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Timely After-Sales Service and Technology Adoption: Evidence from the Off-Grid Solar Market in Uganda

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Problem definition: Adoption and continued use of novel technologies has the potential to significantly accelerate social and economic development in emerging markets. In this paper, we examine to what extent timely after-sales service – i.e., faster resolution of repair tasks – impacts technology adoption. In particular, we empirically assess the impact of service wait times on the adoption of solar home systems by first-time users (i.e., adopters of the technology) in off-grid Uganda. **Academic / Practical Relevance:** Our study sheds light on a previously understudied driver of technology adoption – customers' post-purchase experience related to after-sales service. We also provide evidence on how negative word-of-mouth stemming from long service wait times hampers customer acquisition. **Methodology:** We address our research question using detailed customer-level sales and service data from a leading assembler and distributor of solar home systems in Uganda. We develop a fixed effects base specification and two instrumental variables specifications that leverage different sources of exogenous geo-spatial variation – in service task locations, weather and road quality. **Results:** We find that timely after-sales service experienced by existing customers is a strong driver of adoption by first-time users. A one week increase in average wait time for service decreases adoption by up to 32.4%. The relationship between wait times and adoptions is heterogeneous and depends on the types of pending service cases. We also find that the number of customers acquired through referrals from an existing customer depends on the referring customer's service wait time. This provides evidence of a strong word-of-mouth channel of information sharing. **Managerial Implications:** Our findings have direct implications for the customer acquisition strategies of technology firms and for technology investors in emerging markets. Our results are also relevant for policy makers who aim to harness technology to improve the socio-economic lives of people living in these regions. Importantly, we provide empirical evidence of a direct link between after-sales service and technology adoption, which is of relevance to managers outside of emerging markets as well.

Key words: after-sales; technology adoption; emerging markets; word-of-mouth; instrumental variables
History: December 23, 2021

1. Introduction

Adoption and continued use of novel life-changing technologies across sectors including energy, healthcare, education and telecommunication has the potential to significantly accelerate social and economic development in emerging markets (Akcigit 2017). Examples include mobile payment systems that have brought millions of unbanked individuals into the financial system (Acimovic et al. 2019), pay-as-you-go distributed solar technology that provides electricity to off-grid communities (Guajardo 2019) and drones that supply medicine to remote communities or food to refugees (The Economist 2015). Technological innovation is only part of the solution to tackling challenges to development. Rapid adoption of new technologies and their continued use by consumers is equally important (Hanna et al. 2016). Unfortunately, adoption of technology in emerging markets is slow, even when the benefits of using technology products are apparent (Uppari et al. 2018, Cohen et al. 2010). Unearthing the reasons for low adoption of technology remains an active area of research (Bold et al. 2017).

A new technology product can have many attractive features, yet consumers may be wary of trying it, afraid that they may "break" the product or that it might operate unreliably (The Atlantic 2015). Such concerns might be even more salient in emerging markets, where consumers are less educated, less familiar with technology and more risk-averse when assessing the potential payoff from new technology (Feder et al. 1985). Emerging markets are also characterized by tightly-knit communities (Miller and Mobarak 2014). News of a user's unsatisfactory encounter with a technology can travel fast – through word-of-mouth – to potential new users, deterring adoption. To increase the rate of adoption – and acquire new customers – technology companies operating in emerging markets need to allay such fears in the minds of potential consumers and build trust in their technology. One way to achieve this is to quickly resolve product or service glitches, through timely after-sales service. Knowing to what extent timely after-sales service can aid rapid adoption of technology in these markets would highlight opportunities for firms to increase adoption rates and thus accelerate economic development.

In this study, we examine how timely after-sales service – i.e., fast resolution of repair tasks – impacts technology adoption in emerging markets. In particular, we empirically assess the impact of service wait times experienced by existing users on the purchase rates of solar home systems by first time users (i.e., *adopters* of the technology) in off-grid Uganda. We identify three important findings: (1) Timely after-sales service is a strong driver of technology adoption in emerging markets. (2) The relationship between wait times for service and adoptions is heterogeneous and depends on the types of pending service cases. (3) Customers share their service experience with others in their network. This word-of-mouth mechanism explains our first two findings. We also find that inadequate infrastructure, especially road quality, significantly affects service wait times and impacts technology adoption in emerging markets.

Our research site is a leading for-profit solar distribution company that operates in off-grid communities in East Africa. The company is headquartered in Kampala, the capital of Uganda. It sells solar home systems and basic appliances that can power a house or a small business, through its country-wide network of 46 branches. About three-fourths of the population of Uganda does not have access to electricity (International Energy Agency 2017), posing a significant barrier to its social and economic development. In recent years, several companies, especially in Africa and Asia (such as our partner company), have started to offer different solutions for off-grid access to electricity (Guajardo 2019, GOGLA 2018). Service-related issues are frequent in off-grid solar products – stemming from improper use of the products, manufacturing and installation problems as well as bad weather conditions. Knowing the extent to which after-sales service influences product adoption also informs better decision making on how to best catalyse adoptions and where to allocate resources. It is also a critical input in assessing the viability of solar off-grid electricity providers.

Data on how long it takes to resolve after-sales service issues is hard to obtain. This is even more the case in emerging markets. Our partner company places a high emphasis on after-sales service and collects a wealth of detailed micro-data about its after-sales service processes, making it an ideal research site for our study. To empirically assess how the timeliness of after-sales service experienced by existing customers impacts the purchasing decision of potential adopters, we assembled a branch-week panel dataset from our partner company, with detailed customer-level sales and service data spanning June 2016 to August 2017. In the period of our study, 83% of the company's sales came from adopters of the technology, i.e., customers who had never owned solar home system technology before. Each company branch has a sales team that is responsible for sales in the off-grid communities in the area assigned to the branch. Each branch also has a single service technician, who visits customers to instal products and service them. In this setting, we measure timeliness of after-sales service as the average wait time for service cases that are pending in the week, at each branch.

We face three econometric challenges. The first is potential reverse causality. We are interested in assessing the impact of wait time for service on adoptions. However, an increase in adoptions can increase the likelihood of new service cases and can thus affect service wait times. Our weekly unit of analysis combined with the relatively long time lag between purchase and installation of solar home systems rules out concerns about reverse causality. A second potential concern stems from bias due to unobserved confounding factors. In our base model, we carefully control for seasonality and branch characteristics using branch-month fixed effects (which subsume branch fixed effects). These fine-grained controls account for many unobserved factors including variation in demand, weather, staff competence levels, product quality, customer characteristics and variation in socio-economic development across branches and over time.

The sales team and service technician at the branches operate independently and do not have overlapping duties. None-the-less, any potential coordination across the sales and service staff, to strategically provide service with a view to increasing sales, is not fully accounted for in our base model. Unobserved variation of this kind can bias our coefficients of interest. To address this source of potential endogeneity, we develop two instrumental variables (IVs), leveraging geo-spatial variation in service task locations, weather and road quality. To develop these instruments, we combine hand-collected supplemental customer geo-location data and highly granular data on weather and road quality with our institutional knowledge about the details of the firm's after-sales processes. For our first IV, we take advantage of unpredictability in the timing and spatial dispersion of service tasks that require a branch technician's visit. For the second, we exploit the exogenous logistical challenges – stemming from weather and road conditions – faced in receiving repaired products from the firm's central repair workshop in Kampala.

We find that customers in our sample are highly sensitive to the timeliness of after-sales service. In our base specification with branch-month fixed effects, we find that when the average wait time for service for existing customers increases by a day, adoption of the technology (i.e., purchase by first-time users) decreases by 0.76% ($p = 0.028$). Thus, an increase in average wait time for service by a week (which corresponds to one standard deviation of the average wait time distribution within a branch-month) leads to a 5.3% decrease in adoptions.

From our IV analyses, we find that adoption of solar home systems can decrease by as much as 32.4% ($p = 0.031$) when the average wait time for service increases by a week. Our IV analyses correct for any potential downward bias due to active coordination between the sales and service staff. In addition, they allow us to explore heterogeneous impact of service wait times on adoptions. Our two IVs exploit two separate sources of exogenous variation in average wait time for service and capture local average treatment effects, as opposed to the average treatment effect captured by the base specification (Angrist and Pischke 2008). Our IVs only impact our estimates through cases which require a technician visit or involve the workshop. Such cases typically involve longer wait times than cases resolved via phone. Our IV estimates – which are larger than the estimates from our base specification – suggest that when waits include technician visits or workshop cases, increases in wait time have more damaging consequences. In particular, we find that customers are most sensitive to service wait times from workshop cases. This is expected as customers have to separate from their products for a long time and they may worry that the product will not be returned or will be replaced in worse condition. Also, the wait for workshop cases is the longest. In a separate reduced form analysis, we find that congestion at the central workshop due to a capacity bottleneck leads to a reduction in adoptions, providing further evidence that long waits for workshop related service hurt adoptions.

An important channel through which after-sales service can impact adoption is word-of-mouth. To validate the word-of-mouth channel, we utilize an individual-customer-level model. In March - August 2017, our partner company started a formal referral program. Every month, they rewarded existing customers based on the number of new customers acquired through their referral. Using a panel dataset with customer and month fixed effects, we test whether the number of customers acquired through referrals from an existing customer depends on the referring customer's service experience. We find that the number of customers acquired through referrals decreases by 5.6% ($p = 0.001$) when the referring customer's wait time for service (averaged over the last three months) increases by a day. This evidence suggests that word-of-mouth is a critical channel for customer acquisition for technology firms in emerging markets. Dissatisfied customers share their negative experiences with others, which can significantly impede technology adoption.

Little is known about the extent to which timely after-sales service affects customer acquisition. Perhaps for this reason, product innovation, improved product affordability, access to finance and branding/marketing campaigns have gained more traction than after-sales service as customer acquisition strategies. This is also the case for firms selling technology products in emerging markets (GOGLA 2018). Our study provides the first empirical estimates of the impact of after-sales service on customer acquisition through technology adoption, in an emerging market setting. We find that different types of service waits affect technology adoption differently. This has an important implication for after-sales service resource allocation. In our case, other things equal, customers who have been waiting for workshop cases should be prioritised for service. Prior work on the drivers of technology adoption in emerging markets has primarily focused on the impact of government policies (e.g., see Cohen et al. 2010, Hanna et al. 2016). In contrast, our work highlights the importance of private sector firm operations in achieving this end. Finally, our analysis suggests that the private sector can not operate in a vacuum. Public sector investment in improving road quality and connectivity has a non-obvious impact on technology adoption in these settings.

In Section 2 below, we discuss relevant literature. In Section 3, we discuss background, data and summary statistics. In Section 4, we lay out our empirical strategy, including our base specification and two IV approaches. In Section 5, we provide our results and discuss the word-of-mouth mechanism. We conclude in Section 6.

2. Literature Review

Our paper contributes to three streams of literature. First, we create new knowledge about the drivers of technology adoption in emerging markets, by focusing on the importance of timely after-sales service. Second, we contribute to the literature on peer effects and word-of-mouth. We demonstrate that long service wait times can lead to substantial negative word-of-mouth and lower technology adoption in emerging markets. Finally, we add to the operations management literature on after-sales service by empirically assessing the impact of wait time for service on customer acquisition through technology adoption.

Recent studies in economics and operations management have examined how liquidity and information impact technology adoption in emerging markets. Through randomized controlled trials, Cohen et al. (2010) find that demand for insecticide-treated bednets in Kenya goes down significantly when their price increases. Guiteras et al. (2015) find that in Bangladesh, providing subsidies to households increases ownership of latrines. By modelling customer purchasing behavior, Uppari et al. (2018) find that adoption of small rechargeable bulbs in rural Rwanda can be improved by reducing customers' liquidity constraints and increasing the convenience of recharging. Foster and Rosenzweig (1995) focus on the role of information and report that imperfect knowledge about how to use new varieties of seeds was a significant barrier to their adoption by farmers during the Green Revolution in India.

Researchers have also examined how product quality affects technology adoption in emerging markets. Bold et al. (2017) suggest that smallholder farmers in Africa do not adopt fertilizer and hybrid seeds because the versions of those technologies available in local markets are of low quality. Through a randomized controlled trial, Levine et al. (2018) find that offering a free product trial and money back guarantee that allows consumers to assess product quality significantly increases adoption of solar cook stoves in Uganda. Hanna et al. (2016) conduct a long-term randomized controlled trial on the health benefits of replacing traditional cook stoves with solar cook stoves in Bangladesh and find that solar cook stoves lose efficiency of over time – due to the lack of repair and proper maintenance. Such issues of product reliability and post-purchase customer experience could be just as important in driving technology adoption as liquidity, information or other aspects of product quality. Knowing to what extent they drive adoptions is needed in order to make tradeoffs about what activities to invest in to spur adoption. It is this question that we address.

A large body of literature in marketing and economics focuses on the role of peer effects and word-of-mouth in driving technology adoption. Tucker (2008) finds that employees at an investment bank adopt video-messaging machines when others in their network use them. Miller and Tucker (2009) find that US hospitals adopt electronic medical records when other hospitals in their network do so. Using data on Californian households, Bollinger and Gillingham (2012) find that adoption of solar products is driven by peer effects – the adoption rate of solar increases as the installed base of solar products increases. Similarly, in the emerging markets context, there is substantial evidence that social interactions and word-of-mouth are key channels of information exchange that can heavily influence technology adoption. Miller and Mobarak (2014) find that villagers' decisions to adopt nontraditional stoves in Bangladesh are related to the choices of opinion leaders. This effect is stronger when the opinion leader refuses to adopt the technology after a marketing intervention, suggesting that negative information is more salient than positive information. Conley and Udry (2010) find that farmers in Ghana adjust their use of fertilizers based on the profits achieved by their neighbors. We build on this stream of literature by highlighting that customers also share their after-sales service experience with others. This information has a significant impact on the adoption decisions made by potential adopters.

Researchers in marketing and operations management have highlighted different ways in which after-sales service affect individual customer behavior. Emadi and Swaminathan (2018) show that differences in callers' queue abandonment behavior in call centers is driven by differences in their beliefs about their delays based on contact history. Researchers have also built analytical models to study customer response to service wait times at call centers (e.g., see Akşin et al. 2013). Zeithaml et al. (1996) show the impact of service quality on specific customer behaviors that signal whether customers will remain with or defect from a company. In a retail bank setting, Buell et al. (2016) find that increased competition among firms offering differential levels of service quality can impact customer defection at the incumbent firm. Using structural estimation, Allon et al. (2011) find that customers of the Fast-Food Drive-Thru industry attribute a high cost to their waiting time. Lu et al. (2013) find empirical evidence that the number of customers in a supermarket queue significantly impacts customers' purchasing behaviour. We contribute to this literature by estimating the effect of after-sales service experienced by existing users on the number of new customers acquired through their referrals.

There is also a rich operations management literature on service contracts. Aflaki and Popescu (2013) examine how strategic firms can manage customized service over time to maximize the long-term value from each customer. Guajardo et al. (2015) empirically assess how the interplay between product quality and warranty length affects product demand across different U.S. automobile companies. Chan et al. (2018) study how service contracts are selected by the customers of medical equipment suppliers and how this choice of service contracts affects service costs. Using data on B2B contracts on service renewal in a high-technology industry in Germany and in the U.K., Bolton et al. (2006) find that customers renew their service contracts based on past service quality received. Despite a large volume of work on after-sales service and its impact on customer satisfaction and retention, these studies have so far overlooked the direct impact of service wait times on sales, let alone on adoptions. Our study builds on this stream of literature and answers this important question. By providing an empirical estimate of the value of after-sales service, our study can allow firms to better assess the benefits of implementing strategies that improve their after-sales service versus other strategies for increasing adoptions and sales.

3. Background, Data and Variables

Our partner company is one of the two main branded companies that sold household and business appliances with credit payment options and after sales service support in off-grid communities in Uganda during our study period. They sell high quality products and have a comprehensive after-sales service support. There are many other companies that sell smaller solar solutions or pico-lighting solutions in Uganda – these companies are not direct competitors of our partner company.

The company has a wide network of 46 branches that serve off-grid communities across Uganda. (Its has closest competitor in comparison only operates in a third of the branches covered by our partner company.) Depending on its location, a branch can cover an area with population ranging from below 100,000 in a rural area to a few million in urban centers like Kampala. Each branch has a branch manager who oversees the sales team and service technician in the branch and is accountable for their performance. The company has centrally controlled operations with little autonomy given to its 46 branches. Each branch is primarily a retail store with an in-house branch technician.

The sales team at a branch usually consists of 5-15 employees – the number varies depending on the size of the population covered by the branch. The sales team acquires new customers and maintains good relations with them in order to ensure timely payment and to catalyze repeat purchases. The service staff at each branch constitutes one branch technician and a driver. The technician installs newly purchased appliances at customers' homes and caters to service cases raised by existing customers. The branch technician is not involved in the branch sales activities.

3.1. Adoption

In 2016, only 18% of the rural population in Uganda had access to electricity (World Bank 2016). In off-grid communities, people use candles, kerosene and paraffin lamps to light their homes and businesses after sundown. With the recent development of a competitive and innovative off-grid solar sector that offers a range of solar products and credit-based pay-as-you-go payment options, solar home systems now provide an alternative to traditional sources of lighting in these regions.

The branch sales teams of our partner company visit villages in the off-grid communities around their branches to acquire new customers. They also receive referrals for potential customers from existing customers. In the time frame of our study, June 2016 - August 2017, 83% of the 11,697 solar home systems sold were sold to adopters – i.e., customers who had never previously had electricity and were buying solar home system technology for the first time. The starting panel size of a solar home system offered by our partner company is 50 Watt power (Wp). This allows for a few lights and mobile phone charging points. More advanced products include bigger home systems that support appliances such as television sets, refrigerators, agricultural pumps and hair clippers. Customers can upgrade their solar home systems from time to time by adding new appliances, batteries and solar panels to their current system. This climb up the "energy ladder" provides an opportunity for retaining customers and increasing their lifetime value.

The sales process starts with a sales lead generated by a branch sales representative. A solar home system is an expensive purchase. A basic solar home system in Uganda can cost between 100-500 USD (Ugandan Off-Grid Energy Market Accelerator 2018). In comparison, the average monthly income of a Ugandan household is 453,000 UGX ($\sim$ 122 USD) (Ugandan Bureau of Statistics 2013). To reduce the financial burden of buying a solar home system, our partner company allows customers to buy products on credit, with contract durations ranging from 12 to 24 months under a lease-to-own model. After undergoing a credit check, credit customers make a down payment. Cash customers pay the full price for the product upfront. Once a payment is validated by the accounts team at the company's headquarters, an installation ticket is created. This is considered as the time of sale and therefore adoption in the case of first-time users.

Once an installation ticket is created, the product is dispatched from the central warehouse at the headquarters in Kampala. Two logistics vans take products from the headquarters to the branches, one operating on a North-East van route and the other on a South-West van route. Once a product arrives at a branch, the branch technician is responsible for installing the product at the customer's location. On average, it takes about three weeks from the date of sale to the date of installation. Less than 10% of installations are completed within a week of the sale date. Figure 3.1 shows the sales process at a branch and the average duration in each stage.

3.2. After-Sales Service

An important aspect of our partner company is that they provide all their customers with free after-sales service, irrespective of the type or size of the product they have purchased, their mode of payment or their location.

After-sales service issues are very frequent in our data – of the customers who bought a product in the period of our study, around half of them requested at least one after-sales service in the period of our study. Service issues arise because of different reasons. In our data, around a quarter of the service cases are related to manufacturing, supplier or installation issues. Around 10% of the cases stem from improper use of the products by customers. Weakening of batteries over time and bad weather such as heavy rain, lightening and dust storms are also frequent causes of service cases.[1]

[1] From our data, it is difficult to discern the actual causes of service issues as the data is incomplete and includes overlapping causes. As a result the frequency of different service causes noted here is an approximation.

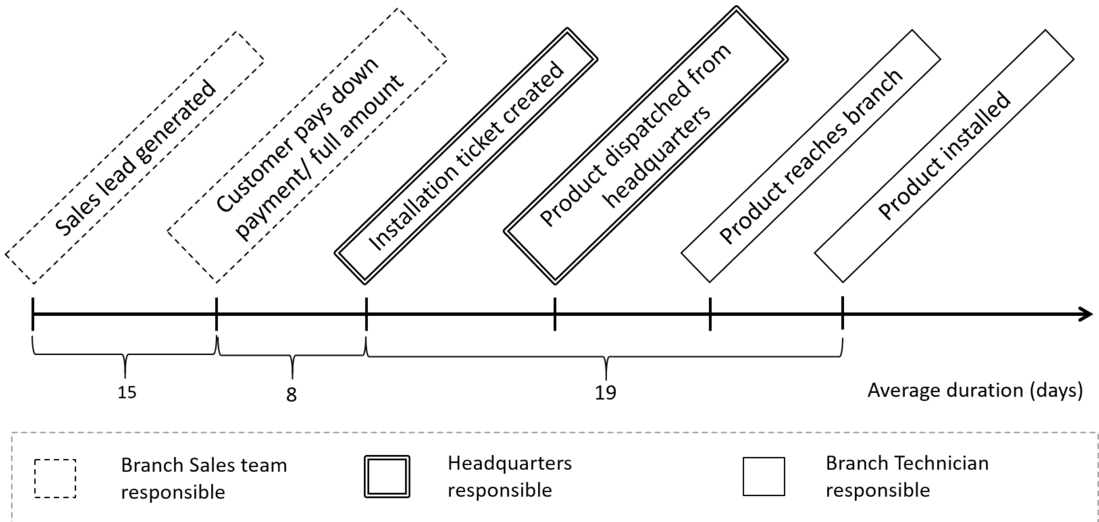

Figure 3.1: Key stages in the sales process of the partner company

Note: The legend describes different parts of the process that are undertaken by the branch sales team, at the headquarters or by the branch technician. The numbers below the stages indicate the average duration of completing the stages. We do not have time stamps for some of the stages in the process.

A service case ticket is created in the company's central SAP system when a customer logs a complaint through a central toll-free number. A customer care representative at the headquarters opens the case and attempts to resolve the issue over the phone. If unresolved, the case is forwarded to the relevant branch technician who visits the customer at her location. The technician decides on his tasks for each week based on the customer locations for pending service tasks and the technical issues that need to be addressed in these tasks. If the technician is unable to resolve the case, he uninstalls the product and brings it to the branch office. The product is then sent to the central workshop in Kampala through a logistics van that visits the branch every week. After the product is repaired at the workshop (or a replacement product is obtained if needed), it is loaded back onto the logistics van and brought to the branch. From here, the branch technician takes the product back to the customer's location and reinstalls it. Once a service case is marked 'done' either by a centrally-located customer care representative or by the branch technician, the audit team at the headquarters calls the customer to ensure that the service case has been resolved. If the case has been resolved to the customer's satisfaction, the audit team closes the case. If not, the case is reopened. A schematic diagram of this process and the average time taken in the different stages is provided in Figure 3.2.

In Table 3.1, we provide summary statistics for wait times for the different types of service cases in our data. In the time frame of our study, we observe 9,786 service cases. Less than 10% of these cases were resolved via phone by a customer care representative. The remaining cases required

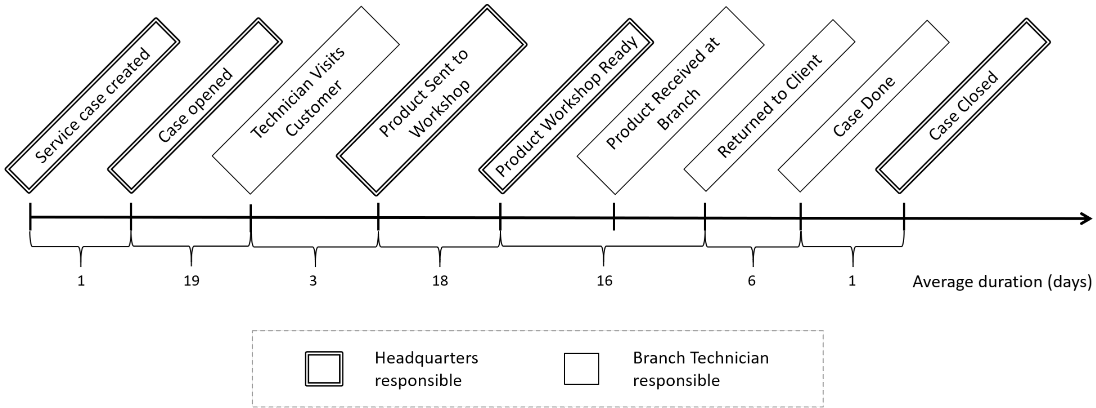

Figure 3.2: Key stages in the service process of the partner company

Note: The legend describes different parts of the process that are undertaken at the headquarters or by the branch technician. The numbers below the stages indicate the average duration of completing the stages. We do not have time stamps for the 'received-at-branch' state.

a visit by the technician. In a quarter of their cases, the technicians send the product to the workshop for repair or replacement. As seen in Figure 3.2 and Table 3.1, service cases that involve the workshop have the longest wait time. The time spent at the workshop depends on factors such as the congestion (or backlog) of pending cases at the workshop, workshop capacity, difficulty level of the tasks and availability of spare parts. In addition, it takes about two weeks from the time when a product is repaired and 'workshop-ready', till when it is reinstalled by the technician at the client's location. A part of this delay is due to the logistics vans facing heavy rainfall and poor road conditions enroute in some weeks.

	Mean	SD	Observations
Duration of service cases (days)	42.1	54.1	9786
Duration of service cases resolved by customer care rep (days)	8.4	14.9	931
Duration of service cases that required a technician visit (days)	24.9	33.0	6675
Duration of service cases that were sent to workshop (days)	47.8	47.6	2180
Duration between workshop-ready and returned-to-client (days)	15.9	25.7	1766

Table 3.1: Summary of after-sales service wait times

Granular data that tracks onsite technician visits and repair processes is challenging to collect and therefore less common, especially for firms operating in emerging markets. Lack of such data may be one of the reasons why post-purchase customer experiences have garnered less attention from empirical researchers so far. Our collaboration with our partner company – a highly data-centric solar distribution company – allows us to measure the timeliness of after-sales service at a granular level and answer our research questions.

3.3. Variables

To identify the impact of after-sales service (provided to existing customers) on adoption by new customers, we aggregate the sales and service data by geography. We aggregate the data at the branch-week level. We choose this level of aggregation for two reasons. First, branch information is available for all customers whereas customer location information at more granular levels such as the county or subcounty level is incomplete. Second, the sales and service teams are specific to each branch. Therefore, it is challenging to control for spillover of sales and service between units at lower levels of aggregation than a branch.

Adoptions in a branch-week refers to the number of sales made to customers who have never owned a solar home system before. We define the installed base in a branch-week as the total kilo-Watt power (kWp) sold in the branch from the start of our data up until the start of the week.

Timeliness of service quality is measured as the average wait time for service cases that are pending in the week. The wait time for a service case is the number of days from its start date, till the end of the week or its closure date (whichever is earlier). How customers observe wait times – and our wait time measure – are likely to suffer from the inspection paradox, i.e., longer cases are likely to be over sampled and shorter cases under sampled. However, we chose to use this as our primary measure of wait time because we believe it is a reasonable reflection of how customers may think of average wait times, based on their observed waits. Note that service wait times, and therefore average wait time for service, span multiple weeks. In order to avoid right censoring, we drop the first three months of our data. We find that 90% of service cases are completed within 90 days. With this modification, we have 65 weeks of adoption and service data for 46 branches between June 2016 and August 2017. We also measure the total number of service cases that opened in each branch-week. Further, congestion at the workshop is measured as the number of products that are waiting to be repaired at the workshop each week.

We collected granular satellite-based rainfall data (measured at half-hourly intervals) from the National Oceanic and Atmospheric Administration (NOAA) for every $0.1°$ X $0.1°$ cell in Uganda. Each cell corresponds to a geographic area of 11 sq. km. For each branch-week, we first count the number of days of rainfall over 12mm (75th percentile of daily rainfall in Uganda) in each cell in the area covered by the branch, and then average this value across all the cells in this area. This gives us a measure of the days of bad weather in each branch-week. As discussed in Section 4.2., we also use weather data to create one of our IVs. A summary of the key variables used in our analysis is provided in Table 3.2.

	Mean	Min	Max	SD
Adoptions (#)	2.6	0.0	298.0	7.5
Total sales (#)	3.2	0.0	299.0	7.6
Installed base (kWp)	11.4	0.0	83.3	10.6
Avg wait for service (days)	50.4	0.0	158.0	24.1
New service cases (#)	2.8	0.0	21.0	2.9
Congestion at the workshop (#)	119.6	8	196	56.1
Days of bad weather	0.5	0.0	4.4	0.6
Observations (Number of branch-weeks)	2990			

Table 3.2: Summary of variables at the branch-week level

4. Empirical Specification

4.1. Base Specification

Our base specification is a fixed effects model with extensive controls, as shown below.

$$\begin{aligned} Adoptions_{bw} = {} & Branch.month_{bm} + \beta_1 Avg.wait.for.service_{bw} + \beta_2 New.service.cases_{bw} \\ & + \beta_3 Installed.base_{bw} + \beta_4 Days.of.bad.weather_{bw} + Week.of.month_w + \epsilon_{bw} \end{aligned} \tag{1}$$

Here, $Adoptions_{bw}$ is the number of sales to first-time solar home system users in a branch in a week. A ‘sale’ is logged on the date when the installation ticket is created. This is when the customers either makes a full payment or down payment for the product. Products are typically installed after three weeks from the date when the installation ticket is created. Due to this lag between sale and installation of a product, reverse causality, i.e., adoptions in a week affecting wait time for service or workload of the technician in the same week, can be ruled out.

$Avg.wait.for.service_{bw}$ is the average wait time for pending service cases in a branch in a week. Because each branch has its own service technician and the branches operate independently, average wait time for service is uncorrelated across branches (conditional on branch-month fixed effects, week-of-month fixed effects and days of bad weather). $New.service.cases_{bw}$ is the number of service cases that arise in a branch in a week. Because of the high likelihood that product quality problems will surface very early (due to the bathtub curve theory of product failure – e.g., see Chan et al. 2018), this variable reflects the effect of product quality. It also reflects the quality of recent installation tasks. $Installed.base_{bw}$ is the total capacity (in kWp) sold up until the start of the week (from the start of our data). $Branch.month_{bm}$ are the branch-month fixed effects. $Week.of.month_w$ are the week-of-month fixed effects.

A number of factors may influence both timeliness of service and adoptions, many of which vary systematically across branches. These include staff, infrastructure, topography, cloud cover, hours of sunshine and customers’ socioeconomic characteristics. To account for these factors, we control for each branch in our model specification. However, instead of including branch fixed effects, which would capture the average characteristics of each branch, we include branch-month fixed effects. These fixed effects allow us to control for all time-invariant branch characteristics and for the average effect of all time-varying characteristics of a branch within a month. In this way, we control for changes in branch characteristics over time, e.g., staff turnover, changes in marketing or sales strategies, changes in customer or product composition and hours of average sunshine – that could otherwise confound our estimates. The branch-month fixed effects further control for any macro changes in factors such as infrastructure, income or education that may affect a branch within the 15 months of our data. By using this fixed effects specification, we exploit the within-branch-month variation in average wait for service and in adoptions – i.e., variation in these variables in the weeks within a month in a branch – to assess the impact of average wait time for service on adoptions. We choose a month as the appropriate period for these time-interacted fixed effects because it is very reasonable to expect that a branch will have comparable operating conditions in such a short time window, even for a company that is expanding rapidly.

Sales and service can differ systematically from one month to the next due to seasonality and time trends. Our branch-month fixed effects capture seasonality for each branch separately, while also allowing different non-parametric time trends for the 46 different branches over the 15 months of our study. We further control for seasonality by using week-of-month fixed effects, which capture the fact that sales and service quality might differ in different weeks within a month. Differences in sales across different weeks in a month could be driven by sales targets that are set for the sales force each month. This could lead to more aggressive sales tactics towards the end of the month. Similarly, sales teams and branch technicians are provided with a travel budget at the start of the month, which depletes over time. This could also affect the sales or service pattern in different weeks of the month.

Heavy rain can deter both the sales team and the branch technician from visiting their customers in the off-grid communities that they serve, as roads become difficult to navigate. Heavy rain may also result in more service cases opening up. As cloud cover reduces efficiency of solar home systems, heavy rain could also deter adoptions. Thus heavy rain could lead to lower adoptions and can also increase the average wait time for service in a branch-week. To address this endogeneity concern, we control for the number of days of bad weather (i.e., heavy rain) in a branch in a week.

Within a branch-month, another reason for an increase in service cases that is potentially endogenous to sales is an increase in recently installed products. Recently installed products can directly impact sales through peer effects (Bollinger and Gillingham 2012). As mentioned above, they can also affect service wait times because quality problems have a high likelihood of arising at the start of the product life cycle. To address this endogeneity issue, we control for the installed base in Equation 1.

Including installed base measured as number of installations in the fixed effects model would result in an endogeneity issue because the number of installations are fully determined by the number of past sales. This leads to concerns similar to those in a dynamic panel, where errors after fixed effects transformation are correlated with the transformed installed base variable. Bollinger and Gillingham (2012) discuss in detail the challenges in estimating the effect of installed base in a fixed effects model. To avoid bias in our estimate of the coefficient of average wait time for service due to including installed base as a regressor when it is fully determined by past sales, we include the total capacity of solar products sold (in terms of kWp) as a proxy for this variable. As different customers purchase different amounts of solar home system capacity, the capacity of the installed base is not fully determined by past sales (Bollinger and Gillingham 2012). About a third of the time, the branch of sale is different from the branch where the product is installed. This further reduces the correlation between past sales at a branch and its installed base.

We cluster errors at the branch-month level and we correct for heteroskedasticity by using heteroskedasty-robust standard errors. Although we have a long panel with 65 weeks of data, non-stationarity is not a concern in our specification because we use branch-month fixed effects. This reduces the variation used to estimate our coefficients of interest to within-branch-month, i.e., only 4-5 weeks.

4.2. Identification using Instrumental Variables

Identification of the impact of timeliness of service quality on sales in our base specification hinges upon the assumption that after controlling for branch-month fixed effects and other controls in Equation 1, the wait time for service is uncorrelated with the regression errors. Although the sales team and the service technician at the branches have separate non-overlapping duties, any active coordination between them to increase sales is a potential source of endogeneity. For example, the sales team might request the branch technician to visit a county where it plans to go next, to reduce customer discontent about long waits. If such coordination occurs, we would underestimate the impact of service wait time on sales in Equation 1. To address this potential source of bias, we develop two geo-spatial IVs. For our first IV, we take advantage of exogeneity in the timing and spatial dispersion of service tasks. For our second IV, we exploit exogenous weather and road conditions faced by the logistics vans. These IVs allow us to tease out the effect of exogenous variation in average wait time for service, which is uncorrelated with factors, such as collusion between the sales and service team and strategic activities by competitors within the branch-month.

4.2.1. IV based on Geographic Dispersion of Service Cases Due to the sparse population, poor road quality and long travel time between locations in off-grid communities in Uganda, branch technicians pool nearby tasks together to increase efficiency. That is, technicians tend to pool together pending service and installation cases at a location and resolve them in the same visit. If a technician's tasks are highly geographically concentrated in a week, his efficiency increases and the backlog of pending tasks decreases faster, reducing average waiting time. On the other hand, if tasks are in spread apart locations, the technician's efficiency suffers and thus average wait time increases. The efficiency gains from pooling nearby service cases together comes primarily from reduction in technicians' travel time. Pooling can also lead to learning-related time savings and economies of scale for the technician as customers living close together may experience similar service cases as they buy similar products. Previous studies in operations management have found that workload affects service quality and performance in different settings (e.g., Tan and Netessine 2014, Song et al. 2015).

Amongst a technician's pending tasks, two specific technician task types arise randomly. First, new service cases arise as products fail. After controlling for branch characteristics, weather conditions, seasonality and the installed base (as in Equation 1), the location and timing of new service cases is exogenous. Second, the time taken for products to be repaired at the workshop is exogenously determined by factors such as the number of pending cases from other branches, workshop capacity, difficulty level of the tasks and availability of spare parts. The workshop is managed by a separate workshop team at the headquarters. Thus, none of the workshop-related factors for service delays are influenced by the decisions made by the sales teams or the service technicians at the branches. Therefore, the number of cases that become workshop-ready in a branch-week – i.e., the number of workshop cases in a week that are ready for return to a particular branch – is also exogenous.

Building on these observations, we create our first instrument. We measure the spatial dispersion of new or workshop-ready service tasks that have arisen for a branch technician in the last six weeks. The spatial dispersion of these tasks is measured in three steps. First, we identify the new or workshop-ready cases associated with customers in each county in a branch, in a week. Next, we count the total number of new or workshop-ready cases in each county-level cluster in each week. Finally, we take the standard deviation of the number of tasks across the counties in a branch, in each week. We consider the technician tasks in the last six weeks because this corresponds to the average duration of service cases in our data. We use this spatial distribution of technician tasks to instrument for the average wait time for service in a branch-week in Equation 1. Given the exogeneous manner in which the new or workshop-ready service cases arise, we expect this IV to meet the exclusion criterion.

To illustrate this instrument, in Figure 4.1, we show the geographic dispersion of the new or workshop-ready technician tasks across the five different counties in the Kabale branch across two consecutive weeks. The upper two plots in Figure 4.1 show that there is substantial variation in the geographic dispersion of these tasks across the two weeks. Also, we see from the lower two plots

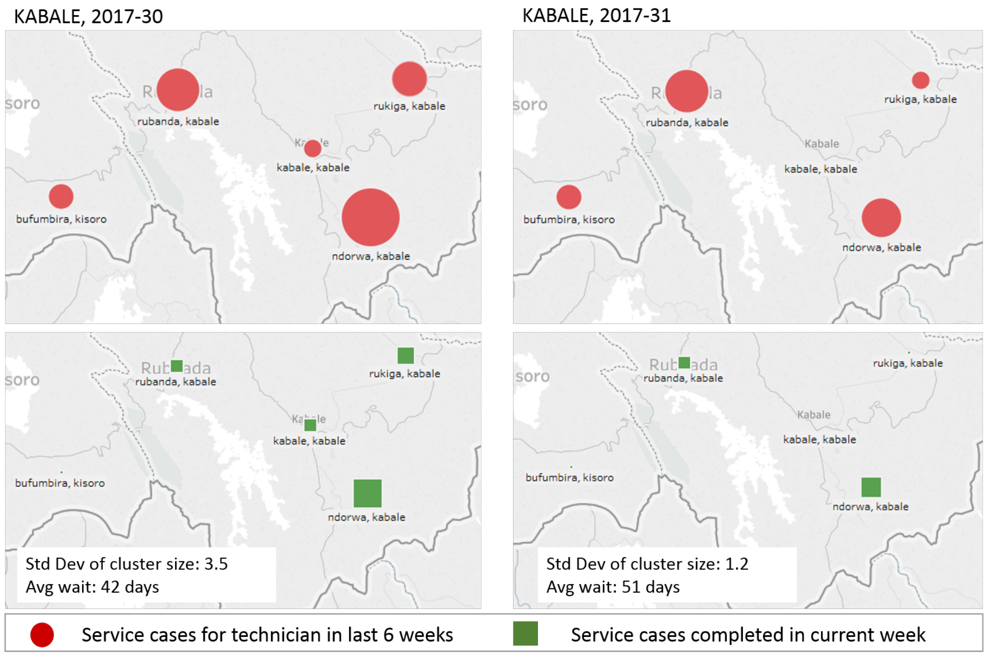

Figure 4.1: Spatial dispersion of new or workshop-ready service cases

Note: This Figure is based on data for the Kabale branch across two consecutive weeks (30th and 31st week in 2017). Each point on the map refers to a county within the area served by the Kabale branch.

that the technician tends to prioritize larger clusters, suggesting a positive correlation between the cluster sizes and number of cases resolved by the technician each week.

To build this instrument, we first geo-locate customers at the county level. We obtained granular customer location data from the company. This data was not standardized or well formatted, so we matched it with a list of county names obtained from the Ugandan Bureau of Statistics. To match the locations, we used exact and fuzzy matching techniques. Finally, we web-scraped the geocodes of the standardised county names from the *geonames.org* website. We matched 75% - 100% of the sales and service data at the county level in 21 branches. Data from these 21 branches are used in this IV analysis. Our estimates for the coefficients in Equation 1 using this subsample are comparable to those using the full sample.

4.2.2. IV based on Weather along Logistic Van Routes For this instrument, we exploit the logistical constraints faced by vans when delivering 'workshop-ready' repaired or replacement products from the workshop to their respective branches. Given the exogeneity in the amount of rainfall in the route of the van, the road quality and the number of products that are workshop-ready in any week, this instrument exploits exogenous variation in average wait time and fulfils the exclusion criterion.

To obtain this IV, we first map each of the two van routes and the fixed sequence of branch locations each van travels to each week, using the Google Maps Application Programming Interface (API). Below in Figure 4.2, we provide a map of the two routes navigated by the logistics vans. One van route (marked in blue in the figure) covers branches in the North East of Uganda. The other van route (marked in red) covers branches in the South West. The number associated with each branch indicates the sequence in which it is visited by the van in each trip. We next identify the rainfall and road quality in the path of the logistics van. We use highly granular satellite data on daily rainfall in Uganda (obtained from the NOAA). The grid in gray in Figure 4.2 denotes the cells (each corresponding to 0.1° X 0.1° on the coordinate system or 11 sq. km.) for which we have half-hourly rainfall data. We develop a measure of road quality using a geospatial dataset of road and river networks in Uganda obtained from the World Food Program and the DIVA-GIS databases, respectively.

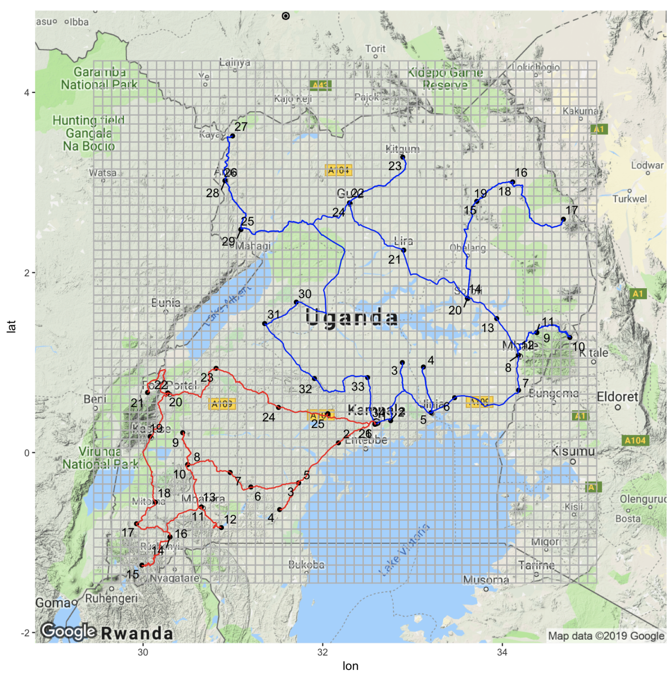

Figure 4.2: Route taken by the logistic vans

Note: The route of the van that goes to branches in the North East of Uganda is in blue. The route of the van that goes to branches in the South West is in red. The grid shows the cells for which we have half-hourly rainfall data.

From the rainfall grid, we identify each 11 sq. km. cell that intersects the van routes. For each cell, in each week, we measure the number of days of bad weather (i.e., rainfall above 12mm). We weight the rainfall in each cell based on the length of the van route covered by the cell. This gives us a weekly *rainfall in route* for each cell. Next, we overlay the Ugandan road network data on the mapped route of each van. This allows us to identify the road sections that are tertiary roads, i.e., roads that are not classified as highways, primary or secondary roads and are therefore not well-suited for heavy motorized traffic. These are often dirt roads that get badly waterlogged during heavy rain. For each cell, we measure the fraction of distance traveled by the van in the cell that is on tertiary roads. Using the GIS data on river networks in Uganda, we identify the number of river crossings (i.e., rivers crossing the van route), in each cell. River crossings on tertiary roads often become impassable in bad weather due to broken bridges or flooding. In each cell, we measure *road quality* by interacting the fraction of tertiary roads and the number of river crossings. Figure 4.3 shows the mapping of rainfall and road conditions between two branches, in a week in May 2017.

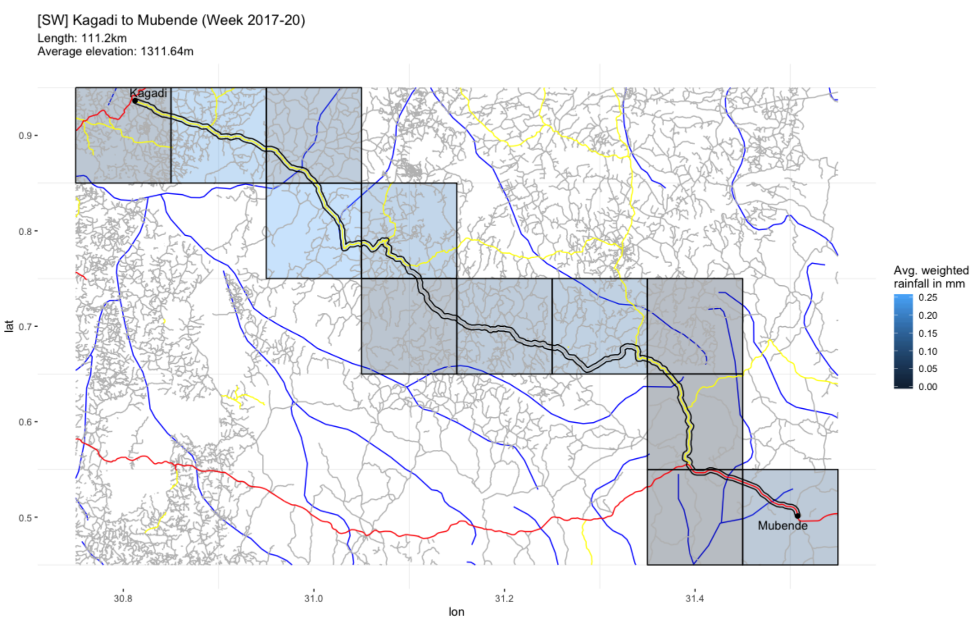

Figure 4.3: Rainfall and road characteristics

Note: This Figure is based on data for a particular week for the route connecting Kagadi and Mubende, two branches on the North East van route. Each cell represents a 11 sq. km stretch of land, corresponding to 0.1° X 0.1° on the coordinate system. The coloured cells provide rainfall information over the underlying road. Red lines denote highways and primary roads, yellow denote secondary roads and gray denote tertiary roads. Rivers are shown in blue.

To obtain a weekly *rainfall-road-condition score* for each cell in a week, we interact the *rainfall in route* measure with the *road quality* measure. For each branch-week, we sum the rainfall-road condition score over all the cells that lie in the path of the logistics van between Kampala and the focal branch. This gives us the *branch-rainfall-road-condition score*. The reliability of the logistics vans' timing is only a concern for customers waiting for service when they are awaiting repaired or replacement products that need to be sent to them from the workshop. Once workshop-ready, products are usually sent to the branch either in the same week or the next week. Thus, in each week, we weight the *branch-rainfall-road-condition score* in the current and the next week by the number of workshop-ready products for the branch (i.e., those that have already been repaired at the workshop and are ready to be picked up). This provides us a *weighted-branch-rainfall-road-condition score*. For each branch-week, we then take the average weighted-branch-rainfall-road-condition score over the last four weeks to capture the current and lagged effect of logistical constraints in the van's route on wait times in the branch-week. This *average-weighted-branch-rainfall-road-condition score* is the measure that we use as our second instrument for average wait time for service.

5. Results and Discussion

We use multiple models to test whether wait time for service has an impact on adoption of solar home systems. First, in Section 5.1, we present two fixed effects models and consider the two IV approaches discussed above. For robustness, we also present alternate measures for timeliness of after sales service in Section 5.2. Finally, in Section 5.3, we present a customer-level fixed effects model to validate the word-of-mouth mechanism that is driving our results.

5.1. Impact of Wait Time for Service on Adoptions

Table 5.1 contains the results of our analysis of the impact of average wait time for service faced by existing customers on the number of purchases made by adopters. Column (1) shows our results from the base specification (Equation 1). We find that as the average wait time for service increases by a day, the number of adoptions decreases by 0.023 customers ($p = 0.028$). In other words, as the average number of adoptions is about 3 customers/ week/ branch, when the average wait time for service increases by one day, there is a 0.76% decrease in adoptions.

We also find in Table 5.1 that adoptions are lower when new service cases start in a week. This suggests that customers express dissatisfaction with product quality or installation quality as well. The installed base at a branch consistently and substantially increases adoptions. With each kWp capacity increase in the installed base, adoptions increase by about 7%. This corroborates earlier studies which show that peer effects are a strong determinant of technology adoption (Bollinger and Gillingham 2012, Guiteras et al. 2015). Although not statistically significant at 10%, days of bad weather has a negative coefficient. This could be attributed to loss of effectiveness of the sales team as they are unable to commute to the off grid communities to acquire customers.

Our dependent variable – the number of adoptions in a branch-week – is a count variable. In column (2), we test if our results hold when we instead use a Poisson fixed effects model

	(1) Fixed Effects	(2) Fixed Effects (Poisson)	(3) IV I (Geographic Dispersion of Cases)	(4) IV II (Weather in Van Route)
Avg wait for service (days)	-0.023**	-0.011***	-0.133**	-0.139**
	(0.01)	(0.00)	(0.06)	(0.06)
New service cases started (#)	-0.188	-0.050**	-0.183**	-0.362**
	(0.12)	(0.02)	(0.09)	(0.17)
Installed base (kWp)	0.191***	0.054*	0.211***	0.212***
	(0.06)	(0.03)	(0.06)	(0.08)
Days of bad weather (#)	-0.820	-0.263*	-0.092	-0.933
	(0.60)	(0.15)	(0.11)	(0.62)
Branch-Month Fixed Effects	Yes	Yes	Yes	Yes
Week of Month Fixed Effects	Yes	Yes	Yes	Yes
KP Wald F statistic	-	-	37.269	33.814
Number of branch-months	690	643	315	623
Observations	2,990	2,789	1,365	2,695

Dependent variable is number of adoptions in a branch-week. In column (1) we report our base fixed effects specification and in column (2) we report a Poisson fixed effects model. In columns (3) and (4) we report the second stage result of the 2SLS regressions. In column (2), observations that do not have variation in the number of adoptions within a branch-month drop out. In column (3), observations drop because we have data on the instrument for only 21 branches. In column (4), we do not have van route information for 3 branches and we drop observations for Kampala as it is the origination of the logistic vans' route. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5.1: Impact of average wait time on adoptions

specification. We find that average wait for service continues to have a negative and significant impact on adoptions. A one day increase in average wait for service decreases adoptions by 1.10% ($p = 0.001$). This impact is slightly higher than that suggested by the linear model used in column (1). IV methods for Poisson fixed-effects models are not well developed (Angrist and Pischke 2008), so we use linear models for our IV analyses.

In columns (3) and (4) of Table 5.1, we validate the relationship between service wait times and adoptions using two different IVs. In column (3), we report results from the IV based on geographical dispersion of new or workshop-ready service cases. We find that a one day increase in average wait time reduces adoptions by 0.133 customers ($p = 0.033$). In column (4), we report results from using the IV based on weather along the van routes. Here, we find that a one day increase in average wait time reduces adoptions by 0.139 customers ($p = 0.031$). From the four different estimates in Table 5.1, we can conclude that average wait time for service has a significant negative impact on the adoption of solar home systems in rural off-grid Uganda.

The IVs suggest a stronger negative impact of service wait times on adoptions than the base specification. Both the instruments are strong instruments, with an F-statistics above the threshold of 10 (Angrist and Pischke 2008). Our IVs also pass the Hansen test for overidentification, suggesting they are valid instruments (χ^2 p-value corresponding to the Hansen J statistic is 0.604).

The first stage results are shown in Online Appendix A1. As expected, we find that lower geographic dispersion of technician tasks decreases the average wait time for pending cases. Also, we find that bad weather in the route of the logistics vans increases the average wait time for pending cases. The impact of poor road conditions (compounded by bad weather) on service wait time highlights the role that the public sector can play in improving off-grid electrification, i.e., by investing in infrastructure that increases connectivity.

Discussion of the Estimates There are two noteworthy observations regarding the estimates of average wait time for service from our base specification in column (1) and from our IV specifications reported in columns (3) and (4) of Table 5.1.

First, our IV specifications address concerns about any unobserved coordination between sales and service staff at a branch. In the specifications in columns (3) and (4), we use two very different sources of exogenous variation in average wait time for service to correct for any potential underestimation of the impact of service wait time due to this coordination.

Second, the pronounced impact of average wait time for service on adoptions in columns (3) and (4) suggests that the impact of average wait time for service on adoptions is heterogeneous. Note that our IV analyses provide local average treatment effects (LATE) as opposed to the average treatment effect (ATE) reported in column (1). The LATE applies only to the subset of the population that are “compliers”, i.e., those affected by the instrument in question (Angrist and Pischke 2008). Thus, our results in column (3) apply to branch-weeks with pending service cases that require a visit from the technician, i.e., cases that are resolved by the technician or those that are returned from the workshop via the technician. Our results in column (4) only apply to branch-weeks with pending service cases where products are returned from the workshop.

The branch-weeks that are compliers to our IVs experience a longer and a different type of wait compared to the non-compliers. The service cases experienced by compliers involve longer wait time for service because the quickest time to service completion is for cases that do *not* require a technician visit or do *not* involve the workshop (Table 3.1). Customers who experience longer waits are likely to be more dissatisfied with the company’s after-sales service and to issue stronger negative publicity about the company. In addition, customers might be especially anxious about having to separate from their products when they are sent to the workshop, and impatient to receive them back. In Online Appendix A2, we compare estimates from our two IVs for different lookback periods and find that for the same lookback period, estimates are higher in magnitude for our second IV (weather in the route of the logistics van). That is, customers are most sensitive to wait from service cases that involve the workshop, followed by wait associated with a technician’s visit. This suggest that service cases involving the workshop should be prioritized by solar service providers.

Our results suggest that existing customers share their service experience with their families, friends and community members. In other words, customers who are deciding whether or not to purchase solar home systems consult with community members who have previously purchased the product. Even if we consider the conservative estimates in column (1) of Table 5.1, our results suggest that one standard deviation increase in within branch-month average wait time for service – which corresponds to around seven days – leads to 5.3% decrease in technology adoption. This suggests an economically significant impact of service wait times on technology adoption in our context.

Solar home systems that are sold by our partner company are expensive purchases for customers living in the rural off-grid communities of Uganda. It is likely that customers who buy the product have higher-than-average income and higher status in the community. The average monthly income of rural households in Uganda is 325,000 UGX (∼90 USD). In contrast, customers of our partner company report having an average income that is seven times higher. Thus, information about long wait times experienced by existing customers – who are influential in their communities – might travel fast around the community. In off-grid communities, solar home systems are high visibility products. They provide electricity after sundown in an area that would otherwise be pitch dark. Electronic appliances such as television sets and refrigerators have rarely been used by off-grid customers before solar home systems became available. Furthermore, some customers buy solar home systems and appliances such as mobile charging units, television sets and refrigerators for their businesses. Businesses are often located in market places, which are a hub for social interactions in rural locations in emerging markets. Thus, long wait times and failure of solar products are easily noticed by potential customers. Our results at the branch level reflect this information effect across the different social clusters within the branch territory.

5.2. Extensions to the Main Analysis

So far, we have assessed the impact of average wait time for service for cases that are pending in the current week, on adoptions. It is possible that customers also consider wait times for cases that were closed in the past, when making an adoption decision. To account for this, we build two moving average variables – by taking a moving average of our average wait time variable over the past 4 and 8 weeks.

In columns (1) and (2) of Table 5.2, we use our two IVs to show the impact of a 4-week moving average of average wait time for service on adoptions. In columns (3) and (4), we show the impact of an 8-week moving average of average wait time for service on adoptions, using our two IVs. As before, IV1 (in columns (1) and (3)) is based on the geographical dispersion of new or workshop-ready service cases and IV2 (in columns (2) and (4)) is based on the weather along the logistic van routes. The moving average in consecutive weeks is highly correlated because of overlapping pending cases, in both the 4 or 8 week lookback period. As a result, the variance of the moving average wait times is lower than that of our original measure of average wait time for service. The variance in the moving average variable is further reduced when we include branch-month fixed effects and use IV specifications. To address this, in the IV specifications, we use branch-half year fixed effects. To control for seasonality across the 15 months of our data, we also include month fixed effects. We continue to include all other controls used in Table 5.1.

Results from columns (1) - (4) of Table 5.2 continue to show a strong negative impact of service wait times on adoptions. This suggests that the impact of service wait times on adoptions is persistent over time and depends on past service as well. Comparing the magnitude of the estimates of the two IVs, i.e., comparing estimates in (1) and (3) with (2) and (4), we find that customers are particularly sensitive to past wait times associated with pending workshop cases. In Online Appendix A3, we further validate our results using additional measures of service wait time including exponentially smoothed moving average wait time variables.

	(1) IV1	(2) IV2	(3) IV1	(4) IV2	(5) Poisson Model
4 Week Moving Avg Wait for Service (days)	-0.058*	-0.138**			
	(0.03)	(0.06)			
8 Week Moving Avg Wait for Service (days)			-0.097	-0.169**	
			(0.06)	(0.08)	
Cases at workshop from other branches (#)					-0.004**
					(0.00)
Cases started in week (#)	-0.013	-0.152*	-0.014	-0.133	
	(0.03)	(0.08)	(0.03)	(0.08)	
Installed base (kWp)	0.239***	0.292***	0.230***	0.314***	
	(0.04)	(0.05)	(0.05)	(0.05)	
Days of bad weather (#)	-0.020	-0.638	-0.066	-0.643	
	(0.10)	(0.45)	(0.10)	(0.46)	
Branch-Half Year Fixed Effects	Yes	Yes	Yes	Yes	
Branch-Month Fixed Effects					Yes
Month-Year Fixed Effects	Yes	Yes	Yes	Yes	
Week of Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
KP Wald F statistic	57.347	16.282	27.027	14.398	-
Number of Branch-Half Years	65	126	64	126	
Number of Branch-Months					638
Observations	1,268	2,534	1,182	2,411	2,703

Dependent variable is the number of adoptions in a branch-week. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5.2: Extensions to main analysis

In our sample, service cases that involve taking faulty products to the workshop incur the longest wait time. Also, the results in Tables 5.1 and 5.2 indicate that customers are highly sensitive to service delays arising from the workshop. One of the major reasons for delay at the workshop is congestion at the workshop, i.e. a backlog of service cases that require repair or replacement at the workshop. We directly assess the impact of this operational bottleneck on adoption in the branches, using the following reduced form specification:

$$\begin{aligned} Adoption_{bw} = Branch.month_{bw} + \delta_1 Cases.at.workshop.from.other.branches_{bw} \\ + Week.of.month_w + \nu_{bw} \end{aligned} \tag{2}$$

This specification is similar to Equation 1, with two changes. First, instead of using average wait time for pending cases as a measure for timeliness of service, we consider the impact of an operational bottleneck, namely, congestion at the workshop. For each branch-week, $Cases.at.workshop.from.other.branches_{bw}$ measures the average number of cases from other branches that have been pending at the workshop in the last three weeks. Second, by considering only cases pending at the workshop from other branches, we identify a source of exogenous variation in after-sales service experience stemming from this operational bottleneck. We continue to control for differences across branches and for seasonality using branch-month fixed effects and week-of-month fixed effects. Since the number of workshop cases that are pending from other branches is not affected by the sales team's or the branch technician's decisions at the focal branch, other controls used in Equation 1 are not relevant here.

Our results from a Poisson model in column (5) of Table 5.2 confirm that congestion at the workshop in Kampala hurts adoptions at the branches. One unit increase in the congestion at the workshop leads to a decrease in the number of adoption by 0.4% (p-value=0.047). Thus, a direct way for our partner company to increase adoptions (and sales) is to reduce congestion at their workshop.

5.3. Mechanism

Our results indicate that the service experienced by existing customers affects purchasing decision made by adopters. This suggests that word-of-mouth is a likely channel through which after-sales service affects adoptions. We first discuss model free evidence that points towards this mechanism. Later, we show that the number of customers acquired through referrals provided by existing customers depends on the service wait time recently experienced by the referring customers.

To document model-free evidence, we develop a topic model using data from a net-promoter score survey conducted by our partner company in 2016. The company reached out – through phone calls made by customer care representatives – to 1,000 randomly selected existing customers who were at different stages in their relationship with the company. The survey included two questions relevant to our study. The first asked customers to self report (on a scale of 0-10) how likely they were to refer the company's products to their friends or family. Customers who gave a response above 8 on this question are coded as promoters, while those that gave a response below 8 are coded as non-promoters. Promoters are more likely to provide positive word-of-mouth about the company's products than non-promoters. The second question asked customers to list what the company should be improving upon. Customers provided a verbal response to this question, which was typed up by a customer care representative.

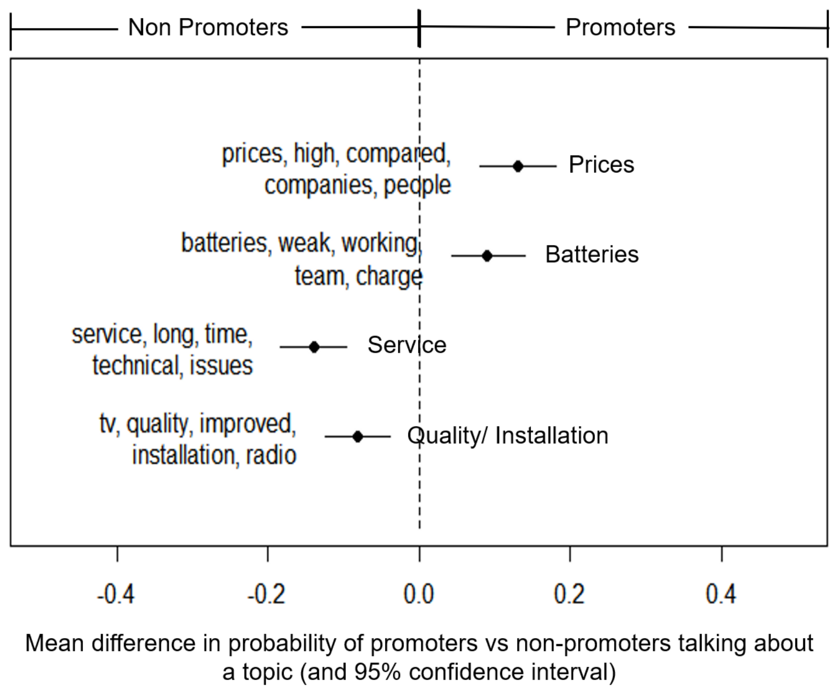

Figure 5.1: Structural Topic Model – Promoters vs. Non-Promoters

Note: This Figure shows differences in the views of promoters vs. non-promoters regarding what the company should improve upon. The model identifies groups of words that were often spoken close together to generate unlabeled 'topics'. Based on the top five most frequently spoken words in each topic, we classified the topics as – prices, batteries, service, and quality/ installation.

From this survey data, we built a Natural Language Processing (NLP) based structural topic model, as shown in Figure 5.1. The topic model indicates that customers want the company to improve along four dimensions – reduce prices, improve batteries, improve service and improve product/ installation quality. More importantly, the model shows that promoters and non-promoters are concerned about different aspects of the company. Promoters are concerned about price and battery quality, whereas, the non-promoters are concerned about after-sales service and product/installation quality. Moreover, the difference in the estimated probability of customers in each of the two groups talking about each topic is statistically different from zero. Figure 5.1 suggests that customers who experience poor after-sales service are less likely to promote the company's products and refer new customers to the sales teams at the branches.

Next, we use referral data provided by our partner company to test whether wait time for service affects the number of customers acquired through referrals from existing customers. In the last six months of our study, March - August 2017, our partner company started a formal referral program. Every month, existing customers were gifted 30,000 UGX (~8 USD) for each customer acquired through their referral. In the six month period, 1221 new customers were acquired through referrals provided by 470 existing customers. We will examine how the variation in the wait times for these 470 customers affect their referral numbers. Around half of the customers who referred others had at least one unresolved service case at some point in the six month period. Using this data, we run the following customer-level specification:

$$\begin{aligned} Referrals_{cm} = & Customer_c + \lambda_1 Days.waiting.for.service_{cm} \\ & + \lambda_2 Num.products.purchased_{cm} + Month.year_m + \omega_{cm} \end{aligned} \tag{3}$$

Here, $Referrals_{cm}$ refers to the number of customers acquired through referral from customer c in month m. $Days.waiting.for.service_{cm}$ refers to the number of days the referring customer has been waiting for service by the end of the month (number of days counted from the start of each service case). $Num.products.purchased_{cm}$ denotes the number of products the referring customer bought in the focal month. We control for the number of products bought by the referring customer in the focal month because recently bought products can affect the number of referrals provided by the customer, and can also affect the number of service cases the customer faces. For example, if a customer buys a solar home system and multiple appliances, the chance of an item failing increases. We control for seasonality using month-year fixed effects.

Results from the Poisson models in Table 5.3 suggest that the number of customers acquired through referrals from existing customers depends on the wait time for service experienced by referring customers. Column (1) shows that when wait time for service experienced by a referring customer increases by a day, the number of customers acquired through her referral decreases by 1.4% (p = 0.019). From column (2), we find that customers are also sensitive to waits for service in the past. When the wait time for service experienced by a referring customer (averaged over the last three months) increases by a day, the number of customers acquired through her referral decreases by 5.6% (p = 0.001). In columns (3) and (4), we examine whether wait times experienced by existing customers nonlinearly impact the number of customers acquired through their referrals. In column (4) we find that customers whose average wait for service in the last three months exceeds three weeks provide less than three times (p = 0.001) the number of referrals as those with no outstanding service cases in the last three months (i.e., the base case). The impact of average service wait times on referrals when customers wait less than three weeks is not statistically different from the base case. Results in column (3) follow the same direction as in column (4) but are not statistically significant at the ten percent significance level.

Referring customer variables	(1) Customers Acquired (#)	(2) Customers Acquired (#)	(3) Customers Acquired (#)	(4) Customers Acquired (#)
Wait for service (days)	-0.014**			
	(0.01)			
Avg wait for service in last 3 months (days)		-0.056***		
		(0.02)		
Wait for service <= 3 weeks			-0.053	
			(0.19)	
Wait for service > 3 weeks			-0.618	
			(0.41)	
Avg wait for service in last 3 months <=3 weeks				0.030
				(0.28)
Avg wait for service in last 3 months >3 weeks				-3.369***
				(0.99)
Total products bought (#)	-0.265		-0.235	
	(0.37)		(0.38)	
Total products bought in last 3 months (#)		-0.677		-0.819
		(0.51)		(0.50)
Customer Fixed Effects	Yes	Yes	Yes	Yes
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Number of customer	470	319	470	319
Observations	2,797	1,276	2,797	1,276

Poisson fixed effects regressions drop observations of referring customers that do not have variation in the number of customers acquired through their referrals in the six months. We also lose observations in column (2) and (4) as we consider variables lagged over three months. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5.3: Impact of service wait time of referring customers on customers acquired through referrals

The median time difference between a new customer being referred by an existing customer and the customer being acquired (i.e., purchasing their first product) is four days. This short time span suggests that the acquired customer is influenced by the referring customer's service experience and not through other channels. Our results continue to hold if we only consider a subset of the referral data where the time difference between being referred and being acquired is below the median. These results indicate that word-of-mouth is indeed a critical channel through which after-sales service experienced by existing customers affects adoption of solar home systems in rural off-grid communities in Uganda.

We have highlighted one mechanism through which word-of-mouth can affect adoption – a formal referral system. There are two other plausible mechanisms. First, existing customers may share their experience of after-sales service with new customers informally. Potential adopters might also observe the service issues being experienced by existing customers in their network. Second, in any week, the sales team at a branch may decide to reduce its sales efforts in areas within its jurisdiction that are experiencing high wait time on pending service cases, because they expect lower sales in these weeks due to negative word-of-mouth. Due to data limitations, we are unable to examine these channels. In our analysis, we find that there is a strong negative impact of long wait times for service on customer acquisition, at our partner company. It is possible that customers who are happy due to quick resolution of service cases provide positive word of mouth and improve customer acquisition. Due to the lack of details of causes and solutions of the service cases and customer satisfaction after case completion, we are unable to test this.

6. Conclusion

Our study sheds light on a previously understudied driver of technology adoption – customers' post-purchase experience of after-sales service. Our results suggest that customers in emerging markets are highly sensitive to service wait times. A one day increase in average wait time for service can decrease adoptions by 0.76% to 4.63%. We find that the relationship between wait times and adoptions is heterogeneous and depends on the types of pending service cases. We also find that capacity limitations at a repair workshop hurt product adoption. Estimates such as ours can help firms determine the appropriate size of their service teams, to better allocate resources to reduce operational bottlenecks that lead to long wait times. They can also inform modeling assumptions in future research in this area. Our analysis highlights the value of micro-level data for informing decision-making in emerging market firms. Methodologically, we introduce two new geo-spatial IVs that can be relevant in other settings as well.

Another important aspect of our study is that we provide direct evidence on the role of word-of-mouth in customer acquisition. Using customer-level data on referrals, we find that the number of customers acquired through referrals from an existing customer decreases by 5.6% when her wait time for service (averaged over last three months) increases by a day. Thus, negative word-of-mouth generated by long wait times can significantly hurt the sales of technology firms in emerging markets. In order to reduce service wait times, solar providers can either build a strong in-house service team or partner with value-chain specialists that focus on repair of solar home systems. Currently, such value-chain specialists, are rarely present in emerging markets. Our results suggest that there is a strong value proposition for this type of business model.

The recent influx of private investments into the solar sector in emerging markets has enabled off-grid solar providers to aggressively pursue customer acquisition (e.g., see GOGLA 2018). To understand the practical implications of our results, we talked with both providers and investors who are active in the sector. We learned that off-grid solar providers and investors consider after-sales service to be important to ensure (i) low default rates by credit customers who make periodic payments to the solar provider and (ii) repeat purchase by existing customers and their growth on the "energy ladder". Our interviews suggest that after-sales service is not viewed as central to the customer acquisition strategies of off-grid solar providers and investors. Against this backdrop, our results suggest that investors and firms should invest in after-sales service, to expand market share.

Around 14% of the world's population does not have access to electricity. Ninety-five percent of this unserved population lives in sub-Saharan Africa and Asia. Thus, reduced adoption of solar technology due to long service wait times has a direct cost on the socio-economic development of off-grid communities that are served by off-grid solar providers in these regions. Our results are also relevant for policy makers who aim to improve the socio-economic lives of people living in these regions. Poor after-sales service can reduce consumers' trust in a technology, thereby stalling adoption. Policies that incentivise technology companies to invest in timely after-sales service can spur rapid adoption. Our IVs also reflect the role of infrastructure, especially roadways, in reducing service wait times. Importantly, public sector investment in infrastructure can substantially improve adoption of solar technology in rural communities in emerging markets.

To the best of our knowledge, we provide the first direct evidence of the impact of timely after-sales service on customer acquisition through technology adoption. While a great many researchers have studied diffusion models since the seminal work of Bass (1969), the focus has mostly been on market conditions, marketing variables or customer heterogeneity as drivers of technology adoption (Geroski 2000). We find that an important operational metric – timely after-sales service – also drives technology adoption. Thus, our results complement existing research which suggests that affordability, awareness and tangible aspects of quality are important drivers for uptake of new technologies in emerging markets (Dupas 2014, Miller and Mobarak 2014).

We focus on one aspect of after-sales service, the wait time for service. There remain other aspects of after-sales service that could affect technology adoption in emerging markets. For example, Calmon et al. (2019) build a theoretical model to show that reverse logistics which supports higher refunds for regret-returns can improve adoption of life-improving technologies in emerging markets. Future studies can identify other operational strategies and bottlenecks that can expedite technology adoption. This domain of research is particularly relevant today as the private sector is getting increasingly involved in providing a variety of new technologies and services to consumers in emerging markets.

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References

Acimovic, Jason, Chris Parker, David Drake, Karthik Balasubramanian. 2019. Show or tell? Improving agent decision making in a Tanzanian Mobile Money field experiment. *Working Paper* .

Aflaki, Sam, Ioana Popescu. 2013. Managing retention in service relationships. *Mng. Sci.* **60**(2) 415–433.

Akcigit, Ufuk. 2017. Economic growth: The past, the present, and the future. *J. of Pol. Econ.* **125**(6) 1736–1747.

Akşin, Zeynep, Barış Ata, Seyed Morteza Emadi, Che-Lin Su. 2013. Structural estimation of callers' delay sensitivity in call centers. *Mng. Sci.* **59**(12) 2727–2746.

Allon, Gad, Awi Federgruen, Margaret Pierson. 2011. How much is a reduction of your customers' wait worth? An empirical study of the fast-food drive-thru industry based on structural estimation methods. *MSOM* **13**(4) 489–507.

Angrist, Joshua D, Jörn-Steffen Pischke. 2008. *Mostly harmless econometrics: An empiricist's companion*. Princeton Univ. Press.

Bass, Frank M. 1969. A new product growth for model consumer durables. *Mng Sci* **15**(5) 215–227.

Bold, Tessa, Kayuki C Kaizzi, Jakob Svensson, David Yanagizawa-Drott. 2017. Lemon technologies and adoption: Measurement, theory and evidence from agricultural markets in Uganda. *The Quar. J. of Econ.* **132**(3) 1055–1100.

Bollinger, Bryan, Kenneth Gillingham. 2012. Peer effects in the diffusion of solar photovoltaic panels. *Mkt. Sci.* **31**(6) 900–912.

Bolton, Ruth N, Katherine N Lemon, Matthew D Bramlett. 2006. The effect of service experiences over time on a supplier's retention of business customers. *Mng Sci.* **52**(12) 1811–1823.

Buell, Ryan W, Dennis Campbell, Frances X Frei. 2016. How do customers respond to increased service quality competition? *MSOM* **18**(4) 585–607.

Calmon, Andre P, Diana J Rajasingh, Gonzalo Romero, Jackie Stenson. 2019. Consumer education and regret returns in a social enterprise. *Working Paper* .

Chan, Tian Heong, Francis de Véricourt, Omar Besbes. 2018. Contracting in medical equipment maintenance services: An empirical investigation. *Mng. Sci.* **65**(3) 1136–1150.

Cohen, Jessica, Pascaline Dupas, et al. 2010. Free distribution or cost-sharing? Evidence from a randomized malaria prevention experiment. *Quar. J. of Econ.* **125**(1) 1.

Conley, Timothy G, Christopher R Udry. 2010. Learning about a new technology: Pineapple in Ghana. *Amer. Econ. Rev.* **100**(1) 35–69.

Dupas, Pascaline. 2014. Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment. *Econometrica* **82**(1) 197–228.

Emadi, Seyed Morteza, Jayashankar M Swaminathan. 2018. Customer learning in call centers from previous waiting experiences. *Oper. Res.* **66**(5) 1433–1456.

Feder, Gershon, Richard E Just, David Zilberman. 1985. Adoption of agricultural innovations in developing countries: A survey. *Econ. Dev. and Cult. Change* **33**(2) 255–298.

Foster, Andrew D, Mark R Rosenzweig. 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. *J. of Pol. Econ.* **103**(6) 1176–1209.

Geroski, Paul A. 2000. Models of technology diffusion. *Research Policy* **29**(4-5) 603–625.

GOGLA. 2018. Off-grid solar market trends report 2018 .

Guajardo, Jose. 2019. How do usage and payment behavior interact in rent-to-own business models? Evidence from developing economies. *Forthcoming in POMS* .

Guajardo, Jose A, Morris A Cohen, Serguei Netessine. 2015. Service competition and product quality in the us automobile industry. *Mng Sci* **62**(7) 1860–1877.

Guiteras, Raymond, James Levinsohn, Ahmed Mushfiq Mobarak. 2015. Encouraging sanitation investment in the developing world: A cluster-randomized trial. *Science* **348**(6237) 903–906.

Hanna, Rema, Esther Duflo, Michael Greenstone. 2016. Up in smoke: The influence of household behavior on the long-run impact of improved cooking stoves. *Amer. Econ. J.: Econ. Pol.* **8**(1) 80–114.

International Energy Agency. 2017. Energy Access Outlook 2017 .

Levine, David I, Theresa Beltramo, Garrick Blalock, Carolyn Cotterman, Andrew M Simons. 2018. What impedes efficient adoption of products? Evidence from randomized sales offers for fuel-efficient cookstoves in Uganda. *J. of Eur. Econ. Assoc.* **16**(6) 1850–1880.

Lu, Yina, Andrés Musalem, Marcelo Olivares, Ariel Schilkrut. 2013. Measuring the effect of queues on customer purchases. *Mng. Sci.* **59**(8) 1743–1763.

Miller, Amalia R, Catherine Tucker. 2009. Privacy protection and technology diffusion: The case of electronic medical records. *Mng. Sci.* **55**(7) 1077–1093.

Miller, Grant, A Mushfiq Mobarak. 2014. Learning about new technologies through social networks: Experimental evidence on nontraditional stoves in Bangladesh. *Mkt. Sci.* **34**(4) 480–499.

Song, Hummy, Anita L Tucker, Karen L Murrell. 2015. The diseconomies of queue pooling: An empirical investigation of emergency department length of stay. *Mng. Sci.* **61**(12) 3032–3053.

Tan, Tom Fangyun, Serguei Netessine. 2014. When does the devil make work? An empirical study of the impact of workload on worker productivity. *Mng. Sci.* **60**(6) 1574–1593.

The Atlantic. 2015. When people feared computers .

The Economist. 2015. The pioneering continent - Technology in Africa .

Tucker, Catherine. 2008. Identifying formal and informal influence in technology adoption with network externalities. *Mng. Sci.* **54**(12) 2024–2038.

Ugandan Bureau of Statistics. 2013. Uganda National Household Survey.

Ugandan Off-Grid Energy Market Accelerator. 2018. Mapping the Ugandan off-grid energy market.

Uppari, Bhavani Shanker, Ioana Popescu, Serguei Netessine. 2018. Selling off-grid light to liquidity-constrained consumers. *MSOM* **21**(2) 308–326.

World Bank. 2016. Data bank, Access to Electricity. URL https://data.worldbank.org/indicator/eg.elc.accs.zs.

Zeithaml, Valarie A, Leonard L Berry, Ananthanarayanan Parasuraman. 1996. The behavioral consequences of service quality. *J. of Mkt.* **60**(2) 31–46.