Reducing Information Barriers to Solar Adoption: Experimental Evidence from India*

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Abstract

Off-grid solar technologies hold promise for unelectrified and low-quality electricity settings; however, their adoption remains low. Important barriers to adoption, such as incomplete information remain relatively unexplored in developing countries. In collaboration with a solar company, a randomized experiment was implemented in three Indian states to test whether alleviating information asymmetries between sales agents and potential customers improved predictors and other indicators of adoption of solar rooftop systems. The company's sales agents were randomly assigned to receive a tablet with either an application designed to ensure potential customers received accurate solar product information during the sales process or only the basic sales catalogue uploaded. Post-treatment, prospective customers approached by the treated sales agents report greater knowledge of the solar products and a better impression of sales agents' product knowledge and professionalism. The treatment significantly increased potential customers' intent-to-adopt, a stated preference measure, by 15%; however, the impact on actual adoption was statistically insignificant.

Keywords: Solar, energy, technology adoption, information, development
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1 Introduction

Worldwide, around 840 million people lack electricity access and another 1 billion are connected to unreliable grids that provide poor quality services with frequent outages and voltage fluctuations (World Bank, 2020). Off-grid solar technologies, which are less polluting than electricity generated via burning fossil-fuels, can serve as a stopgap by either providing electricity services until the grid is extended or by smoothing consumption of electricity until quality improves (Sharma et al., 2020). The latter is particularly relevant in South Asia, where unreliable electricity service is widespread (Pargal and Banerjee, 2014) resulting in more power outages than any other region of the world (Zhang, 2019).

The adoption of off-grid solar, however, remains low. Studies have examined barriers to take-up among low-income households, including low willingness-to-pay relative to prices (Burgess et al., 2020; Grimm et al., 2020; Rom and Günther, 2019; Sievert and Steinbuks, 2020), liquidity constraints (Grimm et al., 2020), and preferences either for the centralized grid broadly (Burgess et al., 2020) or specific appliances that are more feasibly powered by the grid (Lee et al., 2016). A number of other factors, however, likely also impact adoption and require further study (Girardeau et al., 2021). For example, industry reports indicate that incomplete information on solar products and their suitability for different appliances drives low adoption among middle-income households and small firms (Chaudhary, 2018; Trivedi et al., 2017). Although research has shown that information interventions increase the adoption of other environmental technologies (and with more lasting impacts on adoption than credit interventions) (see, e.g., Aker and Jack, 2021), such interventions in the context of solar products remain understudied.

Through a randomized experiment with an Indian solar rooftop company, we study the role of information in off-grid solar adoption within the Indian states of Bihar, Uttar Pradesh, and Odisha. The main solar products sold by this company were 100 and 200 watt (W) home solar products, which were typically sold with a battery (unless the purchaser already owned a battery), and were sufficient to power not only lighting and charging services, but fans, televisions, and other efficient appliances. Prior to the experiment, the solar company highlighted information constraints as a barrier to adoption. Ex-ante, access to credit did not appear to be the main constraint slowing adoption in this context, as the solar company already provided financing options via a pay-as-you-go model prior to the experiment.[1] Additionally, this company relied on sales agents to sell their solar products; a business model common in developing countries (Ashraf et al., 2013), yet vulnerable to information asymmetries between sales agents and potential customers. Sales agents may use potential customers' incomplete information to their advantage by either over-promising on the capacity of a particular solar product or upselling solar products, a finding confirmed by a pre-experiment survey of past purchasers (Sambodhi Research, 2018).

The study tests whether an algorithmic mobile application – designed to reduce information asymmetries between sales agents and prospective customers, loaded onto electronic tablets, and used during the sales process – improved consumer knowledge of these solar products and their returns, thereby increasing adoption. The randomized experiment builds upon the company's existing sales structure, in which sales agents were assigned to a census block as their sales territory. The intervention proceeded as follows: within the solar company's sales regions, 74 census blocks were randomly assigned to either treatment or control status. Sales agents operating in treated census blocks were equipped with a tablet containing a mobile interface (the "treatment app") which was employed during the initial sales visit to collect information about the potential customer (e.g., ability to pay and electricity needs). Information on the most suitable solar product, including details of the appliances feasibly-powered by the product and a product image, were provided. Control group sales agents also used an electronic tablet, but theirs contained only a standard version of the

[1] A pay-as-you-go (PAYG) model allows customers to make a down payment on the product, followed by regular installments (e.g. monthly payments) until the cost of the technology is repaid in full (World Bank, 2020). PAYG models are typically implemented in an effort to relieve credit constraints (Grimm et al., 2020). For example, a product that would cost 8,000 rupees if purchased outright, could be acquired through a pay-as-you-go model with a 1,800 rupee down payment and monthly payments for the balance (plus interest) over a period of 11-, 23-, or 35-months afterwards.

product catalogue without the information guide designed to ensure complete and correct information would be delivered.

Our analyses use the solar company's data on sales agents, the census blocks to which they are assigned, and their historical sales records, all of which are complemented by baseline and follow-up surveys. Surveys were implemented by phone due to the government's COVID-19 lockdowns and were therefore brief. Nevertheless, the surveys collected data on customers' (whether they were households or firms) characteristics, their experiences with electricity and solar products, their knowledge of the solar products, and impressions of the sales' agents knowledge and professionalism. In total, 2,246 existing solar company customers were surveyed for the baseline in June 2020 and 2,328 potential customers (those approached by both the treated and control sales agents) were surveyed for the follow-up during October and November 2020.

We find three main results. First, potential customers approached by sales agents in the treatment group were significantly better informed about their purchase options relative to those in the control group. Second, the tool led to a perceived higher level of sales agents' professionalism and product knowledge. These effects occur despite the control sales agents also utilizing tablets in the sales process. Third, the information treatment led to increases in two indicators of demand for solar. Potential customers in the treatment group report a strong interest in adopting solar home systems that is 6 percentage points higher than the control group. Given multiple visits from a sales agent are typically required prior to a purchase, a reported plan to adopt solar in the near future is a strong predictor of later purchases (in a pre-experiment survey, 46% of consumers who showed an interest in the product went on to purchase it (Sambodhi Research, 2018)).[2] Further, we find only a 1 percentage point increase in actual adoption, which is statistically insignificant, among the treatment group.

[2]The COVID lockdown and resulting income constraints likely lengthened the average time between the first sales pitch and the purchase.

By focusing on lower-middle and middle-income households, the study provides insights on a relatively understudied, yet important, demographic group. The global middle class is expected to play a substantial role in driving the purchases of energy-using assets (Gertler et al., 2016) and government policies (Government of India, 2018). This consumer demographic, not only in India but in other developing countries as well, is not below the poverty line and therefore can potentially afford investing in solar home systems. Moreover, lower-middle and middle-income households may use solar home-systems explicitly for smoothing consumption of electricity services when grid services are unreliable, not only as a substitute for grid electricity.

With the treatment intended to affect potential consumers' information on the returns to solar adoption, our study contributes to both an extensive literature on the microeconomics of technology adoption (see e.g., Foster and Rosenzweig, 2010), as well as the role of information on the returns to investments, such as schooling (Jensen, 2010). In examples specific to energy, high-frequency information on residential electricity usage has been shown to affect consumer price elasticity (Jessoe and Rapson, 2014) and simple information campaigns can impact clean fuel adoption (Afridi et al., 2021). Further, like the digital tool utilized in this intervention, other digital technologies have provided important information channels to a variety of small businesses, such as in the fisheries (Jensen, 2007) and agricultural sectors (Fabregas et al., 2019).

Additionally, this study contributes to our understanding of the barriers to solar adoption in developing countries. By exploring information constraints, this study complements existing evidence on the low take-up of decentralized solar (Burgess et al., 2020; Lee et al., 2016). We do not detect a large effect on solar adoption (although we cannot rule out an effect), but we do observe a large increase in intent to adopt. While the drop-off in actual adoption may be explained by the pandemic-related lockdown, credit barriers may remain a significant deterrent.

The paper proceeds as follows: Section 2 provides some background to electrification in India, and the market for solar home products. Section 3 describes the intervention and data collected, while Section 4 presents results. Section 5 concludes.

2 Background

In this section, we provide background on the electricity sector in India, specifically gaps in electrification and reliable service delivery, which provide a role for off-grid solar to fill. We then provide a framework for conceptualizing the barriers to solar adoption in the study context.

2.1 Electrification in India

Official government sources characterize all three states in our study as having 100% electrification (Ministry of Power, India); however, large numbers from our study sample report having no connection to the national grid.[3] Those who are grid connected often face unreliable power supplies. More than 40% of the surveyed subjects report outages of at least 3 hours in the summer.

In such settings, off-grid sources of electricity, such as rooftop solar, can fill a gap by smoothing consumption during grid outages.

The Government of India set a target of 40 GW to be achieved through the deployment of decentralized rooftop systems, particularly in rural areas (Government of India, 2015). As of 2018, only 14% of the total solar installed was from these rooftop systems (Gulia and Garg, 2020). Since then, uptake of solar has remained relatively low. A number of private actors have entered the market to independently supply households and businesses with decentralized off-grid solar; our partner firm is one such company.

[3] In Bihar and Uttar Pradesh a portion of our study sample – 9% and 13%, respectively – report not being connected to the electricity grid. At 1%, the portion in Odisha is much smaller.

2.2 Conceptual Framework: Barriers to Solar Adoption

Prior to the information intervention, the partner solar company had addressed credit barriers to adoption by implementing a pay-as-you-go purchase model. Through prior consumer segmentation surveys and customer interviews, the solar company determined that limited information on the returns to rooftop solar – and the potential for sales agents to use these information asymmetries to their advantage – remained a substantial barrier to adoption.

There are both financial and non-financial returns to adopting the solar rooftop system. A lot of these returns depend on the number and type of appliances that can be powered by the solar product, as that determines the types of services potentially consumed. Examples of services consumed include lighting, cooking (kettles, electric cookers), cooling (fans), and entertainment (televisions, radios).[4] Solar products vary in the extent to which they may power these appliances. When faced with the purchase of a solar rooftop system, potential consumers may have incomplete information as to which of these services can be powered by different solar products. Additionally, potential customers may not be aware that a rooftop solar panel in conjunction with a battery could smooth their electricity consumption when a grid outage occurs. As a result, potential consumers may lack sufficient information to invest in a solar product that provides power sufficient for their homes' needs.

With incomplete information, the returns to the solar technology may be uncertain to potential buyers even after interacting with a sales agent. The sales agents may provide accurate information, yet the potential customer may not trust or believe the information provided by them. Alternatively, the sales agent may provide incorrect information due to their own misunderstanding or due to incentives to either upsell to a more expensive solar product beyond the potential customers' needs or to overstate the services feasibly provided by a given solar product.

[4]Non-financial returns include e.g. improved social status in one's community from adopting the solar technology

3 Randomized Experiment with Sales Agents

In the sub-sections that follow, we explain the randomized experiment that was designed to address information constraints, detail the data collection processes, and provide results of balance tests using those data.

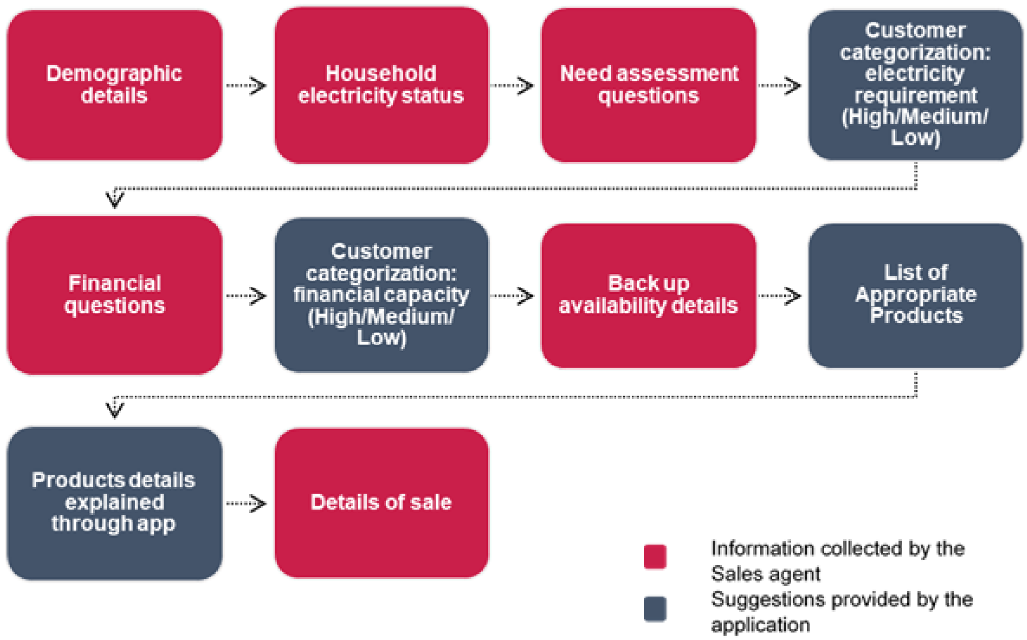
3.1 Intervention and Experimental Design

In collaboration with the solar company, a mobile application, the Sales Support App (SSA or simply, app), was developed using past sales data and pre-experiment surveys of prior customers. The aim of this app was two-fold: first, to provide consumers with accurate and standardized information on the solar products and how they each meet different energy needs and, second, to build customers' confidence in the professionalism of the sales agent and the accuracy of the information they provide.

The app and the tablets are relatively low cost and simple for sales agents to use. The app guides sales agents through a questionnaire to collect information from consumers, after which they are presented with images and information on appropriate solar products. This process of both collecting and providing information within the treatment app is detailed in Figure 1. Further, images of application screen examples through which either information is collected or provision are also shown in Figures 2(a) and 2(b), respectively.

The intervention was designed to isolate the effect of information. First, in order to avoid conflating the treatment app's impact with the potential prestige of having a tablet, a parallel control app, with only the old basic product catalog, was also developed and loaded onto tablets for sales agents in the control group to use. Second, in order to avoid the treatment sales agents targeting systematically different potential customers, both treatment and control sales agents continued to follow the company's sales model that was in place long before the intervention, approaching potential customers from a list generated by the

Figure 1: Description of data collection and provision via the treatment app



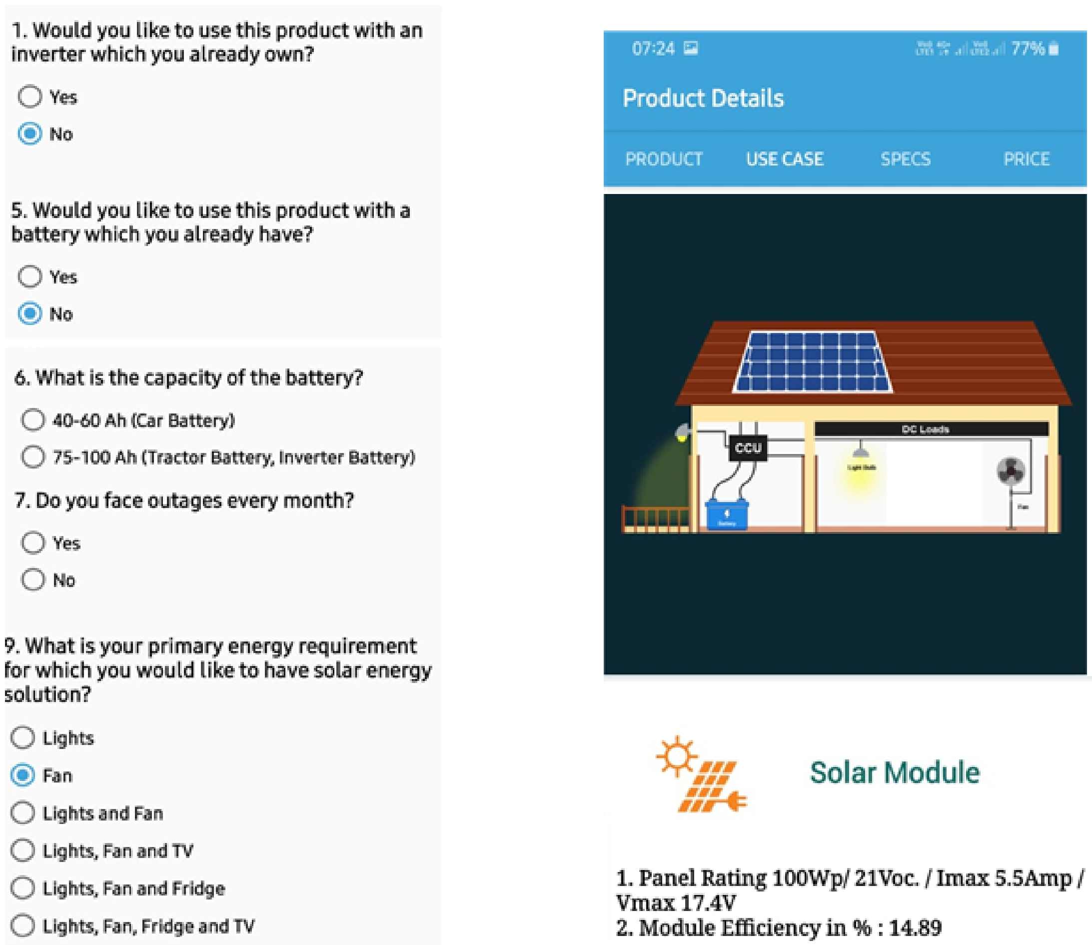
Note: The flowchart above describes how the treatment app guides the interaction between the sales agent and the customer. After collecting bits of information, the app makes various recommendations on how to categorize the consumer in terms of their electricity usage, financial capabilities and finally a list of appropriate products with their details. The control group tablets merely had the catalogue of products, described here as "List of Appropriate Products".

company's network of local village contacts (called an "urja mitra").[5]

The randomized experiment was implemented in 25 districts across the three states of Bihar, Odisha, and Uttar Pradesh (shown in Appendix Figure A.1). Within these states, the 74 census blocks in which the company was operating – and therefore the sales agents assigned to these census blocks – were randomly assigned to treatment and control groups. To ensure the treatment and control groups were balanced on sales agents' characteristics that might affect the outcomes, the randomization code required balance across the treatment and control census tracts for variables that are proxies for sales agents' prior experience and sales ability. These include: total prior sales, total number of customers in the prior year, number of customers that were regularly paying their bills (an indicator of customer satisfaction), the number of customers regularly in arrears (a measure of consumer dissatisfaction and/or

[5]The company had developed a network of urja mitras. These "energy friends" were local village entrepreneurs who were independent agents that used their networks within the villages to help generate sales "leads", potential customers for the sales agents to later approach with more information on the company's solar products.

Figure 2: Examples of information collected and provided by the mobile application



((a)) Information collected ((b)) Information provided

Note: These images are screenshots from the mobile app. The left panel shows the kinds of questions that sales agents ask of respondents, while the right hand side panel is an example of a recommendation made by the app

poor suitability of the product for the consumer), the number of sales agents, the average household side, literacy rate, and share of females within the census tract.

All sales agents received a tablet. Sales agents in both the treatment and control groups were existing sales agents at the time of the experiment and they had all received the same training on the solar technologies available for purchase when they joined the company. The sales agents in both groups were trained on use of the tablet in general and both groups were informed how they could access their list of their sales leads – as provided by the urja mitras – on their tablets. This is something that they would have previously done on their cell phones, prior to receiving the tablets.

After this general tablet training, the remaining training for the treatment and control sales agents diverged and occurred separately. The sales agents operating in control group census blocks were shown how to open the basic general product catalog on the tablet (a pdf version of the paper catalog that they had been using previously in the sales process). The sales agents operating in treatment group census blocks were provided training as to how to use the treatment application. This training and the application itself did not contain any information on the solar products that was new to the sales agents.

The training of sales agents began in February 2020, with interruptions due to India's rapidly developing COVID-19 travel restrictions. Lock-downs affecting company staff movement both interrupted training and decreased the number of potential customers that the sales agents could approach, thereby reducing our study sample. This was particularly the case in Bihar and Uttar Pradesh, where lockdown restrictions were more strict than Odisha. Although the app was designed for sales agents to approach consumers in person, in a few cases, due to lockdown restrictions, the first approach was by phone. This was possible given the customer contact lists generated locally by the urja mitras.

3.2 Data

There are three sources of data used for the analyses in this paper: data collected from the solar company, those available via the 2011 Indian Population Census, and those collected through our baseline and follow-up surveys. The solar company's data included information on sales agents, such as their assigned sales territory (census block) and details on their prior sales. The 2011 Indian Population Census data provide baseline information at the census block level, such as the population as well as educational attainment.

We implement both baseline and follow-up surveys for this study. A baseline survey was conducted in June 2020 by telephone to assess existing customers' take-up and satisfaction with both the sales process and the solar product that they had purchased. This survey was conducted with the company's customers who had bought products prior to the intervention between August 2019 to January 2020. A total of 2246 consumers were surveyed, with 1185 in the subsequent treatment census blocks, and 1061 in the control census blocks, across the states of Uttar Pradesh, Bihar and Odisha.

For the endline, we surveyed customers approached by the treatment and control sales agents following the start of intervention, between February and October 2020. In total, 1539 potential customers were surveyed, comprised of 856 customers from 40 control blocks and 683 potential customers from 34 treatment blocks. The two surveys examined different respondents, creating a stacked panel. The treatment and control block assignments stayed consistent across the surveys and the experiment. The proportion of potential customers surveyed across evaluation groups was similar to the proportion of potential customers approached using the SSA and the Control app. Approximately 73% of the surveyed sample was from the state of Odisha, followed by 15% and 12% from the states of Bihar and Uttar Pradesh, respectively. The distribution of surveys across states was driven by differences in the COVID restrictions across states, which impacts the extent to which sales agents were able to approach potential customers during the study period.

3.3 Baseline Balance Checks

We test for baseline balance across treatment and control census blocks using a combination of data from the baseline and endline surveys and the 2011 Indian Population Census. Table 7 presents these results. We do not find any statistically significant baseline differences between our treatment and control groups. These baseline figures however do provide a sense of the population we are studying. Approximately one-third of our subjects own some form of electricity backup to account for outages[6], while about three-quarters are connected

[6] Almost 43% of respondents report owning some type of backup electricity product. The vast majority (almost 90%) of this group owns an inverter with a battery or just a battery. Only about 4% of all respondents own some sort of solar based lighting system, but these are usually solar lanterns with limited capapity.

Table 1: Baseline balance: characteristics of treatment and control blocks

Panel A: Data from Baseline Survey of Existing Solar Customers

Variable	(1) Control	(2) Treatment	(3) Difference
Own backup	0.36	0.39	0.03
	(0.48)	(0.49)	(0.11)
Connected to grid	0.79	0.77	-0.02
	(0.41)	(0.42)	(0.28)
% of residential customers	0.78	0.80	0.02
	(0.42)	(0.40)	(0.18)
% of enterprise customers	0.22	0.20	-0.02
	(0.42)	(0.40)	(0.18)
Income (Rs.)	211,450.00	229,166.83	17,716.83
	(230,353.52)	(294,800.03)	(0.18)
Correctness of info. from agent	0.87	0.86	-0.00
	(0.34)	(0.34)	(0.80)
Happy with purchase	0.87	0.86	-0.01
	(0.34)	(0.35)	(0.35)
Buyer understood features	0.73	0.76	0.03
	(0.44)	(0.43)	(0.16)
Agent product knowledge	0.89	0.89	-0.00
	(0.31)	(0.31)	(0.91)
Observations	1,061	1,185	2,246

Panel B: Data from the Indian Population Census

Variable	(1) Control	(2) Treatment	(3) Difference
Share of female pop.	0.49	0.49	0.00
	(0.01)	(0.01)	(0.55)
Education: primary or below	0.02	0.01	-0.01
	(0.12)	(0.09)	(0.24)
Higher education	0.58	0.60	0.02
	(0.49)	(0.49)	(0.36)
Observations	856	683	1,539

Notes: The above variables are sourced from the baseline surveys and the Indian Population Census of 2011 for the relevant blocks. The baseline survey shows results from consumer experiences with sales agents in treatment and control blocks before the use of tables and the treatment application.

to the electrical grid. In terms of income, the respondents are not amongst the poorest populations, with over $3000 in annual income. Further, the sample is well educated, with over half reporting higher education, while under 1-2% report only primary or below primary education.

4 Analysis and Results

In this section, we present the regression specifications employed, followed by the results.

4.1 Regression Specification

To measure the effect of the treatment on potential customers' perception of agent professionalism and product knowledge, the potential consumers' own knowledge and assessment of the suitability of the product recommendation, and whether they report intending to purchase a solar product or have made any actual purchase in the short-run, we estimate the following regression:

$$Y_{avb} = \beta \, Treatment_{vb} + \epsilon_{avb}, \tag{1}$$

in which $Treatment_{vb}$ is an indicator variable for potential customer a in village v and block b that equals 1 if the customer is located in a treated census block in which the sales agent was assigned to receive the SSA and equals 0 if located within a control census block. We interpret the coefficient on the treatment variable as an Intent-to-Treat (ITT) estimate, as sales agents may not comply with treatment.

A characteristic of the COVID lockdown in India was restricted movement across villages within blocks. For this reason, there is likely limited correlation between outcomes across villages within a block. Clustering standard errors at the village level, therefore, is a reasonable choice in presenting our regression results, following the discussion in Abadie et al. (2017). Nevertheless, given randomization was at the block level, we also report block level clustered standard errors. In most cases, the results are the same or less than village level clustered estimates.

4.2 Experimental Results

Tables 2 and 3 present the estimated impacts of the informational tool, with the former including impacts on the perceived professionalism of sales agents, their knowledge on solar products, and the knowledge that potential consumers gained from interacting with sales agents. The latter table presents impacts on outcomes such as take-up and intention to adopt the solar products.

We first examine whether the tool indeed decreased information gaps. Table 2 presents the informational tool's estimated impact on consumer perceptions. We find a significant increase in the perceived knowledge (Column 1) and professionalism (Column 2) of sales agents. Perhaps most importantly, the app led to greater self-reported product knowledge among potential customers (Column 3). The treatment, however, did not significantly affect potential customers' perception regarding the product suitability (Column 4).

Table 2: Impact of intervention on knowledge and perceptions

	(1) Agent product knowledge β / SE	(2) Agent professionalism β / SE	(3) Buyer product knowledge β / SE	(4) Product Suitability β / SE
Treatment	0.027***	0.030***	0.031***	0.017
	(0.008)	(0.008)	(0.009)	(0.015)
Constant	0.966***	0.966***	0.955***	0.926***
	(0.005)	(0.005)	(0.006)	(0.010)
Observations	1396	1399	1396	1110
SE (Block clustered)	0.006	0.006	0.009	0.018

Notes: This table presents Intent-to-Treat (ITT) results from the main estimating equation of the effect of the informational tool on various outcomes. Respondents were asked if they strongly agreed, agreed, disagreed, or strongly disagreed with each of the statements, or if the statement was not applicable. Statements were: (Column 1): The sales agent/ RSA who explained the SIMPA products to me had the required/sufficient knowledge about these products. (Column 2): The Simpa sales agent was professional and left a good impression. (Column 3): I was able to understand the product features and the different product options that were explained by the sales agent during the sales pitch interaction. (Column 4): I found the product suggested by the sales staff suitable as per my energy requirement. We then created a binary variable related to each question, which took on value 1 if the respondent agreed or strongly agreed, and 0 otherwise. The coefficient may be interpreted as an increase in the probability that the respondent agreed or strongly agreed with the statement in the question. Standard errors are clustered at the village level. The bottom row also presents standard errors clustered at block the level for the treatment variable. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Next, Table 3 presents insights as to whether the greater knowledge led to changes in

Table 3: Impact of informational tool on indicators of adoption

	(1) Adoption or Interest in Solar β / SE	(2) Adoption of Solar β / SE	(3) Interest in purchasing after COVID lockdown β / SE
Treatment	0.069**	0.010	0.060**
	(0.030)	(0.015)	(0.029)
Constant	0.487***	0.090***	0.397***
	(0.020)	(0.010)	(0.019)
Observations	1539	1539	1539
SE (Block clustered)	0.061	0.021	0.059

Notes: This table presents Intent-to-Treat (ITT) results from the main estimating equation of the effect of the informational tool on various outcomes. Standard errors are clustered at the village level. The bottom row also presents standard errors clustered at block the level for the treatment variable. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

adoption or planned adoption, which are revealed and stated preference measures of demand, respectively. Column 1 indicates that the informational mobile application loaded on the tablet increased take-up or strong interest (pooled together) in buying a solar home-system in the near future by almost 7 percentage points over a baseline of 49%. Breaking this apart and analyzing the two measures separately, we find an effect on actual adoption to be only a 1 percentage point or an 11% increase that is not statistically significant (Column 2). The treatment did lead to a statistically significant 6 percentage point increase in the probability that a potential customer reports a strong interest in purchasing the solar technology at a later date, after the COVID lockdown ends (Column 3).

We consider this last measure – the intent-to-adopt outcome – to be particularly relevant for our study for multiple reasons. Our pre-intervention studies indicated that 46% of potential customers reporting a strong interest in purchasing a solar product, eventually went on to do so. Even before 2020, sales agents typically would visit potential customers multiple times before a sale. With COVID-19 reducing incomes in the short-term and related lockdown restrictions limiting movement, it is reasonable that the sales process would take longer than the short-run time period of our study.

Lastly, in an effort to better understand the potential mechanisms through which the impacts occurred, we investigate potential heterogeneous treatment effects. Results are in Table 4. We find no large differences in rates of purchase or intent to purchase the solar products across a number of factors, including the respondents' own grid connection (Column 1), their ownership of a backup generation sources (Column 2), and whether the respondent represents a firm or household (Column 3). However, these figures are suggestive of the fact that the demand for solar is not driven by people who do not have grid access or do not own backup energy sources: in fact, these groups adopt solar to an equal degree. Finally, we find that households and firms also adopt solar products at similar rates.

Table 4: Heterogeneous impact of informational tool on purchase decision or interest in future purchase (ITT Results)

	Purchase/Intent (1) Heterogeneity 1=Grid Connection 0=No β / SE	**Purchase/Intent** (2) Heterogeneity 1=Own backup 0=No β / SE	**Purchase/Intent** (3) Heterogeneity 1=Household 0=Firm β / SE
Treatment	0.067	0.063*	0.002
	(0.141)	(0.034)	(0.088)
Treat X Heterogeneity	0.004	0.011	0.067
	(0.143)	(0.053)	(0.090)
Heterogeneity	-0.118	0.032	0.072
	(0.084)	(0.037)	(0.055)
Constant	0.600***	0.474***	0.426***
	(0.083)	(0.022)	(0.054)
R^2	0.01	0.01	0.01
Observations	1528	1528	1539

Notes: This table presents Intent-to-Treat (ITT) results from the main estimating equation of the effect of the informational tool on various outcomes. Standard errors are clustered at the village level. The bottom row also presents standard errors clustered at block the level for the treatment variable. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

In addition, we look at heterogeneous impacts across measures of income and find some suggestive evidence that when looking at purchase decisions across the income distribution, the treatment appears to be ineffective for higher-income households (Table 5). More specifically, we see a precisely estimated null impact of income across the distribution when using a continuous income measure. But, when we perform a median split and use a binary variable, we find that those households on the higher end of the distribution appear to be less likely to adopt or show interest in solar when in the treatment group. The main takeaway from this table is that the treatment appears to be much more effective for lower-income households than it is for higher-income ones. One possible explanation could be that higher-income households have better education levels and already have information on solar. In fact, over 60% of the higher-income households have a graduate degree or higher, as opposed to 45% of the lower-income households.

Table 5: Heterogeneous impact of informational tool on purchase decision or interest in future purchase (ITT Results) - by Income

	Purchase/Intent	**Purchase/Intent**	**Purchase/Intent**
	(1)	(2)	(3)
	Heterogeneity HH Income	Heterogeneity 1=High income 0=Low	Heterogeneity No. of rooms
	β / SE	β / SE	β / SE
Treatment	0.103**	0.108**	0.182**
	(0.042)	(0.044)	(0.077)
Treat X Heterogeneity	-0.000**	-0.119**	-0.042
	(0.000)	(0.058)	(0.026)
Heterogeneity	0.000***	0.089**	0.034**
	(0.000)	(0.037)	(0.016)
Constant	0.454***	0.460***	0.389***
	(0.028)	(0.028)	(0.047)
R^2	0.01	0.01	0.01
Observations	1257	1257	1475

Notes: This table presents Intent-to-Treat (ITT) results from the main estimating equation of the effect of the informational tool on various outcomes. Standard errors are clustered at the village level. The bottom row also presents standard errors clustered at block the level for the treatment variable. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Finally, due to COVID lockdown related changes, our distribution of survey respondents became quite skewed, with larger numbers of respondents from the state of Odisha. In order to ensure that our main results are not driven my a small number of respondents in the heavily locked down states of Uttar Pradesh and Bihar, we re-run our analysis for Odisha alone in Appendix Section A.3. We find our results remain robust even for this sub-sample.

4.3 Discussion

To better understand the gap between the stated and revealed preference measures, we analyze responses to a survey question asking potential customers for reasons as to why they had not adopted yet adopted the solar rooftop system. Results are presented in Table 6. We find that 68% of households are reporting financial constraints, either inability to afford the payment (18%) or general lack of funds (49%) as the main reason that they have not adopted a rooftop solar product. Only 22% of respondents report that the solar products offered do not fit their preferences or meet their energy needs. Another 6% of respondents report that electricity or these products are not a priority or are not expected to provide them with much value.

Table 6: Why did respondents not adopt solar rooftop systems?

	Proportion of respondents
Financial constraints	
Cannot afford the payment	0.18
Do not have the funds currently	0.49
Different preferences or needs	
Products do not meet my energy requirement	0.03
I want to run heavier equipment like refrigerator, cooler, TV	0.01
Other company has cheaper solar products	0.02
Prefer other electricity back up sources	0.16
Low priority or value	
None of these products add any incremental value to my life	0.04
Expenditure on electricity is not a priority	0.02
Other	0.06
Observations	1393

Notes: This table presents descriptive evidence from the endline survey conducted on respondents from both the control and treatment groups in our sample.

We interpret the persistence of financial constraints reported in these results and the difference between the stated intent-to-purchase measure and the actual purchase numbers is likely the result of the COVID-19 shock on labor mobility and income in the study regions.

The COVID-19 induced lockdown severely affected mobility across states and villages. Millions of the workforce were rendered unemployed due to the halting of infrastructure and manufacturing activities leading to unavailability of both skilled and unskilled jobs, closure of shops and services and disruptions in the supply chain. Approximately 85% of the solar company's customers surveyed reported a fall in their incomes. Almost 70% of customers report a loss of 50% or more due to the COVID-19 induced restrictions. These dramatic declines were exacerbated for firms and enterprises with 93-96% of enterprise customers reported decreases in income.

Further, to contextualize our stated and revealed preference estimates, we compare our results with those of other studies estimating the impacts of interventions on the demand for decentralized solar technologies. The three papers most closely related to ours study the impact of interventions on the demand either solar lanterns (Alem and Dugoua, 2022; Wong et al., 2022) or microsolar kits (Grimm et al., 2020), sufficient primarily for lighting and charging needs. Grimm et al. (2020) and Wong et al. (2022) both study the impacts of different financial incentives designed to relax the role of those constraints on demand for micro solar technologies. Grimm et al. (2020) found that relaxing liquidity constraints by extending the repayment period from a very short time horizon (one week) to five months increased WTP for solar kits in Rwanda by up to 13%. Wong et al. (2022) found that a financial voucher, redeemable for a discount on a solar kit purchase, increased adoption by more than 34% in Uttar Pradesh, India. Alem and Dugoua (2022) find even larger increases in the WTP for solar lanterns – also in Uttar Pradesh – from treatments inducing peer effects. We hesitate to directly compare our point estimates, as our study involved more expensive and larger capacity solar products (in terms of watts) and the roll-out of our intervention was substantially and negatively impacted by the COVID pandemic. However, the studies above suggest that our results from an information intervention and reasonable.

5 Conclusion

We contribute to a burgeoning literature studying the demand for off-grid energy in developing counties that are either without universal grid access or where electricity service quality is poor. In India, as well as other countries, solar mini-grids and home-systems are touted for their potential to address energy gaps. But, adoption of these technologies remains low.

We investigate the potential to alleviate information constraints, which may be one of the large barriers to solar adoption. To some extent, alleviating the information constraints showed promise. The greater perceived degree of professionalism and knowledge of the treated sales agents, relative to the control agents, matters for the adoption of this technology. Additionally, by presenting a set of products customized to the household's energy needs, the app improved the potential customer perception of the sales agents themselves, and by extension, the products.

We find that relaxing such constraints increases intent-to-adopt, our stated preference measure of demand. It is possible that such an information intervention could also increase actual purchases. We did not find significant effects on this revealed preference measure during the short-run period of our study; however, given the number of sales visits and length of time typically required for purchases of roof-top solar to be completed, it is quite plausible that sales are impacted in the longer-run. Further, this difference between our stated and revealed preference measures also may be indicative that income and credit constraints remain a main barrier to solar adoption, particularly as the COVID-19 pandemic continued to interrupt labor mobility and earnings.

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A Appendix

A.1 Map of Study Area: Uttar Pradesh, Bihar and Odisha

Note: The above map shows the three states, as well as districts covered by our study area.

A.2 Randomization assignment: balance on characteristics of sales agents

Table 7: Baseline balance: characteristics of treatment and control blocks

Variable	(1) Control	(2) Treatment	(3) Difference
Total Sales	24.93	24.85	-0.08
	(28.69)	(28.09)	(0.98)
Sales Record: Happy Customers	18.64	21.45	2.81
	(23.39)	(25.84)	(0.35)
Sales Record: Difficult Customers	1.67	1.85	0.18
	(6.80)	(8.36)	(0.85)
Total Sales Agents	14.94	12.67	-2.27
	(16.38)	(14.57)	(0.23)
Avg. Household Size	5.26	5.22	-0.04
	(0.86)	(0.75)	(0.66)
Share of Female Pop.	0.48	0.48	0.00
	(0.02)	(0.01)	(0.84)
Share of Literate Pop.	0.55	0.53	-0.02
	(0.10)	(0.10)	(0.21)
Share of Workers	0.36	0.36	0.01
	(0.08)	(0.08)	(0.51)
Observations	132	133	265

Notes: The above variables are sourced from sales records of the sales agents assigned to both treatment and control groups.

A.3 Robustness Tests: Main Results for Odisha

Due to limited access generated by various COVID-related lockdowns, our sample sizes fell severely in several locations. Table 8 shows the breakdown of survey responses by state, and treatment assignment. The states of Uttar Pradesh and Bihar had far stricter lockdown rules than Orissa, and our response rates reflect this, with a significant portion of our observations coming from Odisha. In order to make sure our main results are not sensitive to these numbers, we present robustness checks in the form of regressions run only for Odisha, where we have balance in terms of treatment and control numbers, relative to Uttar Pradesh and Bihar.

Tables 9 and 10 show our main estimates for the state of Odisha, and hew very closely to our estimates from Tables 3 and 2.

Table 8: Observations in the treatment and control groups across states

State	Control	Treatment	Total
Bihar	183	47	230
Odisha	595	527	1,122
U.P	78	109	187
Total	856	683	1,539

Table 9: Impact of informational tool on indicators of adoption (Odisha)

	(1) Adoption or Interest in Solar β / SE	(2) Adoption of Solar β / SE	(3) Interest in purchasing after COVID lockdown β / SE
Treatment	0.065**	0.017	0.048
	(0.032)	(0.016)	(0.031)
Constant	0.550***	0.074***	0.476***
	(0.020)	(0.010)	(0.020)
R^2	0.00	0.00	0.00
Observations	1122	1122	1122
SE (Block clustered)	0.039	0.019	0.038

Notes: This table presents Intent-to-Treat (ITT) results from the main estimating equation of the effect of the informational tool on various outcomes for Odisha. Standard errors are clustered at the village level. The bottom row also presents standard errors clustered at block the level for the treatment variable. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 10: Impact of intervention on knowledge and perceptions (Odisha)

	(1) Agent product knowledge β / SE	(2) Agent professionalism β / SE	(3) Buyer product knowledge β / SE	(4) Product Suitability β / SE
Treatment	0.022**	0.025***	0.021**	0.003
	(0.009)	(0.009)	(0.010)	(0.019)
Constant	0.968***	0.969***	0.961***	0.928***
	(0.006)	(0.006)	(0.007)	(0.013)
R^2	0.01	0.01	0.00	0.00
Observations	1035	1038	1035	751
SE (Block clustered)	0.007	0.008	0.010	0.023

Notes: This table presents Intent-to-Treat (ITT) results from the main estimating equation of the effect of the informational tool on various outcomes for the state of Odisha. Respondents were asked if they strongly agreed, agreed, disagreed, or strongly disagreed with each of the statements, or if the statement was not applicable. Statements were: (Column 1): The sales agent/ RSA who explained the SIMPA products to me had the required/sufficient knowledge about these products. (Column 2): The Simpa sales agent was professional and left a good impression. (Column 3): I was able to understand the product features and the different product options that were explained by the sales agent during the sales pitch interaction. (Column 4): I found the product suggested by the sales staff suitable as per my energy requirement. Standard errors are clustered at the village level. The bottom row also presents standard errors clustered at block the level for the treatment variable. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

A.4 Household and Enterprise Customers

Table 11: Breakdown of treatment and control groups by households and enterprises

Potential Customer Type (HH/E)	Control	Treatment	Total
HH Customer	720	627	1347
Enterprise Customer	136	56	192
Total	856	683	1539