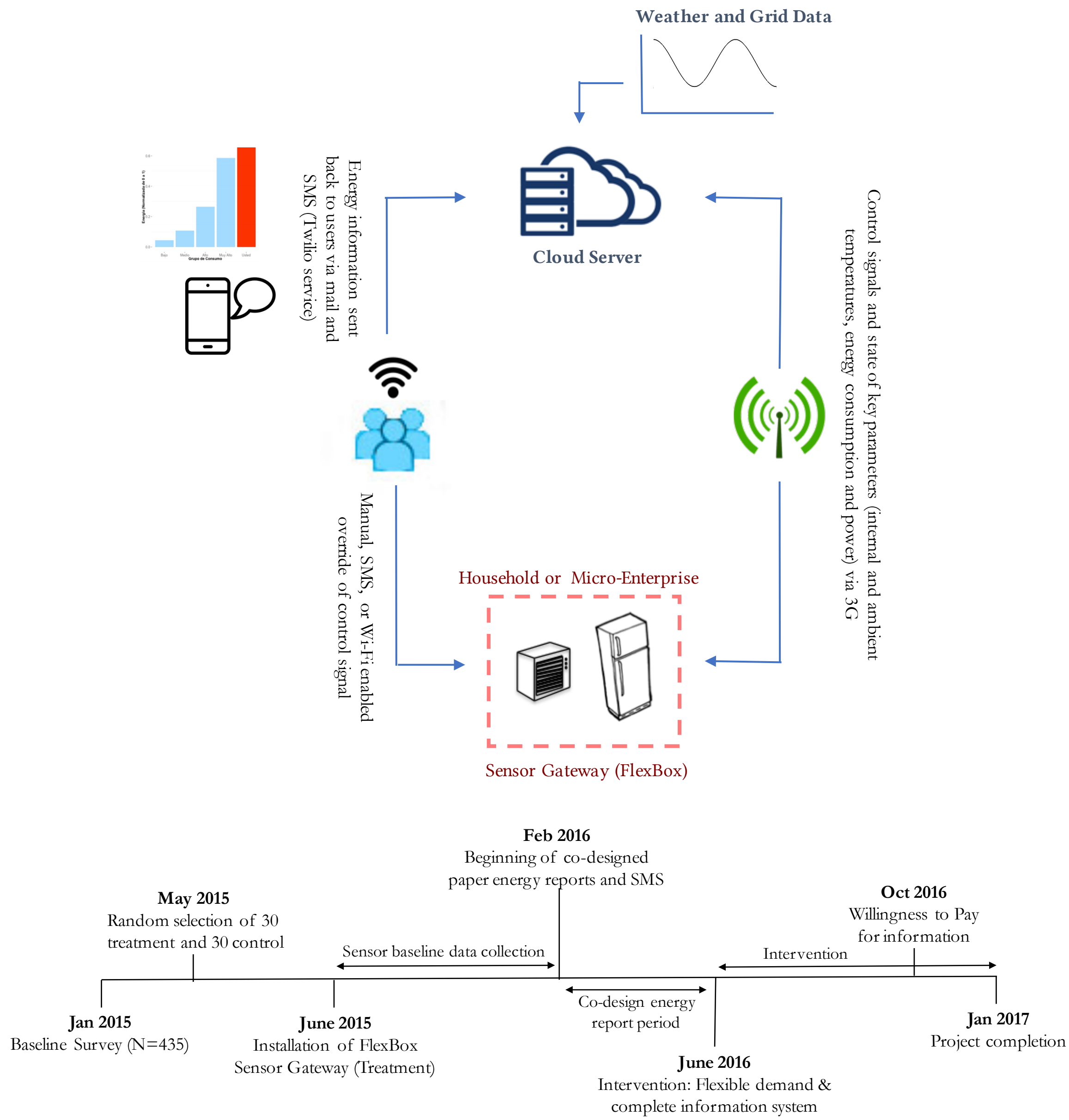


Figure 48. Information System and Sensor Gateway (FlexBox): Key parameter data is retrieved from the household and thermostatically controlled loads (TCLs) via 3G to a cloud server. The cloud server collects all participant data, evaluates dispatch center day ahead prices and schedules peak price events; it also sends energy limit alerts tailored to each participant. Data is aggregated and monthly reports are sent to each participant. The user may override control signals at anytime manually, via SMS or, via local Wi-Fi network.

3.7.3 Methods and Analysis

Given balanced outcomes for treatment and control, we use Bayesian estimation for group comparisons, and inter-group comparisons. The approach provides complete distributions of credible values for group means and standard deviations (and their difference), effect size, and the normality of the data (9, 10). We obtain both the magnitude and uncertainty of estimates related to the difference between central tendencies, as well as the difference in variability between two groups without making assumptions about the underlying distribution of the data. Bayesian inference reallocates credibility toward parameter values that best represent new data, and thus, the analysis necessitates a prior distribution of credible parameter values that could characterize our data given previous knowledge(9). Here, we build a prior distribution using both our baseline survey estimates (N=435), and an extended literature review of behavioral energy efficiency projects across the world (89, 180, 183, 184, 254–257, 263). The credibility of the posterior estimate for differences in central tendency and variability (the probability of the parameters given the data) is the product of the likelihood (data, given the parameters) and the prior, divided by the new evidence (the data). A Marko Chain Monte Carlo (MCMC) algorithm estimates the posterior distribution generating thousands of combinations of parameter values which are graphically summarized by histograms from which one can establish the credibility of a result. When assessing posterior estimates, the high-density interval (HDI) and the region of practical equivalence (ROPE) help determine the credibility of an observed result. The HDI is a 95% density interval where the bulk of the most credible values fall, and ROPE represents parameter sizes that may be deemed negligibly different from the null. In our analysis, we use a ROPE ranging between -2% and 2% (representing group comparisons and the Hawthorne effect)(254)'(180), representing a small reduction, no change, or a slight increase in energy consumption. Results within the HDI and outside ROPE are deemed credible.

Bayesian estimation is used to compare pre- and post-implementation monthly energy consumption (kWh/month), month-by-month differences during the intervention period (e.g., comparing energy difference between August and September 2016) and annual differences between the same months one year afterwards (e.g., August 2015 vs. August 2016). Only the third analysis controls for group differences and seasonal consumption patterns that affect both weather and behavioral patterns in Nicaragua. For flexible demand, we use Bayesian estimation to identify credible differences in refrigerator and freezer energy consumption pre-vs. post-implementation (all hours), and only during peak pricing hour events. Our analysis uses the R statistical programming language (264), the MCMC sampling lag called JAGS (191), and the BEST program for Bayesian means tests in R (9, 10).

3.8 Results and Discussion

3.8.1 Magnitude and Uncertainty of Behavioral Energy Efficiency

We use three different measurements and two methodologies to determine the magnitude, direction and uncertainty of our intervention. The three measures include comparing pre- and post-implementation monthly energy consumption (kWh/month), month-by-month differences during the intervention period (e.g., comparing energy difference between August and September 2016) and annual differences between the same months one year afterwards (e.g., August 2015 vs. August 2016). Figure 49 depicts the posterior distribution obtained via Bayesian estimation for each of these three measurements. A Markov Chain Monte Carlo (MCMC) methodology is used to generate a large representative sample of credible parameter values from the posterior distribution.(9).

Pre-implementation, energy consumption is balanced between treatment (μ_1: 211 kWh/month) and control groups (μ_2: 207 kWh/month), with balanced education levels, neighborhood location, and number of appliances. The posterior distribution in Figure 49A depicts both the 95% high density interval (HDI) and the region of practical equivalence (ROPE). The HDI provides a summary of where most of the credible parameter values lie, with values inside the HDI having a higher probability than those outside of it.(9) Values inside the HDI have ROPE enclose parameter values that are deemed to be negligibly different from the null value, with its size being determined by the application domain, expertise and existing literature.(9) Because we find the ROPE (a difference of 0-5 kWh between groups) to be fully within the HDI we can conclude our treatment and control groups to be not credibly different from each other pre-implementation. Bayesian estimation also provides credible values for the difference in standard deviations between the two groups, the distribution of credible effect sizes, and the credible values of the normality parameter. Similarly, we find the standard deviation differences and effect size to not be credibly different from zero (and ROPE), pre-implementation. Distributions for estimated parameters μ_1, μ_2, $\mu_1 - \mu_2$, sd_1, sd_2, $sd_1 - sd_2$, normality parameter and effect size are provided in the supplemental information.

We use three different measurements to evaluate the effect of our intervention. Post-implementation monthly energy consumption (kWh/month) includes the months during which the treatment group had the intervention (June through October, inclusive). These months are different from the pre-implementation and baseline and are therefore affected by seasonal changes in consumption, federal holiday days (Figure 49B). Month-by-month differences during the intervention period (e.g., comparing energy difference between August and September 2016) are aimed at evaluating whether or not the treatment group experienced consecutive reductions in energy reduction post-implementation compared to the control group, but do not take into account seasonal consumption variation and federal holidays (Figure 49C). Finally, annual differences between the same months one year afterwards (e.g., August 2015 vs. August 2016) control for both seasonal variation in consumption and federal holidays. Thus, monthly energy consumption (kWh/month) of each household or micro-enterprise in the treatment and control group is compared with itself one year ago for every month during the intervention period (Figure 49D).

We use a ROPE of -5 to 5 kWh for post-implementation monthly energy consumption comparisons and find the treatment group to consume 13.4 kWh (6%) less than the control group, on average. However, bayesian estimation suggests both that zero and ROPE fall fully within the HDI, suggesting that there is no credible difference in monthly energy consumption between treatment and control during the intervention months. For month-by-month and month-annual year comparisons we use a smaller rope (-2 to 2 kWh) as we are comparing differences in energy. A reduction of 2 kWh represents up to a 3% energy reduction in our sample, representing a restrictive region in which our results can be credible. On average, treatment vs. control month-by-month energy reductions were 7.46 kWh (4%) lower for the treatment group with a value of zero being fully outside 95% of the most credible values in the distribution. However, a small portion of the ROPE falls within the most credible values, suggesting that our intervention could have led to a reduction merely because of something like Hawthorne effect (described in table 11). We consider the most important comparison to be the month-annual differences to be the most robust as they represent both differences within a household or micro-enterprise for every intervention month against itself one year ago, and a comparison between treatment and control groups. Parameter estimates suggests that, on average, the treatment group experienced a 16.2 kWh (9%) energy consumption reduction when compared to the treatment group. In this case, both zero and ROPE are fully outside about the HDI suggesting that the groups are credibly different from each other. Results for all estimated parameters with each of these measurements are provided in the supplementary information.

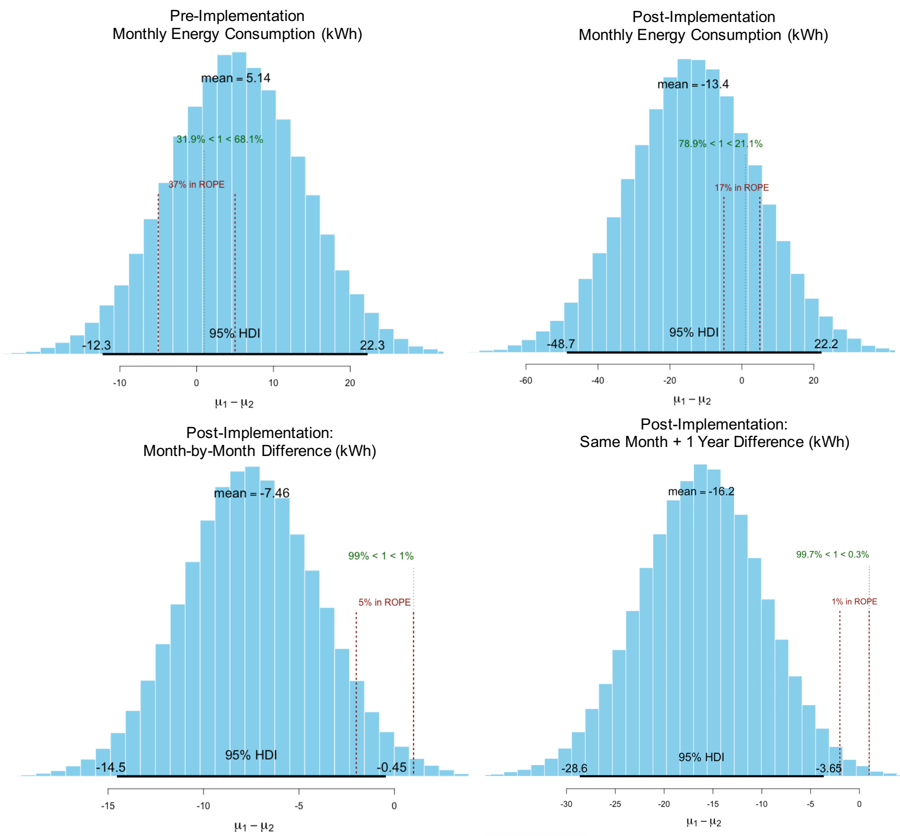


Figure 49. Bayesian Posterior Estimates Treatment (μ1) vs. Control (μ2): [A] Pre-implementation monthly energy consumption (kWh/month), [B] during-implementation monthly energy consumption (kWh/month), [C]month-by-month differences during the intervention period (e.g., comparing energy difference between August and September 2016) and [D] annual differences between the same months one year afterwards (e.g., August 2015 vs. August 2016). Black line on x-axis represents the 95% high density interval (HDI), and the red line represents the regional of practical equivalence (ROPE).

3.8.2 Full Results of Bayesian Estimation - Behavioral Energy Efficiency

The figures below depict the full results from the Bayesian estimation of behavioral energy efficiency. For each figure, the top right shows histograms as representative examples of posterior predictive distributions for both groups superimposed (265). On each figure, the left column depicts the data (marginal) of the five-dimensional posterior distribution (μ_1, μ_1, sd_1,sd_2, and normality parameter). The lower right shows posterior distribution of mean and standard deviation differences, and effect size. The previous section provided comparisons and discussion on changes on energy consumption rather than changes in costs, as costs would be subject to other confounding factors including month-to-month changes including monthly changes to rates performed by the regulator, rates changing due to energy consumption thresholds (e.g., below and after 150 kWh, below and after 300 kWh), and rates varying for households, small-businesses and retirees.

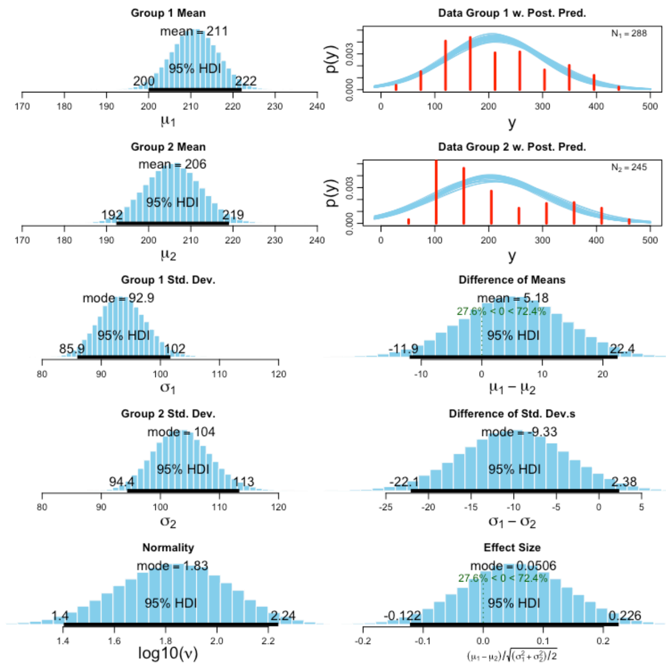


Figure 50. Pre-Implementation Monthly Energy Consumption (kWh) Treatment vs. Control

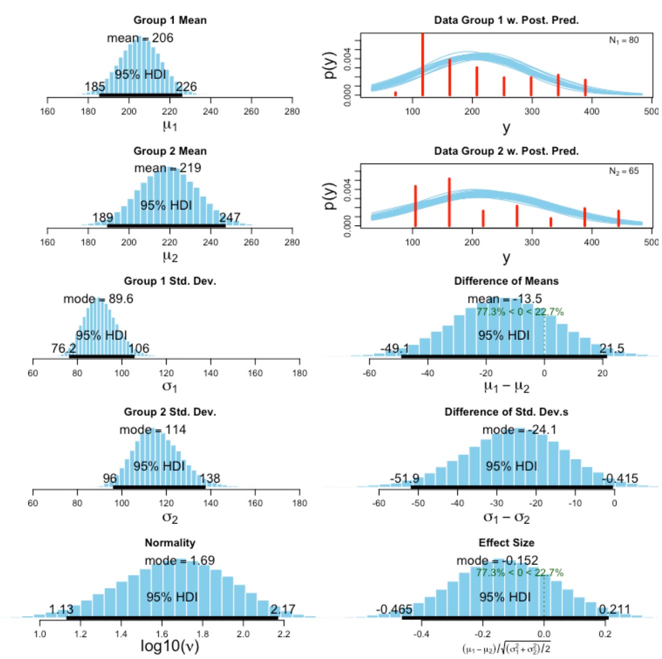


Figure 51. Post-Implementation Monthly Energy Consumption (kWh) Treatment vs. Control

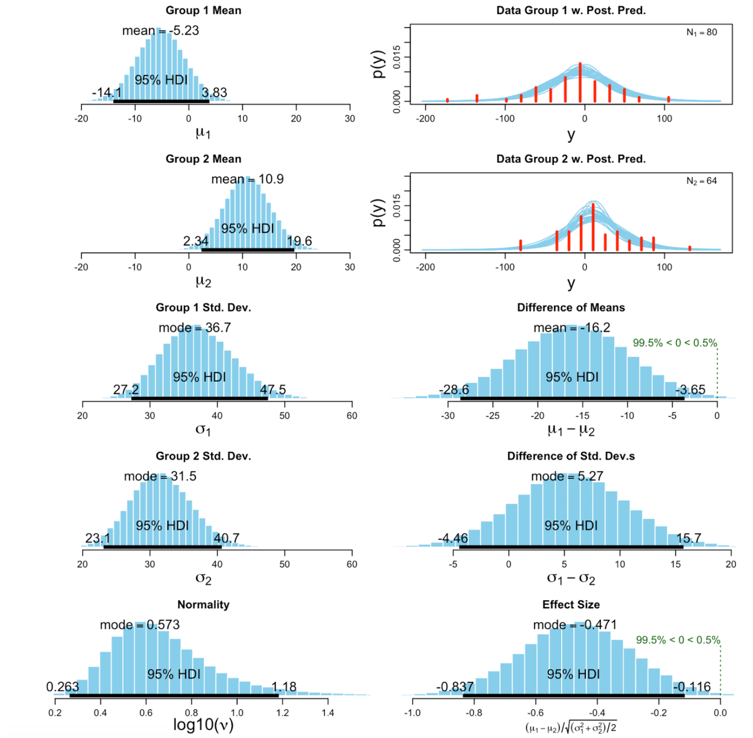


Figure 52. Full Results of Post-Implementation Same Month + 1 Year Difference (kWh) Means test Treatment vs. Control

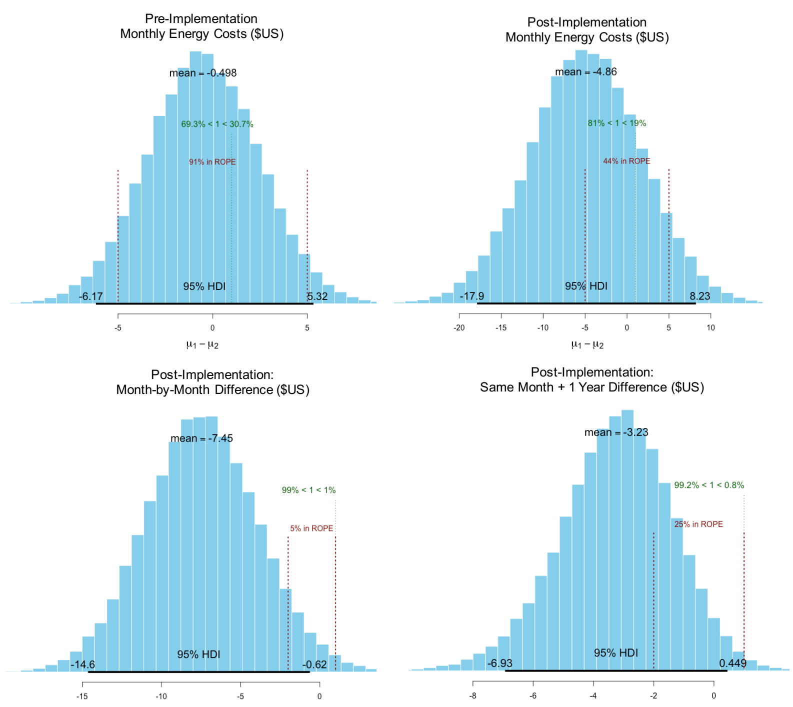


Figure 53. Bayesian Posterior Estimates Treatment (μ_1) vs. Control (μ_2) Pre- and Post Intervention ($US/Month)

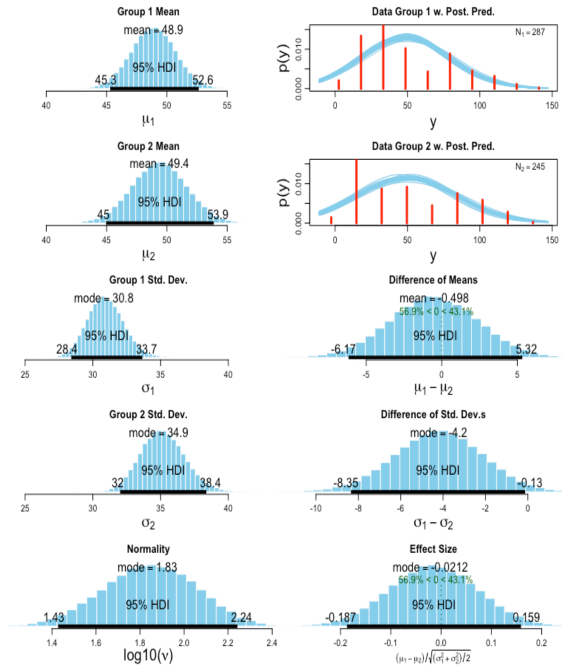


Figure 54. Pre-Implementation Monthly Energy Costs ($US) Treatment vs. Control

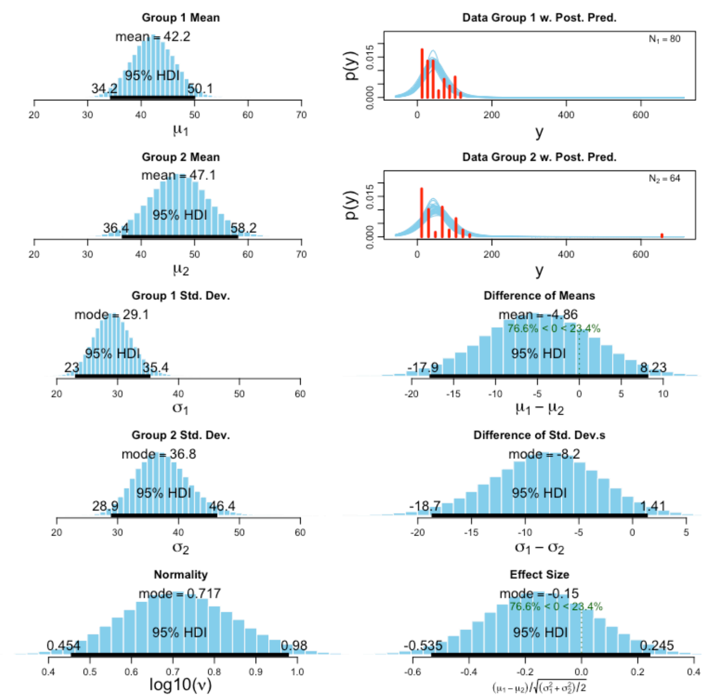


Figure 55. Post-Implementation Monthly Energy Costs ($US)

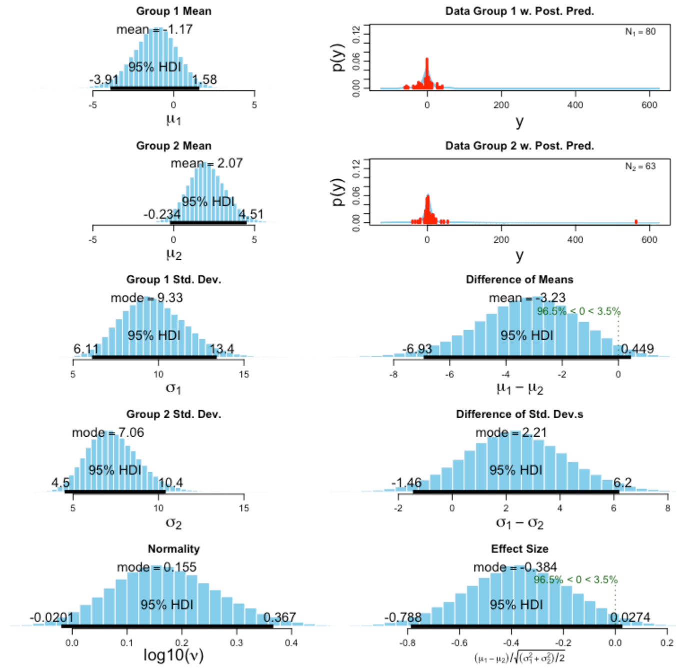


Figure 56. Post-Implementation: Month-by-Month Difference ($US)

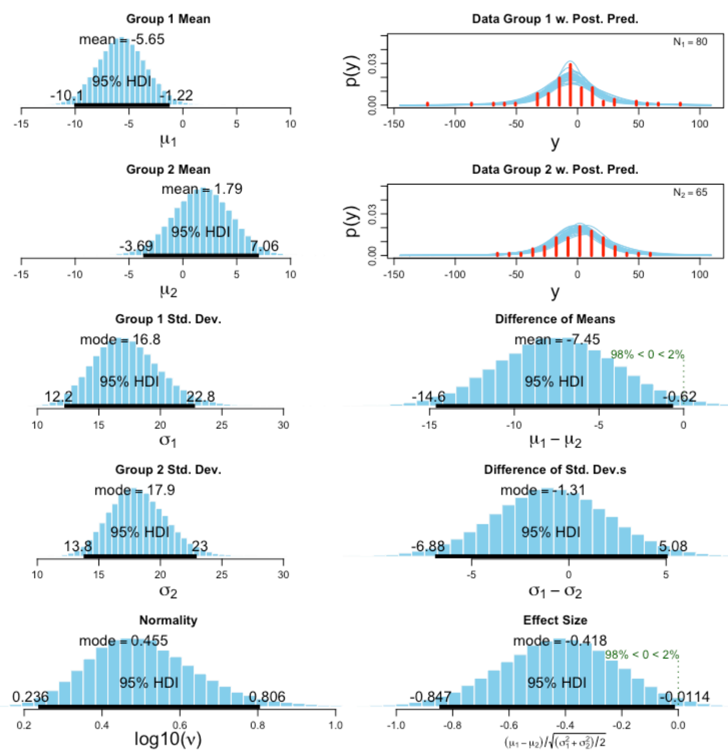


Figure 57. Post-Implementation: Same Month + 1 Year Difference ($US)

3.8.3 Participation and Impact of Flexible Demand

Project participants participated in two different forms of demand flexibility. In the first, participants were able to schedule consumption of their freezer or refrigerator at different times of the day based on preference (e.g., off from 20:00 to 4, or off from 12 to 8 pm). The Flexbox would control and keep track of the hours when the users would like their refrigerator to be disconnected, while allowing the user to re-establish control of the refrigerator at any time (they were also able to change their preferred disconnected hours at any point). For the second, participants would be told the schedule for daily peak price events ahead of time (one day ahead of time, and during the same day of the event) via SMS and they could either participate in the event (and reply nothing to the SMS), or not participate in the event (and reply "No" to the SMS, or simply switch outlets in the power strip provided). No project participants left the project once the demand flexibility intervention began. Figure 58 depicts freezer and refrigerator energy consumption per hour pre- and post- the demand flexibility implementation, the latter displaying a more scheduled and controlled fridge energy consumption pattern.

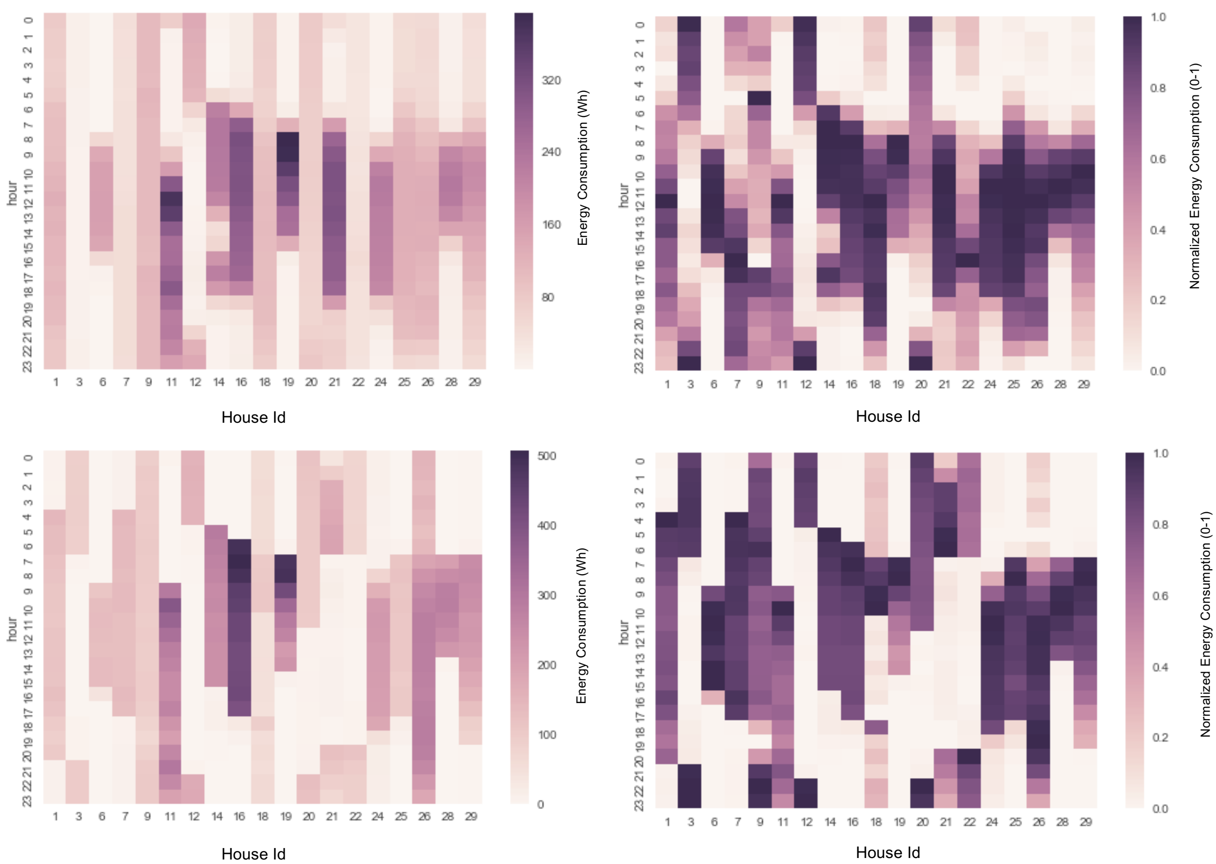


Figure 58. Median Fridge Energy Consumption (Wh) and Median Normalized Energy Consumption (0-1) Pre- and Post-Implementation: [A] and [B] depict fridge energy consumption pre-implementation of fridge and refrigerator demand flexibility. [C] and [D] depict fridge energy consumption post demand flexibility intervention. Post-intervention daily fridge energy consumption is more scheduled in regular daily intervals than in pre-intervention.

Pre-implementation, households and micro-enterprises would attempt to set their freezers and refrigerators on a regular schedule, but data and surveys suggest that users would be regularly unable to adhere to this schedule. For example, anecdotally, users mentioned during the pre-implementation baseline that they would like to turn on their fridge at 4 am but they would not usually be able to wake up on time to do so, and several others mentioned that they would have liked to adhere to a stricter schedule but were unable to do so due to absent mindedness, and multiple priorities competing for their attention. At implementation, all participants were requested to submit their preferred fridge energy consumption schedule, and while many participants preferred to stick to their old schedule, albeit with stricter automated control, others preferred to completely change their schedule (e.g., switching from having their fridge disconnected during the day, to having it disconnected at night). The majority (34%) of peak price events occurred from seven to nine at night, followed by peak price events from ten to eleven at night (17%), and five and six in the evening (15%). The rest of the peak events would be evenly distributed throughout all remaining hours of the day. The top two day-ahead highest predicted grid prices by the national dispatch center would be as high as $US 96/MWH, and as low as $US 45/MWH, with a median value of $US 76/MWH. Full analysis, descriptive statistics and extended results are available in the SI.

Peak price events could last one, two, or three hours through which fridges and freezers would be called-upon to reduce their consumption. The length of the event would be determined one day ahead of time depending on the number of hours (1-3) that would have consecutive high-energy prices. Project participants would participate an average of 40 minutes for every hour of a peak pricing event, (median: 53 minutes, stdv: 20 minutes) or 70% of the time of every event (median: 88%, stdv: 34%). Project participants would participate in events irrespectively of the time (there was no preference for participating on day vs. night peak events). When comparing all hours (0-23), there was no notable difference between pre- and post-intervention fridge energy consumption (mean difference Wh: 0.301, stdv difference Wh: 20). Figure 59B depicts a difference of zero to fall within the 95% HDI, suggesting that there is no credible difference between pre- and post-fridge energy consumption. However, when comparing consumption differences only within peak hour there was a large reduction in usage (mean reduction post-intervention Wh: 78.3, stdv: 48.2). Figure 59C shows the posterior distribution of mean differences within peak hour events falling completely outside of the 95% HDI, suggesting that energy consumption differences between pre- and post-intervention are both large and credibly different. In both cases we use a broad uninformative prior for estimation instead of using and educated guess or the literature as was used earlier. Figure 59A depicts all the hours in which there were coincidental peak pricing events with participants who were available to respond to the event (the plot is predominantly blue, suggesting a significant reduction in energy consumption during peak event hours). Figures 59B and 59C depict the posterior distribution of mean differences pre- and post-intervention for all hours, as well a subset of the hours during which there were events.

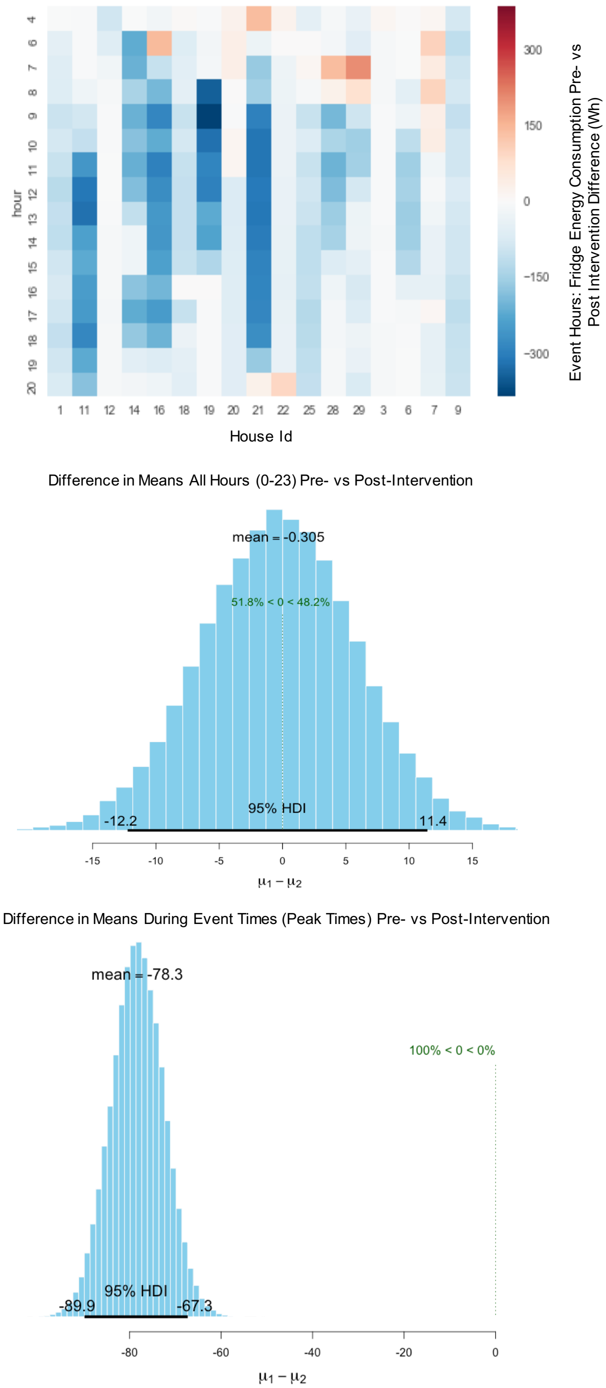


Figure 59. Mean Differences of Pre- vs. Post Intervention Fridge Energy Consumption: [A] Differences pre-vs post intervention for all hours by participant id (differences in Wh), [B] Posterior distribution of mean differences pre- vs post-intervention for all hours (0-23), and [C] Posterior distribution of mean differences within a subset of hours in which there were peak price events. Figure 59B suggests that there is no difference between fridge energy consumption pre- vs. post intervention, and 59C suggests that there was a large credible reduction post-intervention during peak pricing event times.

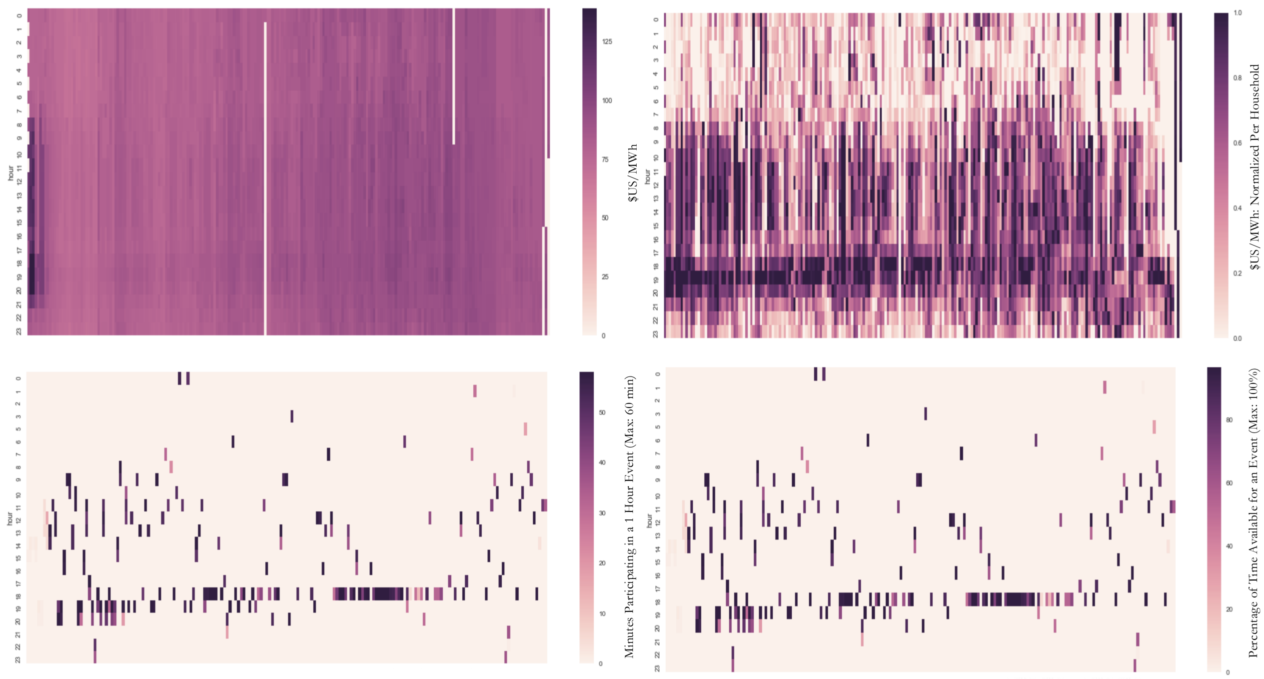


Figure 60: Users and Grid Peak Price Events by Day (July 1st 2016- December 31st 2016). [A] Depicts all data, and [B] depicts featured scaled data that allows to observe intra-day variability. Outliers in [A] obfuscate the data. [C] Depicts the average amount of minutes that users would participate in 1 hour peak price event, and [B] depicts the average time percentage that users would be available to participate in an event. Outliers in [C] obfuscate the data

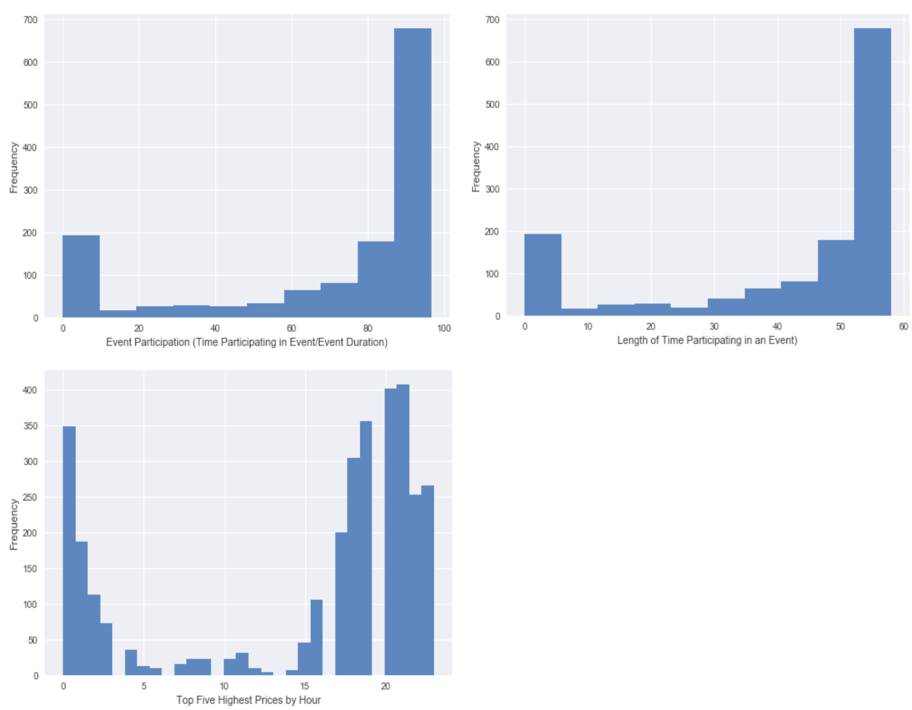


Figure 61: Distributions Depicting Participation and Impact of Flexible Demand throughout Participation Period: [A] depicts the percentage of time that participants were part of an event (minutes participating in an event,

each event would last 60 minutes), [B] depicts the amount of time that participants would be part of an event (in minutes, each even would last an hour), and [C] depicts the five hours that most frequently experience peak energy prices.

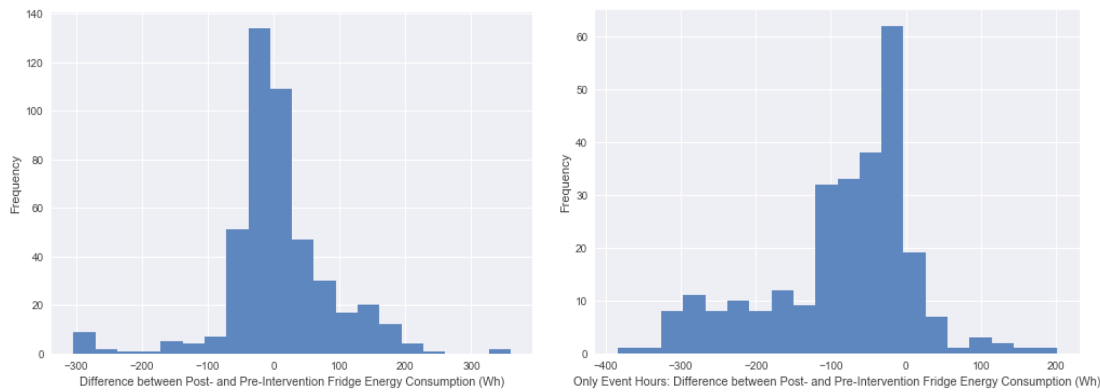


Figure 62: Distributions Depicting Fridge Energy Consumption Pre- and Post-Intervention: Distributions depict same hour comparisons between pre- and post-intervention fridge energy consumption. [A] Compares all hours (0-23) pre- and post-intervention while [B] only compares hours during which there were peak pricing events. Post-intervention, on average, fridges and freezers consumed more energy. During event hours, however, fridge energy consumption reduced significantly.

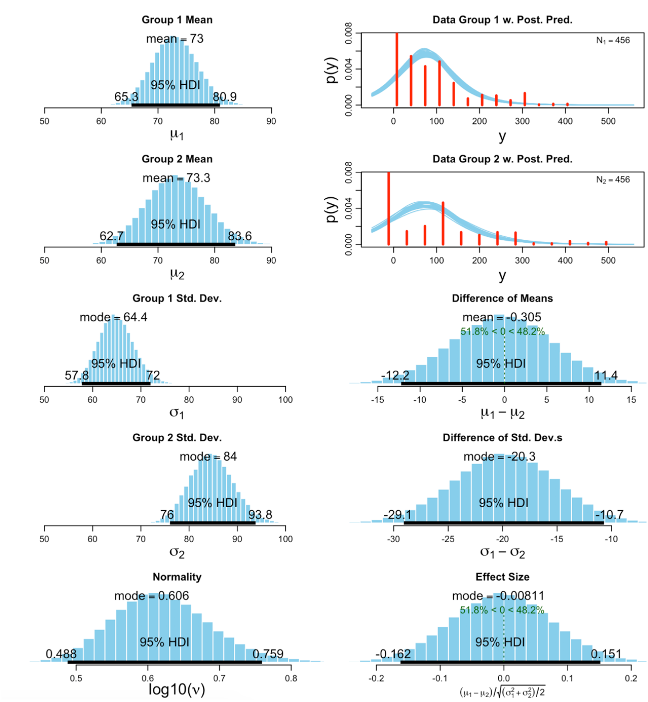


Figure 63. Bayesian Estimation Difference between pre- and post-intervention fridge hourly energy consumption all hours (0-23)

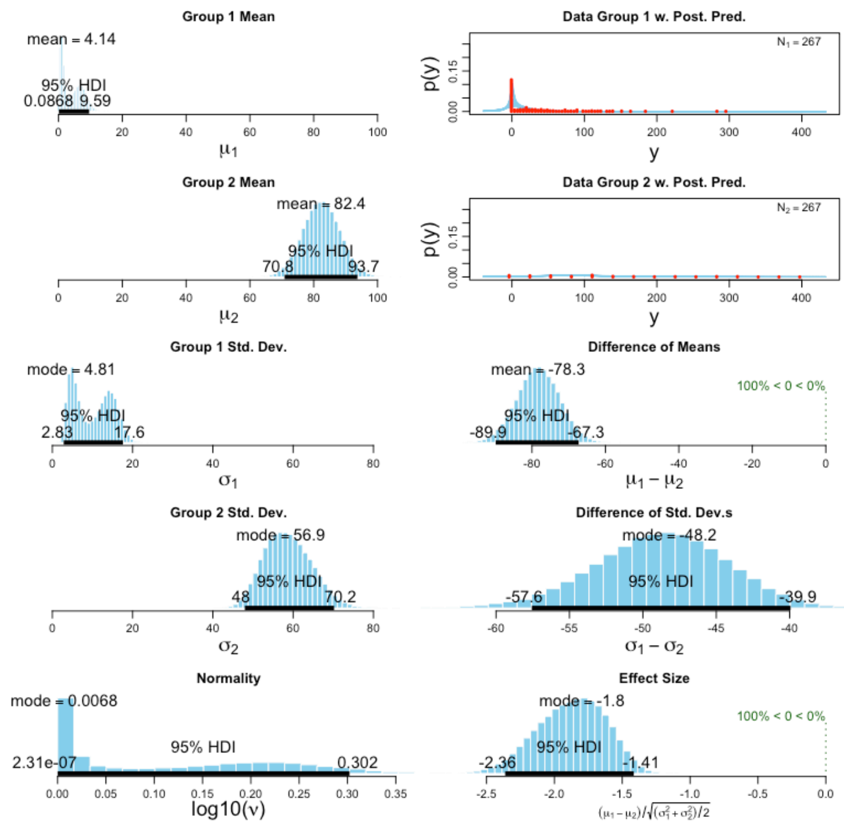


Figure 64. Difference between pre- and post-intervention hourly energy consumption during peak energy event hours.

3.8.4 Social Co-Benefits and the Effect of Scarcity

There are multiple benefits to pairing behavioral energy efficiency and flexible demand projects in enabling environments similar to Nicaragua's. Beyond the obvious energy and cost savings (and associated emissions reductions) for the grid and user, we identify numerous social co-benefits related to education, empowerment, and stress reduction as it relates to the household budget.

For tracking improvements related to education we tracked the accuracy of perceived vs. actual energy consumption ($US and kWh) at baseline, during project implementation, during a midline, and endline for treatment and control. We tracked changes through the use of surveys that were performed on a monthly basis since the baseline for the treatment group, and included the control group for midline and endline surveys. At baseline, the treatment group had a slightly larger overestimate of their energy costs relative to the control group ($US 7 vs. $US 5, respectively), representing 12% and 11% of their actual energy bill respectively. These values are very close to the median energy cost perception estimate found in our large-scale baseline (above). During implementation and before the midline, the treatment group increased its ability to recall its actual consumption to $US 2 and maintained this accuracy above the control group and throughout the midline ($US 3 treatment vs. $US 4 control) and endline ($US 1 treatment vs $US 3 control). Both groups increased their accuracy throughout the project implementation and surveys, but the treatment group observed a greater relative improvement in accuracy of $US 6 vs $US 2 in the control group. Furthermore, the treatment group significantly improved the accuracy of recalling their actual energy consumption (kWh) from a baseline error of 30 kWh (a 10% underestimate of their actual consumption), to a mean underestimate of 14 kWh (median: 0 kWh, sd: 118 kWh). The control group, on the other hand switched to an overestimate of 20 kWh (median: 6 kWh, sd: 117 kWh), or a 10% overestimate above its actual consumption. At the endline we use two additional metrics to evaluate whether increased attention to energy bill data permeated to other non-surveyed metrics including awareness of the unit cost of energy ($US/kWh), and accuracy at recalling monthly water expenditures. On average, the treatment group had almost a perfect grasp of the unit cost of energy with little error (mean error: $US 0/kWh, median error: $US 0/kWh, sd: $US 0.06/kWh), while the control group had a mean error of $US 0.5/kWh (median error: $US 0.07/kWh, sd: $US 0.99/kWh). With regards to water expenditures, the treatment group had, on average, a $US 2/month underestimate of their water bill (median: $US 12/month, sd: $US 101/month), while the control group had a $US 56/month overestimate (median: $US 9.74 month, sd: $US 155/month).

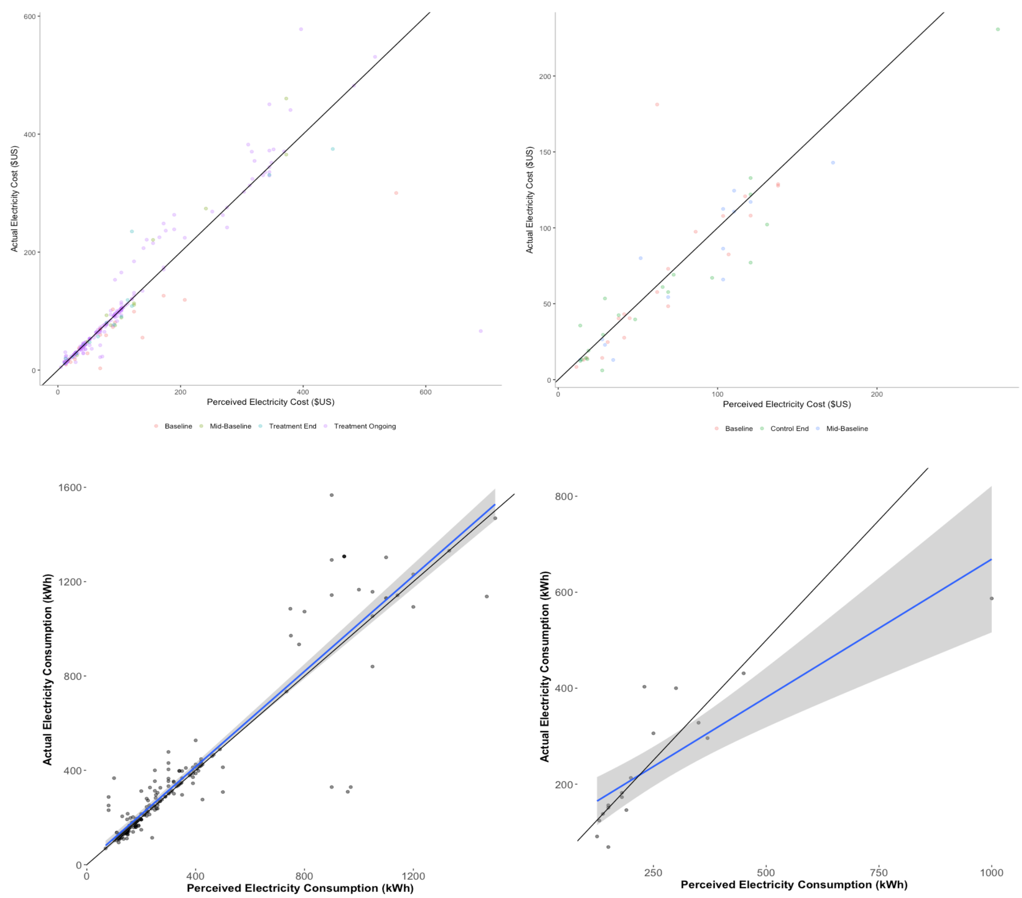


Figure 65. Baseline, Mid-Baseline, Ongoing and Edline Perceived vs. Actual Monthly Energy Costs ($US) [A] and [B] and Energy Consumption (kWh) [C] and [D] (Treatment vs. Control)

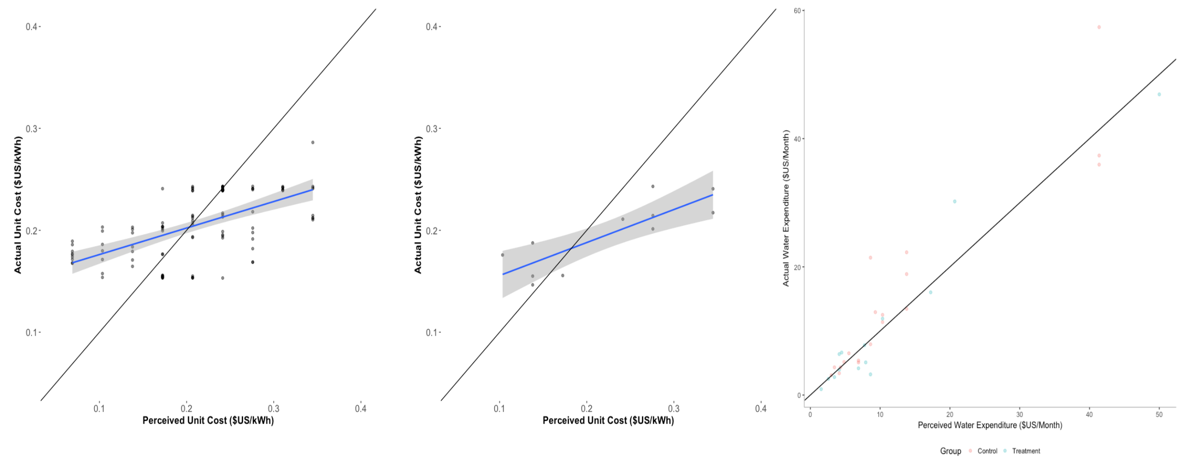


Figure 66: Perceived vs Actual Accuracy: [A] Unit cost of energy in treatment group, [B] Unit cost of energy in control group, and [C] Monthly water expenditures.

Although we are unable to use the same analytical approach used previously due to the paucity of data, these results suggest that the combination of energy reports and text messaging created increased awareness in the treatment group which extended beyond its immediate intention. Furthermore, our surveys and interviews found that the information provided to project participants extended beyond the household, as both energy reports and text messages were forwarded to extended family members and neighbors. While we are unable to explicitly measure the co-benefits of this information spillover (no baseline or energy consumption and cost data for neighbors or extended family), our results may suggest that the benefits of providing information at the household level may be an underestimate, as neighbors and extended family members might also be more aware of their consumption and therefore reduce it because of this interaction.

In our sample, home energy management was performed solely by women. Women were present in households when we performed the first baseline, and were the ones managing the small businesses throughout the study. Only two micro-enterprises had both a man and woman attending their business at all times. Anecdotally, women in both households and businesses mentioned that respect towards their ideas of financial and energy management increased after beginning to receive their energy information. Women would use our detailed energy reports to highlight issues to their husbands and families, or to bring attention to management strategies that they implemented and were successful. There were a broad range of behavioral strategies implemented including unplugging appliances that were not used, prohibiting watching television during the day, optimizing and scheduling activities that require electricity (e.g., washing machine, ironing), adding a thermal mass to fridges and refrigerators (e.g., bottles or bags full of water), adjusting fridge thermostats to less energy intensive settings, and forwarding energy management text messages to the entire household to keep close reign over energy consumption, among many others.

While our intervention was able to have unintended benefits such as the one described above, it failed at reducing the perceived high energy stress or reducing the impact on mental scarcity that energy management has on micro-enterprises and homes. At baseline, the most common feeling amongst treatment and control groups was that electricity was “very hard to pay” (1: easy to pay, 2: more or less hard to pay, 3: very hard to pay, 4: extremely hard to pay). Similarly, at the end of the study there was no improvement at all on the ease of paying energy bills. Neither micro-payments, more controlled scheduling, information, or actual reductions in consumption alleviated the perceived stress induced by a constant thought of an energy bill.

Furthermore, and despite the energy reports including a suite of suggestions and advice on a variety of non-behavioral efficiency measures (e.g., buying efficient light bulbs and a suite of more efficient appliances, swapping a piece of corrugated metal roof for a sun roof, insulating the roof or painting it white to reflect sunlight) none of the project participants implemented actions beyond behavioral changes, or used their micro-payments and savings from energy efficiency for investing in deep retrofits or long-term savings. Reasons for failure to save, or spend money in long term retrofits included the continued reoccurrence of immediate pressing needs (e.g., energy bill, education, health), the fact that micro-payments were too small to be saved (i.e., they were better used for immediate needs), ignorance about how to go about the purchase, retrieval and installation of new appliances, lack of a transportation mode to take old appliances away, lack of time, and lack of more funds for perceived large investments in new appliances. When asked if participants would be willing to forgo their micro-payments in exchange of the project purchasing and installing efficient appliances 85% answered "yes", with participants willing to exchange one micro-payment month or all future payments to receive help in long term energy efficiency retrofits.

The desire for something but not saving to purchase it, spending on immediate pressing issues rather than making investments in the future, and remaining (supposedly) inactive when faced with a constant stressor has been observed before, and is best explained by Scarcity (tunneling, borrowing, the bandwidth tax and lack of slack)(7). The relatively high accuracy of the treatment and control groups at recalling their bills, and the high accuracy of the treatment group at recalling the cost of energy ($US/kWh) and water bills ($US/month) has been observed in other low-income groups before. In the U.S., experiments at the grocery store have observed that low-income individuals recalled what they had just bought at the store (and the value of different items) with three times the accuracy of high-income customers(7). Quantity surcharges are also less frequent in low-income stores, than in high-income stores due to heightened budget vigilance(7).

Tunneling is a behavior that might help solve an immediate primary problem, but a heightened focus on immediacy can make one short sighted, leaving less attention for other less pressing issues that are recurrently neglected. Although our participants had good intentions (saving energy now, spending on other household/business needs now), they were unable to create and follow a savings plan that could have benefitted them in the long run due to a continuous bandwidth tax. For our participants, our surveys elucidated that saving energy was continuous diligent work where one missed text-message, an unexpected family member arriving at their house, or a child falling sick would set them behind, reducing the mental bandwidth (taxing it) that requires planning for the future. Despite the real energy savings and small cash infusions, the lack of slack (mental and financial) and constant external shocks (temporal and financial) would recurrently push our participants into the psychology of scarcity(7). More importantly, our surveys and interviews highlighted that our intervention served as an instrument to weather shocks, allowing participants to reduce uncertainty and instability in their monthly energy bills. Participants often highlighted that the greatest benefit of the project was that it stabilized their energy consumption, reducing the financial shock that a slight oversight over energy management could have on their household budget(7).

Finally, to evaluate whether or not information was truly being of value to our project participants we offered a bidding game to the treatment group, and told them that from that moment onwards they would only be able to keep either the information or the micro-payments they were receiving. Our enumerators carried with them a bag with small pieces of paper that had numbers between 25 and 200 written down in each of them with increments of 25 Cordobas. The bag contained equal amounts of each value. The project participants were explained that a bidding game would be played, where they would have the opportunity to either keep or lose the information. For us, the bidding game would reflect the true value that our participants were placing on the information received. It was explained to the participants that if they bid a number that was lower than the piece of paper that the enumerator would draw from the bag, they would lose the information and keep receiving their micro-payment. On the other hand, if they bid a number that was equal or higher than the paper drawn from the bag they would keep the information, but lose the money. After doing one round of practice bidding with all participants, and ensuring that everyone understood the game, the actual bidding game was played. Out of 20 participants, only two participants bid a zero value, immediately suggesting that they would rather keep the money than the information. For the rest of the participants, the mean bidding value was $US 4 (median: $US 3.4, sd: $US 1.9), with 10 of them winning the bid, and eight of them losing the bid. Non-zero bids suggest that most participants were willing to lose their micro-payments in exchange for information. On average, the highest bids came from participants with the largest energy bills, but there were participants with relatively lower energy bills who also had high bids (thus, their bid as a fraction of monthly expenditures was higher). Rationale for keeping the information (instead of micro-payments) included the opportunity to pursue long-term energy savings, increasing understanding of the household budget, education, and increasing knowledge. Money, our participants mentioned, would simply leave them too fast. All participants continued being part of the flexible demand implementation, albeit this time being rewarded either with micro-payments or information.

These results, we argue, bring forth elements related to the endowment effect, and prospect theory(5),(3),(4). While the participants were unable to put aside time and money to invest in long-term energy efficiency strategies, they were willing to forgo micro-payments in exchange of potential help and high-resolution information. Prospect theory would predict that our participants would become risk-seeking when faced with a mixed gamble, and even more under the possibility of sure losses (loss-aversion)(5, 266). The endowment effect would predict that our participants would demand much more to give up something than they would be willing to pay to acquire it(4). Thus, when faced with the risk of potential future losses if the information was removed, users would rather lose micro-payments today and enter a gamble for potentially higher long term energy efficiency returns. While our participants had little value for energy information at the beginning of the study (and it was provided for free by the utility), by the end of the study they were willing to give $US 4/month to keep it, significantly increasing its value.

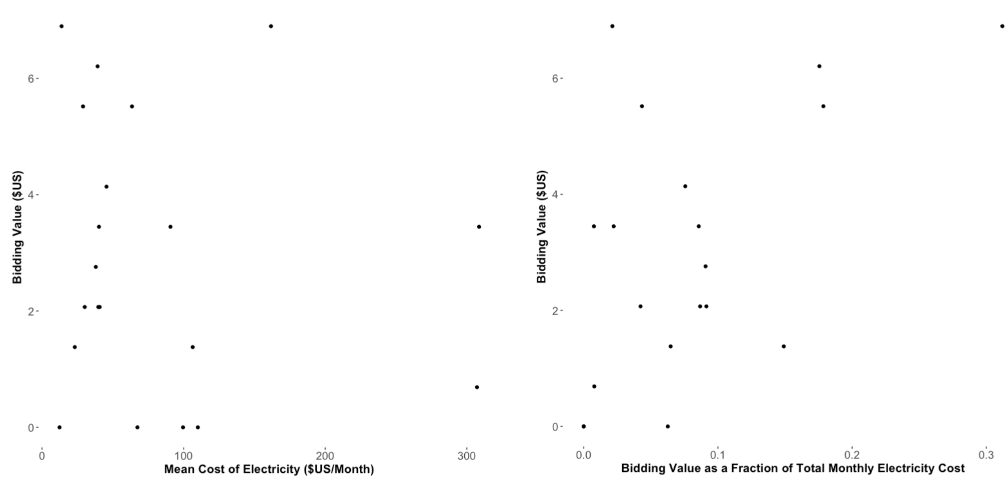


Figure 67: Bidding Value for Information vs. [A] Mean Cost of Electricity ($US/Month), and [B] bidding value as a fraction of total monthly electricity cost.

3.8.5 Opportunities at Scale and Root Challenges

Behavioral energy efficiency and flexible demand has large cost-effective potential in a country like Nicaragua. We argue that at scale (2 million people, or a third of the population engaging in behavioral energy efficiency), the country could save $US 29 million a year using average market prices, and $US 7 million if only 8 percent (or 500,000 people) participated. Avoided CO_2 emissions using an average emissions factor would be XXX tons per year at scale, and XXX with a smaller population participating. Developing user tailored energy information (reports and text-messaging) would require re-designing the existing energy bills according to needs and desires from users, and adding a very small information fee in every bill to cover text-messaging costs for people who chose the be part of a SMS energy control program. Flexible demand at scale could, on the other hand, save $US 18 million every year (using peak prices), and save $US 5 million if only a small fraction of the population were participating. Here, we argue, is where it is possible to do most of the innovation with regards to consumer facing business models. While in the United States and Europe, most pilot projects merely explore paying users for their participation in flexible demand, in settings like Nicaragua there is opportunity to engage in deeper energy efficiency retrofits. For example, where old appliances need to be changed, utilities, governments, or entrepreneurs could provide subsidized appliance swaps for flexible demand enabled appliances in exchange for full flexible appliance control. Or, like this project demonstrated, utilities and entrepreneurs could offer micro-payments and user-tailored information in exchange of full control of flexible appliances. Motivations for participating in low-carbon transitions will vary by country, city, and neighborhood. Monetary rewards, we have found, are not a sufficient motivator to engage flexible demand. Finding non-monetary motivators that make participants both willing and excited to be part of a project, are key elements to developing more-inclusive low-carbon grids.

Challenges for energy efficiency (behavioral and deep retrofits) and flexible demand in settings like Nicaragua are encountered at every level, from the household to the utility level. For energy efficiency and smart grid interventions at the household and micro-enterprise to succeed in low, low-middle income countries (and low, low-middle income neighborhoods in rich countries), they will have to come accompanied with an accompanying suite of enabling products. These products should have the goal of reducing uncertainty and instability in the household or small business budget, while still targeting energy efficiency. The time that is required to learn about energy efficiency and its broad range of options, or finding time (and transportation) to buy efficient appliances (and discard old ones), or filling out the daunting paper work that is required for energy efficiency programs requires bandwidth, and if low, low-middle income neighborhoods don't have this bandwidth they'll be at disadvantage to take advantage of these programs(7).

At the utility scale, there are large misaligned incentives for energy efficiency (behavioral or otherwise) to be successful at scale. In Nicaragua, there is no "de-coupling" (the separation of revenues from sales in places with successful efficiency programs, like California), and thus, efficiency and flexible demand represent lost sales (and revenue) for the electric utility. With no de-coupling, any large-scale efficiency intervention would not be palatable by top-down decision makers. Even a flexible demand strategy, that would arguably allow the utility to increase revenue through the purchase of cheaper energy, would not palatable as they would be forced by the regulator to reduce tariffs due to the very purchase of cheaper energy ('negawatts'). The absence of "decoupling" is ubiquitous across many regions across the world, including states within the United States, Europe, Asia, Africa, and all countries in Latin America. Thus, consumer-facing strategies are essential for behavioral interventions and smart grid solutions to be accepted and for them to spread when faced with top-down roadblocks. Technology driven solutions that take the user in mind, including his/her needs, desires, and motivations are key for the proliferation of sustainable energy solutions.

Although it may seem that technology is increasingly smart and invincible, there are still no cross-cutting magic bullets. The challenges, motivators, and enabling environments through which solutions and technology propagate will vary across neighborhoods, countries and cultures. To develop solutions that succeed at the local level, and are adopted long term, city governments, utilities and development banks must embrace the role of cost-effective pilots and demonstrations(267). Designing systems and solutions from the top-down level is expensive and ineffective if the solutions are not adopted, if the results are far smaller than originally intended (or in the opposite direction)(175), or if the approach is missing key design elements. Recruiting entrepreneurs and local developers to re-imagine existing business models and technologies to local contexts and trying ideas in the field first, and rigorously evaluating results, lessons learned, and steps forward is crucial to innovation and the nurturing of scalable solutions.

4. Conclusion

We live in the era of big data, ubiquitous information systems, unprecedented technological innovation, and affordable access to sustainable technologies. Yet, large-scale transitions towards sustainability and sustainable living are still hard to come by. If we have all the data, technology, and solutions, why does progress toward sustainability remain so slow?

First, large-scale energy transitions can take a very long time (26, 28, 98, 268, 269). Historical analysis of energy transitions has found that large-scale changes can take from several decades to over a century to unfold, with changeover times ranging from 80 (oil/gas/electricity replacing coal steam power) to 130 years (coal steam power replacing pre-industrial use of biomass and wood)(28). Within these timeframes, "core" (first adopters), "rim" (early followers), and "periphery" (late adopters) countries and regions adopt, tinker, and change technology (28). Historically, core adopters have had much slower transition times than late adopters, which is why the most rapid adoption rates and future of our planet's sustainability will likely depend on the choices made by countries and regions of the rising south (e.g., China, India, Brazil, Mexico, Central America, and East Africa)(270).

Second, history and context – and all their associated correlatives – matter. Niche markets, affordability, fashion, scale, industry, local politics, policies (or their absence), stakeholder dynamics, entrenched interests, financing, knowledge, and institutional and organizational quality and structures, among many other factors, influence the presence and pace of transitions towards sustainability. Opposition to change, an intrinsic human characteristic, is as important as any of the previous enabling factors (26). The Luddites who destroyed knitting and textile machinery between 1811 and 1816, Captain Swing who resisted mechanical threshing in rural England in the 1830's (26), and the modern day utility and oil industries who push back against decentralized services through climate denialism, lobbyists, standards, burdensome rules and regulations are all part of a historical process. Top-down technologists and policy makers – for the most part – ignore, or fail to explore, the various contexts that may allow or hinder a variety of paths towards sustainable decarbonization. Disinterest in context is exemplified by 'experts' who lump all countries of the rising south under the term 'developing countries' (e.g., China, Thailand, Mexico, South Africa, Nicaragua), glossing over a wide diversity of regions, situations and sub-cultures, despite their many and large differences (106, 109, 271). This disinterest in context, may be hindering appropriate and local-specific strategies for sustainable decarbonization, as we explore further on.

Third, the end-use, and users are crucial but often disregarded elements in kindling long-term transitions. Take, for example, the fact that as total emissions continue to grow, global increases in energy demand (2%/year) far outpace moderate improvements in global energy system carbon intensity (0.3%/year)(28). Or, that the recent global emissions slowdown has been attributed more to economic factors and energy efficiency, than to 'explosive' growth in wind and solar (246). Transitions in end-use energy services, and users, have historically created positive feedback loops reinforcing transitions in supply side systems (28, 272). For example, stationary and mobile steam power expanded demand for coal, internal combustion engines drove the growth of the oil industry, and electrification of lighting, industrial drives and transport (i.e., trams and locomotives) supported the rise of the electric industry (28). Users have been crucial to many of the climate and technology leaders of today: in Denmark, community opposition to nuclear energy and community-owned wind farms led to its early adoption and development in the 1960's-70's (44, 71, 272), car-sharing in Switzerland was mobilized in the 80's by concerned citizens and cooperatives (272–274), and an advocacy coalition in Germany informed and influenced the German parliament towards their current energiewende (275). A new literature is emerging, however, which sees users and pilot demonstration projects as essential to making progress towards sustainable decarbonization (267, 272). Research in the area of transitions and the role that users play in them is now being defined as single-loop (narrow), broad, or deep learning. Single-loop, or narrow learning, takes user needs, preferences and behaviors for granted and simply tests – or models – new innovations against them (272). Broad learning occurs when actors developing a niche focus not only on technology, but on user preferences, regulatory barriers, as well as environmental and social impacts (272). Deep learning only occurs through actual use, and through active actor and stakeholder engagement. It questions underlying assumptions, incorporates learning by doing, and adapts methods, technology and approaches to the needs of users (272). The research presented in this dissertation has been a combination of broad and deep learning.

Analysis and research in the themes which I've explored here will inevitably have more data in the future. As more countries, states and entire regions adopt practices related to sustainable energy development, data describing their enabling environments, intrinsic characteristics, and motivations must be recurrently collected to understand these transitions. Data-driven policy has yet to have major impact on long-term energy planning, with many countries still making policy around opportunistic investments and geo-politics. Future research would map both demand-side (e.g., enabling environments, intrinsic characteristics and motivations) and supply-side elements (e.g., resource potential maps) deemed necessary for low-carbon transitions in order to find and invest in new niche markets. In the future, data-mining and machine learning techniques will be used to predict which households and small-businesses are best suited to adopt sustainable energy technologies (e.g., smart energy efficiency appliances), however, many of the countries which are transitioning towards low-carbon economies are doing so without system-wide high-resolution data. Closing the gap between great knowledge and inaction surrounding the low-penetration of energy efficient practices, for example, will require much more applied research at the intersection of behavior, data-mining and technology. This intersection will have to grow more in the future to understand, design and implement solutions to close this gap – are we designing useful technology? Is it being used? What behaviors and social practices have not been considered that prevent sustainable energy practices from becoming ubiquitous? Do we need more technology development or better targeted interventions? Future work in this area does not necessarily have to be performed by academics, urban practitioners, entrepreneurs and users to create a body of work to help us fill this gap.

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