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## Article

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Development Engineering

## Provided in Cooperation with:

Elsevier

*Suggested Citation:* Lukuyu, June; Fetter, Rob; Krishnapriya, P. P.; Williams, Nathan; Taneja, Jay (2021) : Building the supply of demand: Experiments in mini-grid demand stimulation, Development Engineering, ISSN 2352-7285, Elsevier, Amsterdam, Vol. 6, pp. 1-24, <https://doi.org/10.1016/j.deveng.2020.100058>

This Version is available at:

<https://hdl.handle.net/10419/242315>

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## Building the supply of demand: Experiments in mini-grid demand stimulation

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### ARTICLE INFO

#### JEL classification:

O13  
Q01  
Q42  
Q56

#### Keywords:

Energy access  
Mini-grids  
Solar energy  
Appliance financing  
Sustainable development

### ABSTRACT

Solar mini-grids are a key element in strategies to achieve universal access to modern energy by 2030. In many settings mini-grids offer a combination of affordability, reliability, and capacity for productive use of power, moreso than most solar home systems and some central grids. Yet the economic sustainability of mini-grids relies on achieving target usage levels, and consumption data to date suggest that they may be commercially unsustainable due to consistently low demand for power once installed—and that newly-connected recipients cannot take full advantage of access. Using a uniquely fine-grained data set spanning 29 villages in East Africa, we test whether credit constraints and the cost of electricity hinder demand growth among mini-grid-connected households. We find that households that purchased appliances under a financing program increased consumption by up to 66 percent compared to matched controls, though a sensitivity analysis suggests this estimate is rather sensitive to bias from unobservable characteristics, and the increase is not sustained. While most customers in the program do not repay loans in full, we find that on average, customers repay about 78 percent of the loan amount. When we analyze developers' return on investment, we find that the profitability of appliance financing programs at a market cost of capital, similar to those evaluated in this study, depends substantially on the types of appliances on offer. With a limited sample size, the tariff subsidy program indicated that lowering the cost of electricity by up to 75 percent substantially increased consumption, albeit with mixed signals for whether overall revenue could be maintained at a lower tariff, therefore calling for further research to find the optimal balance of affordable tariffs and profitable business models for mini-grids in settings like East Africa.

### 1. Introduction

Rural electrification has become a global development priority, embodied most succinctly in Sustainable Development Goal 7, which calls for universal access to affordable, reliable, and modern energy by 2030. While electrification rates are increasing globally, rising populations in sub-Saharan Africa (SSA) mean that little progress is being made in reducing the absolute number of unelectrified households on the sub-continent (Daly and Walton, 2017). Because grid infrastructure is expensive to construct, slow to expand, and suffers frequent outages (Gertler et al., 2017), off-grid technologies have been proposed as a solution to electrification in rural areas. Whereas the electricity grid in SSA has long been dominated by the public sector—in the form of heavily subsidized, often state-owned utilities—private start-ups have

taken up the task of reaching those beyond the grid, with the dominant modern technologies being solar home systems (SHS) and mini-grids (MG).<sup>1</sup> These companies lack the public backing enjoyed by traditional utilities, and thus have been required to innovate on business models as well as technology platforms in search of financial sustainability (Williams et al., 2015).

The two primary technologies used to achieve off-grid electrification differ critically in their dominant business models. SHS providers generally provide customers with the ability to generate, store, and consume as much power as they desire (subject to the physical constraints of the equipment and solar irradiation). Compatible electrical appliances are generally included in the price of the system, which customers often pay for over time on credit. Thus, in the typical SHS model, companies' revenue from a given customer is not directly coupled to the electricity

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<sup>1</sup> "Mini-grid" is essentially synonymous with "micro-grid"; we use the terms interchangeably in this paper.

consumption of that customer. Some MG operators also decouple revenues from consumption to mitigate associated risks by implementing business models based on fixed fees for different levels of service. However, these models remove price signals for consumers about efficient use of scarce shared resources and often require additional equipment to enforce fair use policies. By contrast, many MG operators, including those in this study, have adopted a more traditional utility model, selling units of energy; consequently, MG revenues—just as those for traditional electrical utilities—are linked to electricity consumption.

As such, the sustainability of such MG business models relies on achieving target levels of use by connected customers. However, electricity consumption data from both grid and MG connections shows a troubling pattern of persistently low electricity demand as electricity reaches deeper into rural Africa (Fobi et al., 2018; Williams et al., 2017). Utility operators and MG developers face a similar challenge: how to encourage new customers to consume, and pay for, more electricity? While the challenge of stimulating demand for electricity on utility grids has been confronted before, most of the countries that have made the leap from low to high access did so decades ago, under different technology, regulatory, and business paradigms. To demonstrate the challenge facing utility operators seeking sustainable business models in SSA, in Fig. 1 we plot the evolution of annual residential electricity consumption per household against the electricity access rate for countries in SSA (left panel) and in other regions (right panel). This figure shows a number of prominent countries in SSA that have seen substantially diminishing per-household consumption as more households gain access to electricity, while many countries in other regions have managed to concurrently grow per-household consumption and electricity access rates. While not definitive, these figures indicate that utility operators in SSA (using both grids and MGs) may benefit from strategies to actively promote electricity consumption among newly-electrified households.<sup>2</sup>

There are a number of explanations for the limited adoption of electricity in newly-connected communities. It may be that people have adapted to life without power and simply do not see the need for electricity services, though this would put these populations at odds with those from nearly all other countries around the world. Another hypothesis is that rural Africans would like to use electricity services but do not have and cannot afford the appliances required to access them. In a region where incomes are low, the banked population is small, and access to credit is limited, it may be that people are simply unable to acquire the appliances necessary to fully take advantage of newfound access to electrical power. Furthermore, the availability of appliances for purchase in these areas may be limited due to underdeveloped supply chains. Third, in the specific case of MGs, the cost of unsubsidized electricity may simply be too expensive. While the marginal cost of grid electricity is a fraction of that for MG electricity (Pueyo and DeMartino, 2018), similar trends of stagnating growth in demand have been observed with grid customers (Fobi et al., 2018). This list is by no means exhaustive. Other potential barriers to more intensive adoption of electricity, particularly for productive use, include a lack of awareness of potential uses of electric power, local unavailability of appliances and other economic barriers that limit opportunities for income generation (for example, access to transportation infrastructure and financial services). It is worth noting that high costs and low load factors associated with rural electrification are not a new phenomena. Similar challenges were faced in the early 20th century in the United States (Woolf, 1987)

<sup>2</sup> The patterns in Fig. 1 could also be explained by superior customer segmentation and prioritization in SSA than in other regions: if the very best customers were electrified first in SSA, but in other regions households were connected without regard to expected consumption, this would also lead to a downward-sloping line in the figure. However, there is little reason to believe that utilities have ever diverged from prioritizing connections for the most attractive customers.

which suggests a longer term view on the development of electricity use may be appropriate.

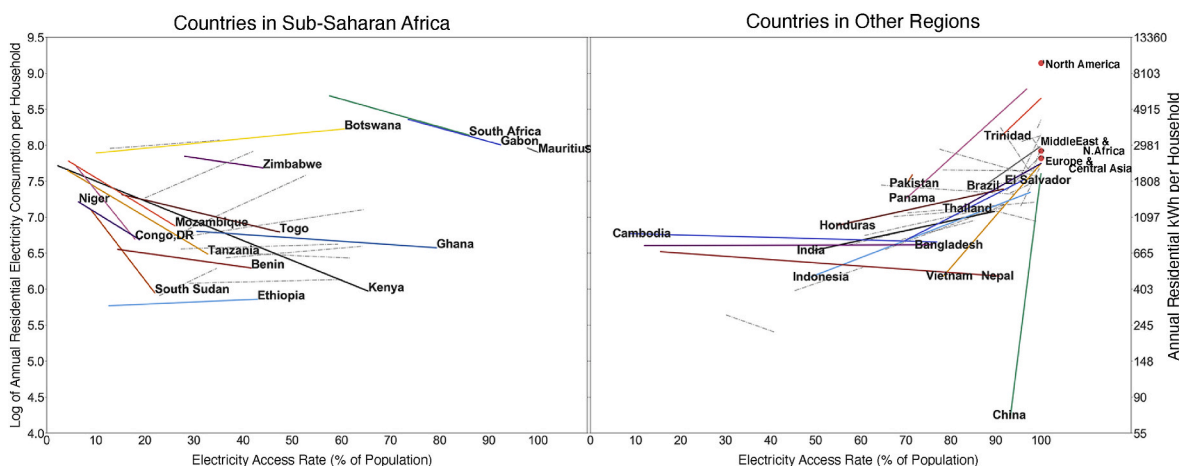
In this paper, we study the effects of two prototype targeted interventions for stimulating demand for electricity among MG customers: appliance financing and tariff subsidies. For appliance financing, we evaluate a program to offer appliances on credit to domestic and small businesses, conducted among nearly 2000 customers at about 30 MG sites, as well as a far more modestly sized tariff subsidy program to reduce the cost of electricity for 116 customers at 2 MG sites. We designed and conducted these programs and evaluations in consultation with the Mini-Grid Innovation Lab operated by CrossBoundary, Energy4Impact, and the MG developers, enabling access to customer surveys, detailed consumption data from smart meters, and loan repayment information. As far as we are aware, our analysis is the first of its kind in the literature – analyzing a large portfolio of mini-grids over a long period at a high level of temporal resolution – and in particular, the detailed analysis of consumption would not have been possible on a typical utility system where smart meter deployments are scarce or nonexistent. The findings from our evaluations yield insights on customer behavior, incentive structures, and demand stimulation program design that are relevant for electricity utilities, developers, policymakers, and development donors all striving towards enhanced electricity access as well as improved economic growth among rural communities.

## 2. Background and context

Electricity is not useful without appliances. In order to benefit from electricity, users must be able to afford the cost of a connection, appliances, and the electrical energy that the appliances use. MG operators often keep initial connection costs low and recover their initial investment by charging higher unit rates. This results in higher electricity tariffs, but permits users to access a connection who otherwise would be unable to do so (Pueyo and DeMartino, 2018). Indeed, Lee et al. found connection rates in newly-electrified areas on the grid are highly sensitive to connection costs (Lee et al., 2016). In effect, these customers are being offered a form of credit. This makes sense in a context in which many rural electricity users are capital constrained and lack access to traditional forms of credit, such as banking services. SHS providers, who face the same barrier of credit constraints, address the issue by combining the electricity generation technology and compatible appliances into a single package or “SHS kit,” and allowing customers to pay for the kit over time.

Thus, for most customers served by MGs, the supply of electricity is effectively financed by the pricing model—but the appliances by which customers might use power are not. This has led to relatively low average consumption per user (ACPU) and low average revenue per user (ARPU)—threatening the economic sustainability of MG business models. In order to stimulate demand for electricity, nascent MG operators in Africa have begun to experiment with programs that finance customers’ use of electricity by offering them credit to acquire electrical appliances. The goals of these programs are to stimulate demand for electricity, increase revenues, and at the same time to permit customers to access energy services that were previously unavailable to them (Williams et al., 2015). For commercial users, this allows businesses to acquire income-generating equipment and use the increased revenues to cover their costs. Households may benefit from reduced expenditure on more expensive alternative forms of energy.

The idea of financing electrical appliances to enable increased use of electricity is not new. In the United States, the Rural Electrification Administration and Electric Home and Farm Authority provided for loans to acquire appliances in the 1930s (Carmody, 1939). Similar public efforts in SSA are limited or nonexistent. However, the MG sector has begun to experiment with financing models, with an eye toward improving their own financial sustainability. The Mini-Grid Innovation Lab has launched a series of prototypes to investigate the financial viability of new business interventions for MGs in different regions throughout Africa. The data generated by the first of these prototypes,



**Fig. 1.** Average residential electricity consumption per household versus electricity access rate. Sources: IEA World Energy Balances (Agency, 2020) and The World Bank Data Bank, 2020 Notes: The dotted gray lines are trends of other countries in the respective regions. They are not highlighted to improve readability of the graph. The primary y axis is the log form of the secondary y axis. (Use color in print).

conducted in East Africa, provide the empirical setting for this paper (as described in Section 3.1).

Academic research on demand stimulation programs is scant, though researchers acknowledge that the provision of electricity connections must be accompanied by complementary services to realize socio-economic impacts (Peters et al., 2019; Jeuland et al., 2019) and that MGs must support and stimulate demand for electricity to achieve impact and financial sustainability (McCall and Santana, 2018).<sup>3</sup> One of these complementary services, particularly for businesses and would-be entrepreneurs, is access to credit (Peters et al., 2011). Access to financial services allows businesses to invest in machinery or appliances and pay for them over time. In turn, the use of electricity for economically productive purposes increases average income. In some settings the increase in income arises from higher labor productivity (which enables higher wages) or higher employment, but in rural settings where most businesses are typically one-person operations where the owner is the residual claimant, higher income typically arises from being able to sell more of the same products, the same products for higher prices (e.g., because of better perceived quality), or new products. As income rises for owners or wage laborers who are also MG customers, this permits customers to afford more electricity. This in turn improves the financial performance of the MG (P. (P) and M, 2019).

Promotion of productive electricity use through this virtuous cycle is a common element of discussion both in the field and among academic researchers. Implicit in the theory of change is the assumption that customers will use their access to credit in part to finance the necessary electrical appliances. To our knowledge, no prior work addresses the effects of offering credit for the specific purpose of acquiring electrical appliances, at least in the context of rural Africa.

In this paper we aim to address the following questions in our appliance financing evaluation: (1) Will people take up domestic and commercial appliances if they are offered on credit? (2) How will electricity consumption be affected among those customers who take up appliances? (3) Do customers repay their appliance loans in a timely and complete fashion?, and (4) Under what conditions do MG developers benefit from providing credit to their customers? In our far more limited tariff subsidy evaluation, we examine the effects on consumption from

<sup>3</sup> A related stream of research, not specific to off-grid settings, considers the heterogeneity that characterizes rigorous empirical evaluation of rural electrification: Some prominent studies suggest that widespread rural electrification has no effect on average, while others suggest important benefits, and highlights the role of complementary conditions in explaining these heterogeneous effects (Lee et al., 2020; Fetter and Usmani, 2019).

reduced tariffs, which is a topic of particular interest in the MG sector.

### 3. Methods and data

#### 3.1. Study area

This study was conducted in 29 villages in Kenya and Tanzania, each with a MG operated by one of five participating private sector developers and no availability of the main grid. The MGs were installed at various times between September 2014 and November 2017. The number of MG customers per village range between about 20 and 190, with an average of about 85 customers.

As noted above, this study was conducted in partnership with the Mini-Grid Innovation Lab coordinated by CrossBoundary, which works directly with mini-grid developers to prototype and test innovations that improve the business model. Once proven, the Lab works with partners – developers, government, and funders – to scale the prototypes across other developers and markets, and shares evidence on successful prototypes’ impact on the business model to inform how partners can best support the prototypes to scale.

#### 3.2. Study design

##### 3.2.1. Appliance financing program

The appliance financing program for residential and commercial (micro-enterprise) customers was implemented in 27 of the 29 villages. All customers at treatment sites were invited to apply for credit to procure one or more of the electrical appliances listed in Table 1. Appliances were selected based on the expected consumption of each appliance, suitability for MG customers’ needs, and developers’ ability to procure them. Any customers who applied for credit, and could make the initial deposit requirement for a given appliance, received the appliance on credit and then proceeded to make regular payments to the developer. Appliances were delivered to customers from February 2018 through mid-July 2018.

Appliances were financed with a loan, secured against the appliances as collateral. Customers who received appliances were required to make monthly payments for each appliance based on monthly compounding at an effective annual interest rate of 35 percent and over a period of 9, 10, or 12 months.<sup>4</sup> These loan terms represent interest rates that,

<sup>4</sup> Developers made individual choices about the loan period; these were set as a policy across all loan applicants and did not differ by customer creditworthiness or other factors.

**Table 1**  
Appliance purchases through the appliance financing program.

Appliance type	Power rating	Number of appliances bought	Number of households who purchased only the listed appliance
Television	30–58 W	211	94
Speaker	25–80 W	157	78
Satellite dish/ decoder	18–20 W	77	25
Fridge or freezer	50–60 W <sup>a</sup>	70	39
Blender	350–450 W	28	4
Hair clipper	11 W	18	6
Electric iron	1.1 kW	13	3
Power tools <sup>b</sup>	3–7.5 kW	10	2
Egg incubator	60–160 W	3	0
Rice cooker	700 W	4	0
Fan	7–11 W	2	2
Laptop	65 W	1	1
<b>Total</b>		<b>544</b>	<b>254</b>

<sup>a</sup> Assuming 12–14 h of operation a day.

<sup>b</sup> Power tools include grinder machine, welding machine, drill, wood sander and compressor.

according to the developers working in these villages, are generally consistent with what they have observed in these villages for other types of purchases by households or businesses; however, the developers also report that their customers generally do not have access to such credit for the purpose of purchasing appliances. market rates. Customers were informed that nonpayment would result in operators repossessing appliances or turning off power. Anecdotally, while some offgrid companies in the region have been known to repossess SHSs or turn off mini-grid power due to substantial payment noncompliance, repossession is generally rare. In practice, repossession is costly and developers face potential reputation damage if they switch off power.

### 3.2.2. Tariff subsidy program

Reduced tariffs were provided to existing customers at the remaining two mini-grid sites, each operated by a different MG operator. Tariffs were set at a level required to cover the operating expenses of the MG operator over the number of years required to pay off the majority of the project investment costs on a given site. This tariff at each of the two sites, based on 12 months of historical costs and consumption data, was calculated as operating expenses over 12 months (\$) divided by the site consumption over 12 months (kWh). The variable subsidy amount was then calculated as the difference between the historical tariff over the previous 12 months and the calculated subsidized tariff. Customers at the first site received a tariff subsidy of 50% in June 2018 and those at the second site received a tariff subsidy of 75% in May 2018. The maximum length of time for the subsidy was chosen as 5 years to enable analysis of the impact of long-term subsidized power.

## 3.3. Data

### 3.3.1. Data sources

A baseline survey, which was conducted in each of the 29 villages participating in either the appliance financing or tariff subsidy program prior to the start of the program (February 2018), gathered information on customer demographics, socioeconomic status and appliance ownership. Seven months into the study, a midline survey was conducted for continued monitoring of socioeconomic and demographic indicators. Lastly, an endline survey was conducted in October 2019. While the baseline and midline surveys were conducted in person, the endline survey was a telephone interview with a shorter overall length. Perhaps due to the change in mode of delivery, only 574 (29%) of the 1965 customers who completed the baseline and midline surveys completed the endline survey.

Participating developers received hourly consumption readings from previously installed smart meters at each customer site, and the data were simultaneously automatically uploaded to a central server. We were not able to obtain data on the electricity consumption patterns of individual appliances. Of the 3388 customers with smart meter data, we were able to match 1953 of these to survey data, linking records by using customer meter numbers. Customer payment data for electricity consumed and (separately) appliance loan repayment were uploaded to the same server, and linked to consumption data by the customer meter number. We excluded data from two appliance financing MG sites in which the developer launched an additional reduced-tariff intervention and from two other sites where there were prolonged service disruptions during the study period. Thus, our appliance financing analysis uses data for 1772 customers in 23 villages served by three of the five developers, while the tariff subsidy analysis uses data for 116 customers in 2 villages served by two of the five developers.

### 3.3.2. Descriptive analysis

**Appliance uptake.** Of the 1772 customers in our sample, appliances were offered to 1654 customers, of which 348 households (about 21 percent) bought at least one appliance. The remaining 118 households were part of the tariff subsidy sites. Table 1 shows that of those households that purchased at least one appliance, most (254) bought just one type of appliance, with the remaining households purchasing more than one type of appliance. The most popular appliances were televisions, speakers, refrigerators or freezers, and satellite dishes.

**Demographic and socio-economic characteristics** First, we consider which households apply for and take up appliances. Table 2 summarizes the distribution of the demographic and socioeconomic characteristics of customers who took up appliances and those who did not, as well as their average consumption, prior to the start of the program. Households that purchased appliances and those that did not are observed to be largely similar in demographic characteristics. However, those who purchased appliances are observed to have a higher average monthly income (\$191 compared to \$154), which is consistent with the fact that appliances were only distributed to customers who could afford to pay a

**Table 2**  
Demographic and socioeconomic characteristics of mini-grid customers.

Variable mean (SD)	Offered appliances; purchased	Offered appliances; did not purchase	75% tariff subsidy site	50% tariff subsidy site
	$N_{max} = 348$	$N_{max} = 1424$	$N_{max} = 61$	$N_{max} = 55$
Age of household head	38.8 (10.2)	41.2 (12.2)	41.4 (7.7)	41.1 (10.2)
Household size	5.0 (2.7)	5.6 (10.9)	5.1 (2.2)	4.2 (2.0)
Number of rooms	3.5 (1.9)	3.6 (2.2)	4.0 (1.4)	3.3 (2.4)
Monthly consumption, kWh	5.3 (11.2)	3.0 (5.5)	1.1 (2.6)	10.7 (17.2)
Monthly income in USD	191.1 (233.7)	154.4 (231.9)	86.6 (48.4)	211 (152.1)
Wealth index	0.06 (1.8)	-0.02 (1.5)	-0.12 (0.44)	0.22 (1.24)
Bank account	24%	18%	8%	18%
<i>Primary source of income for household</i>				
Subsistence farming	59%	63%	84%	24%
Commercial farming	42%	36%	3%	46%
Commerce	30%	27%	36%	53%
Salary work	14%	13%	13%	9%
<i>Appliance ownership before interventions</i>				
Television	41%	30%		
Sound system	28%	17%		
Radio	26%	20%		
Satellite dish	27%	18%		
Refrigerator	6%	4%		

deposit on the appliance. A higher percentage of these customers also report having a bank account compared to those who did not purchase appliances (24% compared to 18%). Appliance ownership prior to the start of the program is higher among customers who purchased appliances, and this is somewhat reflected in their electricity consumption – on average their monthly consumption is 76% higher than those who did not purchase appliances.

Next, we look at the distribution of demographic and socioeconomic characteristics among households in the sites that received 75% and 50% electricity tariff subsidies. The MG sites which received 75% and 50% tariff subsidies are small sites comprising 61 and 55 connections respectively. Although they are demographically similar, we note considerable socio-economic differences between these two sites. On average, the customers in the site that received a 50% tariff subsidy have substantially higher monthly incomes (over 150% higher), with a higher percentage reporting to have a bank account. There is also a substantial difference in consumption between the two sites prior to the tariff subsidy program; about 10 kWh/month in the 50% tariff subsidy site compared to 1.5 kWh/month in the 75% tariff subsidy site. The primary source of income for a majority of the households in the 75% tariff subsidy site is subsistence farming, while for majority of households in the 50% tariff subsidy site, it is commerce.

### 3.4. Methods

#### 3.4.1. Effect of the appliance financing program

If cashflow constraints, or the unavailability of credit, hinder customers’ ability to take up and utilize electrical appliances that are generally available in the open market, then providing financing should result in a sustained increase in power consumption. To evaluate if this is the case, we measure changes in energy consumption and payments for electricity among customers before and after they received appliances, using a difference-in-differences design. The ideal experiment would involve randomly assigning appliances to customers, and then evaluating the behavior of recipients compared to non-recipient customers. However, this program design was determined to be infeasible due to logistical complexity and potential damage to developer-customer relationships. Thus, all customers in our sample were invited to purchase appliances under the program. For the purpose of our matching analysis, the customers who chose to purchase appliances are the ones we consider “treated”.

To evaluate changes in consumption, we used nearest-neighbor propensity score matching to identify one control customer (that did not receive an appliance under the program) comparable to each treatment customer. We select control customers within the same developer based on the estimated propensity to purchase an appliance, which we estimate as a function of average ex ante electricity consumption, the age of the head of household, household income and wealth, and whether the customer had a bank account.<sup>5</sup> All of these variables were measured in the baseline survey, that is, prior to the placement of appliances under the program. For matched controls we assign the “placebo appliance delivery date” as identical to that of the corresponding treatment household.<sup>6</sup> Our preferred specification uses a

<sup>5</sup> In the preferred specification, we calculate wealth as the first component in a principal components analysis (PCA) of a comprehensive set of assets that includes the number of livestock animals, access to various means of transportation, number of rooms, and ownership of a mobile phone. In a robustness check, shown in Table B.2, we match on these individual elements rather than the first component of the PCA.

<sup>6</sup> About one-third of the customers that applied for at least one appliance applied for (and received) multiple appliances under the program. These appliances were not necessarily delivered on the same date. We use the earliest date of the appliance delivery for each customer to define the date of the intervention for that customer.

**Table 3**

Differences between treated, control, and matched control customers.

Variable	(1) Treated	(2) Non- treated	(3) Matched control	(4) Diff (T - NT)	(5) Diff (T - C)
Household wealth	0.06 (1.76)	-0.01 (1.42)	-0.10 (0.97)	0.08 (0.10)	0.17 (0.11)
Bank account	0.24 (0.43)	0.17 (0.38)	0.25 (0.43)	0.06** (0.03)	-0.01 (0.03)
Elec. consumption	5.24 (11.25)	3.23 (6.43)	4.59 (8.28)	2.01*** (0.63)	0.66 (0.75)
Age of HH head	38.82 (10.22)	41.22 (11.98)	38.06 (10.70)	-2.40*** (0.63)	0.77 (0.80)
HH income	190.83 (233.94)	153.84 (224.91)	183.50 (229.76)	36.98*** (13.98)	7.33 (17.73)
Educ. of HH head	7.82 (3.00)	7.56 (3.49)	7.54 (3.38)	0.26 (0.19)	0.27 (0.25)
HH size (persons)	4.98 (2.65)	5.52 (10.49)	5.14 (2.53)	-0.54* (0.32)	-0.16 (0.20)
Number of rooms	3.53 (1.85)	3.61 (2.18)	3.93 (3.40)	-0.08 (0.12)	-0.40* (0.21)
Appliances owned (#)	1.46 (1.50)	1.00 (1.40)	1.19 (1.55)	0.46*** (0.09)	0.27** (0.12)
Owns radio	0.27 (0.44)	0.20 (0.40)	0.22 (0.42)	0.06** (0.03)	0.04 (0.03)
Owns TV	0.42 (0.49)	0.29 (0.45)	0.32 (0.47)	0.12*** (0.03)	0.09** (0.04)
Owns fridge	0.06 (0.24)	0.04 (0.20)	0.08 (0.27)	0.02 (0.01)	-0.02 (0.02)
Owns sound system	0.29 (0.46)	0.17 (0.37)	0.22 (0.41)	0.13*** (0.03)	0.07** (0.03)
Owns satellite decoder	0.27 (0.45)	0.18 (0.39)	0.21 (0.41)	0.09*** (0.03)	0.06* (0.03)

Notes. All values represent characteristics at baseline, prior to intervention. Columns 1, 2, 3 report, respectively, means and standard deviations for customers in treatment group (i.e., purchased at least one appliance under the program), all non-treated customers, and matched control customers. Column 4 (5) reports the mean difference and standard error for treated vs. non-treated (treated vs. control) customers. Significance stars represent the results of t-tests (or  $\chi^2$ -tests for variables that are proportions): \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . Household wealth is the first component of the principal components analysis described in text. Results for appliances owned by less than 2% of households in any group (DVD player, computer, internet access, printer, microwave, iron, hair clipper, mill, blender) available from authors.

one-to-one match of treatment to control customers; in additional specifications shown in B, Table B2, Table B.2 we show that our results are robust to alternative forms of matching that permit many-to-one matches, including kernel and radius matching.

The propensity score matching method relies on assumptions of conditional independence—that is, that potential outcomes are independent of treatment assignment—and common support (that is, customers with the same covariates have a positive probability of being both participants and non-participants) (Caliendo and Kopeinig, 2008a). The first assumption is only partially testable, in that we can test if the treatment assignment is independent with respect to observable covariates, but not to unobservables. Table 3 provides a comparison of mean values for treated customers, all untreated customers, and matched control customers, for socioeconomic and demographic characteristics of customers, at the baseline. The table shows that there are no significant differences between treatment customers and matched controls in terms of the covariates used for the matching assignment (which are also the top five rows in the table), nor in terms of most other observable characteristics. The table also indicates some differences: treatment households have fewer rooms, on average; own more appliances at baseline; and in particular are more likely to own a television, a sound system, and a satellite dish or decoder. It is worth noting that these higher rates of baseline appliance ownership do not come with significantly higher ex-ante electricity consumption; although treatment customers did consume about 15% more electricity than matched controls

in the months prior to the intervention, the variation in ex-ante electricity consumption is substantial, and the difference in means is not significantly different from zero.

The “common support” assumption refers to the idea that treatment and matched control customers have a positive probability of being both participants and non-participants. Fig. B3 Fig. B.3 in B provides graphical evidence that this is the case. Although the quality of the matching approach cannot be fully tested, particularly with respect to unobservable characteristics that may affect treatment status, B provides the results of several additional tests to verify the quality of the propensity score match.<sup>7</sup> That appendix also documents the effects of the intervention under several alternative matching methods, as noted above. We discuss the key implications of these tests for our findings in Section 4.1.

The first question of interest concerns the effect of the appliance financing program on consumption. For this element, we aggregate the hourly consumption data to a total weekly measure per household (in some specifications, we also examine total monthly consumption per household). We limit our sample to the treatment customers (i.e., those that received an appliance under the program) and the matched control customers, and estimate the average treatment effect (ATE) using the following difference-in-differences model:

$$y_{ijt} = \alpha_i + \beta_t + \sum_{\tau=-52}^{93} \delta_{\tau} 1(\text{appliance received in week } t - \tau)_{ijt} + \varepsilon_{ijt} \quad (1)$$

In (1),  $y_{ijt}$  denotes the total energy consumption by household  $i$  in village  $j$  in time  $t$ ,  $\alpha_i$  is a household fixed effect, and  $\beta_t$  is a time (week) fixed effect. This specification allows us to estimate separate effects on the treatment customers for each week leading up to the delivery of the (first) appliance as well as each week after, for 52 weeks before and 93 weeks after delivery. We include household fixed effects to control for time-invariant idiosyncratic variations at the household level (see (Jessoe and Rapson, 2014)), and calendar-week fixed effects to control for seasonality of income or other time-related variations that span the region. We also estimate a specification without household fixed effects, but with household characteristics from the survey data, as well as village fixed effects and other elements. For this latter specification, we aggregate the time series to a monthly (rather than weekly) series, strictly to facilitate display of the results in a tabular (rather than graphical) format, and compare the estimates that use household characteristics to those that use household fixed effects (The results are shown in Table A1).

For both the weekly and monthly series, we describe the week (month) in which the first appliance was delivered to the household as 1 week (month) prior to the intervention and normalize the weeks (months) before and after appliance delivery accordingly.

As noted in the section on background, we also examine whether customers repay appliance loans in a timely and complete fashion, and explore the conditions under which MG developers benefit from providing credit to their customers.

### 3.4.2. Effect of the tariff subsidy program

The effect of the tariff subsidy is reflected in the changes in the monthly average revenue per user (ARPU), which is the metric most commonly used by mini-grid developers to evaluate revenues and the monthly average consumption per user (ACPU) before and after the per unit cost of power was lowered in the participating sites. Similar to the appliance financing program, the ideal experiment would involve randomly assigning a set of subsidized tariffs to a set of mini-grid sites without any other interventions. Customers at these sites would make up the treatment groups, and customers at other mini-grid sites of the same developer, also without any other interventions, would make up the

control group. However, due to the limitations of the appliance financing experiment discussed in the previous section, for one of the developers that implemented the tariff subsidy program, all their other sites that were not part of the tariff subsidy program participated in the appliance financing program, and the other developer only has one site, which was part of the tariff subsidy program. It was therefore impossible to construct a control group for the tariff subsidy sites. We therefore present the changes in ARPU and ACPU in the treatment sites only. We also analyze the customers’ sensitivity to tariff changes by looking at the price elasticity of electricity demand,  $\varepsilon$ , given by Eq. (2)

$$\varepsilon = \frac{\Delta q/q}{\Delta p/p} \quad (2)$$

where  $\varepsilon$  is the price elasticity,  $p$  is the electricity price, and  $q$  is the electricity demand.

## 4. Analysis

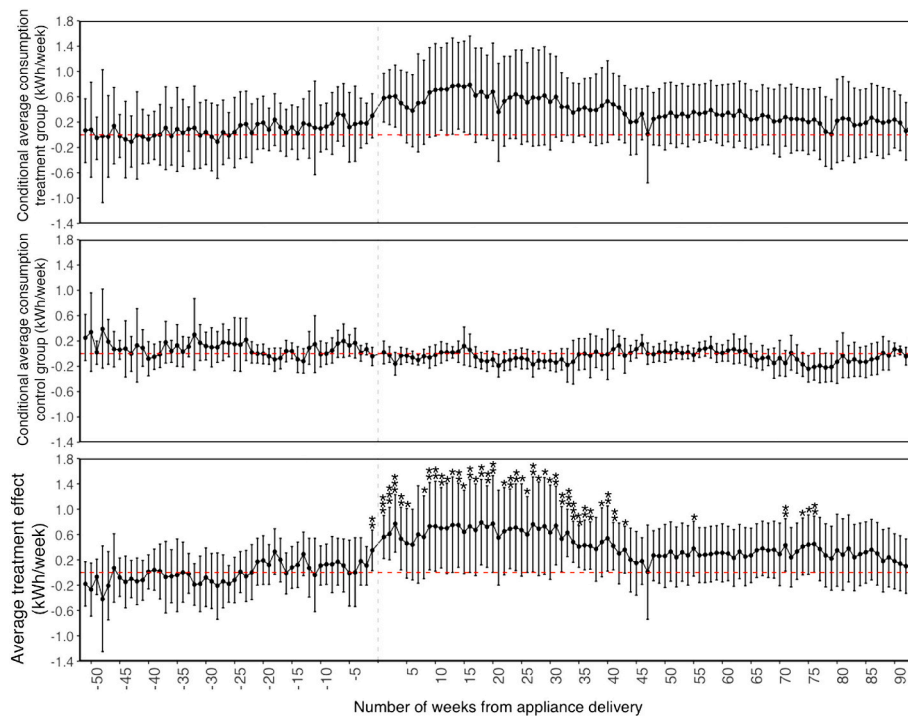
### 4.1. Appliance financing program: effects on consumption

Fig. 2 shows our main results with respect to consumption: prior to the delivery of appliances, consumption among treated customers and matched controls is statistically equal. The week-level results, going back 52 weeks before the initial date of delivery of appliances, support the parallel trends assumption of the difference-in-differences approach. Upon delivery and in subsequent weeks, consumption increases by about 0.6 kWh/week on average (this amounts to about a 66% increase in consumption; the average weekly consumption for an average household prior to the intervention is 0.9 kWh). This increase is sustained for about 7–8 months (30 weeks) after delivery, but then falls gradually and the point estimates level off to about 0.3 kWh/week between about 47 weeks and 85 weeks after delivery, which is roughly a 33% increase in consumption. After 85 weeks, the point estimates begin to drop again to about 0.15 kWh/week.

It is worth reiterating that the estimated increase in consumption is attributable to the treatment only under fairly restrictive assumptions. As discussed in Section 3.4.1, all customers in our sample were invited to purchase appliances under the program. This means that the matched control customers actively declined to purchase appliances, which in turn implies that there are likely to be unobservable characteristics that differ between treated customers (i.e., those who took up the appliances) and matched controls. Furthermore, the bias in the estimated treatment effect is likely to be positive, if the households who voluntarily purchased appliances under the program are also those who were more likely to use them (e.g., have preferences for owning and using electric appliances, or believe they can use them productively) or more likely able to afford them (e.g., feel they have more stable incomes). If so, then these unobservable factors likely play a substantial role in the increase in consumption that we observe. Indeed, a Rosenbaum bounds analysis (Table B1) suggests that even a relatively small amount of “hidden bias” would have to be present in order for us to conclude there is no significant change in consumption. If treated customers were 1.5 times more likely than control customers to select into treatment ( $\Gamma = 1.5$  in the Rosenbaum bounds framework), then the  $p$ -values associated with most of the (month-level) estimated increases in consumption would exceed 0.1, from which we would conclude the treatment had no statistically significant effect on electricity consumption.

The increase and subsequent drop off in consumption is difficult to explain. We look at the change in average consumption of the treatment and control customers separately before and after the program to investigate how these move separately as well as how their difference changes. There is a slight decrease in consumption among the control households in weeks following delivery of appliances to treatment customers, however, there is a comparatively larger increase in consumption among customers who purchased appliances. During the period

<sup>7</sup> We are grateful to two anonymous reviewers for suggesting several of these robustness checks.



**Fig. 2.** Average treatment effect of appliance financing program. *Notes:* Robust standard errors are clustered by village; error bars represent a 95% confidence interval. Includes household fixed effects, calendar-month fixed effects, and relative week fixed effects. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

when consumption among treatment drops after the initial increase, we observe that there is no significant change in consumption among control households. We can therefore rule out spillover effects as a possible explanation for the drop in consumption.

Another possible explanation for the increase and subsequent drop off in consumption could be that MG customers are budget-constrained, therefore after seven months, treatment customers begin to lower their appliance usage in response to higher spending on electricity consumption. We explored this hypothesis further by analyzing whether the electricity payment behavior of the treatment customers could somehow indicate when they realize how costly the additional consumption is. The billing system is pre-paid, where customers purchase units of electricity (kWh) at a given tariff. We therefore looked at the distribution of the frequencies of electricity top-ups per month. We would expect that when customers realize how costly the additional consumption is, they would start topping-up their electricity units less frequently. However, we observed that the electricity payment behavior among treatment customers, as indicated by the trend in the average frequency of top-ups, does not differ from that of control customers, as shown in Fig. A1. Therefore this hypothesis may not explain why we observe a reduction in consumption after the initial increase. In addition, based on customer responses on appliance usage over time during the program, with the caveat that there was high attrition in the endline survey as discussed in Section 4.6, the majority of customers reported similar appliance use over time. Another reason could be that customers do not earn enough additional income from the appliances purchased to be able to consistently cover the costs of both electricity and loan repayment. However, we did not have data on changes in household income during the program to test this hypothesis.

Another reason could be that although we have tried to control for seasonal effects by using calendar-month fixed effects, there may be macroeconomic effects that are not controlled for that drive a decrease in disposable household income. To explore this further we investigate whether the drops in consumption coincide with the lean season, which is the period between planting and harvesting when incomes plummet in agricultural areas. About 75% of the appliance financing customers reported that the main source of income for the household is from

agriculture (farming or post-harvest processing). As shown in Fig. A2, the drop in consumption between weeks 33–52 after appliance delivery coincide with the 2018/2019 lean season which starts in November to the end of February (Food, 2019). The second drop in consumption after 85 weeks also coincides with the start of 2019/2020 lean season. In addition, as discussed in Section 4.6, about 25% of the subset of appliance financing customers who responded to the endline survey reported difficulty in making loan repayments due to limited income during the lean season. It is likely that they also had difficulty making electricity payments as well. However, the fact that the average consumption does not increase after the lean season suggests that there could be confounding factors that we are not able to account for that are also impeding consumption growth. Furthermore, when we compared the effect of the program on customers who reported that their main source of income is from agriculture and those who reported that their main source of income is from commerce, services, or salaried work – i.e., those who may be less affected by seasonality – we observed that in both cases there is a drop in consumption after 30 weeks from the initial increase albeit the drop in consumption between the two groups of customers does not occur simultaneously as shown in Fig. A3.

When the effect of the program was analyzed at an appliance level, consumption among customers who purchased the three most popular devices (televisions, speakers, and refrigerators or freezers) was estimated to increase by up to 1.0 kWh/week, 0.5 kWh/week and 2.5 kWh/week respectively as shown in Fig. 3.<sup>8</sup> This is about a 108%, 98% and 82% increase in consumption from the respective average control customers prior to the delivery of appliances to treatment customers. This increase in consumption is sustained longer among the refrigerator or freezer customers and speaker customers (that is, about 10 months), compared to 8 months among television customers. We also observe that the drop in consumption after the initial increase is more pronounced among television customers, whose the point estimates drop to about 0.1 kWh/week compared to fridge/freezer customers whose

<sup>8</sup> The 124 customers who purchased multiple appliances under the program are excluded from this analysis.



consumption at the end of this study period is about 0.5 kWh/week higher than consumption prior to the intervention. The quicker and more significant drop in consumption among television customers compared to fridge/freezer customers underpins the second reason of inadequate additional income generation from the new appliances to support increased consumption: Fridges and freezers offer a better opportunity for sustained higher income, which may be put towards consuming more electricity, whereas televisions are mainly for residential use, with limited uses for income generation.

Although customers were asked whether they used the appliances they purchased to generate an income as part of the endline survey, the high attrition of this survey, which resulted in a very small sample size, prevented us from comparing the treatment effect of productive use and consumptive use appliances. However, from the responses that were received, a higher percentage of customers reported using their fridges/freezers for income generation compared to the other appliances. Additionally, information on whether customers were enterprises or households was only collected as part of the endline survey; therefore, we are unable to compare the average treatment effect of the program between households and enterprises. However when we compared the average weekly consumption among the subset of customers for whom we were able to classify as residential or business customers, we observed similar behavior after appliance delivery, that is the initial increase and subsequent drop in consumption, albeit the drop starting earlier among residential customers as shown in Fig. A4.

We also consider how the effect of the program on the consumption of customers who purchased an individual type of appliance compares with customers who purchased a blend of appliances. As shown in Fig. A5, after appliances are delivered, both sets of customers are observed to have an initial growth in consumption, which erodes over time. This growth appears to be larger among customers who purchased multiple types of appliances. These customers are likely to be higher income customers as they were able to afford the deposit on more appliances. Section 4.4 describes the implication of appliance offerings to these customers on the economic viability of appliance financing programs in this type of setting.

Our preferred analysis involves using week-level data, as it provides a granular measure of changing consumption patterns over time, and household fixed effects, which control for idiosyncratic variations in household behavior. Nevertheless, as a form of a robustness check, we also analyze the effect on consumption using (1) a simple difference-in-difference analysis without covariates and (2) an analysis using household-level covariates rather than household fixed effects. To facilitate comparisons with the main consumption results we present these results in tabular form, alongside results from a specification with household fixed effects, and to make the table legible we perform this analysis at the level of month rather than week. Table A1 shows the results of this analysis. As the table demonstrates, the results of these various alternative approaches are broadly consistent with the results of our main specification: the parallel trends assumption holds for periods prior to the intervention, and subsequent monthly consumption among treatment households increases substantially immediately after the intervention—then the gap between treatment and control households begins to decrease approximately 7 months after the intervention date.

#### 4.2. Appliance financing program: time-of-use effects

Operators of solar MGs, like any grid, must manage aggregate load profiles to smooth excess consumption over the course of the 24-h period. Storage requirements—or increased operating costs due to the need for backup generation, often through diesel motors—represent a substantial portion of the levelized cost of energy (LCOE), so minimizing demand in excess of current supply helps to reduce the LCOE. Evening, when solar insolation is low or nonexistent but demand is at or near a peak, often represents the time of greatest excess demand. To analyze the effects on peak demand in this setting, we explore shifts in daily load

profiles from adopters of the three most popular appliances (televisions, speakers, and fridges/freezers). We begin by considering the change in load factor, which is the ratio of average to peak consumption in a given time period and measures the efficiency of electricity usage. Prior to the appliance financing program, the consumption of customers who purchased televisions only, and fridges/freezers only, is already somewhat balanced across the day, with a load factor of 47% (Fig. 4). The respective control customers have similar baseline load factors of 45% and 47% respectively. Speaker buyers tend to have higher consumption in the late afternoon to early evening hours, with peak consumption at 5pm resulting in a load factor of 33%. The control customers also have a baseline load factor of 33%. After implementation of the program, we find that television buyers increase evening peak consumption relative to matched control customers resulting in a reduction in the load factor by 4%. For speaker buyers, the increase in consumption relative to the control customers is more spread out throughout the afternoon and evening hours resulting in a load factor increase of 8%. For fridge/freezer buyers, relative to the control, customers show a statistically significant change in the load profile during morning hours resulting in an increase in load factor by 10%.

These results may suggest that a large percentage of appliances purchased through this program were primarily for residential use, particularly during evening hours. As such, the program was not effective in shifting peak evening load to daytime hours, when there is peak solar generation. This means that if MG developers are interested in shifting consumption to match hours of generation in order to amortize the high fixed costs of provisioning energy storage, they need to identify and offer appliances that are primarily used during the day and, at the same time, meet the needs of their customers.

#### 4.3. Appliance financing program: loan repayment

One of the particularly novel features of our data set is that it contains information on customer loan repayment. This is especially notable because data on loan repayment and loan default from private sector providers of off-grid electricity solutions (including SHS and MGs) are often unavailable in the literature; operators often consider this some of their most sensitive information about customers. In this setting, two of the four participating MG operators set a loan term of 12 months in the financing agreement with their customers, while the remaining two set loan terms of 9 and 10 months each. The cumulative distribution function in Fig. 5 shows how customer repayments progress over the course of the loan term and after. It shows the proportion of appliance buyers on the y axis that have less than and up to the corresponding loan balance as a percentage of the expected repayment amount on the x axis at a specified point in the loan repayment period, indicated by each of the lines on the figure.

We observe that in the initial phases of the loan term customers tend to be on time with payments, but the repayment rate steadily deteriorates over the term. One-quarter of the way through the loan term, 61% of customers were on track with repayments; in progressive quarters this falls to 50% then 37%, and by the end of the loan term just 24% of customers have fully repaid the initial loan. The average repayment rate at the end of the term is about 66%: that is, at end of term the average customer had repaid 66% of her loan. Customers do continue to repay loans after the stipulated term; at 125% of the loan term (i.e., past the end of the term), about 35% of customers had repaid loans in full and the average repayment rate increases to 78%. This evidence of good-faith behavior helps to explain why developers infrequently activate the threat of repossession when customers fail to repay on the contract terms, and we hypothesize that this relationship between developers and their customers (and the potential to limit access to electricity) leads to continued payments after the conclusion of the loan term. Yet the relatively high rate of nonpayment suggests MG operators must choose carefully to whom to offer financing, and may have to charge higher rates to all customers in order to mitigate the risk of nonpayment or late

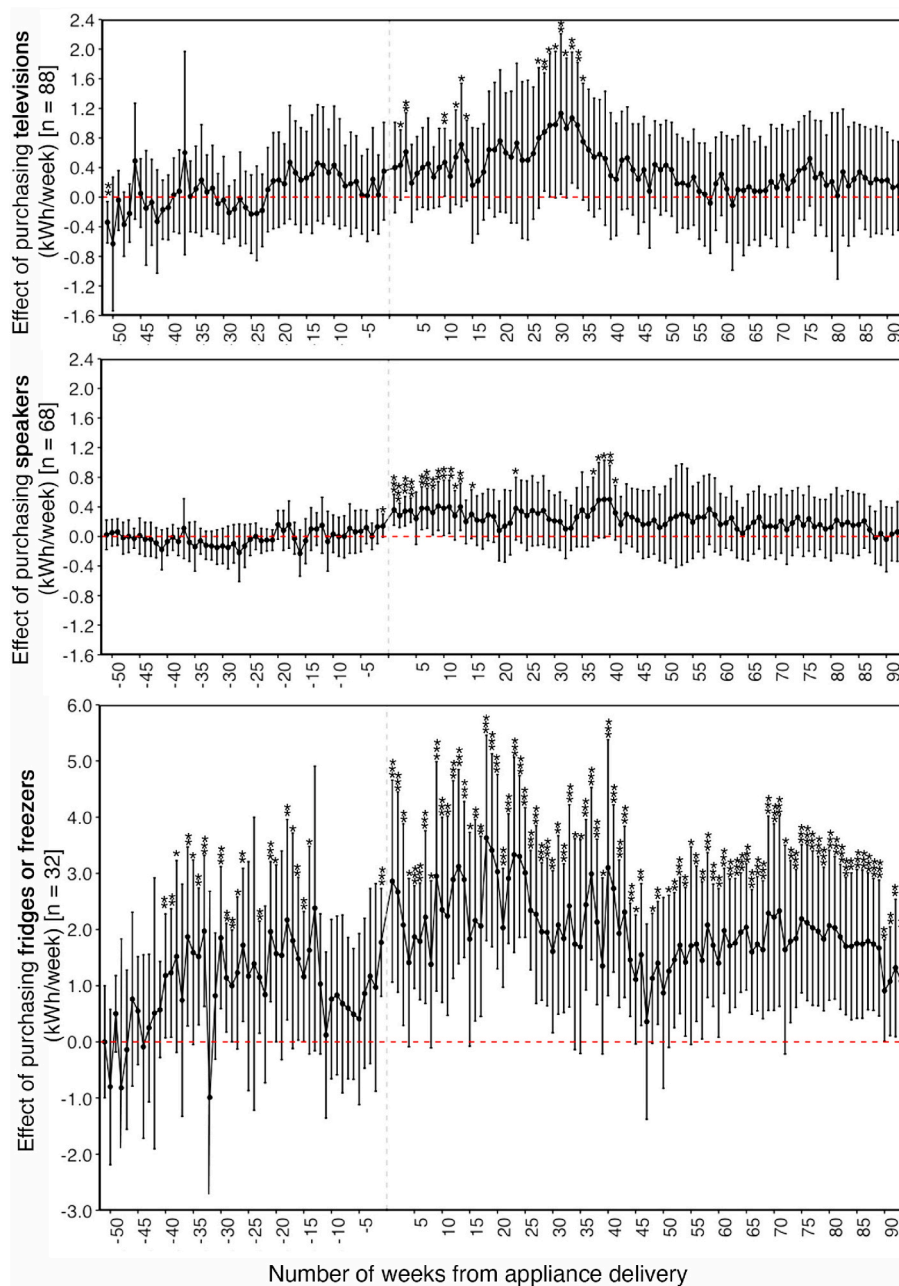


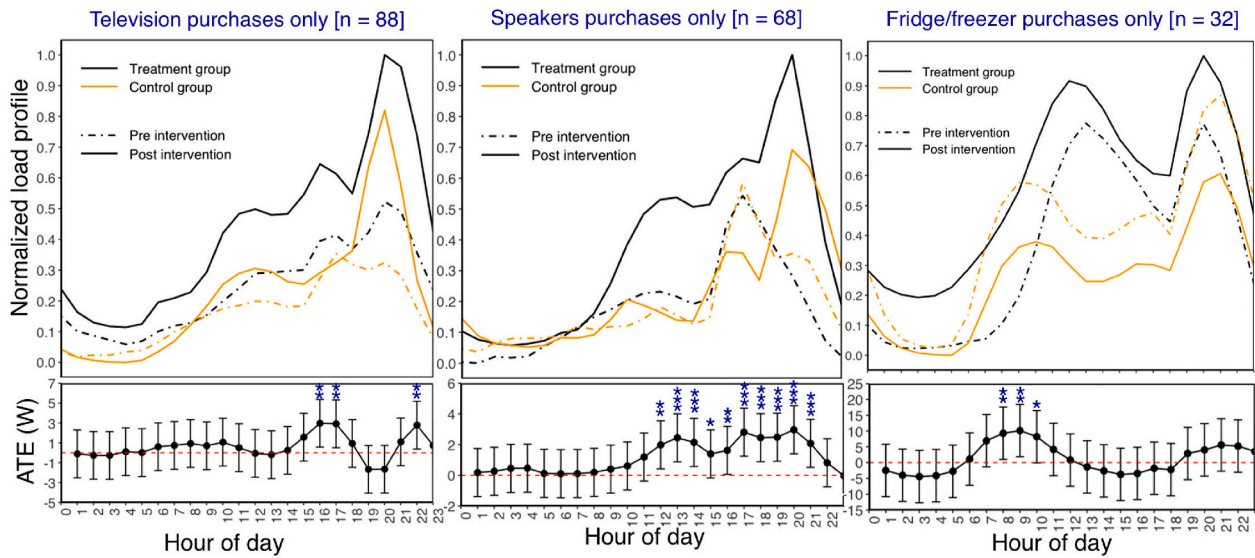
Fig. 3. Treatment effect of individual appliance uptake. Notes: Error bars represent a 95% confidence interval; robust standard errors are clustered by village. Includes household fixed effects, calendar-month fixed effects and relative week fixed effects. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

payment. This is especially true when MG operators must bear the upfront costs of appliance purchases alongside the capital costs for mini-grid development itself. We note that the MG operators in this study did not bear the upfront costs of the appliance purchases, therefore its possible that the problem of moral hazard could also explain why the efforts to enforce loan repayments were more measured.

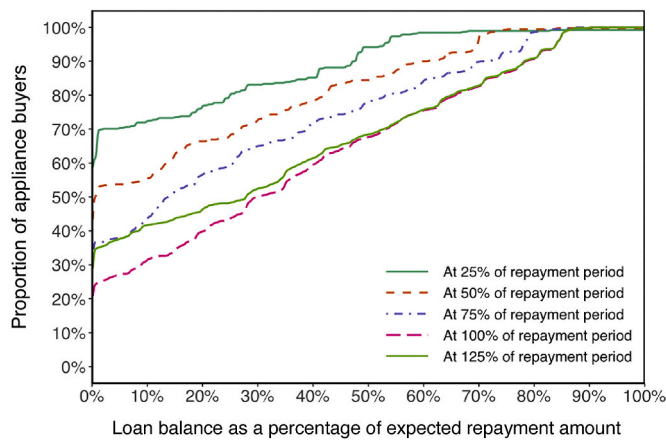
To our knowledge, only a handful of studies have reported information on repayment for household goods purchased on credit in developing-country settings. In the most directly comparable study, researchers working in collaboration with a micro-lender in Orissa, India, offered 12-month loans for rural householders to purchase insecticide-treated bednets (intended to reduce the incidence of mosquito-borne disease including malaria) at market prices (Tarozzi et al., 2014). In that study—in which the market price amounted to three to five times the average daily agricultural wage, and householders paid 20 percent annual interest on loans—researchers found an average

repayment rate of 64 percent after 18 months (i.e., 6 months after the expiration of the contract term.) Table 4 provides a summary of the repayment rate from this study as well as four others that we identified that quantify repayment rates for consumer products in comparable settings. Of note, all of the other studies shown in that table have involved zero-interest loans and shorter contract terms than in our setting. Thus, the repayment rate we observe here is comparable to, and somewhat higher than, that documented in the limited prior literature on comparable (non-zero-interest) household loan repayment in rural low-income settings. We reflect further on the implications of repayment rates in the economic feasibility analysis; see Section 4.4.

We further explored whether the demographic and socioeconomic characteristics of the appliance financing customers could predict timely repayment of appliance loans. We consider three logistic regression models: the first, without any fixed effects and an additional explanatory variable that considers the length of the loan term, the second with



**Fig. 4.** Effect of appliance uptake on daily load profiles. *Notes:* Top panels are normalized daily load profiles; bottom panels show the average effect of individual appliances, distinguished by hour of the day. Error bars represent a 95% confidence interval, calculated from robust standard errors clustered by village. The regressions that generated the coefficients illustrated here include household fixed effects, calendar-month fixed effects, and relative hour fixed effects. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .



**Fig. 5.** Cumulative distribution functions of loan balances for customers who bought appliances.

**Table 4**  
Repayment rates for other consumer goods.

Item	Location	Repayment rate	Monitoring period	Loan period	Interest rate
ITNs	India	64%	18 months	12 months	20%
Cookstoves	Uganda	97%	4 weeks	4 weeks	0%
Cookstoves	Senegal	>95%	10 weeks	10 weeks	0%
SHSs	Rwanda	77%	11 months	1 week to 5 months	0%
Water filters	Kenya	93%	6 months	8 weeks	0%

*Notes.* SHS = solar home systems; ITNs = insecticide-treated nets. Sources: India ITNs from Tarozzi et al. (2014); Uganda cookstoves from Levine et al. (2018); Senegal cookstoves from Bensch and Peters (2020); Rwanda SHS from Grimm et al. (2020); Kenya water filters from Luoto and Levine (2014).

developer fixed effects only, and the third with village fixed effects. The results are presented in Table 5. We expected income to be a strong indicator of customers' ability to repay their loans on time; however, we find that none of the characteristics we considered, including income, are statistically significant indicators of the propensity for customers to

**Table 5**  
Customer characteristics predicting on-time appliance loan repayment.

Dependent variable: Full loan repayment			
Explanatory variables	(1)	(2)	(3)
Household size	-0.137* (0.072)	-0.027 (0.077)	-0.043 (0.095)
Number of rooms	0.037(0.106)	0.044(0.113)	0.137(0.135)
Income (USD)	-0.002(0.002)	-0.001 (0.001)	-0.001 (0.001)
Wealth index	-0.209(0.143)	-0.017 (0.174)	-0.178 (0.276)
Loan amount (USD)	-0.002** (0.001)	-0.001 (0.001)	-0.002 (0.001)
Less than 12 month loan term	1.077*(0.578)		
Village fixed effects	No	No	Yes
Developer fixed effects	No	Yes	No
Pseudo R <sup>2</sup>	0.10	0.24	0.42
Observations	282	282	282
Full repayment by end of loan term	85	85	85

*Notes:* Regression uses a logit model, in which the dependent variable is coded as 1 if a customer repaid their loan in full (including interest) by the end of the loan term, and 0 otherwise. \*\*\*, \*\*, and \* indicate statistical significance at 1%, 5%, and 10%. Robust standard errors, clustered at village level, are in parentheses.

fully repay their loans on time.

Another question of interest is how consumption changes after customers' appliance loans are fully paid off. For instance, we might expect to see an increase in electricity consumption when loans are paid off, if we believe that customers' demand for the services these appliances provide does not change before and after full repayment, but disposable income increases after the loans are fully repaid. If we see such an effect, this suggests that customers may be credit-constrained in a way that hinders their ability to purchase appliances, but not in a way that hinders their ability to purchase electricity, conditional on owning the appliances they desire. On the other hand, if we see no substantial change in electricity consumption after loans are fully repaid, this would suggest that customers may face constraints on their ability to purchase electricity, over and above the constraints on initial appliance purchases. Fig. 6 shows the average day-to-day change in consumption for customers who fully repaid their loans, for 10 months before and after

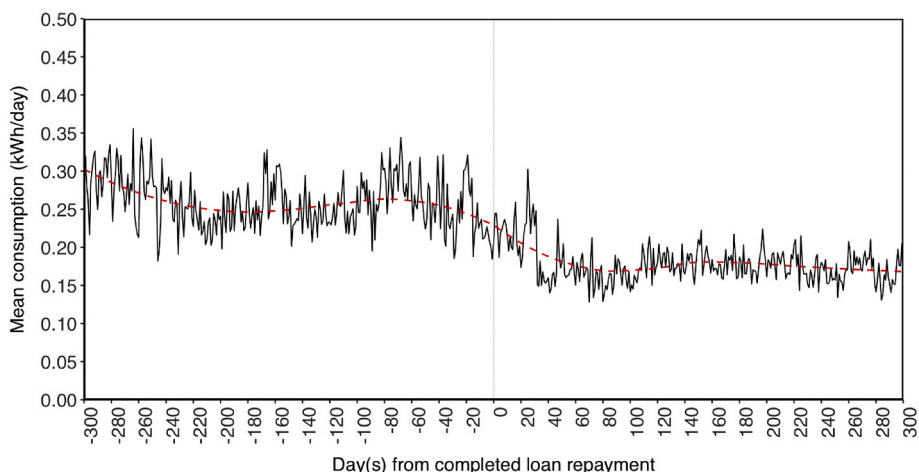


Fig. 6. Average daily consumption prior to and after full loan repayment. Includes those customers who paid loans in full, regardless of whether the payment was within the loan term [n = 131 (35%)].

completion of loan repayment. Customers’ consumption begins to drop before they complete their loan repayments and we see this drop continue for a couple of months even after they complete their repayments. This suggests that customers face additional constraints that adversely affect their ability to purchase electricity (and realize the benefits of access), even after loans are repaid.

4.4. Appliance financing program: economic analysis

Should developers implement appliance financing programs similar to the one we study here? To shed some light on this question, we consider a hypothetical mini-grid operator who could borrow funds (or divert funds from other investments) to purchase appliances and then sell them to customers, with financing. Developers’ net revenue from

offering an appliance financing program is equal to

$$\Delta R = P\Delta Q + A(1 + APR^c) \times REPAY - A(1 + APR^d),$$

where  $P$  is the price per unit (e.g., kWh) and  $\Delta Q$  is the change in consumption;  $A$  is the cost of the appliance; and  $APR^c$  and  $APR^d$  represent the cost of capital for the customer and the developer, respectively. As we show in Section 4.3, not every customer repays their loan in full;  $REPAY$  is the average amount of the appliance loan that is repaid. We assume that developers face a cost of capital of 20% per year and charge customers 35% per year, which is the rate several developers used in the present study; we also assume developers sell power at a price of \$1.50 per kWh. For our hypothetical scenario we use the observed appliance cost  $A$ , as well as the average values of  $\Delta Q$  and  $REPAY$ , from our empirical analysis. For each individual appliance shown in the figure, we limit the sample to those treatment households that purchased only that appliance, and corresponding matched control households, and run the regression in (1) on that sub sample. We then calculate  $\Delta Q$  as a simple average of the difference in consumption (i.e., treatment minus matched controls), over all weeks following appliance delivery. It should be noted that to the extent that the estimated increase in consumption is biased upwards due to self-selection among the treatment customers (see Section 4.1), this financial analysis may have limited external validity—for instance, the specific conclusions about net payoffs may not hold for another setting, or if developers scale up an intervention to a much broader set of customers. Nevertheless, the findings about relative profitability across different appliances, and perhaps the approach to assessing potential profitability, may be instructive for some developers considering similar programs.

Fig. 7 shows the result. To show the appliances on an equal footing, the vertical axis shows the change in ARPU divided by the appliance cost  $A$ .<sup>9</sup> The downward-sloping line shows where net developer revenues equal zero; points above this line represent appliances that would return positive net profits, while points below the line represent unprofitable investments. We also plot a point for the blend of customers and appliance offerings that comprise the program that we analyzed (the “any appliance” marker); note that this blend additionally includes the customers who took up multiple appliances. While our blended appliance program did yield a positive net profit, the overall findings suggest that developers may see the strongest results by implementing appliance

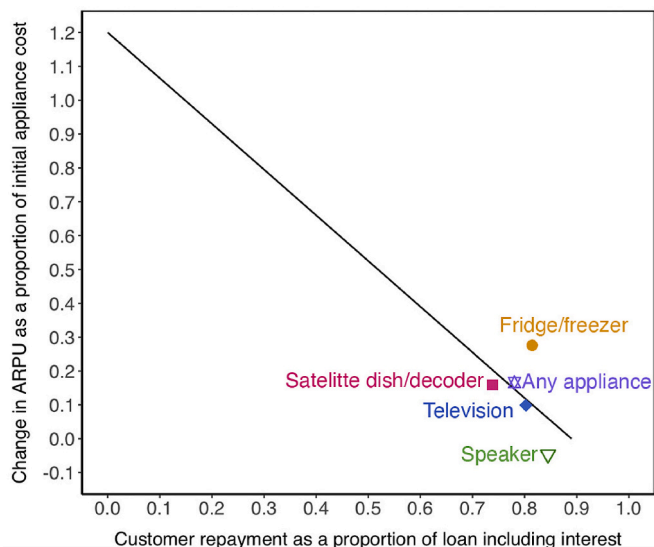


Fig. 7. Financial analysis for appliance financing program. Notes: Vertical axis measures the average weekly change that we observed in revenue per user, as a proportion of the initial appliance cost; see text for details. Horizontal axis measures the customer repayment rates we observed for individual appliances (and, for the “any appliance” marker, the actual mix of appliances we observed). The downward-sloping line shows where net developer revenues, under the assumptions detailed in the text, equal zero. Points above this line represent appliances that would return positive net profits, while points below the line represent unprofitable investments, for a developer operating under the parameters detailed in the text.

<sup>9</sup> For instance, the refrigerator/freezer in our setting costs USD 207, and customers who bought only this appliance increased consumption relative to controls by about 0.73 kWh per week; thus, the ratio of ARPU to  $A$  is  $0.73 \times 52 \times 1.5 / 207 = 0.276$ .

financing programs only for select appliances (e.g., refrigerator/freezers). Alternatively, developers may be able to realize profits from other appliances if they can access low-interest sources of capital, thus driving down  $APR^d$ , or if they have reason to believe their customers would repay loans at a higher rate (increasing  $REPAY$ ) or increase consumption ( $\Delta Q$ ) by a greater degree than we found in our setting. Charging a higher rate to customers ( $APR^c$ ) or a higher unit price ( $P$ ) could be feasible depending on policy or market conditions, but would likely come at a tradeoff of decreasing  $REPAY$  or  $\Delta Q$  or both.

4.5. Appliance financing program: robustness analysis

To test the quality of the estimates obtained using the nearest one-to-one neighbor matching, we compute estimates using two additional matching algorithms using propensity score matching: radius matching with replacement and kernel matching. As before, the variables used to match households are the average daily energy consumption in the three months preceding the first appliance delivery to any household in the sample, household size, and the household asset index. In both these algorithms, there may be many-to-one matching between the control and treated households. We bootstrap the standard errors for these estimates (Lechner, 2002).

The radius matching algorithm generates counterfactuals for each of the treated households within the common support using control households whose propensity scores are within a given caliper. A caliper is a maximum permissible distance between the propensity score of the treated and counterfactuals (Cochran and Rubin, 1973). Each of these households within this caliper is assigned the same weight  $w_{ki} = \frac{1}{N_i^C}$  such that  $N_i^C$  is the number of counterfactual households matched with the  $i$ th treated household. Consequently, the number of control group households that are matched to each of the treated households may vary. The quality of matching is superior relative to kernel matching since only those control group households are used as matches that have propensity scores similar to the treated household.

The kernel matching algorithm matches each treated household in the common support to a weighted average of all the control group households. We use weights that are derived from kernel weights using a normal distribution. These weights are a function of the distance between the propensity scores of the households in the treated households and control group households (Caliendo and Kopeinig, 2008b). This method of matching contains more information about the control group

as all households in this group are used to match each time. This lowers the variance of the estimator.

The difference-in-difference estimates computed after matching using various propensity score matching techniques are presented in Table B2. These results indicate that our estimates obtained using the nearest one-to-one neighbor matching method are consistent across different matching algorithms.

4.6. Appliance financing program: customer perspective

To gain insight on how customers perceived the appliance financing intervention, we consider the responses of customers who were part of the endline survey on program satisfaction. However, as a result of attrition in the endline survey, our observations are based on 178 appliance financing customers (51% of the total customers who obtained an appliance). 78% of these customers reported that if they could go back in time, they would still buy an appliance through the program. Almost none reported that they stopped using their appliances. When asked about the ease or difficulty in making monthly loan repayments, 25% reported medium to high difficulty, stating the reason why as limited income.

4.7. Tariff subsidy program: effects on consumption

Fig. 8 shows our main results with respect to the effect of the tariff subsidy on average revenue and consumption per user. The tariff structure in the 75% subsidy site is a time-of-use tariff, where a lower tariff is charged during off-peak hours than during peak usage hours, while the structure in the 50% subsidy site is a block tariff, where the price per kilowatt-hour changes at different levels of consumption.

Immediately after the 75% tariff subsidy took effect, the ACPU in this site increases by about 72%, with an accompanying decrease in ARPU by about 37%. In subsequent months, we observe a steep upward trend in the change in ACPU, reaching roughly a 240% increase that leads to an 18% recovery in ARPU, which translates in to a 19% decrease in ARPU 9 months after the program took effect. The increase in consumption could be attributed to the fact that following the tariff cut, some customers at this site used the additional disposable income to purchase appliances through a community member who facilitated sales from local vendor. However, we have no knowledge of whether there was a change in the usage patterns of their existing appliances.

In the site that received a 50% tariff subsidy, a 46% increase in ACPU in the month after the subsidy took effect is accompanied by only a 2% decrease in ARPU. In the subsequent months, the growth in consumption is more measured compared to the site with a 75% tariff subsidy, culminating in a 68% increase in consumption 9 months after the subsidy took effect. At 9 months, the ARPU at this site is about 5% less than the value at the start of the program. We have no information indicating whether the increase in consumption is due to customers purchasing additional appliances or increasing the usage of their existing appliances. A majority of community members at this MG site are pastoralists, whose economy is centered around cattle rearing. We observe a notable dip and peak in the ARPU trend at 2 months prior and 3 months after the tariff cut respectively, which fall on April, which is the start of the rainy season and August, which is the peak of the dry season respectively. A possible explanation could be that during the dry season, when there is scarcity of pasture, the MG customers sell their cattle and thus have increased disposal income which they use to purchase more electricity units, while the expectation of an abundance of pasture during the rainy season may cause the customers to direct more of their disposable income to the replenishing and maintenance of their herd (Burnham, 2017).

Since the customers in the 50% tariff subsidy site were already significantly higher consumers, with higher monthly incomes than the customers in the 75% tariff subsidy site prior to implementation of the tariff subsidy program as shown in Table 2, we cannot definitively attribute the differences in the effect of the program on ARPU and ACPU

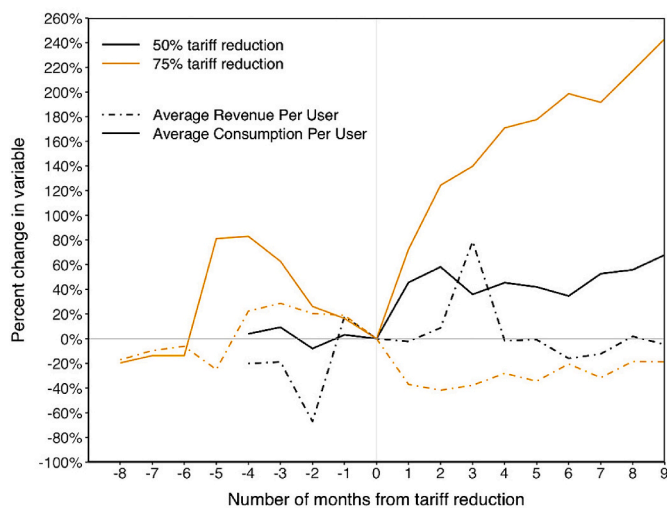


Fig. 8. Effects of tariff reduction program. Notes: The figure shows the change in average revenue per user and average consumption per user after a 50% and 75% tariff reduction from their average values prior to the tariff subsidy program.

between these sites solely to the difference in the tariff subsidy provided.

Given the three tariff levels, that is, at 100%, 50% and 25%, and their corresponding average consumption per user values, as shown in Fig. 9, we calculate the price elasticity of electricity demand as  $-1.2$ . This means that a 10% reduction in electricity tariff leads to a 12% increase in the average consumption per user. This shows that mini-grid customers in this admittedly limited sample are very sensitive to changes in the electricity price and there is room for developers to impact the consumption of their customers with moderate changes to the electricity price index. However, we caution that these conclusions should be taken lightly, as the sample MG customers are distinctly different (see Section 3.3.2) and the sample size is quite constrained.

Lastly, we explore the impact of the tariff subsidy program on the hourly load profiles of residential and small commercial customers. Data on the classification of customers as either a residential connection or a business connection were only available for the site that received a 75% subsidy. In both cases there is an increase in consumption intensity in the load profile, rather than a broader range of consumption hours, as shown in Fig. 10. This indicates that the increase in the magnitude of consumption of both residential and business customers is not accompanied by a significant change in the timing of consumption. In the case of an MG developer trying to encourage customers to shift their consumption away from peak evening hours, these results suggest that applying a uniform tariff subsidy may not be the right approach. However, given that mini-grid customers are highly sensitive to changes in the price of electricity, a more effective approach may be to apply different tariff subsidy levels to time-of-use tariffs.

### 5. Discussion

Developers, governments, donors, and communities are increasingly interested in the potential for MGs to provide power to hundreds of millions of people who lack it, particularly in South Asia and sub-Saharan Africa. Given that grid infrastructure is expensive and time-consuming to construct and is often subject to routine load-shedding, it is evident that off-grid solutions will form part of the solution to achieve universal access to affordable, reliable, and modern energy, especially in rural communities far from the grid. While increasingly popular SHS can provide power for common uses such as lighting, mobile phone charging, and perhaps even refrigeration, these are insufficient for many commercial applications. MGs offer the potential of a combination of affordability, reliability, and capacity to service areas

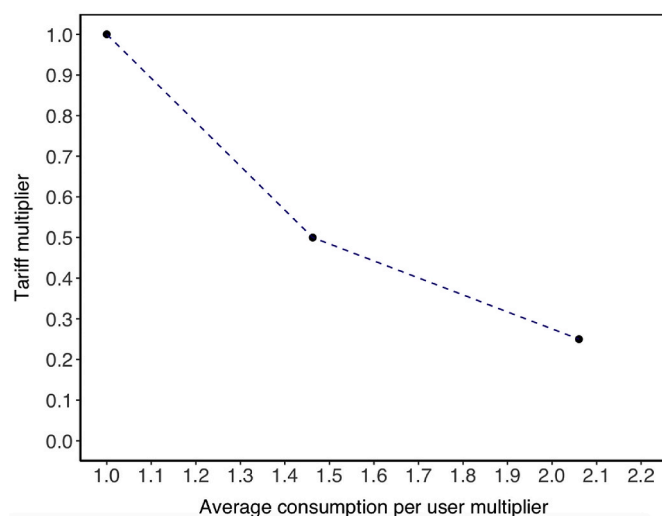


Fig. 9. Price elasticity of electricity demand for tariff subsidy customers. Notes: The figure reflects the 116 households that were treated under the tariff subsidy program.

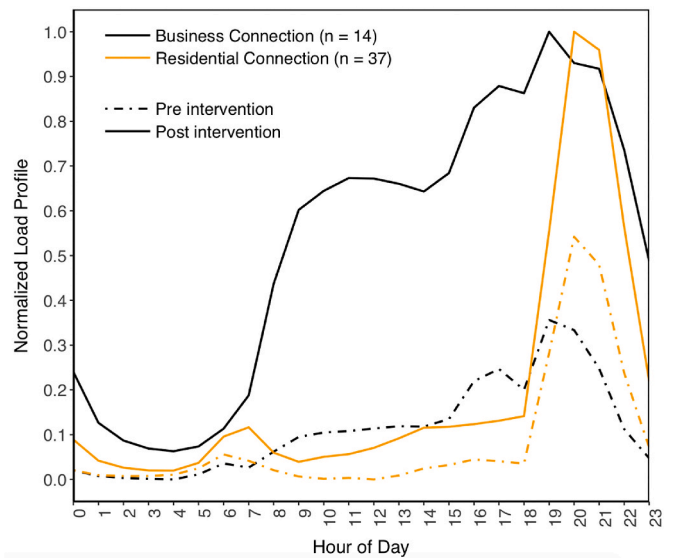


Fig. 10. Normalized daily load profile of residential and small business customers prior to and after a 75% tariff reduction.

that need more power than a home solar panel can provide, but do not have enough load density for the central grid. At the same time, MG developers face their own challenges, chief among them whether their business models are economically sustainable—and, therefore, that the potential benefits of MGs for communities will be realized.

In this context, interventions that aid developers, donors, and researchers to better understand the constraints on demand among MG customers are especially helpful. We study the effects of an appliance financing intervention conducted among roughly 2000 households in 27 microgrid-powered villages in East Africa, using a novel and unique data set on hourly electricity consumption, payments, and customer demographics to analyze the effects on consumption, repayment dynamics, and the economic returns of the program for developers. The results support the idea that customers face credit constraints that hinder demand growth, and relieving those constraints by providing market-rate financing to purchase appliances increases consumption—at least for several months. However, the increase in consumption does not appear to be sustained, relative to a matched control sample of customers who were offered appliance financing but did not take it up. We also report important results regarding loan repayment rates; to our knowledge, these results represent the only rigorous analysis (and indeed, the only publicly-available analysis) of loan repayment timeliness in the sector.

### 6. Conclusion

In this paper, we have analyzed two approaches for stimulating electricity consumption among residential and commercial customers of privately-operated mini-grids in East Africa. Our results show that the program offering a range of appliances to customers on market-rate credit terms yielded appreciable yet uneven gains in consumption growth, with a notable initial increase—the measurement of which proves to be rather sensitive to potential selection bias arising from unobservable characteristics of customers who selected into the program—eroding over time. In particular, refrigerator/freezer units showed two key benefits relative to other appliances offered: (1) significant changes in consumption that imply overall profitability of an appliance financing program based solely on these appliances and (2) time-of-use consumption patterns that complement rather than exacerbate existing evening-heavy daily consumption profiles on mini-grids.

These findings are relevant beyond the mini-grid sector. Grid operators in sub-Saharan Africa also struggle with low consumption in rural areas that, combined with high infrastructure costs per connection, result

in significant financial losses (Fobi et al., 2018). Low levels of electricity use also suggest that public funds invested in grid extension may not be achieving significant economic development gains, at least in the short term. Appliance finance programs could also be implemented in rural areas served by the grid. Lower grid tariffs may in fact permit beneficiaries to increase their electricity use more than on mini-grids.

With a smaller sample size, the tariff subsidy program we evaluated indicated mixed signals for whether overall revenue could be maintained at a lower tariff. We believe that this small-scale experiment calls for further research to find the optimal balance of increased consumption for livelihood development while driving a profitable business model for electricity service companies in settings like East Africa.

Overall, the importance of developing new and effective strategies for demand stimulation is not only important for the sustainability of emerging electricity service companies, but also, and especially so, for the mostly rural citizens gaining access to life-changing, foundational electricity services. Our work can serve as a step towards enabling those crucial gains.

### Appendix A. Effects of Appliance Financing Program

**Table A.1**  
Month level dynamic treatment effects of appliance financing program: Alternative regression specifications

Dependent variable: Monthly electricity consumption (kWh)			
	(1)	(2)	(3)
-12 months prior:treatment	-0.122 (0.648)	-0.042 (0.370)	-0.022 (0.434)
-11 months prior:treatment	0.022 (0.770)	0.100 (0.536)	0.228 (0.584)
-10 months prior:treatment	-0.027 (0.853)	0.370 (0.643)	0.476 (0.688)
-9 months prior:treatment	0.381 (1.133)	0.511 (0.778)	0.784 (0.931)
-8 months prior:treatment	0.247 (0.935)	0.234 (0.639)	0.498 (0.824)
-7 months prior:treatment	0.094 (1.015)	0.050 (0.665)	0.241 (0.825)
-6 months prior:treatment	0.391 (0.941)	0.314 (0.674)	0.605 (0.783)
-5 months prior:treatment	1.258 (1.063)	1.197 (0.839)	1.534 (0.963)
-4 months prior:treatment	0.909 (1.134)	0.889 (0.932)	1.295 (1.048)
-3 months prior:treatment	0.694 (0.948)	0.762 (0.739)	1.204 (0.910)
-2 months prior:treatment	0.656 (0.918)	0.752 (0.710)	1.151 (0.894)
-1 months prior:treatment	0.846 (0.965)	0.983 (0.694)	1.374* (0.822)
1 months after:treatment	2.915*** (1.021)	3.029*** (0.937)	3.355*** (1.082)
2 months after:treatment	2.615** (1.193)	2.735*** (1.042)	3.064** (1.298)
3 months after:treatment	3.447*** (1.284)	3.577*** (1.175)	3.896*** (1.488)
4 months after:treatment	3.318** (1.326)	3.524*** (1.263)	3.764** (1.509)
5 months after:treatment	3.246** (1.410)	3.484*** (1.330)	3.797** (1.641)
6 months after:treatment	3.093** (1.360)	3.321*** (1.265)	3.576** (1.586)
7 months after:treatment	3.306** (1.554)	3.530** (1.495)	3.827** (1.724)
8 months after:treatment	2.780** (1.223)	2.940*** (1.092)	3.219** (1.324)
9 months after:treatment	2.111* (1.273)	2.231** (1.029)	2.595** (1.181)
10 months after:treatment			

(continued on next page)

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Acknowledgements

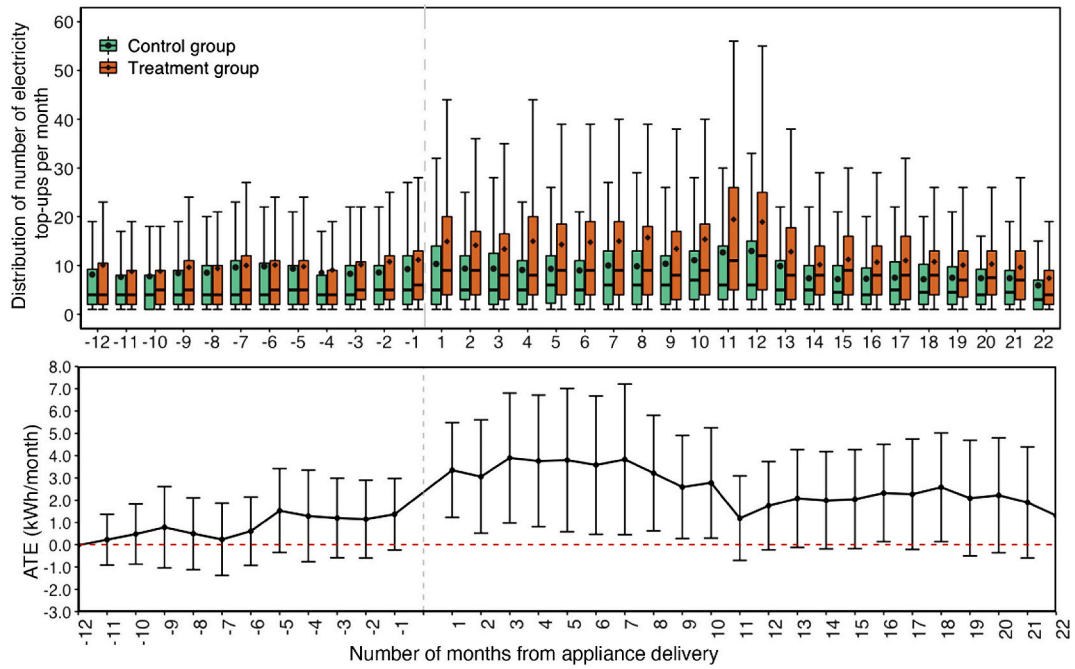
We thank the CrossBoundary Mini-grid Innovation Lab, the Rockefeller Foundation, New York, United States (2018 POW 004), Energy4Impact, the Africa Minigrid Developers Association, and participating mini-grid developers for providing access to the data we analyzed. We are grateful for insightful comments and suggestions from two anonymous reviewers as well as from Marc Jeuland, Maria Knott, Aaron Leopold, Erika Lovin, Shaun McRae, Robyn Meeks, Subhrendu Pattanayak, Jörg Peters, and Jonathan Phillips, and the participants of the Sustainable Energy Transitions Initiative and the Environment for Development conference in Bogotá, Colombia. All remaining errors are our own.

**Table A.1** (continued)

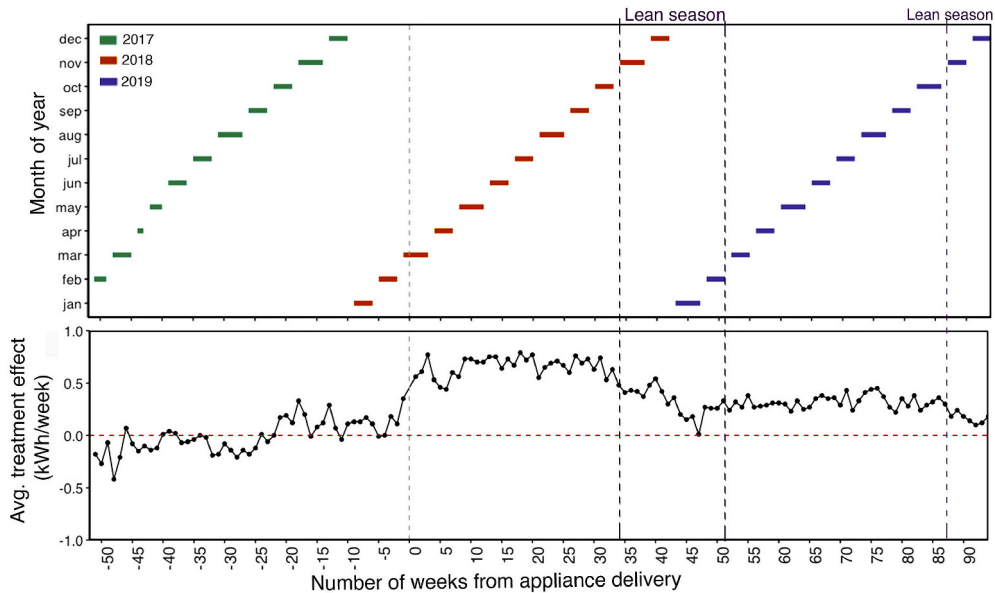
Dependent variable: Monthly electricity consumption (kWh)			
	(1)	(2)	(3)
	2.167*	2.214**	2.776**
	(1.307)	(1.045)	(1.263)
11 months after:treatment	1.685	0.903	1.193
	(1.336)	(0.746)	(0.968)
12 months after:treatment	1.255	1.159	1.751*
	(1.188)	(0.765)	(1.009)
13 months after:treatment	1.204	1.128	2.077*
	(1.289)	(0.822)	(1.121)
14 months after:treatment	1.065	1.003	1.993*
	(1.361)	(0.844)	(1.115)
15 months after:treatment	1.102	1.052	2.045*
	(1.397)	(0.853)	(1.134)
16 months after:treatment	1.407	1.309*	2.323**
	(1.290)	(0.788)	(1.115)
17 months after:treatment	1.220	1.356	2.269*
	(1.326)	(0.887)	(1.263)
18 months after:treatment	1.550	1.674**	2.578**
	(1.293)	(0.850)	(1.246)
19 months after:treatment	1.116	1.202	2.094
	(1.414)	(0.954)	(1.324)
20 months after:treatment	1.364	1.535	2.222*
	(1.409)	(0.975)	(1.315)
21 months after:treatment	1.016	1.263	1.898
	(1.311)	(0.891)	(1.273)
22 months after:treatment	0.579	0.583	1.311
	(1.369)	(0.785)	(1.095)
Household income		0.0002	
		(0.002)	
Household wealth index		-0.311**	
		(0.125)	
Number of rooms		0.187	
		(0.395)	
Household size		-0.119	
		(0.234)	
Relative month fixed effects	Yes	Yes	Yes
Calendar month fixed effects	No	Yes	Yes
Village fixed effects	No	Yes	No
Household fixed effects	No	No	Yes
$R^2$	0.19	0.19	0.69
Observations	20,318	20,318	20,318
Treatment sample	348	348	348
Control sample	342	342	342

Notes: \*\*\*, \*\*, and \* indicate statistical significance at 1%, 5%, and 10%. Robust standard errors, clustered at village level, are in parentheses.

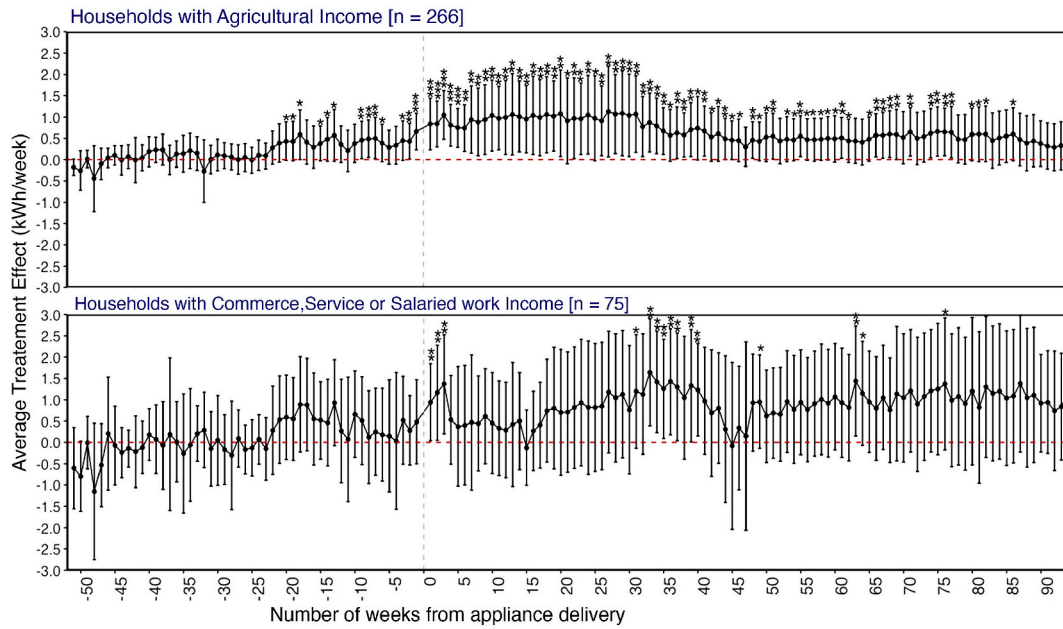




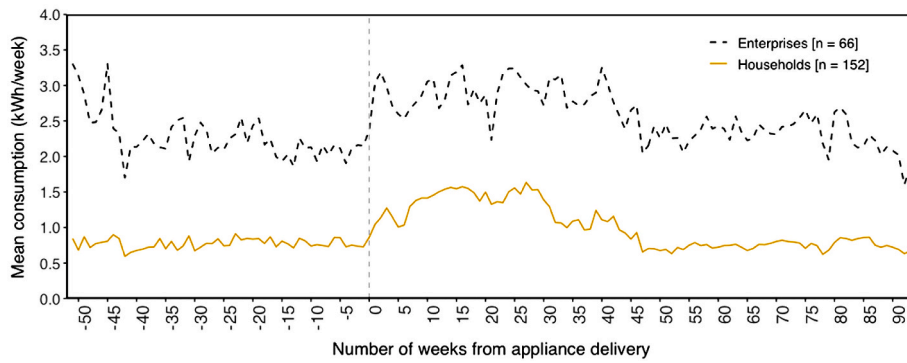
**Fig. A.1.** Distribution of frequency of electricity top-ups per month among treatment and control customers before and after appliance delivery. *Note:* Bottom panel shows the average treatment effect of the program. Error bars represent a 95% confidence interval; \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .



**Fig. A.2.** Weeks from appliance delivery that coincides with the lean season. *Notes:* Top panel shows the months of the year that the weeks from appliance delivery in the bottom panel fall on for majority of the sample during each week.



**Fig. A.3.** Average Treatment effect of program among customers whose reported primary source of income is from agriculture and those whose reported primary source of income is from commerce, services or salaried work. *Notes:* Error bars represent a 95% confidence interval; robust standard errors are clustered by village. Includes household fixed effects, calendar-month fixed effects and relative week fixed effects. Note: \*p < 0.1; \*\*p < 0.05; \*\*\*p < 0.01.



**Fig. A.4.** Average weekly consumption among residential and business customers prior to and after appliance delivery. *Note:* Includes only a subset of the appliance financing customers for whom we have information on their connection type.

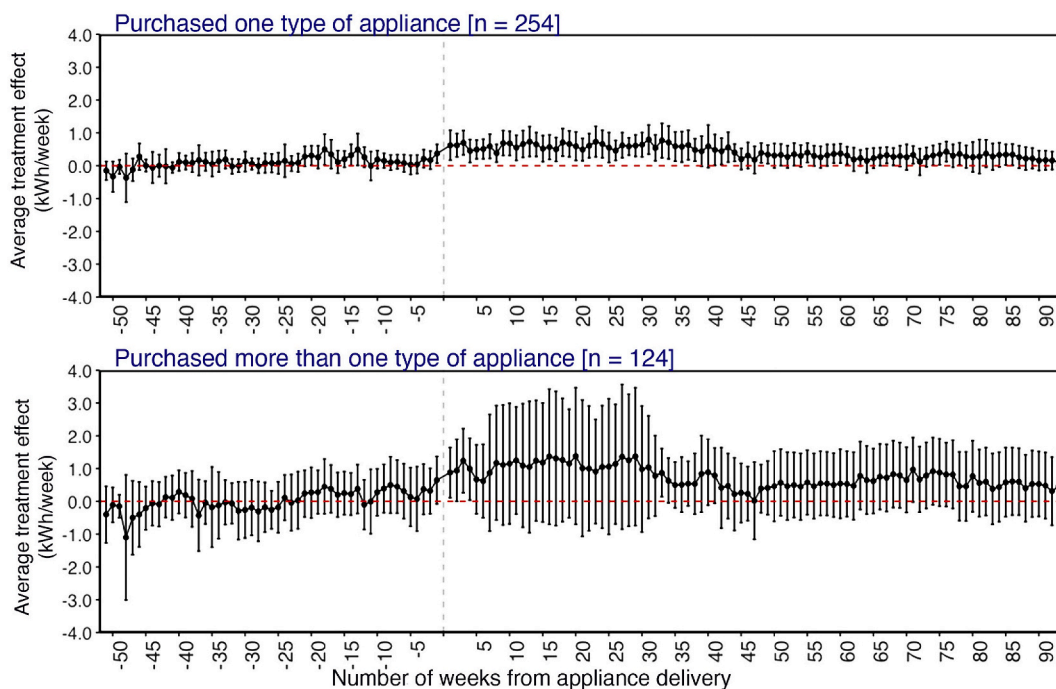


Fig. A.5. Treatment effect of taking up individual appliances and treatment effect of taking up multiple types of appliances. Notes: Error bars represent a 95% confidence interval; robust standard errors are clustered by village. Includes household fixed effects, calendar-month fixed effects and relative week fixed effects.

### Appendix B. Matching Quality Indicators and Alternative Matching Methods

As noted in Section 3.4.1, the identification of treatment effects based on matching treatment and control observations relies on two key assumptions: conditional independence (i.e., potential outcomes are independent of treatment assignment), and common support (i.e., that there is sufficient overlap in the characteristics of treated and non-treated units to find sufficient matches) (Caliendo and Kopeinig, 2008a). While it is impossible to test these assumptions fully, particularly the conditional independence of unobservable characteristics; however, this appendix presents the results of several tests to supplement the analyses provided in the main text.

First, to further investigate whether covariates are balanced across the two groups, we conduct a test of joint orthogonality (McKenzie, 2015), which evaluates whether these variables (even if not individually significant) co-vary in a way that jointly predicts treatment assignment. We fail to reject ( $p = 0.56$ ) the hypothesis of joint insignificance. In a similar test, over all of the demographic and socioeconomic variables shown in Table 3, we also fail to reject the null hypothesis of joint insignificance ( $p = 0.17$ ). These tests complement the individual variable tests (Table 3) in suggesting that the demographic variables used to identify matched control customers do not vary significantly (in this case, jointly) over assignment into treatment and matched control groups.

Second, we evaluate match quality by regressing treatment status on the characteristics used to identify matched controls in two samples: (i) the full set of treated and non-treated customers, and (ii) the set of treatment customers and matched controls (Caliendo and Kopeinig, 2008a). We then compare two statistics across the regressions on these two samples: (a) pseudo- $R^2$  values, and (b) the likelihood ratio for the joint significance of all regressors (i.e., the regression with the characteristics used to identify matched controls, versus regression on a constant). We find that before matching, the pseudo- $R^2$  for regressing treatment status on covariates is 0.018 and the likelihood ratio is 29.17 ( $p = 0.0000$ ). After matching, the pseudo- $R^2$  is 0.004, and the likelihood ratio is 4.00 ( $p = 0.5488$ ). The finding that the post-matching pseudo- $R^2$  is very close to zero, and that the likelihood ratio test suggests that the match covariates do not significantly increase the likelihood compared to an empty model, suggests there are no systematic differences in the distribution of covariates between the treatment group and matched controls. This in turn supports the notion that our propensity score matching approach succeeded in producing a group of matched controls that is substantially similar to treated customers, except for the treatment itself.

Third, we perform a sensitivity analysis, using the Rosenbaum bounds approach, to quantify how the estimated treatment effect would change under a violation of the assumption of conditional independence. This approach allows us to determine how strong the “hidden bias” from unobserved confounding variables must be in order to undermine the implications of the matching analysis. We use a range of values for the parameter  $\Gamma$  (expressed in terms of the odds ratio between assignment to the treatment and control groups) and calculate both the upper bound p-value (i.e., the significance level for the test of the null hypothesis), and the upper and lower Rosenbaum bounds for the Hodges-Lehmann point estimate.<sup>10</sup> Table B1 Table B.1 provides the resulting Rosenbaum bounds for values of  $\Gamma$  ranging from 1.0 to 1.5.<sup>11</sup> Within this range of odds ratios, both the upper bound p-

<sup>10</sup> Note that the Hodges-Lehmann point estimate is roughly equivalent to the difference in medians across the treatment and control groups; more precisely, it is the median of the distribution that arises from pairing every treatment outcome to every control outcome and calculating the difference. In any case, the Rosenbaum bounds for the Hodges-Lehmann point estimate do not represent a 95% confidence interval (or any other confidence interval) corresponding to the Rosenbaum bound p-value.

<sup>11</sup> There is no hard and fast rule to inform the appropriate range of values over which to consider the potential for hidden bias. One author (Keele, 2010) suggests that 1.0 to 1.5 is a typical range of values applicable to most social science analyses, but the right range is surely driven largely by the specific context of a given study.

value and the Rosenbaum bounds for the Hodges-Lehmann point estimate are relatively stable, at least for the months immediately following the intervention; above 1.5, we quickly see the upper bound  $p$ -values rise to greater than 0.1 for all months (except the very first month after appliance delivery, which is still significant at the 10% level until  $\Gamma = 1.9$ ). From this we conclude that if an unobserved variable caused the odds ratio of treatment assignment to differ between treatment and control groups by more than 1.5 and if this variable's effect on post-treatment consumption was sufficiently strong that it almost perfectly determines whether the post-treatment consumption is bigger for the treatment or the control case in each pair of matched cases in the data, then the effect of the treatment would be considered not statistically significant (DiPrete and Gangl, 2004). Considering that our matched control customers were offered the appliance financing program and actively declined to take it up, it seems possible that unobservable factors could drive a difference of this magnitude. This leads us to conclude that our results are moderately sensitive to hidden bias, even as the other tests in this section present somewhat encouraging evidence for the stability of our results to deviations from the conditional independence assumption.

Fourth, we estimate the time-varying treatment effects of the appliance financing program under a range of alternative matching assumptions, with the results shown in Table B2. Comparing column (1), which shows our preferred matching method, to the other columns, shows that although the magnitude of the month-by-month treatment effects is somewhat different for matched controls identified with alternative methods (and usually smaller), the overall pattern of the treatment effects—notably, the finding that treatment effects are significant and positive for the first six to nine months after treatment, and then positive but not significant in subsequent months—are similar across all other matching methods. Fig. B1 shows the week-by-week treatment effects for treatment customers compared to controls identified using the kernel matching method, and Fig. B2 shows the same for the radius matching method.

Finally, Fig. B3 shows the distribution of propensity scores for the treated and untreated observations so as to illustrate the region of common support. As the figure shows, the propensity scores among treatment and matched control customers overlap relatively well, including in relative frequency, especially for the developers identified as “Developer 1” and “Developer 2”. The overlap for Developer 4 is not as strong, particularly for the higher values of propensity scores for treatment customers (above 0.4 or so). Treatment customers in this region were not matched to control customers in the 1:1 propensity score match approach, and are excluded from the analysis.

**Table B.1**  
Rosenbaum sensitivity analysis for average treatment effect of appliance financing program

Period	$\Gamma = 1.0$			$\Gamma = 1.1$			$\Gamma = 1.3$			$\Gamma = 1.5$		
	p-critical	LB	UB	p-critical	LB	UB	p-critical	LB	UB	p-critical	LB	UB
13 months prior:treatment	0.999	-1.09	-1.09	1.000	-1.29	-0.89	1.000	-1.59	-0.59	1.000	-1.79	-0.39
12 months prior:treatment	1.000	-1.27	-1.27	1.000	-1.47	-1.07	1.000	-1.77	-0.77	1.000	-2.07	-0.57
11 months prior:treatment	0.999	-0.78	-0.78	1.000	-0.98	-0.58	1.000	-1.28	-0.38	1.000	-1.48	-0.18
10 months prior:treatment	0.997	-0.59	-0.59	1.000	-0.79	-0.39	1.000	-0.99	-0.19	1.000	-1.19	0.01
9 months prior:treatment	0.997	-0.56	-0.56	1.000	-0.76	-0.36	1.000	-0.96	-0.16	1.000	-1.16	0.04
8 months prior:treatment	1.000	-0.75	-0.75	1.000	-0.95	-0.55	1.000	-1.15	-0.35	1.000	-1.35	-0.15
7 months prior:treatment	1.000	-0.84	-0.84	1.000	-1.04	-0.64	1.000	-1.34	-0.44	1.000	-1.54	-0.24
6 months prior:treatment	1.000	-0.86	-0.86	1.000	-1.06	-0.66	1.000	-1.36	-0.46	1.000	-1.56	-0.26
5 months prior:treatment	0.996	-0.41	-0.41	1.000	-0.61	-0.21	1.000	-0.81	-0.01	1.000	-1.01	0.09
4 months prior:treatment	1.000	-0.62	-0.62	1.000	-0.82	-0.42	1.000	-1.12	-0.22	1.000	-1.32	-0.02
3 months prior:treatment	1.000	-0.50	-0.50	1.000	-0.70	-0.30	1.000	-0.90	-0.10	1.000	-1.10	0.00
2 months prior:treatment	1.000	-0.68	-0.68	1.000	-0.88	-0.48	1.000	-1.08	-0.28	1.000	-1.28	-0.08
1 month prior:treatment	0.994	-0.38	-0.38	1.000	-0.58	-0.18	1.000	-0.78	0.02	1.000	-0.98	0.12
1 month after:treatment	0.000	1.25	1.25	0.000	1.05	1.45	0.000	0.75	1.75	0.002	0.55	1.95
2 months after:treatment	0.000	0.67	0.67	0.001	0.47	0.87	0.031	0.27	1.07	0.222	0.07	1.27
3 months after:treatment	0.000	0.81	0.81	0.000	0.61	1.01	0.007	0.41	1.31	0.088	0.21	1.51
4 months after:treatment	0.000	0.94	0.94	0.000	0.74	1.14	0.005	0.44	1.44	0.060	0.24	1.64
5 months after:treatment	0.004	0.49	0.49	0.026	0.29	0.69	0.246	0.09	0.89	0.652	-0.11	1.19
6 months after:treatment	0.000	0.68	0.68	0.004	0.48	0.88	0.084	0.28	1.18	0.381	-0.02	1.38
7 months after:treatment	0.000	0.77	0.77	0.001	0.57	0.97	0.027	0.37	1.27	0.187	0.17	1.47
8 months after:treatment	0.000	0.63	0.63	0.003	0.43	0.83	0.059	0.23	1.13	0.299	0.03	1.33
9 months after:treatment	0.025	0.38	0.38	0.104	0.18	0.58	0.489	-0.02	0.78	0.849	-0.22	1.08
10 months after:treatment	0.014	0.40	0.40	0.066	0.20	0.60	0.384	0.00	0.90	0.771	-0.20	1.10
11 months after:treatment	0.944	-0.25	-0.25	0.988	-0.45	-0.05	1.000	-0.65	0.05	1.000	-0.75	0.25
12 months after:treatment	0.359	0.06	0.06	0.612	-0.04	0.16	0.922	-0.24	0.36	0.992	-0.44	0.56
13 months after:treatment	0.312	0.07	0.07	0.555	-0.03	0.17	0.893	-0.23	0.37	0.986	-0.33	0.57
14 months after:treatment	0.477	0.01	0.01	0.714	-0.09	0.21	0.952	-0.29	0.31	0.995	-0.49	0.51
15 months after:treatment	0.276	0.10	0.10	0.509	-0.10	0.30	0.867	-0.20	0.50	0.980	-0.40	0.60
16 months after:treatment	0.267	0.11	0.11	0.498	-0.09	0.31	0.860	-0.19	0.51	0.978	-0.39	0.61
17 months after:treatment	0.516	-0.01	-0.01	0.743	-0.21	0.19	0.958	-0.41	0.39	0.996	-0.61	0.59
18 months after:treatment	0.327	0.09	0.09	0.565	-0.11	0.29	0.893	-0.31	0.49	0.985	-0.41	0.69
19 months after:treatment	0.623	-0.06	-0.06	0.819	-0.26	0.14	0.976	-0.36	0.24	0.998	-0.56	0.44
20 months after:treatment	0.662	-0.07	-0.07	0.839	-0.17	0.03	0.977	-0.37	0.23	0.998	-0.57	0.43
21 months after:treatment	0.908	-0.26	-0.26	0.970	-0.36	-0.16	0.998	-0.56	0.04	1.000	-0.76	0.24
22 months after:treatment	1.000	-0.64	-0.64	1.000	-0.84	-0.44	1.000	-1.04	-0.34	1.000	-1.24	-0.14

Notes:  $\Gamma$  refers to the ratio of odds of treatment assignment. The  $p$ -critical value shown is the Rosenbaum upper bound  $p$ -value, that is, the significance level for the test of the null hypothesis. LB and UB denote the the lower and upper Rosenbaum bounds, respectively, for the Hodges-Lehmann point estimate.

**Table B.2**  
 Month level dynamic treatment effects of appliance financing program: Alternative matching methods

Dependent variable: Monthly electricity consumption (kWh)				
	(1)	(2)	(3)	(4)
	1-to-1 match	1-to-1 match	Kernel	Radius
	(PSM with wealth index PCA)	(PSM with individual elements)	matching	matching
12 months prior:treatment	-0.022 (0.434)	-0.063 (0.410)	-0.136 (1.203)	-0.070 (1.093)
11 months prior:treatment	0.228 (0.584)	-0.589 (0.802)	-0.525 (1.070)	-0.370 (0.953)
10 months prior:treatment	0.476 (0.688)	-0.242 (0.689)	-0.132 (0.965)	-0.324 (0.929)
9 months prior:treatment	0.784 (0.931)	0.224 (1.095)	0.005 (0.980)	0.163 (0.917)
8 months prior:treatment	0.498 (0.824)	0.157 (1.191)	-0.259 (0.985)	-0.187 (0.928)
7 months prior:treatment	0.241 (0.825)	-0.551 (1.211)	-0.267 (0.927)	-0.243 (0.876)
6 months prior:treatment	0.605 (0.783)	-0.046 (1.030)	-0.366 (0.954)	-0.313 (0.901)
5 months prior:treatment	1.534 (0.963)	0.111 (0.883)	0.346 (0.979)	0.258 (0.944)
4 months prior:treatment	1.295 (1.048)	-0.604 (0.931)	-0.267 (0.974)	-0.400 (0.915)
3 months prior:treatment	1.204 (0.910)	0.018 (0.811)	-0.184 (0.977)	-0.233 (0.931)
2 months prior:treatment	1.151 (0.894)	-0.026 (0.945)	0.100 (0.985)	0.191 (0.917)
1 month prior:treatment	1.374* (0.822)	0.760 (0.988)	0.323 (0.959)	0.311 (0.909)
1 month after:treatment	3.355** (1.082)	2.65*** (1.019)	2.108** (0.945)	2.003** (0.907)
2 months after:treatment	3.064** (1.298)	2.279 (1.474)	1.781* (0.956)	1.735* (0.902)
3 months after:treatment	3.896** (1.488)	3.347** (1.610)	2.762** (1.131)	2.774** (1.081)
4 months after:treatment	3.764** (1.509)	3.471* (1.852)	2.398** (1.190)	2.250** (1.141)
5 months after:treatment	3.797** (1.641)	2.699 (1.674)	2.274** (1.121)	2.230** (1.093)
6 months after:treatment	3.576** (1.586)	3.572** (1.739)	2.246** (1.124)	2.033* (1.085)
7 months after:treatment	3.827** (1.724)	2.956* (1.737)	2.118* (1.223)	1.916 (1.177)
8 months after:treatment	3.219** (1.324)	2.058** (0.846)	1.299 (0.947)	1.125 (0.895)
9 months after:treatment	2.595** (1.181)	1.867* (1.038)	0.857 (0.950)	0.613 (0.891)
10 months after:treatment	2.776** (1.263)	1.227 (1.098)	1.343 (0.927)	1.078 (0.877)
11 months after:treatment	1.193 (0.968)	0.236 (1.120)	0.392 (0.956)	0.117 (0.915)
12 months after:treatment	1.751* (1.009)	0.393 (0.890)	0.755 (1.013)	0.231 (0.921)
13 months after:treatment	2.077* (1.121)	1.166 (1.069)	0.959 (0.993)	0.480 (0.877)
14 months after:treatment	1.993* (1.115)	1.019 (1.108)	0.787 (0.974)	0.388 (0.875)
15 months after:treatment	2.045* (1.134)	1.099 (1.102)	1.424 (0.988)	1.001 (0.893)
16 months after:treatment	2.323** (1.115)	1.250 (1.118)	0.921 (0.929)	0.599 (0.883)
17 months after:treatment	2.269* (1.263)	1.618 (1.090)	0.906 (0.937)	0.673 (0.890)
18 months after:treatment	2.578** (1.246)	1.297 (1.139)	0.822 (0.956)	0.562 (0.903)
19 months after:treatment	2.094 (1.324)	1.178 (1.089)	1.030 (0.975)	0.731 (0.915)
20 months after:treatment	2.222* (1.315)	1.486 (1.177)	1.148 (0.985)	0.763 (0.937)
21 months after:treatment	1.898 (1.273)	1.143 (1.118)	0.796 (0.994)	0.438 (0.938)
22 months after:treatment	1.311 (1.095)	0.608 (0.998)	0.512 (0.980)	0.188 (0.925)
Relative month fixed effects	Yes	Yes	Yes	Yes

(continued on next page)

Table B.2 (continued)

Dependent variable: Monthly electricity consumption (kWh)				
	(1)	(2)	(3)	(4)
	1-to-1 match	1-to-1 match	Kernel	Radius
	(PSM with wealth index PCA)	(PSM with individual elements)	matching	matching
Calendar month fixed effects	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
R <sup>2</sup>	0.68	0.71	0.70	0.70
Observations	20,318	20,287	51,011	51,011
Treatment sample	348	348	348	348
Control sample	342	342	1347	1347

Notes: \*\*\*, \*\*, and \* indicate statistical significance at 1%, 5%, and 10%. Robust standard errors, clustered at village level for 1-to-1 matching and bootstrapped for kernel and radius matching, are in parentheses.

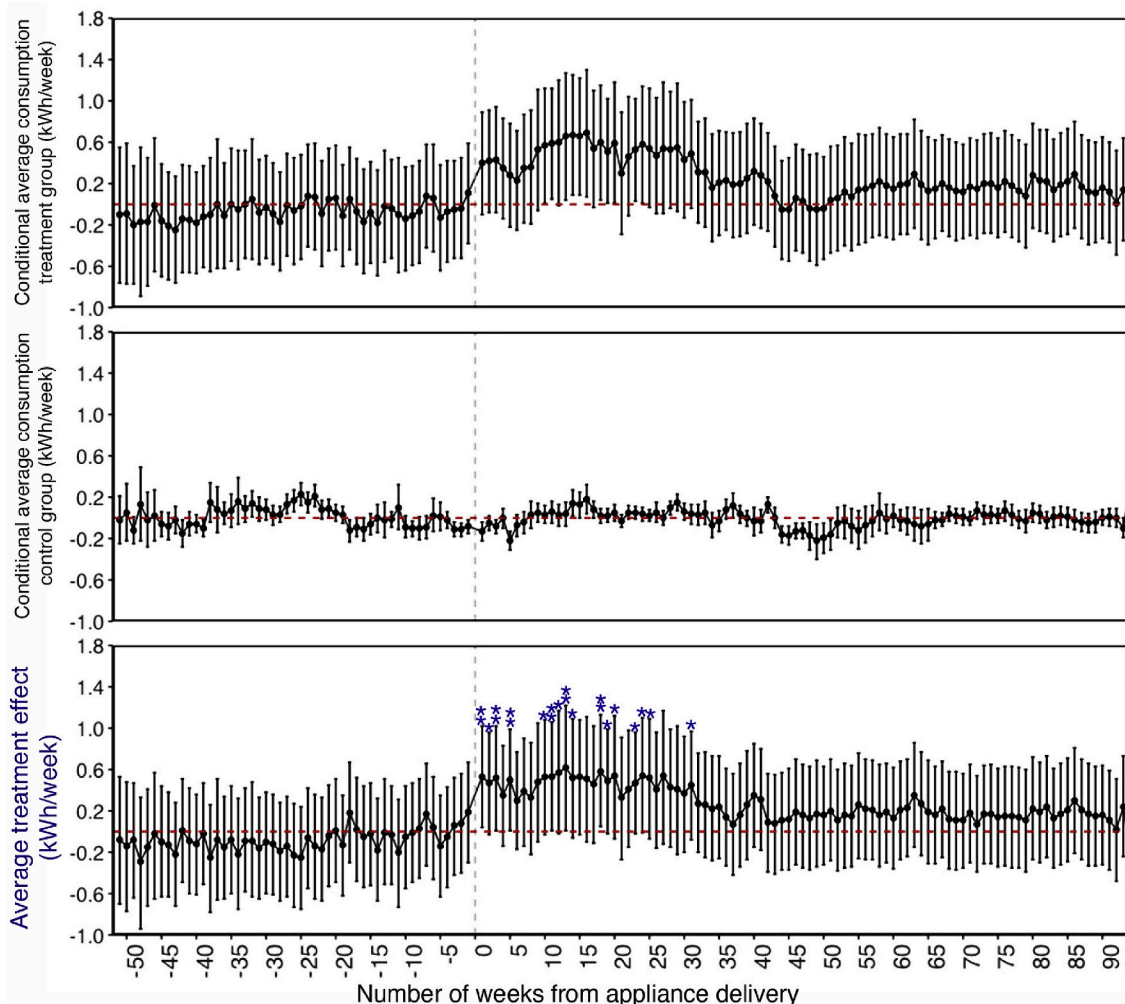
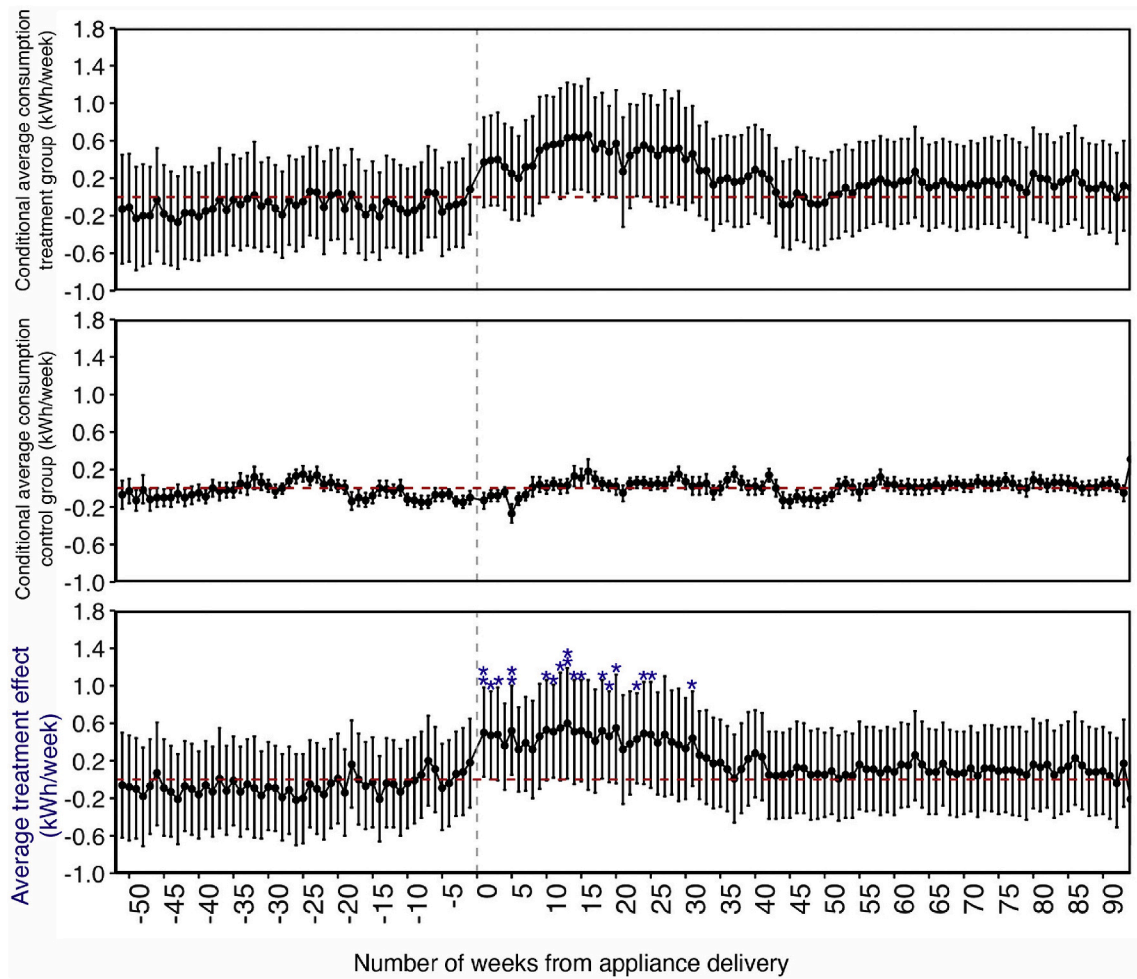


Fig. B.1. Average treatment effect of appliance financing program from kernel matching technique. Standard errors are bootstrapped; error bars represent a 95% confidence interval. Includes household fixed effects, calendar-month fixed effects, and relative week fixed effects. Note: \*p < 0.1; \*\*p < 0.05; \*\*\*p < 0.01.



**Fig. B.2.** Average treatment effect of appliance financing program from radius matching technique. Standard errors are bootstrapped; error bars represent a 95% confidence interval. Includes household fixed effects, calendar-month fixed effects, and relative week fixed effects. Note: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

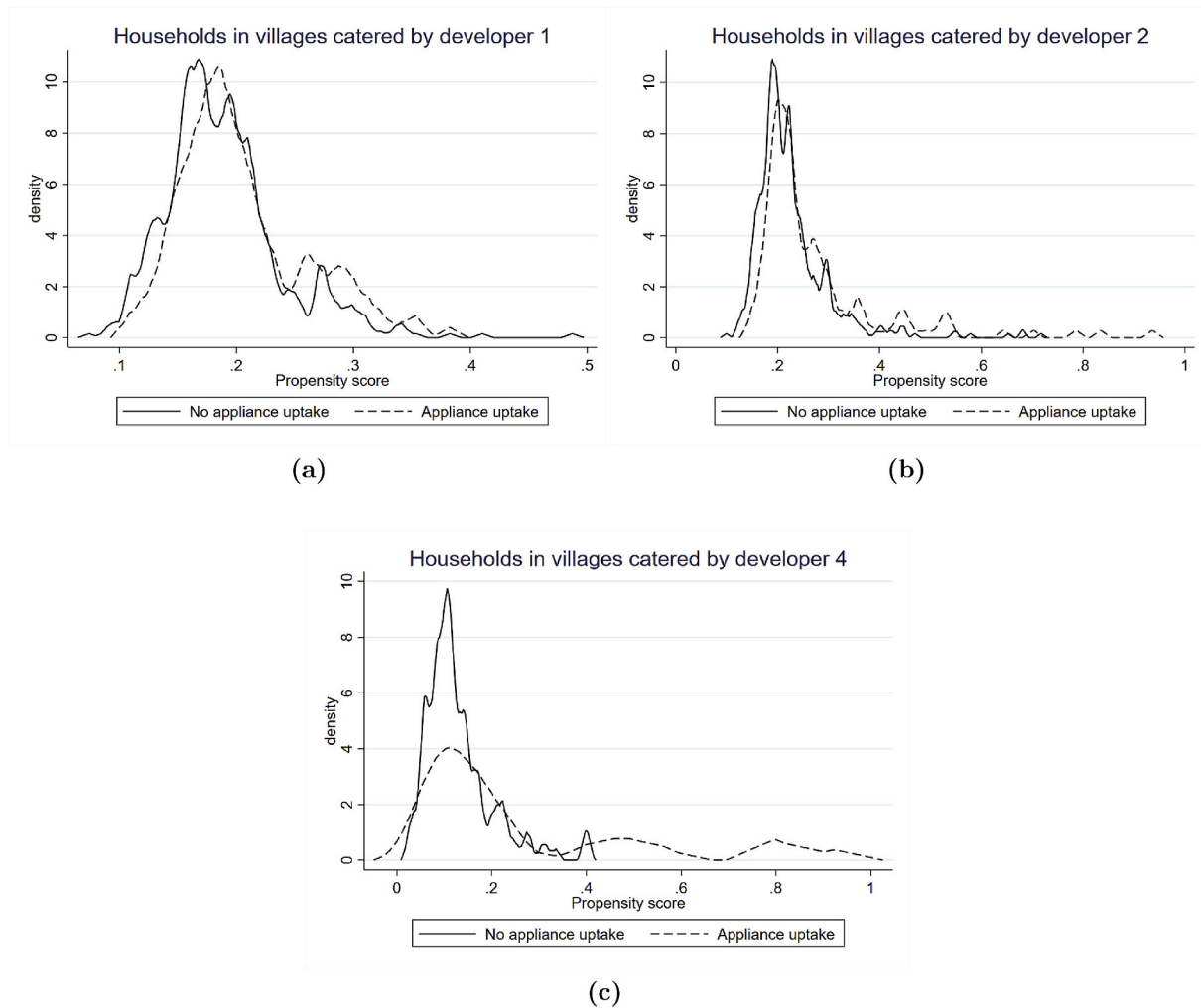


Fig. B.3. Propensity scores for households in treatment (appliance uptake) and matched control (no uptake) groups indicating domain of common support

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