REACHING THE LAST-MILE

WOMEN'S SOCIAL AND SUSTAINABLE ENERGY ENTREPRENEURSHIP

FEBRUARY 2018

SOLAR SISTER

wPOWER
PARTNERSHIP ON WOMEN'S ENTREPRENEURSHIP IN RENEWABLES

CITE

TABLE OF CONTENTS

About Us

CITE, the Comprehensive Initiative on Technology Evaluation at the Massachusetts Institute of Technology (MIT), is a program dedicated to developing methods for product evaluation in global development. CITE draws upon diverse expertise across MIT and globally to evaluate products and build an understanding of what makes different products successful in emerging markets. The United States Agency for International Development (USAID) had funded much of the work CITE has completed to date. For more information, see http://cite.mit.edu.

Solar Sister, a social enterprise with operations in Nigeria, Tanzania, and Uganda, works to eradicate energy poverty while also empowering women with economic opportunity. A deliberately woman-centric direct sales network that brings clean energy technology to remote communities in rural Africa, Solar Sister's vision is to provide light, hope, and opportunity for everyone, everywhere. Since its inception in 2010, Solar Sister has recruited and trained over 2,600 women entrepreneurs, reaching an estimated 877,000 beneficiaries. For more information, see http://solarsister.org.

wPOWER, the U.S. Department of State's Partnership on Women's Entrepreneurship in Renewables program, seeks to shine a light on and expand the role of women in clean energy entrepreneurship and in addressing climate change through the diffusion of clean energy technologies and services. By 2018, the wPOWER program aims to empower 8,000 women in clean energy entrepreneurship to deliver clean energy access to 3.5 million people. Research for this report was made possible through a grant from wPOWER. For more information, see http://wpowerhub.org.

This report and the summary report can be accessed online at http://bit.ly/LastMileEvaluation.

INTRODUCTION

Throughout rural Sub-Saharan Africa, grid electricity coverage remains sparse. In Tanzania, the site of this study, only 15% of the population has access to electricity. A substantial urban bias exists: 41% of the urban population has access to electricity, while only 4% do in rural areas, where 68% of the country's 55 million people live (World Bank 2017). Even in areas where grid electricity is accessible, it remains out of reach economically to low-income households, who find hefty connection fees and recurring monthly utility bills prohibitive. As a consequence, low-income households desire more lighting options, especially given the ongoing expenses associated with, and the health ramifications of, kerosene lamps, the predominant lighting source in rural Africa (Tracy and Jacobson 2012).

Even as the Government of Tanzania's (GoT) efforts to provide for the energy needs of its citizenry have been met with some success, issues of affordability and availability continue to pose significant challenges to rural development. This presents an opportunity for innovation and entrepreneurship, both in terms of technologies and service delivery models. As a result, non-state actors have begun to try to fill this "energy gap" by providing rural households with various off-grid energy options, often in the form of solar lighting. Although some for-profit firms are engaged in trying to reach remote, "last-mile" households, the cost and effort of reaching them at scale remains a challenge. Further, one-off drives, campaigns, or giveaways, while certainly helpful to households in the short-term, do not address the structural barriers that continue to hinder people's sustained access to energy. A middle ground between a purely for-profit or purely philanthropic approach, social enterprises have emerged as a business model that can, in principle, reach those households most removed from the grid and who likely lack few electricity and energy alternatives.

This study seeks to understand the impact of one such social enterprise in Tanzania, Solar Sister, in providing access to clean energy—in the form of household solar lanterns—to remote, rural areas, or what we call "last-mile" households throughout this report. Solar Sister's business model uses a network of trained women entrepreneurs—Solar Sister Entrepreneurs, or SSEs—to sell solar lanterns in their local communities. The argument for employing women in this way is not only that it promotes gender empowerment through economic opportunity, but also that such a model, where the salesperson is embedded in her community, reaches customers that other social enterprise and business models do not.

The study's findings reveal that, first, based on a three-indicator last-mile index (LMI), Solar Sister is indeed reaching remote households. Second, rural customers in the areas where Solar Sister operates have few alternative options for clean energy. Solar Sister thus plays a crucial role in bringing clean energy to communities that other organizations are not reaching. Third, some indication exists of a bias against saleswomen, underscoring the role gender-conscious interventions may play in combatting such prejudice. Finally, rural customers appear to place considerable importance on the social aspects of a purchase, such as whether local after-sales service is available and whether a salesperson is someone familiar and trusted. This preference far exceeded even the financial consideration of paying for a product in installments, validating Solar Sister's approach to champion locally-embedded entrepreneurs.

As Niethammer and Alstone (2012) note, women's role in the energy sector in developing contexts is often overlooked or misinterpreted. Indeed, while some studies have been conducted to understand the connection between gender and energy access, most of this research measures the effect of energy technology access *on* women—women as beneficiaries—as opposed to the impact *of* women on energy access—women as facilitators. This study, therefore, seeks to address this gap in the research to further illuminate the relationship between gender and energy access in a way few have done empirically.

The next section of the report discusses the objectives and design of our study, followed by analysis and discussion of our main findings. The conclusion and next steps section closes the report.

RESEARCH OBJECTIVES AND DESIGN

Two research objectives drove our study. These objectives and the subsequent research design were created and refined through an iterative process with Solar Sister staff in Washington, D.C. and Tanzania. A summary of the research objectives and design is shown in Table 1.

Objective	Research question	Sample population	Sampling method	Research instrument	Measure	*N*
(1) Efficacy of social enterprise	Is Solar Sister reaching last-mile customers?	Solar Sister customers	Purposive	Survey	LMI[1], competitor access	260
(2) Preferences of rural residents	What are rural customers' preferences for sales channels or salespeople?	Solar Sister non-customers in Solar Sister-adjacent villages	Random walk stratified by sub-village	Survey with embedded conjoint experiment	LMI, AMCE[2]	350

Table 1: Overview of research objectives and design

OBJECTIVES

Using Solar Sister's network of women entrepreneurs as a specific case of a women-centric social enterprise engaged in clean energy distribution, our objective was to answer two questions:

1. Is Solar Sister reaching last-mile customers, especially relative to other organizations promoting clean energy?
2. What aspects of a business model or salesperson resonate most with rural residents when purchasing a small clean energy product?

The first objective aims to provide evidence on the efficacy of social enterprises generally, but also on the nature of social enterprises who train and recruit women, a model used throughout the world (see, for instance, ENERGIA 2017). The second objective is broader, attempting to understand what sales channel

[1] LMI: Last-mile index. This is discussed in detail in the Reaching Last-Mile Customers

[2] AMCE: Average marginal component effect. This is discussed in the Understanding Rural Customers' Preferences section

and salespeople characteristics rural consumers prefer. That is, when given a choice, what sales channel and salespeople characteristics matter most in making a solar lantern purchase?

DESIGN

With the above objectives in mind, we created a research design that drew from two separate populations: rural households who are Solar Sister customers (to determine if Solar Sister is currently reaching last mile customers for Objective 1) and non-Solar Sister customers in rural areas (to determine which sales channel and salesperson attributes new customers value without an existing bias towards the Solar Sister model – Objective 2.)

OBJECTIVE 1

For the first objective, to determine whether Solar Sister is reaching remote customers, we interviewed Solar Sister customers. Our goal was to establish whether or not SSEs were reaching last-mile households. This required, as a first step, to define what is meant by last-mile and, second, how to measure it. The conception of last-mile originates in discussions of supply chains, and the challenges associated with reaching customers in remote or otherwise difficult-to-reach areas. The concept has also been used to describe communities where infrastructure and utilities, such as telecommunications networks or roads, terminate. This understanding of last-mile is primarily geographic. In discussions of last-mile households in development discourse, the last-mile is further associated with poor, rural areas *beyond* the reach of most infrastructure. That is, in addition to a geographic component, last-mile is also based on economic and/or infrastructural notions. For instance, a recent brochure on scaling up energy access defines the last mile as “rural communities which are largely at the base of the market pyramid” (ENERGIA 2017).

Though the last-mile is often invoked, its meaning remains ill-defined. What is the last-mile, practically? How should we define and measure it? For our study, we sought to provide a useful definition that captures several aspects of being last-mile, with specific reference and applicability to the energy sector. Our hope is that other researchers and practitioners can use and improve upon this definition and its measurement in subsequent studies on efficacy in reaching remote households.

Last-mile dimension	Operationalization
Economic	Level of household wealth (e.g., income-based, asset-based)
Infrastructural	Access to energy infrastructure (e.g., grid electricity)
Geographic	Distance from infrastructure or populated area (e.g., paved road, town)

Table 2: Components of what it means to be “last-mile”

As shown in Table 2, the last-mile index, or LMI, we develop measures the degree to which a household is last-mile across three different dimensions: economic, infrastructural, and geographic. These dimensions can be operationalized, or measured, in several different ways. Take the geographic dimension as an example. Physical remoteness begs the question, “Remote relative to what?” This could be distance from a paved road, which would indicate proximity to mature transportation networks; or distance to the nearest gas station, which is often co-located with other infrastructure and indicative of a more “developed” area; or distance to the nearest populated area, such as a city or town with a sizable population (say, 10,000 or more), which serves as a proxy for distance from a bundle of infrastructure generally associated with urban life. In this study, we analyze the three dimensions in the following manner:

- For the economic dimension, we elect to use a poverty score based on the Progress out of Poverty Index® (PPI), a country-specific asset-based measure of a household's wealth;
- For the infrastructural dimension, we take distance to an electrical grid connection as a measure of (lack of) access to infrastructure. Distance here is measured based on self-reported walking time to the infrastructure and assuming a walking speed of 4 km per hour.
- For the geographic dimension, we use distance from the main highway system as a measure of geographic remoteness. Distance here is using self-reported data from customers.[3]

These measures are meant to be complementary. For instance, poverty level can indicate whether purchasing various products or services is within reach for a household, while relative access to the electrical grid indicates the likelihood that a connection is possible, regardless of cost (e.g., a household in a village that already has a grid connection is more likely to get a connection, all other things being equal, than a household in a village lacking any grid connections).

Because last-mile can and does mean many things, an index that aggregates these multiple aspects is appropriate. This is in keeping with the view that, like poverty generally, "last-mileness" is multidimensional and cannot be captured by a single element or indicator (see, for instance, Alkire and Santos 2014). The LMI we develop is by no means exhaustive or comprehensive in capturing every aspect of last-mileness, but we believe it to be a step in the right direction by attempting to provide a standard, measurable value that can be applied across different contexts. It should also be noted that the LMI is based on a household-level analysis of being last-mile, in distinction from other scales, such as being last-mile at the community or village level. We discuss the precise formulation of the LMI as part of the section on Analysis & Findings.

Because a fully random sample of all Solar Sister customers proved logistically onerous, and because the customer population is unknown,[4] we worked with Solar Sister staff to obtain a purposive sample that was nonetheless heterogeneous in its set of customers. First, we chose four regions based on a balance of their customer representativeness and our ability to travel to them during our time in the field. Once this was finalized, we worked with Solar Sisters' Business Development Associates (BDAs)—regional managers who are responsible for training, recruiting, and maintaining SSEs—to select a subset of their SSEs who had a wide range of customers. Then, during brief interviews with each SSE, we would ask her to identify, relative to her own house, how many close, medium, and distant customers she had. That is, we sought to get a sense of the number of customers and their relative geographic distribution. We would then attempt to interview customers in roughly the proportions that the SSE told us. SSEs would then act as guides and accompany us to their customers' houses, where researchers and their translators would conduct surveys privately in order to avoid any possible bias by having the SSE present.

[3] GPS coordinates were also recorded for each respondent. Substituting GPS measurements for self-reported distance yield qualitatively similar results vis-à-vis LMI score distribution.

[4] Solar Sister does not track the identity or location of the SSE's customers, so the only way to reach them was by working directly with the entrepreneurs.

In addition to survey questions on asset ownership used to generate poverty scores and questions on distance to the nearest grid connection, researchers also recorded GPS coordinates of each customers' household to determine physical remoteness. The customer GPS data was also compared to existing power grid maps in an attempt to measure physical distance from a grid connection. However, the customer responses were deemed to be more accurate since the grid maps were dated and the presence of infrastructure does not necessarily imply that it is active.

OBJECTIVE 2

For the second objective, to determine the sales channel and salesperson preferences of rural residents, we collected information to calculate LMIs for non-Solar Sister customers[5] and also employed a survey-embedded conjoint experiment, also called a discrete choice experiment. Conjoint experiments were first used in marketing (Green and Wind 1975; Green and Srinivasan 1990) in order to gain insight on individuals' preferences and perceptions, but has subsequently been used in several other fields, including public health (Kruk et al. 2009; Van Rijsbergen and D'Exelle 2013), agriculture (Alwang, Larochelle, and Berrera 2017), and more recently political science (Carnes and Lupu 2016; Oliveros and Schuster 2017).

Conjoint experiments prove conducive to achieving our second objective. They allow us to identify, measure, and compare the independent effects of various characteristics in a single experiment (Hainmueller, Hopkins, and Yamamoto 2014). The CITE team was able to benefit from the experience of MIT Governance Lab researchers who have administered conjoint experiments in Tanzania and have developed tools for their administration in developing country contexts (Meyer and Rosenzweig 2016).

The conjoint technique offers several methodological advantages over conventional survey-based questions that ask respondents about their preferences explicitly, as well as other types of survey experiments. First, randomization of attribute levels sufficiently addresses both omitted variable bias and reverse causality bias, which plague observational studies. Second, conjoint experiments reduce social desirability bias by not only giving respondents multiple reasons to justify their choices, but also because it allows respondents to make choices based on relative, as opposed to absolute, preferences (Hainmueller, Hopkins, and Yamamoto 2014). Third, conjoint experiments allow for the simultaneous estimation of the effects of several attributes, an impossibility using other survey experiment techniques. Fourth, the way in which choices are presented to respondents, where they must make tradeoffs between preferences for different attributes that are bundled together, represents a more realistic choice relative to the direct elicitation of preferences for attributes along a single dimension (Hainmueller, Hopkins, and Yamamoto 2014). Owing to these strengths, the external validity of conjoint experiments proves more robust when compared to other experimental techniques (Hainmueller, Hangartner, and Yamamoto 2015).

Conjoint experiments use a choice-based design in which respondents are asked to choose between hypothetical profiles with randomly varying characteristics, or attributes. Each attribute can then take on one of two values, or levels. One of the disadvantages of the conjoint technique is that the more attributes

[5] Existing Solar Sister customers were excluded in this part of the research because they had already inherently expressed their sales channel and salesperson preferences by buying a lantern from Solar Sister.

and levels are included in the experiment, the larger the sample size needs to be in order to achieve statistically significant results. Based on the time and resource limits for fieldwork, the CITE team needed to limit the attributes to four characteristics with two levels each. While we carefully chose the four attributes as described below, it is possible that additional attributes that were not included could contribute heavily to a customer's choice of sales channels and salesperson characteristics.

The attributes and levels included in our study, shown in Table 3, were decided upon through a collaborative and iterative process that relied on relevant reports and academic literature, conversations with Solar Sister staff in Washington D.C., a survey of Solar Sister Business Development Associates (BDAs) throughout Tanzania, and conversations with other clean energy-providing organizations. The four final attributes were chosen to represent aspects of Solar Sister's business model as well as those of similar organizations working in the same areas. While Solar Sister offers local assistance from familiar people (often women) within one's social network, other organizations offer monthly payment schemes, typically rely on intermittent after-sales service from traveling staff members, and tend to have a male-dominated workforce. In total, 350 respondents completed the conjoint experiment, for a total of 3,500 observations (350 respondents $\times$ 5 rounds of salesperson choice $\times$ 2 observations per round).

Attribute	Level
After-sales assistance	Assistance available via phone, local assistance unavailable In-person local assistance available
Familiarity	Do not know the salesperson Know and trust the salesperson
Gender	Male salesperson Female salesperson
Payment	Single payment of 15,000 TSh ($6.70) Multiple payments, 6 of 4,000 TSh ($1.80) each (24,000 TSh, $10.80 total)[6]

Table 3: Salesperson attributes and levels for conjoint experiment

Due to the design of the conjoint experiment, we were able to assess the independent and interactive effects of after-sales assistance, gender, familiarity, and payment scheme on the salesperson preference of respondents. In our case, we ask randomly chosen rural household members to choose between pairs of hypothetical salespeople who are selling household solar lanterns. Each respondent was presented with five rounds of paired salespeople from which to choose. Because we were dealing with a context in which literacy levels varied widely, we developed a script to be read to each respondent and visual representations of each salesperson that the respondent could look at when making his or her decision. The script and example of the visual representation is shown in Figure 1.

SSEs were asked to identify villages adjacent to or near to their own village, but where they had not made any attempts to sell solar lanterns. These villages comprised the population from which we sampled for the conjoint experiment. Non-customer conjoint respondents were randomly selected in these villages using a random walk methodology stratified by sub-village. Our intent was to find customers similar to

[6] Additional mark-up for payment in installments based on figures reported in Gong et al. (2017).

those that SSEs are reaching, but who did not have direct contact with Solar Sister or its SSEs, so that their preference choices would remain independent of any bias such interaction would introduce.

Script: Pretend that you are buying a solar lantern like this one for your home [enumerator shows example solar lantern]. I am going to show you a pair of salespeople with solar lanterns for sale and read descriptions of each salesperson. [Show respondent first pair.] The first salesperson is "A" [Point to left column]. The second salesperson is "B" [Point to right column]. Salesperson A is a [man / woman] who [is known to you and trusted / you do not know.] He/she or someone who works with him/her [is available in person if you need help / lives far away and is only available by phone] and [accepts payment in one lump sum/accepts monthly payments over a six-month period.] [Repeat for Salesperson B: "Salesperson B is a…"] From which salesperson would you prefer to buy the solar lantern? Circle the letter at the bottom of the page that corresponds to the salesperson that you prefer most.
[Repeat four times for a total of five rounds per respondent]

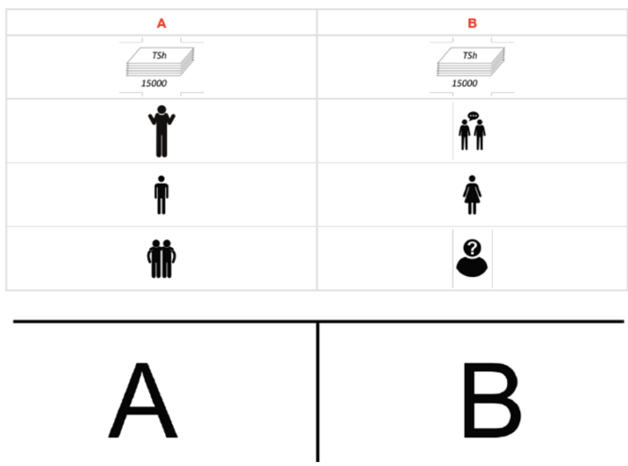

Figure 1: Conjoint experiment script (above) and visual representation example (below)

Two Interpreters and two enumerators were hired and trained regarding the research objectives of the study, as well as guidelines for ethical interaction with human research subjects. All enumerators and interpreters had either worked with Solar Sister-affiliated researchers, or had administered conjoint experiments, before. Together, the four of them translated both survey instruments from English to Swahili to agree upon standard language and to thus ensure consistency across surveys.

MIT's internal review board, the Committee on the Use of Humans as Experimental Subjects (COUHES), approved our research design on July 11, 2017.[7] SSEs and non-Solar Sister customers given bags of sugar,[8] which was deemed a culturally appropriate form of non-monetary remuneration based on conversations with Solar Sister and other researchers who have also conducted research in Tanzania. Because the Solar Sister customer survey only took 10 to 15 minutes to complete, we elected not to compensate them.

[7] COUHES Protocol #1706010321
[8] 2 kg for SSEs, who typically spent a full day with us; and 0.5 kg for a non-Solar Sister customer, whose survey took between 30-60 minutes to complete.

Analysis & Findings

After a brief discussion of descriptive statistics that give a sense of our respondent samples, we report our findings by each of our two research objectives.

Sample and Descriptive Statistics

Fieldwork and data collection occurred over five weeks in July and August 2017. Geographically, our surveys were conducted in 28 villages—13 Solar Sister customer villages and 15 non-customer conjoint villages—spread throughout four regions of central and eastern Tanzania: Manyara, Dodoma, Kilimanjaro, and Tanga.

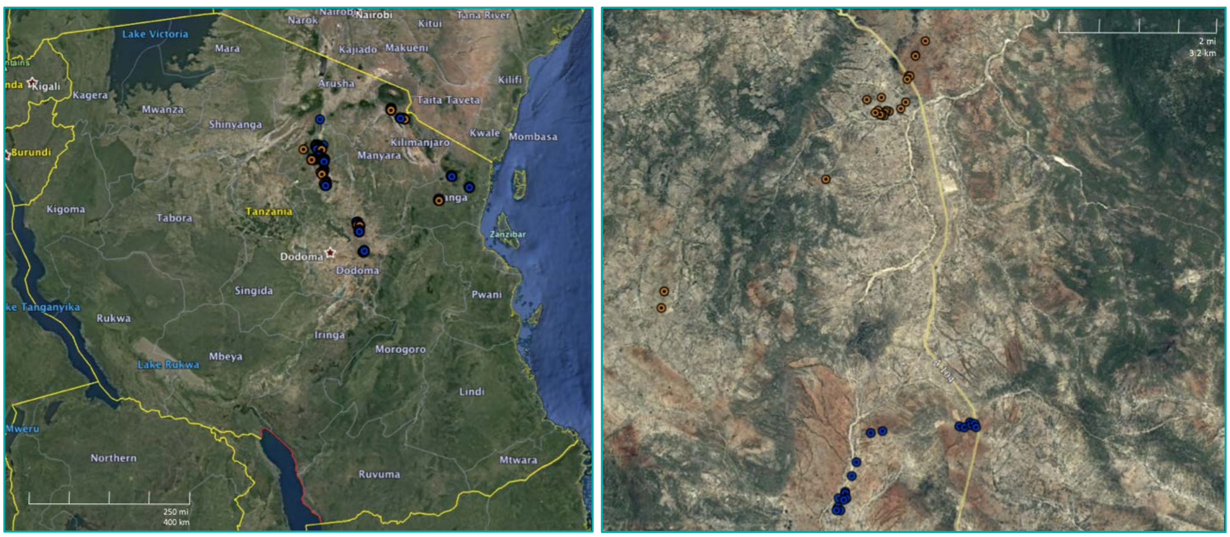

Figure 2: Respondents' geographical distribution. Orange: Solar Sister customers, blue: Non-customers/conjoint respondents. Left: total sample, right: zoomed in example from one day of field collection in the Manyara region (yellow line is the main highway).

As can be seen from Table 4, a total of 610 respondents were surveyed: 250 Solar Sister customers and 360 non-customers who participated in the conjoint experiment. Across the two populations, 65% of respondents were female, while 35% were male. The age distribution of customers and non-customers is relatively similar. Our sample is weighted toward respondents in Manyara region, as this is a region in which Solar Sister is quite active relative to other regions.

For the poverty component of the LMI score, the team decided to use the Progress out of Poverty Index, which was developed in 2006 by the Grameen Foundation and Ford Foundation, and is currently managed by the Innovations for Poverty Action (IPA). The PPI is based on a 10-question survey specific to each country and computes the likelihood that the household is living below the poverty line; a high PPI score means that a household is likely *not* living in poverty. Since we use the poverty score as one of the constituent parts of the LMI, and because higher LMI scores indicate a greater degree of last-mileness, the CITE teams' poverty score is the inverse of the PPI (i.e., 100 – PPI score): that is, a high CITE poverty score means that a household *is* likely living in poverty.

Customers

Region	Gender		Age			
	Male	*Female*	*Min*	*Median*	*Max*	*Std Dev*
Manyara	45	102	18	45	91	14.01
Dodoma	4	36	19	44	85	15.47
Kilimanjaro	4	36	20	47	80	13.94
Tanga	9	24	19	44	80	17.25
Total	62	198	18	45	91	14.65

Non-Customers

Region	Gender		Age			
	Male	Female	Min	Median	Max	Std Dev
Manyara	58	95	19	39	82	15.19
Dodoma	21	50	18	37	89	14.65
Kilimanjaro	18	23	19	42	76	14.48
Tanga	30	55	18	39	76	14.00
Total	127	223	18	38.5	89	14.71

Table 4: Descriptive statistics

As can be seen from Figure 3, the poverty distributions of the customer and non-customer sample populations are quite similar. For both samples, more than half of the population has a CITE poverty score above 50, indicating that they are more likely to be living in poverty.

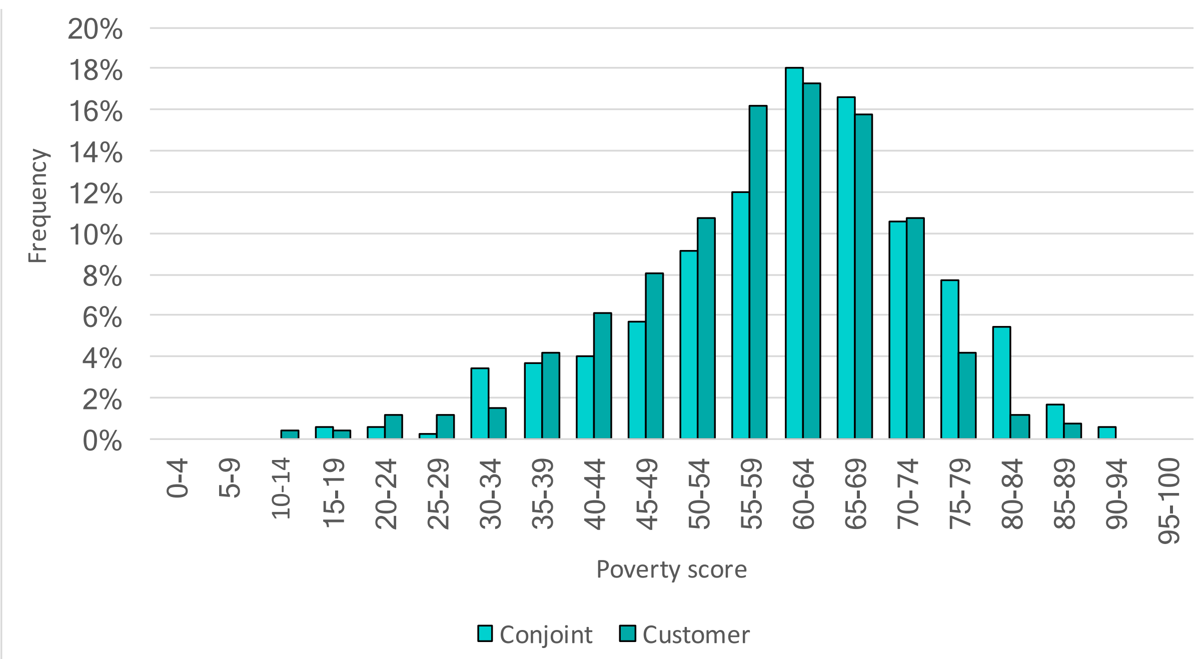

Figure 3: Poverty score distribution by respondent type. 0: least likely to be impoverished, 100: most likely to be impoverished.

REACHING LAST-MILE CUSTOMERS

Three components make up the LMI: a poverty level indicator, an access to grid energy indicator, and a physical remoteness indicator. All scores were normalized to a 0 to 1 scale, with values closer to 1 indicating a greater degree of last-mileness (more poverty, less access to energy, greater physical remoteness). Table 5 lists the indicators used in the LMI calculation.

Indicator	Code	Explanation
Poverty level	P	Inverse of Progress out of Poverty Index® (PPI) score
Grid access	G	Self-reported proximity to a grid connection
Remoteness	R	Self-reported distance from nearest highway (est. time x average peed)
Last-mile index	LMI	P1 + G1 + R (equal weighting)

Table 5: Last-mile indicators

For poverty level, as described in the section above, we use the inverse PPI score. This score is based on ten survey questions that ask about the household asset ownership of the respondent. The customer and non-customer distributions are quite similar, with a median of 0.595 for Solar Sister customers and 0.615 for non-customers. Relative to the $2.00/day poverty line (2005 PPP), this means that the median household in both samples has between a 64% and 77% likelihood chance of living in poverty. That is, the median household in both samples is more likely than not to be living in poverty.

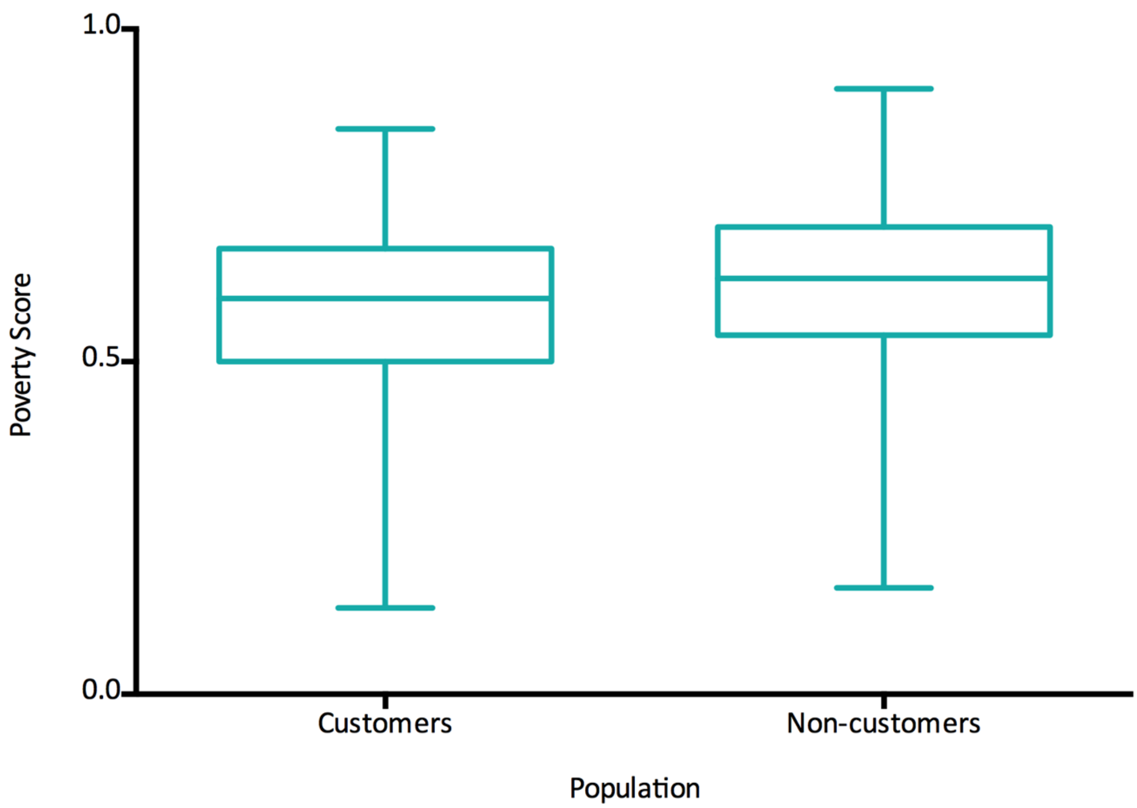

Figure 4: Poverty score distribution by respondent type. Boxplot represents the minimum, first quartile, median, third quartile, and maximum.

For energy access, we asked respondents to gauge their proximity to the nearest grid infrastructure: whether they had a grid connection; whether anywhere in their village had a grid connection; and the time it took to walk to the nearest location with a grid connection. Based on the answers provided, we created a step function to generate the (lack of) grid access score. Points were given to each household based on the presence of a grid connection at their household or in their village, as well as how long it took to walk to the nearest place with a grid connection. The point scheme was created to reflect the time it takes to traverse a 7 km-by-7 km village,[9] which is used to determine last-mileness in terms of grid access. Further, for households in villages where a grid connection already exists, the scores were reduced by 25%, in recognition of the fact that grid infrastructure in a village represents overcoming a significant hurdle to realizing electricity access: a household in a village that already has grid infrastructure present will, all else being equal, be more likely and more capable of gaining a grid connection should they wish than an identical household in a village without any grid infrastructure. Table 6 summarizes the points scheme we adopted and Figure 5 shows the distribution of the grid access scores.

Time to nearest grid connection (walking, min)	Grid score	
	Grid in village	*Grid not in village*
0 (household connection)	0	—
1-9	8	10
10-24	19	25
25-49	38	50
50-74	56	75
75-99	68	90
100 or more	75	100

Table 6: Points scheme for (lack of) grid access score.

The points associated with each grid score follow a nearly linear function. The more moderate slopes at the edges that produce non-linearity in the point distribution reflects the fact that very close and very far distances associated with walking time matter less in terms of access. That is, a grid connection within 10 minutes or less is can be seen as akin to having grid access, were it not for other factors, such as cost: such close proximity points to the feasibility of access for that household. Moreover, as the time to walk to a grid connection increases, the likelihood of the same time unit having the same effect on access decreases a 30-minute walking difference matters more when moving from 30 to 60 minutes, as opposed to 170 to 200 minutes. This is in keeping with findings from Nerini et al. (2016) concerning the relative linearity of supply-side costs for providing electricity as a function of distance from the grid in rural areas.

Surprisingly, grid access scores are generally quite low, as shown in Figure 5, indicating relative proximity to grid infrastructure across both respondent groups. Further, quartile three (50th-75th percentile) covers

[9] The average village population is Tanzania is about 2,700, and the average population density is 51 people per km^2. This means that the average village in Tanzania is 53 km^2, or 7.2 km-by-7.2 km. At a walking rate of 4 km per hour, a villager would be able to walk across an average village in just over 100 minutes. As a result, we use 100 minutes, or the time it takes to walk across an average village, as the cutoff for being last-mile in terms of grid access.

a wide range, from about 0.2 to 0.7. This may be due to the fact that, in both sample populations, 62% of respondents reported that a grid connection existed in their village.

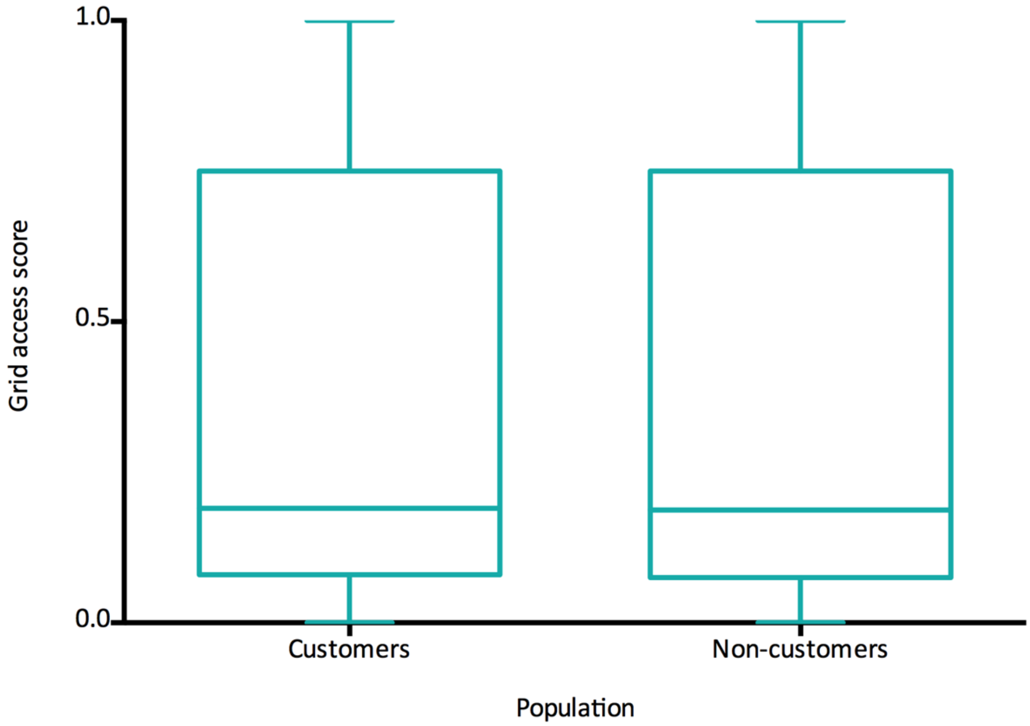

Figure 5: Grid access score. 0: close proximity to grid, 1.0: distant proximity to grid

Physical remoteness was calculated by asking respondents how long it took them to get to the nearest main road upon which inter-regional buses travel (i.e., the highway system). A distance of approximately 16 km in one direction was deemed to be the cutoff for a score of 1.0—the logic being that, at a rate of 4 kilometers per hour walking, a roundtrip of 32 km would take the entire day. This seemed to be a plausible cutoff for being last-mile: that is, a full day of walking. as a check on the self-reported data, GPS coordinates were collected to trace the distance from a household to the nearest highway. A log transformation of the distances was used to estimate a cubic polynomial function that would generate a distance function.[10] As shown in Figure 6, both Solar Sister customers and non-customer distributions are skewed heavily toward 1: that is, toward being physically far removed from the main highway.

[10] The remoteness score distribution based on GPS coordinates is qualitatively similar to the self-reported distribution.

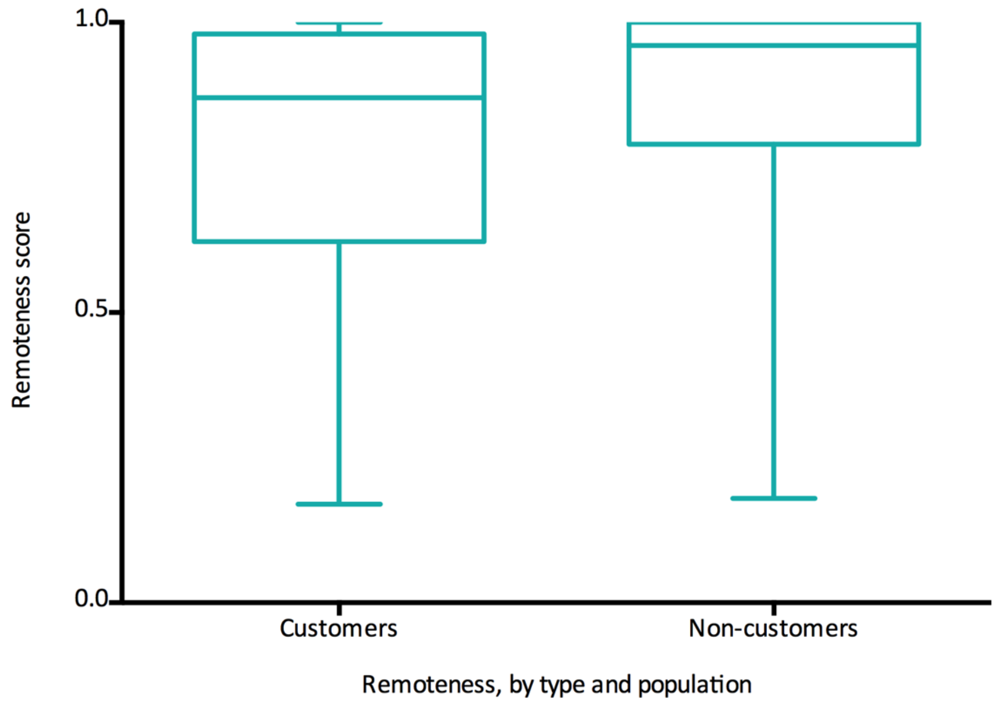

Figure 6: Remoteness score distributions

Taking the three distance indicators above and combining them with equal weighting, we generate the LMI scores shown in Figure *7*. Notably, the LMI median is 0.56 for Solar Sister customers. At just above 0.5, this indicates that most Solar Sister customers in our sample are more last-mile than are not.

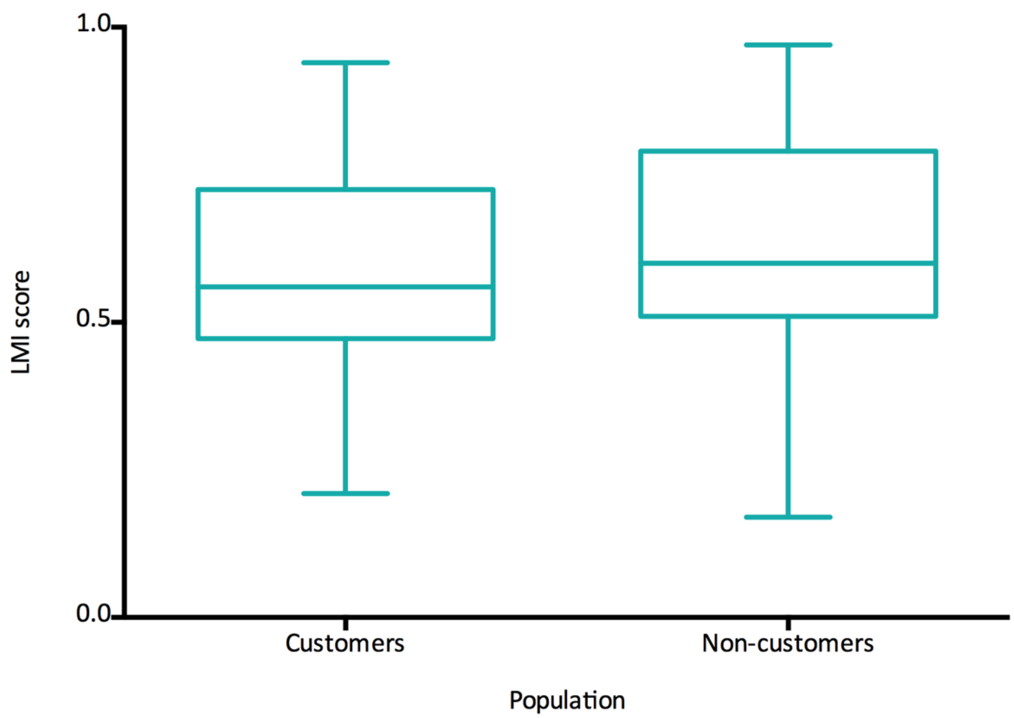

Figure 7: LMI score distributions

In addition to the LMI analysis, we also asked both customers and non-customers about their alternative sources for solar lighting products, as well as whether they had heard of, have access to, and have purchased from any sources or organizations selling such products.[11]

As can be seen from Table 7, local retail (which includes monthly and weekly village markets and traveling salesman) dominates as the main source for purchasing household solar lighting products. However, some respondents noted that the quality of products is often poor or questionable at local markets and from traveling salesman. Further, in the case of traveling salesman, some respondents also noted that after-sales assistance proves largely impossible since they do not have any way to contact him.

While some respondents had heard of other organizations selling solar lanterns,[12] few had access to Solar Sister alternatives beyond local markets or traveling salesman. Even fewer people noted having purchased a product from another organization. The most popular organizations, both in terms of purchases and hearsay, were M-Power/Zola and Mobisol. Both private companies sell large solar home systems and so do not offer a direct alternative to Solar Sister, whose primary product focus is household solar lanterns. Further, several respondents noted having installed these systems, or having known someone who had, only to later discontinue use after the recurring monthly cost become too expensive. This lends credence to the idea that Solar Sister's women entrepreneurs are penetrating into markets and communities that have few alternatives for reliable and affordable clean lighting products.

Competitor org.	Access and have purchased			Access but have not purchased			Heard about but no direct access		
	Customers	*Non-customers*	*Total*	*Customers*	*Non-customers*	*Total*	*Customers*	*Non-customers*	*Total*
Solar Sister	260	0	260	N/A	2	2	N/A	22	22
Local retail	87	117	204	38	49	87	10	22	32
M-Power / Zola	12	17	29	20	31	51	71	121	192
Mobisol	1	9	10	13	20	33	37	68	105
Sun King	0	0	0	4	5	9	14	27	41
Ensol	0	0	0	0	1	1	17	11	28
Little Sun	0	0	0	1	0	1	9	13	22
Solar Kiosk	0	0	0	1	0	1	14	5	19
Total	0	0	0	0	0	0	14	3	17
Ongeza	0	0	0	2	2	4	12	0	12
School Program	5	3	8	0	0	0	1	0	1
World Vision	1	1	2	0	0	0	0	0	0

Table 7: Differing levels of access to solar lighting

We now turn to the results from our non-Solar Sister customer population in the next section.

[11] This data was collected in lieu of being able to obtain direct sales data from organizations other than Solar Sister.

[12] An important caveat: some respondents noted that they do not pay attention to organization or brand names.

UNDERSTANDING RURAL CUSTOMERS' PREFERENCES

Figure 8 shows the results from the conjoint experiment. Point estimates for each attribute level represent their average marginal component effect (AMCE) relative to the baseline level, along with 95% confidence intervals. To illustrate with an example, the AMCE for the Assistance attribute is the difference in probability that a respondent would choose a salesperson who is able to provide local assistance relative to an otherwise identical salesperson who cannot provide local assistance. These probability differences can be interpreted as additional or diminished utility derived from one attribute level as compared to the baseline level. Put another way, utility can be conceived as placing more or less importance, and therefore preference, on an attribute level.

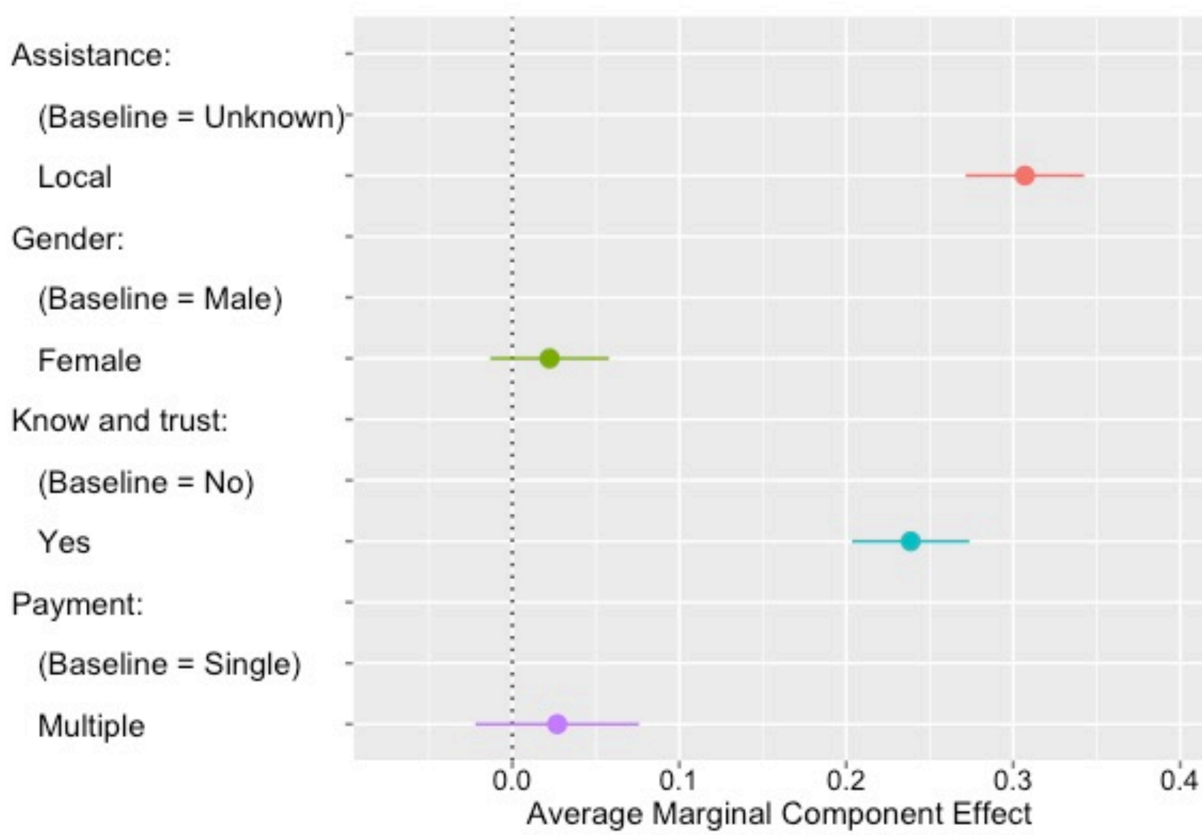

Figure 8: Conjoint experiment results

Notes: Based on 3,500 observations from 350 respondents. Bars around point estimates represent 95% confidence intervals. Attribute values are relative to the baseline value (i.e., 0). The Assistance and Know and trust attributes are significant at p<0.001. The Gender and Payment attributes are not statistically significant, at p>0.1.

The conjoint results reveal that:

1. Respondents ascribed 31 percentage points more utility from salespeople who could provide local assistance relative to those who could not; and

2. Respondents ascribed 24 percentage points more utility from salespeople who they knew and trusted relative to ones they did not know.

Both of these results are statistically significant at $p<0.001$ and the 95% confidence intervals do not include zero, such that we can report these results with a high degree of certainty.

In contrast to the above two results, and despite being slightly positive, the point estimate for utility derived from a female salesperson relative to a male one is small (0.02), statistically insignificant ($p<0.22$), and its 95% confidence interval includes zero; the same applies to a salesperson who can offer multiple payments relative to one who can offer a lump-sum payment. Taken together, these results indicate that rural consumers value a business model that can provide them with local assistance from someone they know and trust; the gender and payment scheme prove less important in their decision-making. These results prove somewhat surprising, since a large literature points to the importance of both gender and financing in the diffusion of technologies at the bottom of the pyramid.

While gender and payments are not particularly important in the baseline specification from which Figure 8 is derived, when including two-way interaction effects between the four attributes, they become somewhat more important, though still not at statistically significant levels (see Figure 9). Of the six possible two-way interactions between the four attributes,[13] three yield statistically insignificant results with large p-values (between 0.44 and 0.78) when added to the baseline specification, while the three others yield results with p-values just above and below 0.1. The three interactions that generate more precise results are interactions between: assistance and payment (AP), gender and familiarity (GF), and familiarity and payment (FP).

We can interpret the three interaction effects with p-values indicating greater significance (p-values in parentheses) as follows. First, for AP, respondents who chose multiple payments from a local salesperson receive, on average, 4.9 (0.125) percentage points more utility relative to a baseline of a single payment from an unknown salesperson. Second, for GF, respondents who chose a female salesperson that they know and trust receive, on average, 4.8 (0.115) percentage points less utility relative to a baseline of a male who in unknown to the respondent. Third, for FP, respondents who chose multiple payments from someone they know and trust receive, on average, 5.2 (0.099) percentage points more utility relative to a baseline of a single payment from a salesperson who is known and trusted. While this result is only statistically significant at $p<0.1$, it does indicate that higher levels of trust may be preferable, easing transaction costs when engaging in payment schemes that require collecting installments over time.

Moreover, all three interactions that include the gender attribute reveal a preference for males over females (with the caveat that the effect is small in magnitude and statistically insignificant). More specifically: a male offering no local assistance is preferred over a female who can offer local assistance; a male who is unfamiliar is preferred over a female who is known; and a male who can offer a single payment scheme is preferred over a female who offers multiple payments. While perhaps discouraging, this result also points to the importance of empowering women through entrepreneurial activity, which may help dissuade such pervasive bias.

[13] The six possible two interactions are between: assistance and gender (AG), assistance and familiarity (AF), assistance and payments (AP), gender and familiarity (GF), gender and payment (GP), and familiarity and payment (FP).

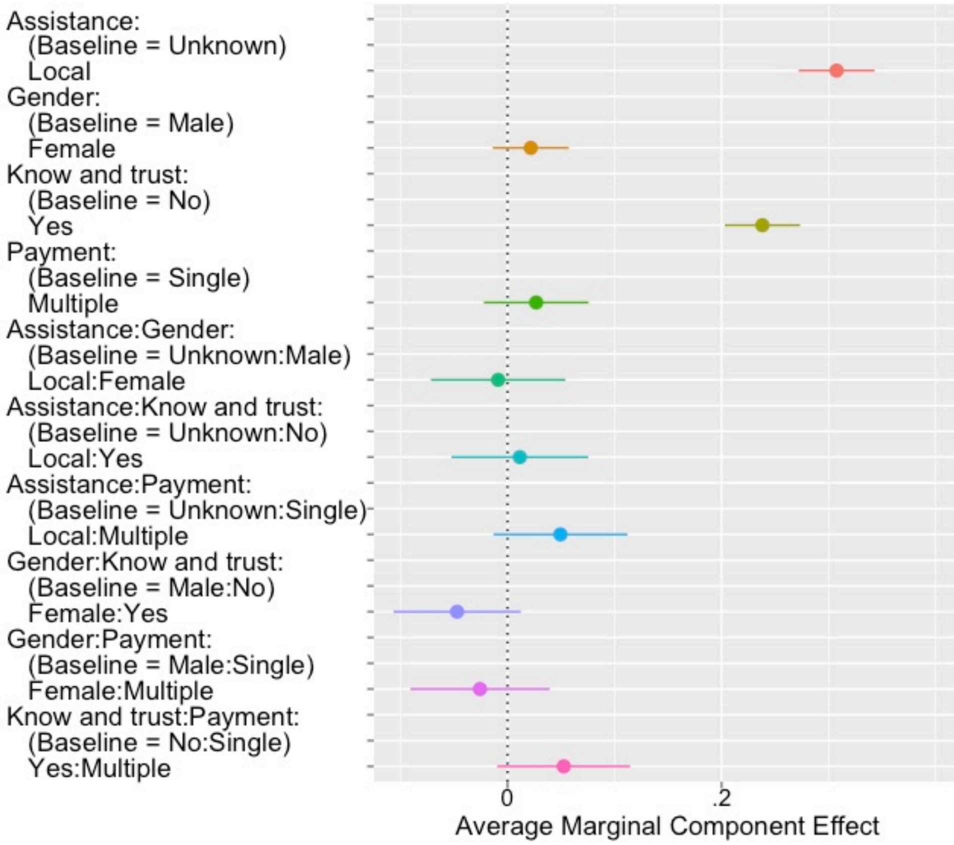

Figure 9: Conjoint experiment results, with interaction effects

In addition to interactive effects, the conjoint results can be disaggregated by respondent categories: namely, LMI score and gender. As shown in Figure 10, the results conditional on LMI score quantile show that, as LMI increases—that is, as respondents become more last mile—preference for local assistance and a familiar salesperson remains stable. In contrast, as LMI increases, the preference for multiple payments over a single payment increases slightly, the gender preference of the salesperson switches from female to male, and. Though the switch for gender preference is small in magnitude, it may indicate that gender bias is higher in last-mile areas, where gender roles tend to be more traditional and fixed. Indeed, evidence for such bias can be found in other developing contexts, such as in south Asia (e.g., Saikia 2011; Behrman 1990).

As shown in Figure 11, categorizing the results by respondents' gender reveals that females preferred local assistance 33 percentage points more than unknown assistance; for males, the preference was 27, or 6 percentage points less than females. Female respondents had a slightly greater preference for female salespeople (3 percentage points) than did male respondents (0.6 percentage points). Familiarity was equally as important for male and female respondents at about 24 percentage points, while females had a slight preference for multiple payments (5 percentage points) and males had a small preference for single payment (0.6 percentage points).

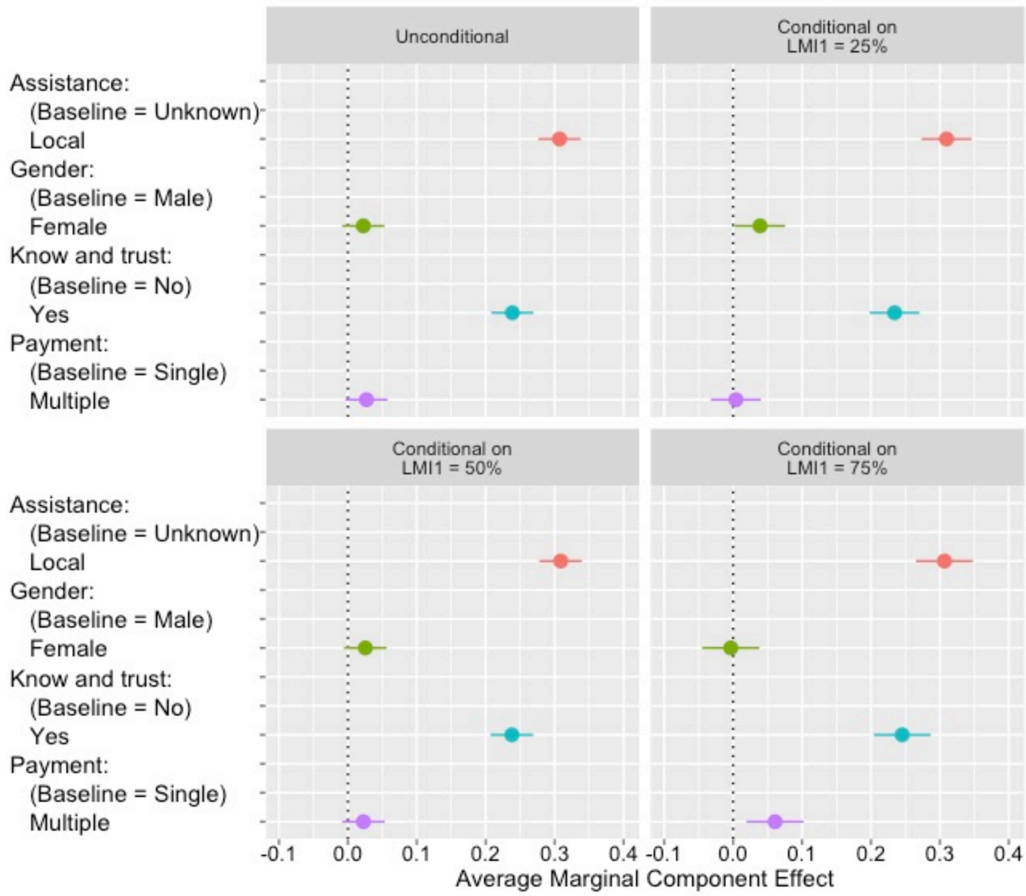

Figure 10: Conjoint experiment results, conditional on respondent LMI score

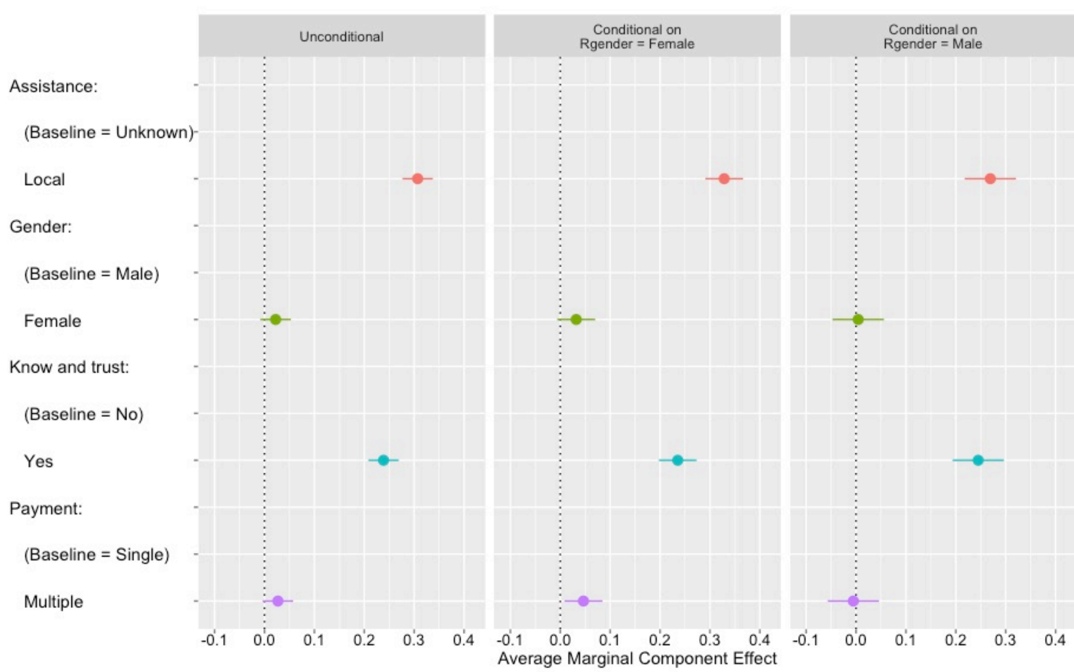

Figure 11: Conjoint experiment results, conditional on respondent gender

Conclusion & Next Steps

Efforts to reach last-mile customers need to be met with greater care and precision in determining which customers, in practice, are being reached. In a similar vein, while much has been written on the merits and shortcomings of various business models aimed at reaching last-mile consumers, relatively little research has been conducted on the view from below: that is, the preferences of rural residents for different kinds of sales channels and salespeople. This is in contrast to a larger literature concerning the technological preferences of low-income consumers.

Our study seeks to address both of these gaps, providing new empirical evidence on the relationship between gender and clean energy promotion in developing contexts. First, we create a new last-mile index, or LMI, that consists of three dimensions—economic, infrastructural, and geographic—and further develop and conduct surveys to operationalize their measurement. We find that Solar Sister does appear to be reaching relatively last-mile customers. Second, we conduct a survey-embedded conjoint experiment to uncover the salesperson and sales channel attributes rural residents find important when considering purchasing a small household product, such as a solar lantern. We find that rural villagers place great importance on local, in-person after-sales assistance and close familiarity with the salesperson.

In contrast, far less importance is given to the gender of the salesperson and the payment scheme offered (single versus multiple payments), though the importance given to these attributes increases when taking into consideration interactive effects. We also find that women and more last-mile respondents place greater importance on local assistance than men and the relatively less last-mile, and that there may be gender bias when it comes to the perceived capability of a salesperson. While perhaps discouraging, this result also points to the importance of empowering women through entrepreneurial activity, which may help dissuade such pervasive biases.

As meaningful as the findings of this study are, additional research could build on them to elucidate further insights. Replicating the methods used in this study, whether the last-mile indicators and LMI or the conjoint experiment, in other countries and contexts will offer several advantages. For one, doing so would help achieve a more nuanced and robust understanding of how women-centric social enterprises perform, exposing both strengths and weaknesses of such a business model. Further research along these lines would also reveal the extent and nature of biases against women salespeople. Finally, it would help gain insight as to whether the findings regarding rural customers' preferences presented in this report are universal or whether they prove conditional on additional mediating, context-specific characteristics.

REFERENCES

Alwang J, Larochelle C, and Barrera V. 2017. "Farm Decision Making and Gender: Results from a Randomized Experiment in Ecuador." World Development 92: 117-129.

Alkire S and Santos ME. 2014. "Measuring acute poverty in the developing world: Robustness and scope of the Multidimensional Poverty Index." World Development 59: 251-274.

Behrman J. 1990. "Intrahousehold Allocation of Nutrients and Gender Effects: A Survey of Structural and Reduced-Form Estimates." In Osmani S (ed.), Nutrition and Poverty, Oxford: Oxford University Press.

Carnes N and Lupu N. 2016. "Do voters dislike working-class candidates? Voter biases and the descriptive underrepresentation of the working class." American Political Science Review 110: 832-844.

ENERGIA. 2017. "Scaling up energy access through women-led businesses."

Gong S et al. May 2017. "Pay as you go solar as a means to combat energy poverty." School of International and Public Affairs, Columbia University.

Green PE and Wind Y. July-August 1975. "New Way to Measure Consumers' Judgments." Harvard Business Review.

Green PE and Srinivasan V. October 1990. "Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice." Journal of Marketing 54(4): 3-19.

Hainmueller J, Hangartner D, and Yamamoto T. 2015. "Validating vignette and conjoint survey experiments against real-world behavior." Proceedings of the National Academy of Sciences 112: 2395-2400.

Hainmueller J, Hopkins DJ, and Yamamoto T. 2014. "Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments." Political Analysis 22: 1-30.

Kruk ME, Paczkowski M, Mbaruku G, de Pinho H, and Galea S. September 2009. "Women's Preferences for Place of Delivery in Rural Tanzania: A Population-Based Discrete Choice Experiment." American Journal of Public Health 99(9): 1666-1672.

Meyer A and Rosenzweig L. 2016. "Conjoint Tools for Developing Country Contexts." The Political Methodologist. February 18.

Nerini F, Broad O, Mentis D, Welsch M, Bazilian M, and Howells M. 2016. "A cost comparison of technology approaches for improving access to electricity services." Energy 95: 255-265.

Niethammer C and Alstone P. 2012. "Expanding women's role in Africa's modern off-grid lighting market: enhancing profitability and improving lives." Gender & Development, 20(1): 145-157.

Oliveros V and Schuster C. forthcoming. "Merit, Tenure, and Bureaucratic Behavior: Evidence From a Conjoint Experiment in the Dominican Republic." Comparative Political Studies.

Saikia H. April 2011. “Transformation of Rural Gender Discrimination and Women’s Empowerment in Assam.” Asian Journal of Literature, Culture, and Society .

Tracy J and Jacobson A. April 2012. “The True Cost of Kerosene in Rural Africa.” Lighting Africa.

Van Rijsbergen B and D’Exelle B. 2013. “Delivery Care in Tanzania: A Comparative Analysis of Use and Preferences.” World Development 43: 276-287.

World Bank. 2017. “World Development Indicators.” World Bank DataBank. Available online: <http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators#> (Accessed 27 September 2017).

Authors & Team Members

MIT-CITE

Jonars B. Spielberg*
Sara Lynn Pesek
Jennifer Green
Bish Sanyal, Principal Investigator

Cornell University

Kaitlin Green

Solar Sister HQ

Abby Mackey
Katherine Lucey
David O'Connor

Solar Sister Tanzania

Fatma Mouzo
Neema Nko
Amina Bakari
John Nyallu
Victoria Mfinanga
Ansila Evans Makup

Interpreters and enumerators

Vanessa Hanji
Wandalala Mkumbo
Victoria Mwanziva
Kisha Scotia

*Corresponding author: jspiel@mit.edu

Front cover: A solar lantern charges in front of a home in rural Tanzania.
Photo credit: Sara Lynn Pesek