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 unexplored, particularly among lower-middle-income populations in developing countries. In collaboration with a solar company, a randomized experiment was implemented in three Indian states to test whether alleviating information asymmetries improves indicators of adoption of solar rooftop 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 during the sales pitch. Post-treatment, 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. The treatment significantly increased intent to adopt by 15%. Actual adoption increased by a statistically insignificant 11%.

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

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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 emit less pollution than traditional fossil-fuel based electricity, 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 for the centralized grid (Burgess et al., 2020) and appliances that can be powered only by certain electricity sources (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), interventions designed to relax information constraints on 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. 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.[1] This company relies on sales agents to sell the solar product; a business model common in developing countries (Ashraf et al., 2013), yet prone to information asymmetries between sales agents and potential customers. *Ex ante*, sales agents may use potential customers' incomplete information to their advantage by upselling solar products, a finding confirmed by a pre-experiment survey of past purchasers (Sambodhi Research, 2018). We test whether an algorithmic mobile application – designed to reduce information asymmetries between sales agents and prospective customers, loaded onto electronic tablets, and used during the

[1]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).

sales process – can improve 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 a single sales agent was 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 product catalogue without the information guide designed to ensure complete and correct information was delivered.

Our analysis uses 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 therefore brief. 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) were surveyed for the follow-up during October and November 2020.

We find three main results. First, potential customers in the treatment group were significantly better informed about their purchase options due to the informational tool. 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 baseline of 49%. 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 a 11% increase in actual

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

adoption, albeit statistically insignificant, among the treatment group.

With the treatment application affecting 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). 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 app 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). Further, we focus on lower-middle and middle-income households, a relatively understudied, yet important, demographic group given the expected role of the global middle class in driving the purchases of energy-using assets (Gertler et al., 2016) and government policies (Government of India, 2018). This consumer demographic uses solar home-systems explicitly for smoothing consumption of electricity services, not only as a substitute for grid electricity.

2 Background

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 face unreliable power. 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 grid's power supply. 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

[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.

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.

2.2 Conceptual Framework: Barriers to Solar Adoption

Prior to the information intervention, the partner solar company had already addressed credit barriers to adoption by implementing a pay-as-you-go purchase model. Through prior consumer segmentation surveys and customer interviews, we determined that limited information on the returns to rooftop solar 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.

Absent the information intervention, the returns to the solar technology may be uncertain to potential buyers even after interacting with the 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 either due to their own misunderstanding or due to incentives to upsell.

3 Randomized Experiment with Sales Agents

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. The goal of the SSA was to ensure that

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

the company's sales agents presented accurate information in recommending a solar product to potential customers.

The app and the tablets are relatively low cost and 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 provide consumers with information on the solar products and how they meet their energy needs and, second, to build confidence in the information provided by the sales agent.

The intervention was designed to isolate the effect of the information intervention. 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 a 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, approaching potential customers from a list generated by its local village contacts (called an "urja mitra").

For the randomized experiment, the company's census blocks of operation were randomly assigned to Treatment and Control groups. The sales agents operating in treatment group census blocks provided access to the SSA and training to use it. The sales agents operating in control group census blocks were provided access to the Control app and were trained separately.

The training of sales staff began in February 2020, with interruptions due to rapidly developing travel restrictions. Lock-downs affecting company staff movement both interrupted training and decreased the number of potential customers approached, 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.

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 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. Despite our original plan to have an even spread of respondents across states, 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 due to COVID restrictions.

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

4 Analysis and Results

4.1 Regression Specification

To measure the effect of the treatment on 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:

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

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 product knowledge among potential customers (Column 3).

Next, Table 3 Column 1 indicates 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%. Breaking this down, we find an effect on adoption to be a 1 percentage point or 11% increase, but it is not statistically significant (Column 2). 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 before 2020, sales agents typically would visit potential customers multiple times before a sale. With COVID and related lockdown restrictions, it is reasonable that this process would take longer.

Lastly, in an attempt to better understand the potential mechanisms through which the impacts occurred, we investigate potential heterogeneous treatment effects. 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. Finally, we find that households and firms also adopt solar products at similar rates.

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. We find that relaxing such constraints can increase adoption. Additionally, 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. 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.

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

	Purchase/Intent	**Purchase/Intent**	**Purchase/Intent**
	(1)	(2)	(3)
	Heterogeneity	Heterogeneity	Heterogeneity
	1=Grid Connection	1=Own backup	1=Household
	0=No	0=No	0=Firm
	β / SE	β / SE	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

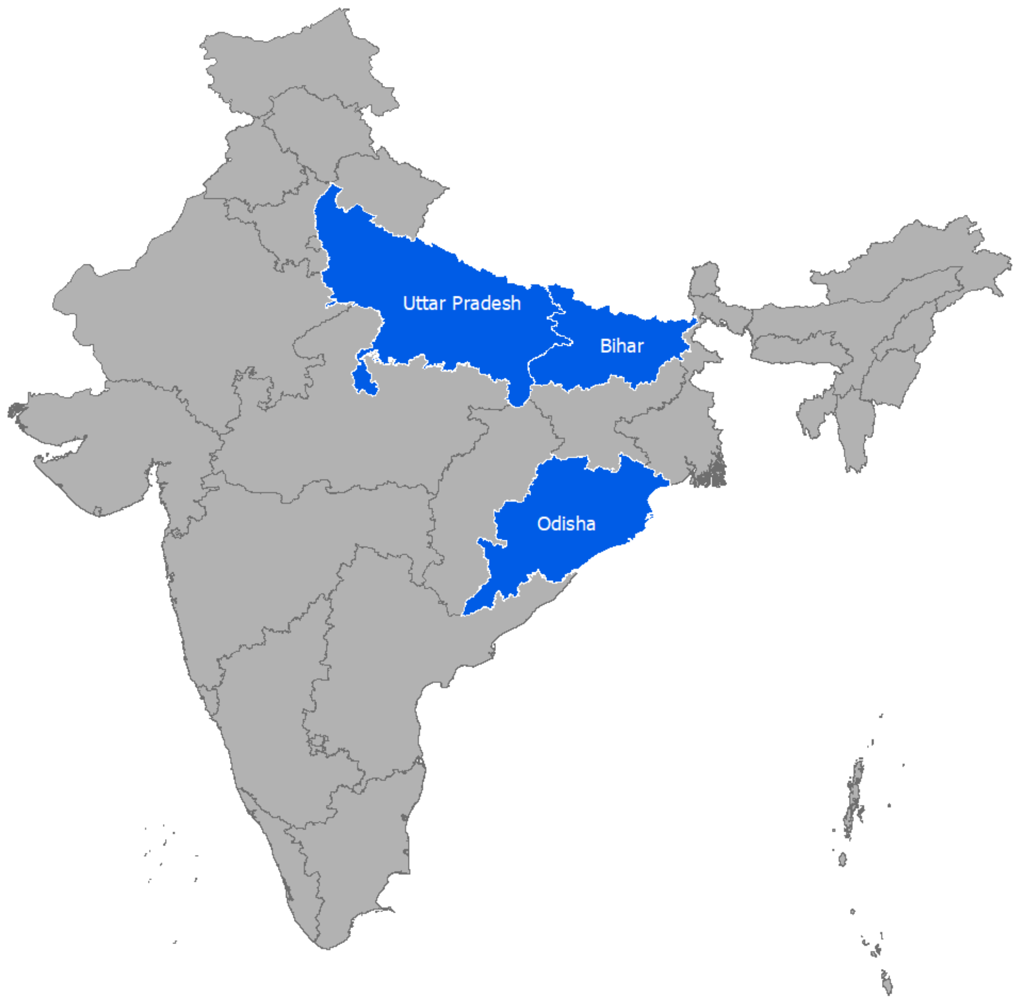

Table 5: Impact of informational tool (ITT Results)

	(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 6: 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 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. 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.