Link Foundation Fellowship Report

Evaluating the Potential of Ubiquitous Flexible Energy Loads to Provide Grid-Scale Balancing in Resource Constrained Environments: A Case Study in Nicaragua

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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*. By 2050, it is expected that seven out of ten people will be living in cities. 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). 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. 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.

Using a field deployment pilot in Nicaragua as a case study, the Link Foundation fellowship allowed me to explore opportunities for information and communication technologies (ICTs) and the internet of things (IOT) in resource constrained environments. I used ICTs and IOT to implement the first paired behavioral energy efficiency and flexible demand pilot in Latin America. The work involved the design, implementation, and exploratory data analysis of a sensor gateway (the FlexBox) for enabling behavioral energy efficiency and demand side flexibility, a Bayesian estimation analysis evaluating energy reduction, participation in demand side flexibility, impacts on welfare, and behavioral economics insights, and a Bayesian updating framework to better understand the efficiency gap in this environment. I 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. I 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, I found 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. The evidence suggests 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) 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 my 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.

1. Papers, Reports and Presentations Acknowledging the Link Foundation

**** Ponce de Leon Barido**, D., Wolfson, D., Callaway, D. The Marginal Value of Energy Information in Urban Resource Constrained Environments (In Adv Prep).

** Marsters, P., Castro Alvarez, F., **Ponce de Leon Barido, D**., Kammen, M.D. Sustainability lessons from shale development in the United States for Mexico and other emerging unconventional oil and gas developers. Renewable and Sustainable Energy Reviews 2017. Renewable and Sustainable Energy Reviews Link.

**** Ponce de Leon Barido, D**, Nsutezo, S., and Taneja, J. The natural and capital infrastructure of potential post-electrification wealth creation in Kenya (Published in Energy, Sustainability, and Society 2017 7:28) Energy, Sustainability and Society Link.

with support from the Link Foundation:

Ponce de Leon Barido, D., Suffian, S., Callaway., Kammen. M.D. Enabling Behavioral Energy Efficiency and Flexible Demand in Data-Limited Low-Carbon Resource Constrained Environments (Accepted: Applied Energy).

(Best Paper Finalist) **Ponce de Leon Barido, D**., Rosa, J., Suffian, S., Brewer, E., Kammen, M.D. Enabling Micro-Level Grid Flexibility in Resource Constrained Environments. IEEE IoTDI '17 Proceedings of the Second International Conference on Internet-of-Things Design and Implementation. Pages 233-245. Pittsburgh, PA, USA — April 18 – 21, 2017. ACM Link

Presentations acknowledging support from the Link Foundation

• The Cities and Climate Change Intergovernmental Panel on Climate Change (IPCC) Science Conference (Edmonton, Alberta, Canada). Panel on Smart Cities and Their Promise for Addressing Climte Change in Cities: "Behavioral Energy Efficiency and Flexible Demand in Little- data Low Carbon Resource Constrained Environments: A Case Study in Nicaragua". March 6th 2018.
• U.S. Department of Energy Webinar on Approaches to Energy Efficiency from Around the Globe: "Going for Gold: Medal-Worthy Approaches to Energy Efficiency from Around the Globe". Panel on 'Behavioral Energy Efficiency and Flexible Demand in Little-data Low Carbon Resource Constrained Environments: A Case Study in Nicaragua'. February 8th 2018.
• Stanford University Energy Week. Panel on 'Experiences in the Development and Implementation of Smart Grid Technology for Resource Constrained Environments'. October 17th 2017.
• Behavior and Energy Climate Conference. A Field Pilot to Enable Flexible Demand and Behavioral Energy Efficiency in Low-Carbon Resource Constrained Environments. January 22nd 2018.
• IEEE Internet of Things Design and Implementation. Pittsburgh, PA. Enabling Micro-Level Demand-Side Grid Flexibility in Resource Constrained Environments. April 20th 2017.
• INCMTY Entrepreneurship Conference. Monterrey, Mexico 'niuera – tecnología para una transición energética baja en carbono, justa, y sustentable'. November 2016.

Presentations with the support from the Link Foundation:

• 1st National Geographic Explorers Festival in Latin America (Mexico City). Environmental Justice and Technological Activism: Issues and Breakthrough Solutions. February 8th 2018.
• Stanford Energy Club. Enabling Micro-Level Demand-Side Grid Flexibility in Resource Constrained Environments. May 25th 2017.
• Mexican Consulate in San Francisco, CA 'Academia Meets Tech' – 'El Nexo Energia, Tecnologia, Sociedad'. October 2016.
• Banato Auditorium Sutardja Dai Hall, University of California Berkeley. Faculty Forum on 'Resilience in the face of Global Change'. 'The Distributed Energy Collective: Opportunities and Challenges in the Transition to a Post-Petrol Future'. September 2016.

2. <u>How did the fellowship make a difference?</u>

None of my work research would have been possible without the support of the Link Foundation Fellowship. As an international student, there are extremely limited scholarships that I could apply to for pursuing research that would allow me to create and implement field projects at the intersection of technology innovation, data mining and behavioral science. The fellowship gave me the opportunity to travel, design technology, develop partnerships, collect and analyze data and publish at will. I will forever be indebted to the Fellowship and I'm immensely thankful for the opportunity. Now, I have turned some of my research into a company xinampa.io, and in large part, the Link Foundation Fellowship made this possibility come true. I will contribute to the betterment of our society through work and research that is ground on evidence, science and equity. Thank you.

3. <u>Executive Summary of Results</u>

The increased penetration of uncertain and variable renewable energy presents various resource and operational electric grid challenges. Micro-level (household and small commercial) demand-side grid flexibility could be a cost-effective strategy to integrate high penetrations of wind and solar energy, but literature and field deployments exploring the necessary information and communication technologies (ICTs) are scant. In this first section I present an exploratory framework for enabling information driven grid flexibility through the Internet of Things (IoT), and a proof-of-concept wireless sensor gateway (FlexBox) to collect the necessary parameters for adequately monitoring and actuating the micro-level demand-side. In the summer of 2015, thirty sensor gateways were deployed in the city of Managua (Nicaragua) to develop a baseline for a near future small-scale demand response pilot implementation. FlexBox field data has begun shedding light on relationships between ambient temperature and load energy consumption, load and building envelope energy efficiency challenges, latency communication network challenges, and opportunities to engage existing demand-side user behavioral patterns. Information driven grid flexibility strategies present great opportunity to develop new technologies, system architectures, and implementation approaches that can easily scale across regions, incomes, and levels of development.

Our research pilot in Managua (Nicaragua) consisted of thirty FlexBoxes attached to twenty freezers (micro-enterprises) and ten refrigerators (households) and a centralized server that stored data, performed analyses, and provided control signals. Each FlexBox collected fridge inside temperature, humidity, TCL energy consumption, and total household energy consumption and stored it in a local database. Data was sent over 3G to a centralized server where it was merged with time stamped open access grid and weather data. Statistical and control scripts in the server can algorithms and simulations, and when necessary, actionable DR signals would be sent to participatng thermostatically

controlled loads (TCLs, refrigerators and fridges) to either be turned off or return to their normal cycling schedules. This central server also provided 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.

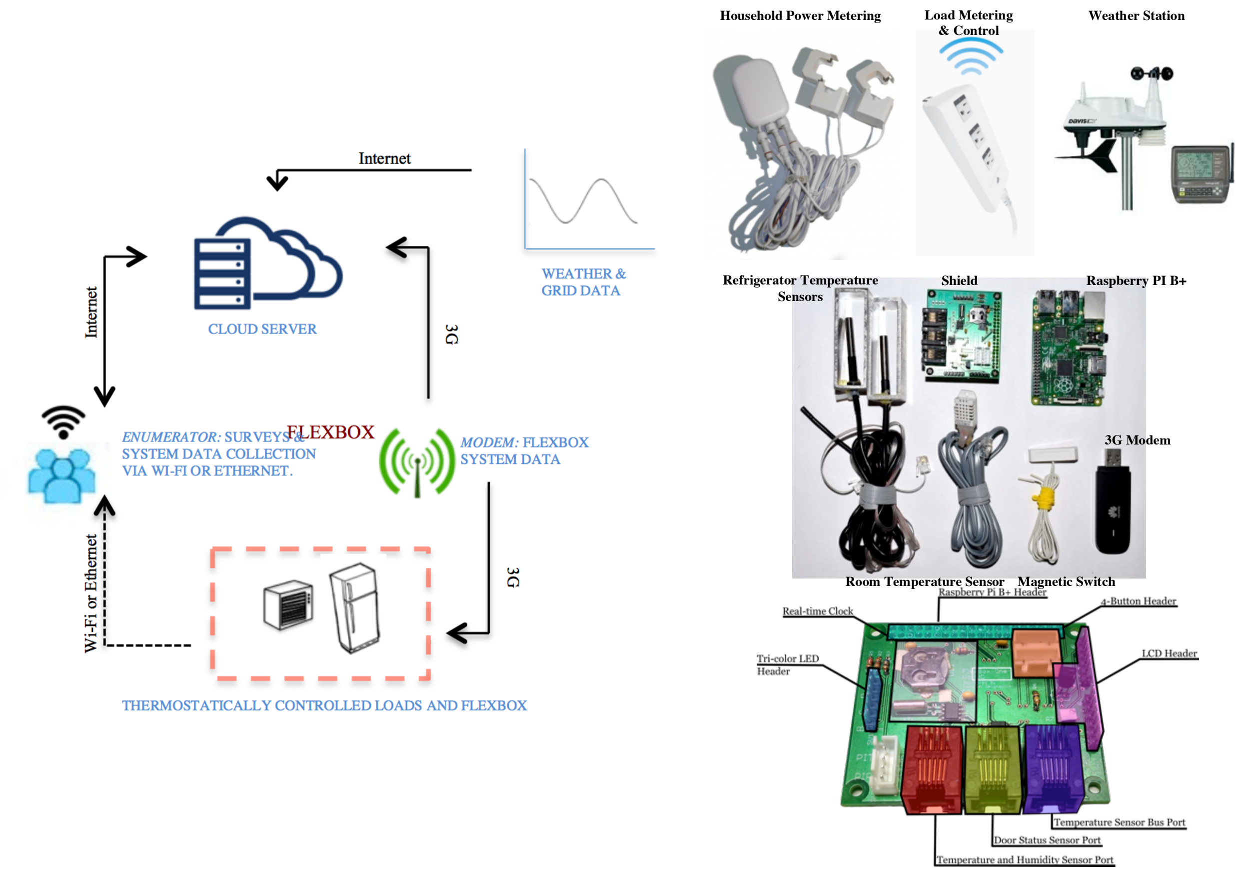

Figure 1: [A] FlexBox System Concept: The enumerator downloads new FlexBox software and new surveys from the cloud server. The enumerator also collects data from the FlexBox via Ethernet or Wi-Fi and sends it to the cloud server. A Huawei E3531 modem opens two-way communication streams between the FlexBox 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, and **[B] FlexBox Wireless Sensor Gateway Components.**

Data collected via the FlexBox allowed us to understand important thermal parameters and characterize energy-ambient and communication dynamics that would allow for us to control refrigerators remotely without affecting products inside the refrigerator and without affecting participants and the usage of their appliances. The figures below summarize some of our field deployment findings.

Parameter	Symbol (Units)	Mean (SD: Min -- Max)
Ambient temperature	θ_a (°C)	30 (3: 10 -- 41)
Dead-band width	δ (°C)	9 (4: -10 -- 35)
Temperature set point[1]	θ_{set} (°C)	-20 -- 5
Duty cycle	D (-)	0.52 (0.31: 0.1 -- 0.9)
Coefficient of performance[2]	η (-)	0.01 - 0.03
Efficiency performance index	η.e (-)	1.8 (2.4: .0045 - 18)
Power consumption[1]	P (kW)	0.1 -- 2.2
Mean Annual Energy Consumption per TCL[1]	MAEC (kWh)	280 -- 6000
Actual Mean Annual Energy Consumption per TCL	AMAEC (kWh)	1400

[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, we did not observe this in our controlled experiment. COP is a ratio of Q_c (heat removed from a cold reservoir) over W_{ref} (the work input required to remove heat from the cold reseroir). Experimentally, we calculated the COP for a freezer and refrigerator that were empty, but on the field we assumed freezers and refrigerators to be 3/4 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.

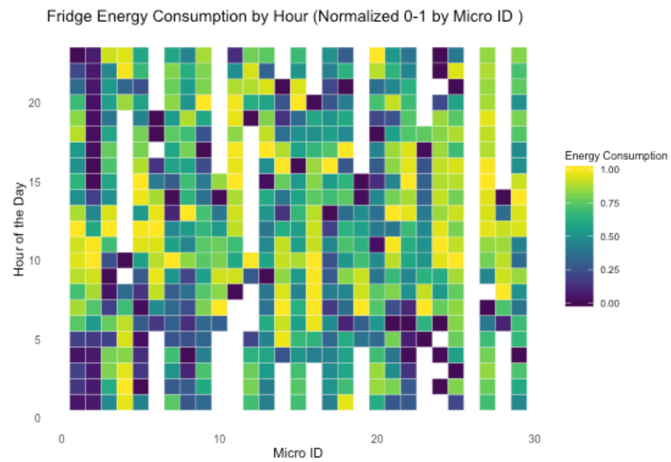

Figure 2: [A] Table 1: Field Data and Thermostatically Controlled Load Parameters, and [B] Normalized TCL Energy Consumption by Unit. **Contrary to previously held assumptions that assumed no changes, key parameters such as the duty cycle, the coefficient of performance, energy consumption, and the efficiency performance index all varied in time, user behavior and temperature.**

Data collected in the field allowed us to characterize real load parameters for the TCL population that we would be controlling, and that were very different than those that would have been assumed by a theoretical model (and these are usually assumed to stay constant). For example, 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. Our 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.

There were many more findings in our research, but very broadly, we found that 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.

Image 1. The FlexBox in a Micro-Enterprise in Managua, Nicaragua. One can see the thermocouples inside the freezer, the box with the modem, microprocessor, modem, and telemetry, and in the back the switch controller that would be turned on and off at different times of the day depending on grid signals.

Randomized Controlled Trial Implementation

After fully understand the thermal parameters, and constructing an entire technology framework to control TCLs remotely, we proceeded to implement a randomized controlled trial with 60 participants in low-middle income neighborhoods across the city of Managua. Below, I briefly present results of the first randomized pilot providing tandem behavioral energy efficiency and flexible demand services through the use of distributed sensor networks in Latin America (Managua, Nicaragua). My analyses show that the houses and micro- enterprises randomly assigned to the intervention reduced their energy consumption by nine percent relative to the control group, and participated at length in peak-shaving flexible demand events (380% of events). Identified social co-benefits included increased energy literacy, financial management and user empowerment, and find that improved access to energy information was more important than cash when incentivizing project participation with a high user willingness to pay. Several challenges may hinder the success of smart systems in resource constrained environments, including temporal and financial scarcity at the household level, lack of institutional support, and a panoply of top-down misaligned incentives. I document the multiple barriers to scale flexible demand and energy efficiency strategies, including bottom-up (e.g., appliance financing) and top-down (e.g., decoupling) challenges and discuss ways to overcome them. As more low, low-middle income countries transition away from fossil fuels, the use of sensor networks and information and communication technologies for building smart and inclusive smart systems will become increasingly necessary and attractive.

The intervention, consisted of a sensor gateway configured to collect consumption and temperature data and to interrupt power to connected refrigerators (also called a Flexbox), monthly reports with high-resolution energy information, real time energy alerts (warning users when they approached their monthly energy consumption goals), and a demand flexibility program that curtailed appliances using the Flexbox according to user-defined schedules and during daily peak grid pricing events. In exchange for participation, the treatment group received co-designed and user-tailored energy information and real time alerts, as well as a $US 6 flexible demand monthly payment. Each FlexBox contained a switch to interrupt power to connected appliances and sensors measuring fridge or freezer internal temperature, room temperature and humidity, fridge door activity and fridge energy and power consumption. We monitored household and business power consumption at the electric service panel and used a GSM modem for data transmission and switch actuation.

The intervention had three features: Monthly reports, real time energy alerts and a demand flexibility program that included a US$6/month payment. Monthly reports were co-designed with participants and provided (i) Nicaragua's monthly electricity generation by resource, (ii) the user's current and historical monthly values for: average hourly consumption (total and fridge only), weekly consumption (total and fridge only), and monthly total consumption and (iii) relationships between: ambient temperature and consumption (household and fridge), fridge door openings and fridge consumption, and fridge internal temperature and consumption. For monthly real-time energy alerts, users set a consumption goal for the upcoming month and texted it to our cloud server, which then sent SMS energy alerts to the user as various energy consumption thresholds were crossed (e.g., "Careful! You have reached 90% of your monthly energy budget!"). Demand flexibility could be programmed by users (e.g. off in specified hours of the day) and by our servers on days with high forecasted wholesale electricity prices. Users were notified of flexible demand events lasting from one to three hours one day in advance and were able to opt out any time before (by sending a text message), or during a flexible demand event by switching outlets on a power strip provided by the project.

Sample	
Houses	N = 219
Micro-Enterprises	N = 216
Age - Mean (Standard Deviation)	47 (SDV = 15)
Education	First two-years of high school
Household size	5.5 people per household
Average vs. Disposable Income ($US/Month)	
Houses	$550 vs $70
Micro-Enterprises	$520 vs $182
Median Monthly Energy Consumption (kWh/month), Energy Costs ($US/month) and Cost per Unit of Energy ($US/kWh)	
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
Financial Burden[2]	
What is a problem that is recurrently on your mind?	
(1) Energy, (2) Food, (3) Access to basic services	23%, 20%, 12%
What is the biggest financial burden on your small business?[2,3]	
(1) Energy, (2) Loans, (3) Employees	88%, 5%, 3%
Approximately what fraction of your total costs are energy related costs? Median (25th percentile - 75 th percentile)	
Houses	8% (4% - 19%)
Micro-Enterprises	30% (12% - 48%)
Future Issues[3]	
Of the following issues, which ones do you consider to be of most concern in the future?	
(1) Climate change, (2) Oil dependency, (3) Electricity prices	36%, 24%, 20%

[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 manages to be below a monthly consumption of 150 kWh/month

[2] Perceived financial burden

[3] Only the three most popular perceived financial burdens andf future issues are presented.

Table 2: Selection of baseline characteristics and perspectives on financial burden and future concerns.

The FlexBox allowed us to continuously collect key parameters for monitoring energy consumption and the state of participants' thermostatically controlled loads (TCLs), fridges and refrigerators. For example, the sensor network presented evidence to suggest that the temperature inside households and micro-enterprises was higher than outside ambient temperatures during the hottest part of the days due to the use of non-reflective infrastructure materials that would capture heat and provide no insulation. This led to the energy consumption of TCLs to vary across our sample depending on ambient temperature (a characteristic that is not taken into account in most thermal models). The duty cycle (the ration of time it takes for a refrigerator to travers its dead-band in an on state vs. total time in compressor on and off states) was also found to fluctuate during the way (a parameter that is kept constant in most thermal models). Sensor data presented evidence that diverges significantly from previous TCL modeling assumptions that have been published elsewhere. The data distribution of key TCL thermal parameters included ambient temperature (mean: 30°C, standard deviation: 3°C), dead-band width (mean: 9°C, sd: 4°C), temperature set point (min: -20°C, max: 5°C), duty cycle (mean: 0.52, min: 0.1 – max: 0.9), coefficient of performance (0.01 – 0.03), and efficiency performance index (mean: 1.2, sd: 2.4).

Sensor baseline data was collected from July 2015 to January 2016, during which there was no interaction with the participants. From January 2016 to July 2016 there was a co-design period where we worked with the treatment group (roughly once per month) to develop clear and useful information snippets (text and figures) for the monthly paper reports they would receive, as well as to ensure that the real-time SMS energy alerts were clear and understandable by everyone. The intervention (monthly energy reports, flexible demand and real-time text-messaging) began in July 2016 and lasted until December 2016. No project participants left the project once the demand flexibility intervention began. Further intervention details are provided in the SI.

Given the balanced outcomes of our treatment and control group participants, we use Bayesian Inference for inter-participant and group comparisons. The approach is robust for two groups and small samples, handles outliers, and provides complete distributions of credible values for group means and standard deviations (and their difference), effect size, and the normality of the data. Thus, Bayesian Inference estimates five parameters: means of treatment and control (μ_1 and μ_2), standard deviations of treatment and control (s_1 and s_2), and the normality of the data between treatment and control (v).

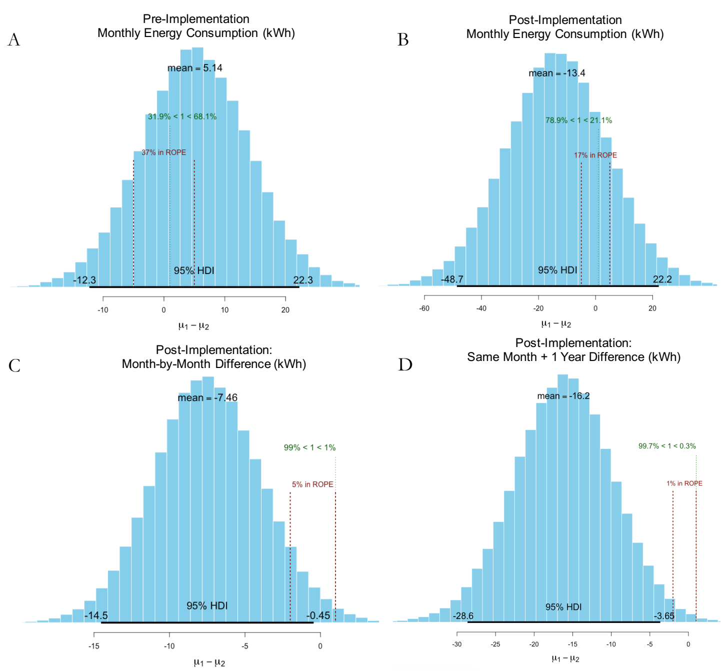

Figure 3. Bayesian Posterior Estimates Treatment (μ_1) vs. Control (μ_2): [A] Pre-implementation monthly energy consumption (kWh/month), [B] post-intervention monthly energy consumption (kWh/month), [C]month-by-month differences (kWh/month) during the intervention period (e.g., comparing energy difference between August and September 2016) and [D] annual differences (kWh/month) 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). Median temperature was 30.6 °C in 2015 (sd: 14.5 °C) vs 31.2 °C in 2016 (sd: 15.1 °C), median temperature pre- vs.

post intervention months was 31.5 °C in (sd: 14.8 °C) and 30.4 °C 2016 (sd: 15.1 °C) respectively. We highlight year-to-year temperature comparisons, having [D] as our most robust result. The treatment group experiences energy reductions, despite a small increase in ambient temperature (measured by a weather station).

We evaluate three different results: (A) pre- vs. post-implementation monthly energy consumption (e.g., August 2015 – June 2016 vs July – December 2016), (B) month-by-month differences during the intervention period (e.g., comparing energy differences between August and September 2016), and (C) annual differences between the same months one year afterwards (e.g., August 2015 vs. August 2016). Users are compared to themselves during and at these three different time points to control for number of appliances, household characteristics that affect ambient temperature (e.g., roof and wall type, presence of sky lights), people in household, education, and other baseline characteristics. The comparison in (C) controls for seasonal variations in consumption and federal holidays that affect both weather and behavioral patterns, and is thus our most robust comparison. For flexible demand, we use Bayesian estimation to identify credible differences in refrigerator and freezer energy consumption pre-vs. post-implementation (all hours), and a subset of peak pricing hour events. The SI includes full Bayesian estimation results. Our analysis uses the R statistical programming language, the MCMC sampling lag called JAGS, and the BEST program for Bayesian means tests in R.

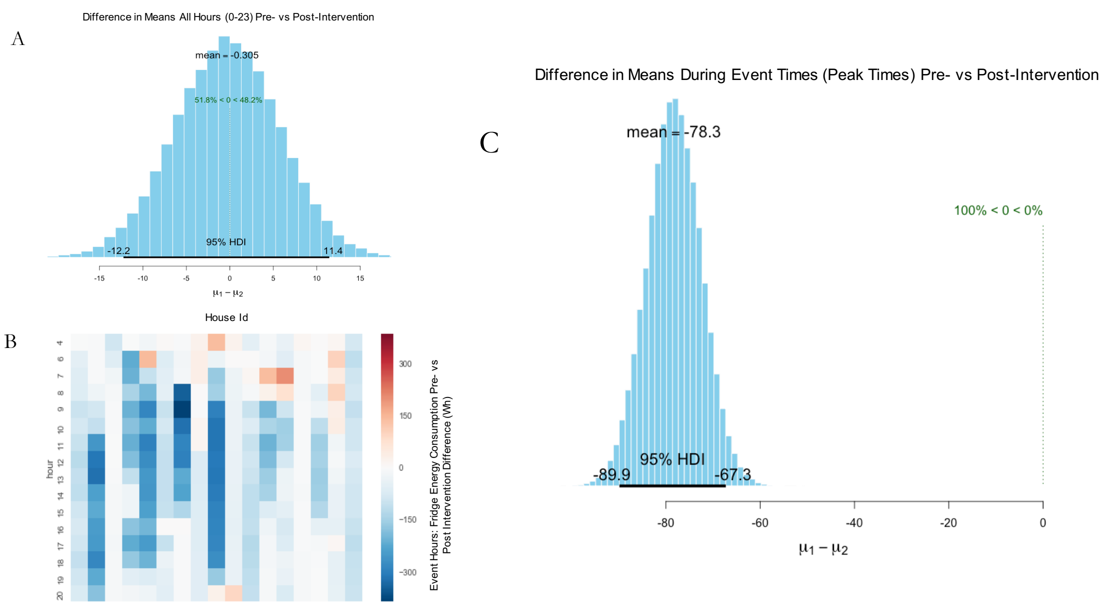

Figure 4. Bayesian Estimation Results Pre- vs. Post Flexible Demand Intervention: Mean Differences of Pre- vs. Post Intervention Fridge Energy Consumption: [A] Posterior distribution of mean differences pre-vs post-intervention for all hours (0-23), [B] Differences pre-vs post intervention for all hours by participant id (differences in Wh), and [C] Posterior distribution of mean differences within a subset of hours in which there were peak price events. [A] suggests that there is no difference between fridge energy consumption pre- vs. post intervention, and [C] suggests that Event Hours: Fridge Energy Consumption Pre- vs Post Intervention Difference (Wh) there was a large credible reduction post-intervention during peak pricing event times.

We use three different measurements to evaluate the effect of our intervention on total energy consumption: (A) post-intervention monthly energy consumption (e.g., August 2015 – June 2016 vs. July – December 2016), (B) month-by-month differences during the intervention period (e.g., July vs. August 2016), and (C) differences between the same months in consecutive years (e.g., August 2015 vs. August 2016). The latter controls for both seasonal consumption variation and federal holidays (e.g., Independence Day), with each participant in the treatment and control group being compared with itself one year ago for every month during the intervention period. We compare differences in treatment and control for (A), (B), and (C) using Bayesian estimation and as described in the methods and SI.

We observe the treatment group reducing its total household or small-business energy consumption relative to the control group in all these comparisons, by (A) 13.4 kWh (6%), (B) 7.46 kWh (4%), and (C) 16.2 kWh (9%) respectively (Figure 3). For post-intervention and month-by-month comparisons, however, our high-density interval (HDI) falls over zero and within the region of practical equivalence (ROPE) suggesting that our results are not credibly different from zero or from values with a significant effect size. For month-annual differences, however, both zero and ROPE are fully outside the HDI suggesting that our results are credibly different from each other and zero. We consider the latter to be the most robust result as it controls for several unobserved factors such as variation in seasonal consumption, federal holidays, within household variability (e.g., behavior, number of appliances), and compares both groups to each other.

Peak prices for flexible demand events were identified one day in advance; events lasted up to three hours (see SI for details). Project participants were opted-in to the flexible demand events (with ability to withdraw at any given time), and participated an average of 40 minutes for every hour of a peak pricing event, (median: 53 minutes, sd: 20 minutes) or 70% of the time of every event (median: 88%, sd: 34%). Pooling together all hours, there was no credible difference between pre- and post-intervention fridge energy consumption (mean difference Wh: 0.301, sd difference Wh: 20). However, there was a large usage reduction during flexible demand event hours (mean reduction post-intervention Wh: 78.3, sd: 48.2) Based on these results we estimate that if one third of the population (2 million people) received paper reports and energy alerts, Nicaragua could save $US 29 million in wholesale energy costs annually (using average prices), and if this same population participated in flexible demand they could save $US 18 million annually (using differences between peak and off-peak prices). Using actual generation emissions from Nicaragua's grid in this scenario, behavioral energy efficiency could save over 6 million metric tons of CO_2eq annually (using average monthly emissions) and flexible demand would avoid over 3 million metric tons of CO_2eq (using peak prices hourly average emissions).

For tracking improvements related to energy literacy, we measured the accuracy of perceived vs. actual energy consumption ($US and kWh) at baseline, intervention, midline, and endline. At baseline, the treatment group had a slightly larger overestimate of their perceived energy costs relative to the control group (median: $US 7 vs. $US 5, respectively). When the intervention began, and likely due to the co-design of the energy information mechanisms, the treatment group had improved its ability to recall its actual consumption within an error $US 2 and largely maintained this improved accuracy throughout the midline (error: $US 3 treatment vs. $US 4 control) and endline surveys (error: $US 1 treatment vs $US 3 control). Although both groups increased their accuracy throughout the pilot, the treatment group had a greater improvement in accuracy of $US 6 against a $US 2 improvement by the control. The treatment group also significantly improved the accuracy of recalling their actual energy consumption (kWh) from a baseline underestimate of 30 kWh, to a mean endline underestimate of 14 kWh (median: 0 kWh, sd: 118 kWh). The control group, on the other hand switched from an underestimate of 30 kWh to an overestimate of 20 kWh (median: 6 kWh, sd: 117 kWh). During the final survey, we used two additional metrics to evaluate whether increased attention to energy bill data permeated to other non-previously surveyed metrics: accuracy at recalling the unit cost of energy, and monthly water expenditures. On average, the treatment group had almost a perfect grasp of the unit cost of energy (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), which is 2.5 times higher than the actual unit cost of energy. 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).

Identified co-benefits through surveys and interviews include information spillover, user empowerment, and the potential for high-resolution information to reduce energy-bill induced stress. Some project participants reported that they forwarded energy information to others (extended family and friends), suggesting that the recorded information benefits could be an underestimate, as those others might have also reduced energy consumption in response. In our sample, home and small business energy management was performed mostly by women, several of whom reported that post-intervention they received new respect for their financial and energy management ideas. Women would use information to highlight management strategies that were being successful including limiting consumption (e.g. televisions only in certain hours, fans only during the day), and scheduling some energy-consuming activities such as washing once a week or bi-weekly. Research elsewhere, however, has found that interventions to support behavioral energy efficiency can negatively impact household power (and gender) dynamics, with men suggesting to reduce the use of common gender specific appliances (e.g., hair dryers) and placing the workload of energy management primarily on women. Though limiting use of comfort appliances such as fans could have negative side- effects (e.g., heat stress), these issues were not brought up by participants.

Our intervention, however, was unable to reduce the user's perceived high stress of energy bills. 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). At the end of the study, stress remained the same and was unaffected by flexible demand payments, more controlled scheduling, information, or actual reductions in consumption. Furthermore, although energy reports included suggestions and advice on a variety of efficiency retrofits, the participants implemented none. Reasons for failure to neither save, nor spend money on retrofits included the continued reoccurrence of immediate pressing needs (e.g., energy bill, education, health), perceptions that flexible demand payments were too small to be saved (i.e., it was better to use them for immediate needs), lack of awareness about how to purchase, retrieve and install new appliances, lack of transportation and time, and perceived high cost of new appliances. When participants were asked if they would forgo payments if someone else purchased and installed efficient appliances for them, 85% answered "yes", with participants willing to exchange one payment month or all future payments to receive help in long term energy efficiency retrofits.

Spending new income on pressing needs rather than making investments in the future, and inability to act (or choosing not to) to resolve constant stressors are well explained by the psychology of scarcity. In scarcity, 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 (e.g., saving energy now), they were unable to create and follow a long run savings plan. Our surveys indicated that saving energy involved diligent work where one missed text-message, an unexpected visitor, or a sick child would impede saving energy plans. Despite real energy savings and small cash infusions, the lack of slack (mental and financial) and constant external shocks (temporal and financial) caused actions consistent with the psychology of scarcity]. Participants highlighted that their greatest perceived benefit was bill stability, which presumably reduced financial shocks to their household budget.

Our research shows that information systems provide multiple benefits beyond their immediately intended goals in low-carbon, resource constrained environments. First, this work has demonstrated that flexible demand interventions can be incredibly successful if they consider inherent behavioral and social characteristics of end-users. This was exemplified by turning the high-resolution data collected for automation and control of flexible loads (e.g., freezers and refrigerators), into high-resolution real-time feedback that led to important behavior change and energy efficiency savings. Equally important were the derived co-benefits from our implementation. Energy literacy, knowledge creation, empowerment and budget management all emerged as co-benefits beyond the immediate energy, environmental and cost savings of our program. At the same time, there are multiple challenges for energy efficiency and flexible demand services in 'real world' settings like Managua, and services that do not provide a suite of enabling products will unlikely receive popular end-user support.

The results and lessons learned from our implementation suggest that there are important design elements that may lead to the success or failure of future applications of tandem behavioral energy efficiency and flexible demand programs. Three key elements for a successful implementation include: *(1)* High resolution interaction, co-design and good customer service, *(2)* understanding and support of user intrinsic motivations, and *(3)* creation of new locally relevant business models. In communities with little top-down support for energy efficiency, or waste management, as our demonstration project suggests, the combination of *(1)*, *(2)* and *(3)* can lead to high end-user engagement, positive interactions with the local community, increased persistence, and the creation of new models of end-user engagement that are not dependent on top-down stakeholders (e.g., governments, utilities). These opportunities, however, are only capitalized if they are thought about from program design, as it is necessary to continuously collect data to validate improvements or hypotheses to be explored. In our implementation, *(1), (2)*, and *(3)* were manifested in the form of *(1)* co-design of information systems with users so that feedback mechanisms would be immediately useful and easily understood (only variables that users deemed important were provided to them), *(2)* encouraging program participation by mainly focusing on energy independence and monetary savings, and *(3)* identifying all the barriers that users faced to achieve their desired energy efficiency goals (e.g., access to finance, inefficient appliances, and needed household retrofits) and providing information for end-users to access solutions that could reduce these barriers (e.g., access to sustainable financing for new appliances and retrofits).

Design flaws that may jeopardize future energy efficiency and flexible demand implementations (small pilot projects or large scale deployments) include not collecting prior knowledge of household, business or community dynamics (e.g., budget preferences, consumption patterns, budgetary goals and restrictions), having little prior knowledge of end-user behavior, and no data or understanding of the local dynamics regarding the psychology of scarcity. These design flaws can lead to poorly designed mechanisms to overcome the energy efficiency gap (e.g., requesting access to a savings account to provide financing, when 49% of adults in Latin America do not have access to traditional financial services), rebound effects (e.g., users increasing their energy consumption after implementation of an efficiency pilot), and lack of deep and permanent benefits for project participants. For example, in our pilot, not having designed a final services program in parallel to our flexible demand and behavioral energy efficiency intervention meant that our participants were not able to make long-term investments towards their home, business, or budget. Future successful programs would reduce budget uncertainty and instability, reduce the time required to learn about energy efficiency, provide transport to buy efficient appliances (and discard old ones), and simplify paperwork, among many other challenges that end-users commonly face.

There are also important top-down challenges to scale energy efficiency and flexible demand projects in resource constrained environments. Because there is no utility de-coupling (splitting the utility's earnings from its sales) in most (if not all) countries of the rising south, efficiency and flexible demand interventions at scale would generate a loss and hence not be palatable to most utilities. A flexible demand strategy that would arguably allow a utility to increase revenue through the purchase of cheaper energy, for example, would be rejected as the utility would be required by a regulator to reduce near-future rates due to their purchase of cheaper energy. The absence of financial mechanisms or structures to incentivize utilities to participate in large-scale and effective energy efficiency and flexible demand means that support for this important resource dwindles depending on political favor and interest. Thus, and faced with serious top-down implementation barriers, user-focused strategies are crucial for behavioral, energy efficiency, and smart city interventions to be successfully scaled.

To develop solutions that succeed at the local level, city governments, utilities, and development banks must embrace the role of cost-effective pilots and demonstrations. Designing top-down systems and solutions is expensive and ineffective if solutions are not adopted, if the results are far smaller than originally intended (or in the opposite direction), or if the approach is missing key design elements. Recruiting entrepreneurs and local developers to re-imagine existing business models and technologies in local contexts, and piloting these innovations, is crucial to scaling energy efficiency, and socially inclusive smart city solutions. If well implemented, pilot projects can lead to understanding behavioral community and technology dynamics that are crucial to make changes to existing technology, and future large scale programs, to avoid past mistakes and prevent future ones. Cities and neighborhoods that champion these small steps and pilot initiatives like likely reap the benefits of better use of funds, and deeper and more widespread benefits towards local-participants.

With support from the Link Foundation Fellowship I've presented some results from Latin America's first pilot of micro-level (households and micro-enterprises) demand-side management and behavioral energy efficiency in low-income neighborhoods of Managua, Nicaragua. Previous studies evaluating these two strategies often explored them separately, and further, they usually investigated issues related to behavior, technology, and opportunities for social co-benefits in isolation. Despite a large potential for behavioral energy efficiency and demand-side management in low, low-middle income communities, real-world pilot programs remain scant. We used a randomized experiment in which thirty participants (households and micro-enterprises) received a wireless sensor gateway that enabled flexible demand of their refrigerators and freezers, and provided them with co-designed high-resolution energy information. Another thirty participants were part of a control group. The treatment-group reduced their energy consumption by nine percent relative to the control, and participated extensively in peak-shaving flexible demand. Increased energy literacy, improved financial management and user empowerment were also identified as intervention co-benefits. We found that improved access to energy information was more important than cash when incentivizing flexible demand participation, and documented the multiple barriers to scale flexible demand and energy efficiency strategies, including bottom-up (e.g., appliance financing) and top-down (e.g., decoupling) challenges as well as ways to overcome them. As more low, low-middle income countries transition away from fossil fuels, interventions such as this one will become increasingly necessary and attractive.

Figure 5. Bottom-Up and Top-Down Opportunities and Challenges for Flexible Demand and Behavioral Energy Efficiency in Data-Limited Low-Carbon Resource Constrained Environments.