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

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June 11, 2021

Abstract

Although off-grid solar technologies have great promise in unelectrified and low quality electricity settings, their adoption remains low. Important barriers to adoption, such as incomplete information, remain unexplored, particularly among lower-middle income populations. In collaboration with a solar company, a randomized experiment was implemented in three Indian states to test whether alleviating information asymmetries increases planned adoption of solar home systems. The company's sales agents were randomly assigned to receive a tablet consisting of an application designed to ensure potential customers received accurate information on the solar products and a customized product recommendation. The treatment led to a significant increase in intent to adopt by 15% and an increase in actual adoption by 11% (albeit statistically insignificant). Prospective customers approached by treated sales agents report greater knowledge of the solar products, as well as a better impression of sales agents' product knowledge and professionalism.

Keywords: Solar, energy, technology adoption, information, development
JEL Codes: C93, D8, O1, O13, Q56

*We are grateful to Varun Dutt for invaluable project assistance. We thank Taryn Dinkelman, Teevrat Garg, Gaurav Khanna, Kelsey Jack, and Anant Sudarshan for helpful feedback. Funding for this evaluation was provided by the Asian Development Bank. This randomized controlled trial was registered in the American Economic Association Registry under trial number #AEARCTR-0007377. All views expressed in the paper and any errors are our own.

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1 Introduction

Worldwide, an estimated 840 million people lack electricity access and another 1 billion are connected to unreliable electrical grids that provide poor quality electricity services with frequent outages and voltage fluctuations (World Bank, 2020). Off-grid solar technologies, which emit less pollution than traditional fossil-fuel based sources of electricity generation, can serve as a stopgap for these populations by either providing electricity services until the grid is extended, or smoothing consumption of electricity services until the quality supplied by the existing grid 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).

Even with this potential, the adoption of off-grid solar remains low in many settings. Existing studies have examined some barriers to take-up among very low-income households, focusing primarily on low willingness-to-pay relative to prices (Burgess et al., 2020; Grimm et al., 2020; Rom and Günther, 2019; Sievert and Steinbuks, 2020) and liquidity constraints (Grimm et al., 2020), a preference for the centralized grid when it is available (Burgess et al., 2020) and differences in the appliances these electricity sources can power (Lee et al., 2016). A number of other factors, however, likely also impact adoption (Girardeau et al., 2021) and require further study. For example, some industry reports suggest that low adoption among middle-income households and small firms is due to potential customers' incomplete information on solar products and their suitability to power appliances (Chaudhary, 2018; Trivedi et al., 2017), yet interventions designed to relax these information barriers remain understudied. In addition, adoption decisions of lower-middle and middle income households are under explored. This gap is important as this group may form a more receptive target group for solar home systems than very poor households due to their higher disposable incomes and potentially greater demand for electricity services.

Through a randomized experiment conducted in collaboration with an Indian company selling solar rooftop systems, we study the role of information in the adoption of off-grid solar in the Indian states of Bihar, Uttar Pradesh, and Odisha.[1] This company relies on sales agents to make sales; a business model not uncommon in developing countries (Ashraf et al., 2013), but one that is prone to information asymmetries between the agents and potential customers. *Ex ante*, potential customers' incomplete information on the returns to solar adoption (e.g., the capacity of each solar product to power various appliances) or product

[1]Credit constraints are not a significant barrier in this context, as the solar company began providing financing options via a pay-as-you-go model prior to the experiment. A pay-as-you-go model allows customers to make a down payment on the product, followed by regular payments (e.g. monthly) until the cost of the technology is repaid in full (World Bank, 2020).

suitability were perceived as persistent barriers to adoption. Sale agents may be perceived to use these information asymmetries to their advantage: convincing potential customers that low wattage solar products could power more appliances than is technologically feasible, a finding confirmed by a pre-experiment survey of people who purchased solar products (Sambodhi Research, 2018). We test whether a digital informational tool – an algorithmic mobile application loaded onto electronic tablets used during the sales process, and designed to reduce information asymmetries between sales agents and prospective customers – can improve consumer knowledge of these solar products and their returns, and further simplify the information needed to make a decision, thereby increasing adoption. Understanding the details about each product in the catalogue can be quite complicated and the app simplifies this by customizing suggestions based on consumer needs.

The intervention proceeded as follows: within the solar company's sales regions, 74 census blocks were randomly assigned to either the treatment or control status. Typically, one sales agent is assigned to a census block as their sales territory. Sales agents operating in treated census blocks were equipped with a tablet containing a mobile interface (the "treatment app") that guided them through the sales process. The "treatment app" was employed during the initial sales visit to collect basic information about the household (e.g., its ability to pay and its electricity needs) and then accordingly recommended the most suitable solar product, accompanied by images of the solar product and the appliances feasibly-powered by such a product. In doing so, the treatment app ensured that potential customers received the correct information on the solar technology and also simplified the choice set for the household. Sales agents operating in the control group also used an electronic tablet in the sales process, but it only contained a standard version of the product catalogue and did not make any recommendations on what product customers should buy.

The study sample, which covers the solar company's target demographic – lower-middle and middle income households and small enterprises that are often connected to an electrical grid providing intermittent service – provides a unique opportunity to contribute to the literature on solar adoption in developing countries. Existing work addressing solar adoption focuses primarily on low-income households (Burgess et al., 2020; Lee et al., 2016). Although the Indian government targets and incentives have been primarily directed towards urban or lower-middle/middle income groups (Government of India, 2018), relatively little work exists examining the take-up of solar among these relatively wealthier populations compared to previous work. This is an important demographic for study, given the expected role of the global middle class in driving the purchases of energy-using assets (Gertler et al., 2016).

Our empirical analysis makes use of 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 brief, as they were implemented by phone due to the government's COVID-19 lockdowns. Nevertheless, the surveys collected data on household and firm 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) surveyed for the follow-up during October and November 2020.

We find three main results. First, 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 baseline of 49%. In this setting, repeat visits are often necessary to secure a purchase, and they are usually limited to households that express an interest in considering solar in the near future. In fact 46% of consumers who show an interest in the product go on to purchase it, from a pre-experiment survey (Sambodhi Research, 2018). Typically, multiple visits from a sales agent are required prior to a purchase occurring; with the COVID lockdown and the resulting binding income constraints, the time period required for a sale was likely lengthened. Therefore, in several cases, a strong interest in purchasing may have translated to an actual purchase had the conversation taken place on the phone, so we take this to be our main variable of interest. It should be noted that the high adoption even among the control group is indicative that this income group may be far more suited to being targeted for renewable energy adoption compared to the lowest income groups targeted in the past (Burgess et al., 2020). We find a 11% increase in actual adoption among the treatment group (statistically insignificant, due to lower than planned sample sizes after the COVID lockdown was enforced). Given the fixed cost of developing the app, our intervention is relatively cost-effective and scalable. As such, this is a large magnitude considering the simplicity of the intervention: using a straightforward application to recommend a suitable product.

Second, the tool also results in the perception of a higher level of professionalism in the sales agent, as well as their level of knowledge on the product catalogue. We see this effect despite the fact that the control group also observes a tablet in the hands of the sales agent. This observed effect is therefore the result of the algorithmic application and the sales dialog, complete with accurate sale product information, that it entails.

Finally, consumers in the treatment group are significantly better informed about their purchase options due to the informational tool helping sales agents make customized recommendations. In addition to these results, we present descriptive evidence of consumers using these solar home-systems as a power backup during the spike in electricity demand precipitated by the COVID-19 lockdown. This is particularly important, given almost 20% of the survey respondents reported that grid electricity supply was affected during the COVID-19 lockdown, almost all of which reported an increase in the frequency of power cuts.

We contribute to an extensive literature on the microeconomics of technology adoption (for a review see e.g., Foster and Rosenzweig, 2010). With the treatment application reducing information constraints with respect to the returns to solar adoption (e.g., the appliances powered by each solar product) as well as product suitability among potential customers, we engage with work testing the impacts of information on the returns to other investments, such as schooling (Jensen, 2010). Further, digital technologies are increasingly documented as an important way to provide information to small businesses, such as in the fisheries sector (Jensen, 2007), and customized information to farmers (Fabregas et al., 2019). More recent work shows the role information campaigns can play in simplifying and demystifying information and how it affects the adoption or response to policies (Afridi et al., 2021).

Additionally, we contribute to the relatively new literature on the role of solar technologies in developing countries. An innovation of our work is to explore new mechanisms that may explain the low take-up of decentralized solar, and complement work on the response to prices explored in previous literature (Burgess et al., 2020; Lee et al., 2016), as well as studying a group (lower-middle and middle-income households) that have not been examined in this literature. The long-term impacts of this evaluation are not within the scope of this study, but we do observe sustained interest in the product, and reported satisfaction with it close to a year after being offered the product. We also find evidence that consumers use solar home-systems explicitly to help smooth electricity consumption and do not see it as a replacement to grid electricity. There exists substantial evidence on the benefits from electrification for development (Lee et al., 2020; Lipscomb et al., 2013), labor supply (Dinkelman, 2011) and other indicators of household welfare (Aklin et al., 2017; Barron and Torero, 2017); however, other than an experiment by Meeks et al. (2020), the benefits arising from smoother electricity consumption are relatively less examined.

Ours is one of the first papers to also look at firm take-up of solar, in addition to households, and this is an important dimension to examine for two reasons: First, solar has the potential to be an important backup in a context where power outages are one of the biggest constraints for the industrial and commercial sector (Allcott et al., 2016; Rud, 2012). And second, commercial consumers are usually required to pay a higher tariff rate for grid electricity, and this may affect their preferences for solar as a cheaper alternative. Having firms, in addition to households in our sample is a unique feature of this study.

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

We first document the status of electrification in India, specifically within the three states of this study, and explain the importance of these off-grid solar technologies given the status of electrification. Next, we provide a conceptual framework describing the potential role for information to act as a barrier to adoption.

2.1 Electrification in India

Although India has achieved 100% electrification of its villages on paper, there remain around 1.39 million households without electricity.[2] While official government sources characterize all three states in our study as having 100% electrification, 3% of our sample from these states report not having a connection to the national grid.[3] Those who are grid connected face unreliable power supplies. More than 40% of the surveyed subjects report outages of at least 3 hours in the summer. Additionally, 13% of the sample report being dissatisfied (or very dissatisfied) with the reliability of the power supply. This leaves an opening for off-grid sources of electricity, such as rooftop solar, to fill a gap by smoothing consumption during periods of grid outages.

The Government of India has made substantial efforts in the energy sector, including developing a number of recent energy market reforms and deploying a considerable amount of renewable electricity, notably solar. The government set a target of 175 GW for local renewable energy by 2022, of which solar power would be expected to contribute 100 GW. Almost half of this target, 40 GW is expected to be achieved through the deployment of decentralized rooftop systems, particularly in rural areas (Government of India, 2015). However, as of 2018, only 14% of the total solar installed was from rooftop solar, well below targets (Gulia and Garg, 2020). Since then, uptake of solar has remained relatively low.

Given the goals set by the Indian government for the country's solar targets, a large number of private actors have entered the market to independently supply households and businesses

[2]According to the website of the Indian Ministry of Power. Further, the government categorizes a village as "electrified" if power cables from the grid reach a transformer in each village and 10% of its households, which may imply that far more households remain without electricity than official numbers might suggest.

[3]In Bihar, 9% of our sample reports not being connected to the grid, while in Uttar Pradesh and Odisha, these numbers are 13% and 1% respectively

with decentralized off-grid solar. The private and social enterprises take advantage of a number of government schemes and subsidies in order to sustain their business models (Plutshack et al., 2019). They typically sell rooftop solar products to households and businesses, and apply for rebates or subsidies from the government ex-post (Malhotra et al., 2017). Within this ecosystem, a number of small start-up companies have emerged and our partner firm is one of them.

2.2 Conceptual Framework: Barriers to Solar Adoption

Prior to the intervention ,the partner solar company had already addressed one barrier to solar – credit constraints – with its pay-as-you-go payment model. Through prior consumer segmentation surveys and interviews with potential customers, we determined that limited information on the returns to rooftop solar adoption remained a substantial barrier to adoption.

There are both financial and non-financial returns to adopting the solar rooftop system. Most, but not all, 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, or services the potential customers might aspire to consume, include lighting, cooking (kettles, electric cookers), cooling (fans, air conditioners), and entertainment (televisions, radios).[4] Solar products, including rooftop solar, vary in the extent to which they may power these appliances. And, when faced with the option of purchasing a solar rooftop system, potential consumers may have incomplete information as to which of these services can be powered by different solar product options. Additionally, potential customers may not be aware that a rooftop solar panel in conjunction with a battery could smooth their electricity consumption, by acting as a backup when a grid outage occurs. As a result, potential consumers may not have complete information to invest in a solar product with the returns appropriate for their homes' needs.[5]

Even after interacting with the sales agent, the returns to the solar technology may be uncertain to potential buyers. 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 either due to their own misunderstanding of the products or due to commissions incentivizing them to deceive the potential customer into buying a product that is either insufficient to meet their energy needs or more expensive

[4]There might be some non-financial returns, however, such as improved social status in one's community from adopting the solar technology, which would not depend on the appliances.

[5]This is conceptually similar to the perceived returns to education impacting investments in schooling (Jensen, 2010).

than they require.

Finally, the sheer range of products available on the market can create a phenomenon called "choice overload", where consumers may be unable to make a decision because of the complexity of the choice set. Questions about customer satisfaction can be quite effective in quantifying the size of the cognitive overload (for a review of the literature on choice overload, see Chernev et al., 2015). From consumer segmentation surveys conducted prior to our study, we noted a significant number of respondents reporting low levels of satisfaction with the sales process, suggesting the existence of overload in the sales context. An important consideration when trying to mitigate choice overload is providing a careful choice architecture to help consumers make decisions without overload (McShane and Böckenholt, 2018). A mobile application streamlining these choices in the context of solar home-systems, and presenting a more customized and abbreviated list of products to households and businesses may alleviate some of these problems.

3 Randomized Experiment with Sales Agents

Of the barriers to solar, incomplete and complex information is one that may be relatively low cost to fix. To address this barrier in the solar product sales process, we collaborate on a randomized experiment with a company selling rooftop solar products. In the following sub-sections, we describe the intervention, experiment design, data collection and baseline balance tests.

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. The goal of the SSA was to ensure that the company's sales agents presented accurate information on the solar products when making a sales pitch to potential customers in rural areas and to assist the sales agents in recommending the appropriate solar product, based on the potential customer's specific electricity needs.

The app was developed from analysis of the company's past sales data and research on potential solar customers over several years. A segmentation survey of potential solar customers was implemented in the states of Uttar Pradesh, Bihar, and Odisha to better understand the rural population's electricity needs. Multiple iterations of the app were created and field tested prior to its widespread launch the field experiment.

The SSA is relatively simple for sales agents to use. The app guides sales agents through a questionnaire for consumers, after which they are presented with a product recommendation and its description. The aim of this app was two-fold: first, to help consumers find products better-suited to their energy needs and, second, to provide confidence in the product recommended by the sales agent. In order to assess the impact of this app – and to avoid conflating that impact with that of approaching potential customers with a tablet – a parallel control app was also developed and loaded onto tablets for sales agents in the control group to use. The control app included only a mechanism to collect basic information on the potential customers and a standard product catalog in a basic document format. The control app did not customize recommendations.

The randomized experiment was designed to understand the impacts of information on the take-up of solar home-systems in rural India. The company's blocks of operation were randomly divided into Treatment and Control groups. The sales agents operating in treatment group census blocks were provided access to the SSA and were trained in using it. The sales agents operating in control group census blocks were provided access to the Control app. The app itself and the tablets used are relatively low cost.

There was extensive training of sales staff in the use of the app in February and March 2020 with frequent interruptions and modifications due to the rapidly developing COVID-19 related restrictions. After a two month halt in proceedings due to the COVID lockdown, sales agent training on the application resumed in June 2020. The solar sales company also maintained contact with the sales agents throughout, encouraging their use of the app. The app was designed for sales agents to approach consumers in person. In a few cases, due to lockdown restrictions, the sales agents made the first approach by phone. Also, due to slowdowns related to COVID and related restrictions, the number of potential customers approached decreased, thereby reducing our sample size. This was particularly the case in Bihar and Uttar Pradesh, where lockdown restrictions were more strict than Odisha. Despite a smaller sample size than originally planned, we are able to identify most results with statistical precision.

3.2 Data

There are three sources of data used for this analysis: data from the solar company, data collected via baseline and follow-up surveys, and the 2011 population census data.

A baseline survey was conducted in June 2020 by telephone to assess factors associated with existing customers' take-up and satisfaction with both the sales process and the solar product that they had purchased.[6] 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 prospective customers that were approached by the treatment and control sales agents following the start of intervention, between February and October 2020. The endline survey was conducted in October and November 2020, with 2328 potential customers (spread across 42 control census blocks and 42 treatment census blocks) attempted to be surveyed. In total, 1539 potential customers were surveyed, comprised of 856 potential customers from 40 control blocks and 683 potential customers from 34 treatment blocks. 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. By our original design, we had aimed to have an even spread of consumers across the three states; however, the COVID-19 lockdown differentially affected the company's areas of operation, with RSA movement and sales – and the consequent usage of the apps – more negatively impacted in Bihar and Uttar Pradesh than Odisha.

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 2 presents these results. We do not find any statistically significant baseline differences between our treatment and control groups.

We survey different groups in our baseline and endline surveys. For our baseline surveys, we targeted consumers who had taken up solar products from our partner firm before the start of our experiment. The endline survey in particular was a follow-up with those households and enterprises who were approached during the intervention. While each survey examined a different set of respondents, the treatment and control group assignments (across census blocks) stayed consistent across the surveys and the experiment. We may therefore interpret the balance of characteristics based on the baseline survey as being indicative of the conditions faced by endline survey respondents in the same blocks.

[6] Due to the difficulty of telephonic survey we were forced to cut down the survey questions substantially.

4 Analysis and Results

4.1 Regression Specification

To measure the effect of the treatment on our outcomes of interest, including whether customers purchase the solar products or intend to, their perception of agent professionalism and knowledge, and the consumer knowledge and assessment of the suitability of the product recommendation, we estimate the following regression:

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

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 bloc 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 we cannot verify compliance by sales agents or the extent to which the sales agents correctly used the app in the field. Given this interpretation, the ITT effect sizes we find may be an underestimate of the true effect, when compared to an average treatment on the treated.

Due to restrictions related to the COVID-19 lockdown, our sample size was lower than planned before March 2020. As a result, we had a total of only 74 blocks – the level at which the informational tool was randomized – and clustering at the block level therefore produces underpowered estimates for certain outcomes. However, another characteristic of the COVID lockdown in India was restricted movement across villages with 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). In our setting, Uttar Pradesh and Bihar had the strictest lockdowns and this affected our ability to train sales agents to use the app, which was one of the reasons for a small sample from these states. We were able to more readily train agents in Odisha, but there was still restricted mobility between villages in effect. Nevertheless, we also report block level clustered standard errors and in most cases it is the same or less than village level clustered estimates.

4.2 Experimental Results

Tables 3 and 4 present the estimated impacts of the informational tool, with the former including outcomes such as take-up and intention to adopt the solar products and the latter 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.

Results in Table 3 Column 1 indicate that the informational mobile application loaded on the tablet increased take-up or strong interest in buying a solar home-system in the near future by almost 7 percentage points over a baseline of 49%. Table 3 also presents disaggregated estimates for the effect of the treatment on adoption and intent-to-adopt separately. We find an effect on adoption to be a 1 percentage point or 11% increase, but it is not statistically significant (Column 2). Corresponding with the adoption result, we find that the treatment also led to a statistically significant 6 percentage point increase in a strong interest in purchasing the solar technology post-COVID (Column 3).

We consider the intent-to-adopt outcome measurement to be most 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. However, even pre-COVID, sales agents typically would visit potential customers multiple times before a sale could be made. This sales process could take multiple months for potential customers to decide and purchase a solar product. With COVID and related lockdown restrictions, it is reasonable to think that this process would take longer than before. Due to our study timeline, the follow-up survey occurred roughly half a year after the intervention start. There is a reasonable probability that these consumers would have purchased the products had more time passed between the intervention onset and the follow-up survey.

Table 4 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. In addition, the app led to greater product knowledge among potential customers (Column 3).

Lastly, we investigate potential heterogeneous treatment effects in an attempt to better understand the potential mechanisms through which the impacts occurred. We find no large differences in rates of purchase or intent to purchase the solar products across a number of factors, such as respondents' own grid connection (Column 1), their ownership of either backup generation sources (Column 2), or across firms versus households (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. The majority of respondents in our sample are connected to the national grid, and we find that their decisions are similar to those who are not. This also holds true for those who previously own a backup source to smooth consumption due to unreliable electricity supply and those who do not. Finally, we find that households and firms also adopt solar products at similar rates. However, these magnitudes are imprecisely estimated due to lower sample sizes, particularly among firms.

5 Conclusion

We contribute to a burgeoning literature aimed at understanding the demand for off-grid energy in developing counties that are either without universal grid access or where electricity service quality is poor. In parts of India, as well as other countries, solar mini-grids and home-systems are touted for their potential to address energy gaps. And in an era where countries, including India, have ambitious clean energy goals, solar take-up in rural areas could be a major step in that direction. Yet, in many places adoption of these technologies remains low. One reason offered in previous studies pertains to the preference that consumers have for grid power. Although universal grid power is the ideal long-term goal, however, it is currently far from reality in many locations. Even those connected to the grid continue to experience high degrees of unreliability, with frequent blackouts and brown-outs. The COVID-19 pandemic has reminded the importance of reliable electricity to people who stayed homes under stressful conditions.

We investigate the potential to alleviate information constraints, which may prevent solar adoption. We find that relaxing such constraints can increase adoption, an indication that the demand for solar may be higher than it appears. Additionally, the greater perceived degree of professionalism and knowledge of the treated sales agents, relative to the control agents, matters for the adoption of technology. 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. This is a helpful counterpoint to previous findings showing that community trust is not a big factor in adoption (Aklin et al., 2018). While the tablets and app may not have directly affected community trust, they appear to raise individual trust in the seller, a factor that increased adoption. Studying the role of trust and choice architecture may be an avenue worth pursuing for future research.

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Figures and Tables

Table 1: Balance of characteristics across treatment and control blocks

Panel A: Baseline Survey

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: 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: We do not find any economically or statistically significant differences in characteristics of households across treatment and control groups. The above variables are sourced from the baseline and endline surveys, and the last 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.

Table 2: Balance of characteristics across treatment and control blocks

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

Notes: We do not find any economically of statistically significant differences in characteristics of households across treatment and control groups. The above variables are sourced from the endline survey and the last Indian Population Census of 2011 for the relevant blocks.

Table 3: Impact of informational tool on adoption (ITT Results)

	(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)
R^2	0.00	0.00	0.00
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%.

Table 4: Impact of informational tool on consumer perceptions (ITT Results)

	(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)
R^2	0.01	0.01	0.01	0.00
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. 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 5: 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%.

A Appendix

A.1 Additional Figures and Tables

Figure 1: Our Study Area: Uttar Pradesh, Bihar and Odisha

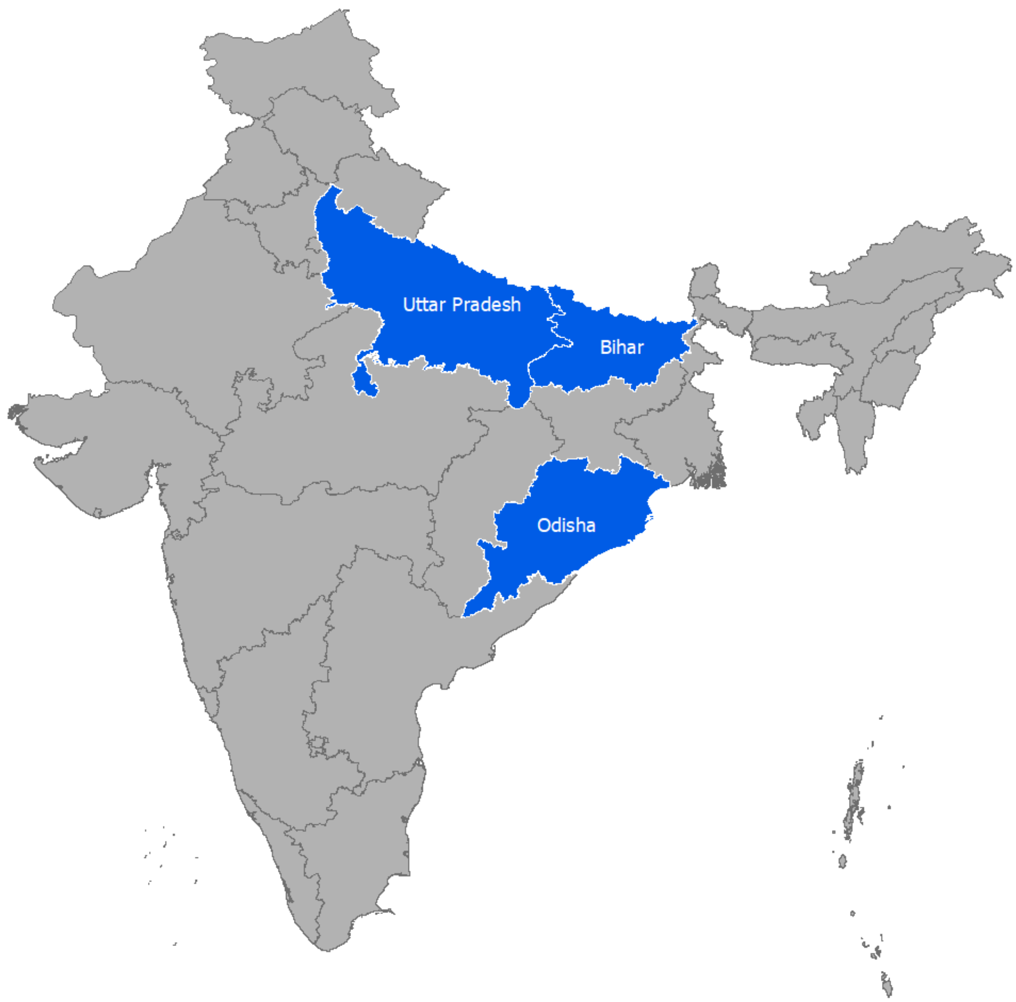

Table 6: Impact of informational tool (ITT Results)

	(1) Satisfied with info. provided β / SE	(2) Happy with product purchase β / SE	(3) Increase in elec. duration β / SE
Treatment/Control	0.014	0.014	0.001
	(0.018)	(0.018)	(0.016)
Constant	0.130***	0.130***	0.103***
	(0.012)	(0.012)	(0.010)
R^2	0.00	0.00	0.00
Observations	1534	1534	1528
SE (Block clustered)	0.029	0.029	0.025
SE (Village clustered)	0.018	0.019	0.016

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%.

Table 7: Why did respondents not adopt Simpa's solar homesystems?

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

A.2 The effects of the COVID-19 Lockdown

The COVID-19 induced lockdown severely affected mobility across states and villages. Millions among 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. These dramatic declines were exacerbated for firms and enterprises with 93-96% of enterprise customers reported decreases in income. Almost 70% of customers report a loss of 50% or more due to the COVID-19 induced restrictions.

Almost 20% of survey respondents report that grid electricity supply was affected by the lockdown, with almost all of them reporting an increase in the frequency of power cuts. The most common reasons for increase in power cuts include disruption in power generation due to supply chain constraints, disruption in grid maintenance due to difficulty in availability of technicians for repair and maintenance, stress on utility operators due reduction in bill payment by users. Non availability of services to fix electrical appliances and inverters/batteries was the second most reported reason for reduced power supply.