Financial Inclusion and Rural Electrification: Evidence from Togo*

Paul Brimble ⓡ Toni Oki ⓡ Deivy Houeix ⓡ Axel Eizmendi Larrinaga†

(Click here for the most recent version)

December 17, 2024

Abstract

Most people in sub-Saharan Africa still lack access to electricity, despite rural electrification being a policy priority. We provide evidence that high transaction costs, particularly transportation expenses to access mobile money agents for bill payments, are a key friction for rural households. In rural Togo, these costs account for 28% of solar electricity-related expenditures, rising to 43% in more remote areas. To assess the impact of transaction costs on policy outcomes, we analyze the staggered rollout of two nationwide policies in Togo in 2019: a solar home system subsidy and an expansion of mobile money agents. The subsidy, which nearly halves electricity prices, more than doubles adoption rates. However, the effects vary significantly: households with lower transaction costs—those with direct access to mobile money agents—adopt at much higher rates and decrease the number of payments they make in response to the price reduction. The mobile money agent expansion led to nearly a threefold increase in adoption, an effect similar to that of the subsidy. By reducing transaction costs, these policies enable bulk purchases and lessen the need for frequent payments. Our findings highlight the complementary roles of subsidies and financial inclusion in improving rural electrification and access to essential services.

JEL Codes: O13, Q48, Q41, Q21, C23

*We are grateful to David Atkin, Steve Cicala, Esther Duflo, Amy Finkelstein, Rema Hanna, Kelsey Jack, Asim Khwaja, Cynthia Kinnan, Gabriel Kreindler, Ben Olken, Andrei Shleifer, Tavneet Suri, Dean Yang and Hoyt Bleakley for valuable suggestions. We also thank participants of the MIT, Harvard, Oxford, Michigan and Tufts seminars for constructive comments. Richard Kuessi provided exemplary research assistance and fieldwork support.

†Brimble: Department of Economics, University of Michigan; Oki: Department of Economics, Harvard University; Houeix: Department of Economics, MIT; Eizmendi Larrinaga: Department of Economics, Tufts University. The names appear in certified random order generated by the AEA author ordering tool.

1 Introduction

Nearly 800 million people still lack access to electricity, predominantly in rural areas of South Asia and sub-Saharan Africa (International Energy Agency, 2022). This situation has prompted significant investment in electrification from governments and development institutions. However, recent academic studies suggest that demand for electricity remains limited at current prices in lower-income rural areas (Lee et al., 2020b; Grimm et al., 2020; Burlig and Preonas, 2022). This disparity presents a potential puzzle: low estimated demand coincides with high public investment.

In this paper, we explore a key friction that may contribute to this puzzle and weaken policy effectiveness. We argue that rural households, often liquidity-constrained, face significant *transaction costs*—primarily transportation expenses to pay bills—which hinder their ability to afford services. Our analysis focuses on solar electrification, a recent and growing trend in global electrification efforts (Burgess et al., 2023; Lang, 2024b).

We examine two nationwide policies in Togo that target electricity costs in distinct ways—through price subsidization and transaction cost reduction—and present evidence that transaction costs are substantial, suppress electricity demand, and impede electrification efforts. In doing so, we examine whether and how policies targeting financial inclusion can complement electrification efforts. We conduct this study in rural Togo, where electricity access remains among the lowest globally (Government of Togo, 2016). We combine proprietary customer-level data from a large solar provider in Togo with government and survey data, and exploit the scattered rollout of two government policies implemented in 2019: a subsidy program for solar electricity and a major expansion of mobile money agents.

First, the "CIZO" policy, launched in early 2019, aims to achieve universal electricity access by 2030, with nearly half of newly electrified households using off-grid solutions. "CIZO" is one of the first demand-side subsidy programs for solar in Sub-Saharan Africa,[1] offering a uniform price subsidy ranging from 19% to 44% of the monthly cost, depending on the SHS kit.[2] The subsidy was phased in from March to June 2019 across three groups of districts, enabling an event-study analysis to causally measure the intention-to-treat (ITT) impact on adoption.

Second, the Togolese government, in partnership with the major mobile operators,

[1] Other African countries have subsidized Solar Home Systems (SHS), but have typically focused on the supply side by providing financing to service providers to reduce the cost of reaching low-income households (e.g., Fonds Mwinda in the DRC and Endev in Rwanda).

[2] The majority of rural customers select the entry-level kit, which saw a 44% price reduction and includes three light bulbs and a phone charger.

subsequently initiated a nationwide campaign to recruit and train mobile money agents in remote villages, called the "granular agent network" policy, rolled out in phases. This policy aims to enhance financial inclusion—still limited in Togo, as in many similar contexts (Suri, 2017)—by directly reducing transaction costs for households far from mobile money agents, thereby facilitating electricity payments. We interpret these two policies as targeting both the price of electricity and the transaction costs of making payments—two key factors that potentially influence electricity demand.

This study focuses on solar electrification, an increasingly prominent electrification method discussed in both policy and academic circles (Aklin et al., 2018; Abdullah and Jeanty, 2011; Grimm et al., 2020; World Bank, 2020; Burgess et al., 2023; Lang, 2024a). In Togo, as in most of Africa, the high costs of expanding the grid into rural areas limit electricity access. However, the declining cost of solar technology offers a viable alternative for electrifying rural households. By 2040, 70% of rural Africans gaining electricity are expected to do so via off-grid solutions (Africa Progress Panel, 2017).[3] Despite the affordability of solar, upfront SHS costs remain high for low-income families. "Pay-as-you-go" (PAYGO) technologies partly address this by allowing households to purchase SHS on credit with flexible repayments. After making an initial down-payment, customers continue to pay at a set daily rate until full ownership is achieved. The SHS serves as "digital collateral," enabling providers to remotely deactivate units if payments are missed (Gertler et al., 2024).

A crucial feature of PAYGO is that payments are typically made via mobile money. However, many rural residents primarily transact in cash and often must travel long distances—the median distance in our sample is 6.7km—to reach a mobile money agent. While PAYGO alleviates liquidity constraints, it introduces substantial transaction costs for those living far from agents. To quantify this fact, we collect survey data that reveals that transaction costs are massive and account for approximately 28% of the total cost of solar in rural Togo, rising to 43% in the most remote regions (75th percentile). This estimate likely understates the true transaction costs, as it only captures transportation expenses, excluding the cost of time. These billing costs are not unique to solar electricity; they also affect other essential services that operate under a PAYGO model, like water. They can significantly reduce demand by making frequent small payments financially burdensome, especially for households unable to save or access credit to make larger, less frequent purchases. This paper highlights how and why these transaction costs, com-

[3] For rural Togolese households without grid access, SHS is one of the few available options for electricity. In our data, more than 95% of SHS customers lacked electricity, prior to adoption, and used flashlights, kerosene, or lanterns for lighting. Less than 0.5% owned a generator before acquiring a SHS.

bined with liquidity constraints, pose major barriers to rural electrification.

We utilize data from three main sources to support this claim. First, we partnered with a leading SHS provider in Togo, with over 30,000 customers across more than 2,500 rural villages, covering a substantial portion of the country.[4] The company's data includes daily records of electricity consumption, comprehensive payment records, and customer characteristics. This detailed data helps us evaluate the subsidy's effects on both the extensive margin of gaining electricity access and the intensive margin of electricity consumption and payment behavior. Second, we collaborated with the Togolese government to obtain the GPS location and date of introduction of all mobile money agents in Togo. Third, we conducted surveys at various mobile money locations in rural Togo to measure transportation costs and quantify the transaction costs associated with travelling to pay for electricity.

We develop a simple conceptual framework to predict the impacts of price and transaction cost reductions on household adoption (extensive margin) and payment behavior (intensive margin). We predict that high transaction costs and liquidity constraints suppress electricity adoption by raising the income needed for households to afford SHS. Reducing electricity prices and transaction costs should therefore increase adoption, with price reductions being more effective in areas with lower transaction costs due to complementary effects. On the intensive margin, households using PAYGO face a choice between infrequent large payments (bulk purchases) and more frequent smaller payments incurring higher total transaction costs. Reductions in price unambiguously decrease payment frequency, while reductions in transaction costs have an ambiguous effect when households are liquidity constrained. Lowering transaction costs may increase payment frequency as each payment is less costly. However, it may also lead to fewer payments due to an income effect, as households become relatively wealthier, enabling bulk purchases and offset the need for frequent payments. Our framework shows that addressing both liquidity constraints and transaction costs can complement each other to enhance electrification efforts.

The main finding of this paper is that transaction costs play a critical role when liquidity constraints are present, highlighting the need for policy complementarity through simultaneous reductions in price and transaction costs. Throughout the analyses, we exploit the scattered rollout of the two policies across villages over time. We follow Sun and Abraham (2021) and implement the "interaction-weighted" event-study estimator, to estimate the dynamic intent-to-treat effects of the policies. We begin by showing that

[4]In 2016, these villages had a particularly low electrification rate, with only about 7% of rural households accessing any electricity source (Government of Togo, 2016).

the subsidy significantly boosted adoption: using the staggered rollout, we find that the adoption rate more than doubled with the 44% price reduction, with a 149% increase in applications. We then present four pieces of evidence to support and quantify the importance of financial inclusion in explaining this large effect.

First, we find that the subsidy's impact on extensive-margin adoption varies with baseline transaction costs. Villages with a mobile money agent saw a 190% increase in SHS applications in response to the subsidy, 37 percentage points higher than in villages without a mobile money agent. We use geospatial estimates of village wealth derived from phone-use and survey data to test the robustness of the results and confirm that baseline wealth disparities across areas do not drive the results. We further show that our results are not driven by differences in population density and subsidy access.

Second, we examine the subsidy's intensive margin effects on consumption and payment behavior among existing customers. The subsidy leads to an immediate and persistent 18% reduction in payment frequency, allowing customers to purchase electricity in bulk while maintaining their overall consumption. This shift towards consolidating payments underscores the critical role of transaction costs.

Third, we evaluate the impact of the policy expanding the mobile money agent network, rolled out after the subsidy's full launch. This expansion led to a 188% increase in new customers, a substantial increase coming after the subsidy rollout and comparable to the subsidy effect itself. Unlike the subsidy, impacts take time to materialize, peaking roughly 12 months after villages are treated. A back of the envelope calculation suggests that, by reducing transaction costs, the expansion policy lowers total electricity-related expenditures by 34%.

Fourth, we find no statistically significant effects on payment frequency. This last finding indicates that an income effect partially offsets any potential increase in the number of payments—resulting from lower transaction costs—by enabling households to purchase electricity in bulk.

Taken together, these findings highlight the importance of complementarity between price reductions and transaction cost reductions, particularly in settings with significant liquidity constraints. Addressing these market frictions together is key to increase demand for electricity and adoption rates. From a policy standpoint, simply reducing electricity prices may not suffice. Implementing a policy that reduces transaction costs, such as expanding the mobile money agent network, may be necessary for the subsidy's effectiveness.

This study engages with three distinct strands of the development literature. First, it extends the research on transaction costs and the broader role of financial inclusion in affecting economic outcomes and technology adoption in low-income countries (Burgess and Pande, 2005; Suri, 2011; Jack and Suri, 2014; Fink et al., 2020; Breza and Kinnan, 2021; Fonseca and Matray, 2022; Berkouwer et al., 2023). More broadly, this study provides empirical support to the idea that large-scale investments may fail to yield intended outcomes when transaction costs are overlooked (Devoto et al., 2012; Duflo, 2017). We use the context of solar electrification to show how financial inclusion, by lowering transaction costs—such as the distance to billing facilities—can improve economic outcomes by increasing access to essential services.

Second, the study contributes to literature on the demand for electricity in low-income rural areas. We provide a direct estimate of the demand for SHS in a different context, adding to recent papers finding limited demand for electricity (Lee et al., 2020b; Grimm et al., 2020; Burgess et al., 2023). We find higher demand when transaction costs and liquidity constraints are considered, highlighting the importance of addressing these frictions. This study demonstrates that the effectiveness of policies designed to increase adoption relies on complementary measures aimed at reducing key frictions, such as expanding the mobile money agent network.[5] Without addressing these frictions, the potential welfare impacts and effectiveness of electricity subsidies may be limited.[6]

Third, this paper contributes to the growing literature on pre-paid metering via the PAYGO model, a common approach for new electric connections in rural low-income areas (Gertler et al., 2024). We focus on off-grid solar solutions, complementing recent work that emphasizes grid connections (Lee et al., 2020a,b). While pre-paid metering has proven cost-effective in urban settings (Jack and Smith, 2020), evidence from rural areas with severe liquidity constraints and high transaction costs, like Togo, remains limited. Our analysis provides further evidence on the role that transaction costs play in adoption and consumption decisions in rural settings—see also Lang (2024b). We complement recent work by Lang (2024a), which highlights the adoption effects of the same subsidy policy. By leveraging two complementary policies in this context (subsidy and mobile money expansion), we instead focus on the role of transaction costs themselves in shaping both extensive and intensive electricity demand.

The remainder of the paper is organized as follows: Section 2 describes the setting and the policies. Section 3 presents our theoretical framework for the role of transaction

[5]Policy complementarities are plausible in many contexts. For instance, Moneke (2020) finds that simultaneous investments in road and electricity infrastructure have markedly different impacts on sectoral employment and income than separate investments.

[6]The welfare impacts of electricity access are mixed in the literature. Some studies indicate positive effects on economic outcomes like productivity (Rud, 2012), housing values (Lipscomb et al., 2013), labor supply (Dinkelman, 2011; van de Walle et al., 2017), and children's education (Khandker et al., 2013), while others find more limited and heterogeneous effects (Lee et al., 2020a; Burlig and Preonas, 2022).

costs in consumer demand. Section 4 details the data sources and empirical framework. Section 5 discusses the main empirical findings. Section 6 concludes with discussions on potential policy implications.

2 Study Background

2.1 Rural Electrification in Togo

Togo, with a population of 8.5 million and a GDP per capita of $2,200 (PPP, 2017), relies heavily on the agriculture sector, with agriculture employing the majority of the labor force and contributing to 29% of GDP. In 2015, over 50% of Togolese lived below the international poverty line of $1.90 per day. Financial inclusion remains low, with only 45% of adults holding accounts at financial institutions or mobile money providers in 2017, primarily in urban areas (World Bank Group, 2017). Moreover, 30% of the population still lacks access to a SIM card (GSMA, 2021).

While global electricity access has risen to 90%, access remains low in Sub-Saharan Africa, and Togo is no exception. Urban electrification has improved, with 45% of households connected, but rural areas remain starkly underserved, with just 7% electrified (Government of Togo, 2016). The high cost of grid electricity, driven by sparse populations and low consumption, has hindered rural electrification.

However, the recent rise of cost-effective off-grid solutions, particularly solar power, has changed the landscape. The cost of photovoltaic cells dropped from $2 per watt in 2010 to $0.19 in 2020, creating new opportunities to electrify rural areas. Some of the key differences between grid and off-grid electricity include: *(1) Flexibility.* Off-grid systems can be deployed quickly at the household or village level, unlike the slow and centralized grid expansion. *(2) Usage.* Off-grid solutions typically support low- to medium-power appliances, such as general lighting, phone charging, fans, whereas grid connections or larger solar setups are needed for high-power appliances and industrial use. *(3) Reliability.* Urban areas in Togo suffer frequent grid outages (Kpemoua, 2016), making off-grid solar more reliable, though it may still be expensive for poor rural households reliant on subsistence farming and lacking formal credit access.[7] While off-grid solar presents a flexible and potentially more reliable alternative, its affordability remains a challenge for the rural poor, typically engaging in subsistence farming and without access to formal credit.

[7]Shortages may still happen with solar solutions in areas experiencing consecutive heavy rainy days, especially for medium-power appliances.

2.2 PAYGO Solar Home Systems

This limited access to electricity has spurred the development of PAYGO solar home systems (SHS) by private companies, enabling rural households to purchase SHS on credit. These systems require a modest upfront downpayment, followed by recurring payments that better align with the irregular income profiles of rural households.

Customers select a solar home system bundled with high-efficiency appliances such as light bulbs, rechargeable radios, flashlights, phone chargers and TVs. The cost of the bundle depends on the number of devices and the size of the solar panel. After selecting a bundle, customers make a downpayment, which secures the installation of solar panels, a battery for electricity storage, and the chosen appliances in their home. This initial payment also serves as a screening mechanism to exclude the households who may not be able to meet the full payment. Customers then "pay-as-they-go" until they reach the bundle's total price, typically equivalent to three years of continuous usage in this setting. The daily rate for solar access varies based on the number of appliances included in the bundle. This study uses data from a large SHS provider in Togo, which offers three bundles:

1. *Basic kit*: Includes a small solar panel, three light bulbs, and a phone charger. Downpayment (including 30 days of electricity): 8,960 CFA (around $15). Subsequent daily rate: 160 CFA ($0.27) or $8 per month, with USD 1 = CFA 600.

2. *Plus kit*: Includes the Basic kit plus a radio. Downpayment (including 30 days of electricity): 12,320 CFA ($20.5) and $11 per month.

3. *Premium kit*: Includes the Plus kit plus a TV. Downpayment (including 30 days of electricity): 21,000 CFA ($35) and $ 19 per month.

Unlike most grid electricity payment systems, the PAYGO model allows customers flexibility in when and how much they pay over time. Customers purchase electricity in daily units, gaining unlimited access to their SHS for the duration purchased. If access time expires, the solar company can remotely lock the SHS, preventing further use until additional days are purchased—a form of "digital collateral" (Gertler et al., 2024). While there is some flexibility in payment timing, customers who do not make payments for over sixty consecutive days are considered "in default," and the solar company may repossess the SHS after 120 days of inactivity. The combination of remote lockout and the credible threat of repossession makes PAYGO contracts enforceable, even in settings with weak institutions, as observed in similar systems in Rwanda (Lang, 2024b).

2.3 High Transaction Costs Inherent to Electricity Payments

Customers must pre-pay for electricity access time using their mobile phones via "mobile money." However, most rural Togolese households typically transact and earn income in cash, and therefore must travel to a mobile money agent in order to deposit cash into their accounts.[8] Figure A1 plots the distribution of customers' distance to the nearest mobile money agent before the subsidy and highlights that this distance is often substantial, with a median of 5.6 km. The distance is even larger, 6.7km, when we consider the entire universe of villages in our data, including those that had no customers (Figure A2). This distance creates a significant transaction cost in the electricity payment process, particularly for households that both live far away from agents and must make frequent payments due to liquidity constraints, preventing them from saving or buying in bulk.

The survey data we collected reveals that transaction costs are massive and account for approximately 28% of the total cost of electricity in rural Togo, rising to 43% in the most remote regions (75th percentile). This estimate only includes transportation costs, suggesting it likely underestimates the true transaction costs.[9]

2.4 Policy 1: Nationwide Subsidy

In 2019, the Government of Togo launched the CIZO policy, meaning "light up" in Mina, one of the Togolese languages, with the goal of achieving universal access to electricity by 2030. This policy combines both grid extension and off-grid technologies to achieve electrification in the most cost-effective way, with nearly 50% of additional households expected to be connected through off-grid solutions. Specifically, the government's goal was to install SHS for 550,000 rural households. Off-grid companies began operating in Togo only in 2017, and to further boost off-grid adoption, the government introduced a nationwide public subsidy for SHS. The subsidy was rolled out over six months, reaching three different groups of districts at three different times, which we exploit in the analysis as described further in Section 4.2.1.

While other African countries have also subsidized SHS, these efforts typically focus on the supply side by providing financial support to service providers to reduce the cost

[8] In Rwanda, Lang (2024b) finds that most PAYGO customers visit a mobile money agent for every solar payment, rather than saving money in their mobile wallets. We assume a similar pattern in rural Togo, a comparable context.

[9] To obtain these estimates, we first calculate the total distance covered to make payments each month. We multiply the median customer distance to the nearest mobile money agent prior to subsidy launch, by the average number of payments customers make each month, times two (to account for the round trip). We then multiply this total travel distance by the median price per km for hiring a moto taxi, which we measure in our survey of transport costs in rural villages (section 4).

of reaching low-income households, structured as results-based financing (e.g., Fonds Mwinda in the DRC and Endev in Rwanda). The Togolese program is distinct as it offers an untargeted demand-side subsidy, the first of its kind in Africa to our knowledge. This subsidy consists of a uniform price reduction of CFA 70 per day, regardless of the bundle chosen (approximately $0.12 per day of electricity purchased, or roughly $3.5 per month), which equates to about a 45% reduction in the cost of a "basic" kit.

Practically, the subsidy works as follows: (i) customers still make an initial downpayment, including the first month's electricity (this is not subsidized by the policy), and (ii) for subsequent months, customers pay $3.5 less than their monthly rate to access a full month of electricity. For instance, with the "basic" kit, the subsidy reduces the monthly cost from around $8 to about $4.5, a 44% price reduction. For customers with higher-tier plans, the subsidy results in a 32% reduction (from around $12 to about $8 per month) for the "plus" kit and a 19% reduction (from around $20 to about $16 per month) for the "premium" kit. Given Togo's 2019 monthly GDP per capita of $57, this subsidy represents a significant portion of rural households' income. The subsidy is proportional to the amount paid by customers, with the government matching electricity purchases up to $3.5 per month. Customers who make no payments or default on the product do not receive the subsidy.

Eligibility and Subsidy Outreach Conditional on payment, all rural households who used PAYGO SHS were technically eligible for the subsidy. The evidence suggests, however, that not all customers actually received the subsidy. One of the reasons for this is that the government required SHS payments to be made through a personal mobile money account that was linked to the customer's solar account. This was designed to ease implementation and encourage digital financial inclusion in rural areas. In reality, however, it limited subsidy outreach, especially in the first few months (Figure A3), due to technical issues with sharing account numbers between the government agency and telecommunication private companies. We take this into account in our empirical strategy, described further in Section 4.

2.5 Policy 2: Mobile Money Agent Expansion

In August 2019, the Togolese government partnered with the Post Office to launch a large-scale campaign to recruit and train mobile money agents, deploying them across over 200 villages nationwide. This initiative was part of a broader effort to boost financial inclusion. The expansion was not based on a predetermined pattern; instead, local Post

Office supervisors were given discretion to identify villages lacking mobile money access and include them in the rollout.

We take advantage of this discretionary process in our empirical strategy (see Section 4) and leverage this unique and rapid expansion to study the impact of mobile money agent access, as well as the complementarity between subsidies and the mobile money agent rollout. In total, about 101 villages received their first mobile money agent through this campaign at different times between September 2019 and December 2021. Crucially, the agent expansion stopped in April 2020 with the onset of COVID, and resumed at the start of 2021. Figure A4 illustrates the sharp increase in the number of villages gaining access to a mobile money agent due to the expansion campaign. Figure A5 maps the spatial distribution of villages that received agents.[10]

3 Conceptual Framework: Impact of Transaction Costs on Electrification

This section provides a theoretical framework to formulate predictions about how transaction costs and liquidity constraints affect the adoption of Solar Home Systems (SHS) and the frequency of electricity payments. See Appendix C for the derivations and further details.

3.1 Setup

The framework considers households that receive income over two periods and decide whether to adopt SHS based on the household's income, the price of electricity, and the fixed transaction costs per payment.

Households choose the optimal payment plan to maximize their utility from electricity consumption. They decide how much to consume and how many days of electricity to buy, considering their income and assets. They face a choice: buy electricity in bulk with one payment or spread payments across two periods, influenced by the cost of each transaction and their income.

[10] We use a 3km distance of the mobile money agent to the village center as a reasonable distance within which an individual might choose to walk to reach a mobile money agent, without incurring monetary costs.

3.2 Adoption

Households adopt SHS if they have enough income to cover the cost of electricity over the two periods. Without liquidity constraints, households can borrow against future income, making adoption easier. However, if households are liquidity-constrained and cannot borrow, they must have enough income in the first period to cover at least one day of electricity.

The level of adoption depends on the proportion of households that meet this income requirement at baseline. Adoption is lower with liquidity constraints since some households cannot afford the upfront cost. Reducing the price of electricity or the transaction costs increases adoption, especially in areas where transaction costs are already low, as more households can then afford the SHS.

3.3 Frequency of Payments for Electricity

Without Liquidity Constraints In the absence of liquidity constraints, households aim to smooth their consumption over time. They decide whether to buy electricity in bulk or spread payments based on the costs. If the money saved from making fewer payments is greater than the transaction cost, they will choose to buy in bulk. Therefore, reducing electricity prices leads to fewer payments, while reducing transaction costs encourages spreading payments over time.

With Liquidity Constraints When households are liquidity-constrained and cannot borrow against future income, their payment decisions are more complex. Households with higher liquidity constraints must spread payments as they can't afford the bulk purchase upfront. For those who can afford bulk payments, they face a tradeoff between having non-smooth consumption and incurring transaction costs.

Price reductions generally lower the number of payments by alleviating income constraints. Reducing transaction costs, however, has an ambiguous effect: it can make it cheaper to spread payments but also allows more households to afford bulk payments (income effect).

3.4 Framework Predictions

The framework helps formulate the following predictions (as outlined in Appendix C):

1. Price reductions increase adoption.

2. Transaction cost reductions increase adoption.

3. There are complementary adoption effects of reducing price and transaction costs: price reductions in villages with low transaction costs should have higher effects on adoption than in villages with high transaction costs.

4. Price reductions decrease payment frequency.

5. Transaction cost reductions have an ambiguous effect on payment frequency.

For Prediction 5, transaction cost reductions have ambiguous effects on payment frequency because while lower transaction costs have a direct impact increasing the number of payments as each payment is less costly, the income effect—as households are relatively wealthier due to incurring lower transaction costs—may enable households to optimally make larger, less frequent payments.

This framework illustrates the nuanced interactions between transaction costs, liquidity constraints, and household behavior in adopting SHS and deciding on the frequency of electricity payments. It can be easily extended to other bill payments, such as grid, water, which often involves payment at a particular place.

4 Data and Empirical Specifications

In this section, we describe our data and lay out the core empirical specifications used for our analysis.

4.1 Data, Outcomes of Interest, and Variable Construction

PAYGO Customer Data We utilize data from two primary sources. First, we obtain household-level administrative data on customer payments from a leading provider of off-grid solar home systems (SHS) in rural Togo. This data includes transaction-level details on customer behavior and household-level registration information, such as household characteristics and previous energy sources. Second, we have detailed subsidy data provided by the Government of Togo.

The company data covers approximately 53,000 households across 2,600 villages up to December 2021. During the study period, there were two major off-grid solar companies in Togo, with the second covering around 5,000 households. Given the similar products and pricing structures, we believe the data is reasonably representative of the SHS population in Togo. Table A1 presents descriptive statistics for households in February 2019 (before the subsidy launch) and May 2020 (about a year after the launch). At baseline, the average household head was 41 years old; 78% worked in agriculture, 10% owned a business, and 11% were employees. Before adopting SHS, 53% of households used kerosene, lanterns, or had no access to energy, while 44% relied on flashlights. Fewer than 2% had access to electricity through the grid, a generator, or solar energy.

From the transaction-level data, we constructed several variables to track electricity usage over time. Table A1 details the bundle choices customers made at registration. They chose between three options: (i) the basic kit (a small solar panel with three light bulbs and a phone charger), (ii) the intermediary kit (basic kit plus a radio), and (iii) the premium kit (intermediary kit plus a TV). Conceptually, we consider that households first decide whether or not to adopt the solar panel at the proposed basic kit's price. After making this decision, they add additional items at their convenience like a radio or TV, increasing the overall price. The share of households selecting the basic kit increased from 32% at baseline to 46% in May 2020.

We measured the number of payments made each month, the average payment size, and how these payments translated into electricity consumption, as indicated by the utilization rate. A 100% utilization rate means the customer purchased electricity for every day of the month. While there is some variation across customers, the average utilization rate was 72% at baseline and 74% at endline. Most customers in our estimating sample had electricity for most of the month, with an average of 27 days and a notable mode of 30 days (Figure A6). Figure A7 shows the distribution of monthly payments in the four months before the subsidy rollout. On average, households made 1.63 payments per month, with significant variance. Notably, 51% of the sample made one payment per month on average, suggesting they bought in bulk, while the rest made two or more payments per month.

Finally, we match the subsidy data to the company's records using customers' phone numbers and transaction dates. Due to the complex matching process, subsidy outreach was limited, as detailed in Section 2.4.

Mobile Money Agent Location Data We use data from the Ministry of the Digital Economy and Digital Transformation in Togo, which detail the longitude and latitude of all mobile money agents in the country from 2010 to 2024, on a monthly or yearly basis. This data is instrumental to assess how the effects of the subsidy vary based on the distance to a mobile money agent before the subsidy rollout.

Additionally, we obtain data on the large-scale mobile money agent expansion program implemented by the Togolese government and the Post Office, as detailed in Section

2.5. This includes the names, coordinates, and introduction dates of villages where new agents were established.

Transport Costs Data Rural residents, including SHS customers, frequently rely on motorbike taxis to reach nearby villages when walking is too time-consuming. To estimate the cost of traveling to the nearest mobile money agent for electricity payments, we collected transport data from moto-taxi drivers in 34 rural villages across Togo's five regions. For each village, we recorded the price, distance, and travel time to multiple nearby villages, resulting in 126 origin-destination observations. This data helps us quantify the monetary savings from consolidating electricity payments into fewer transactions, thereby reducing the number of trips to a mobile money agent. Since we collected this data in 2023, we deflate prices to 2019, the period of analysis.

Wealth Data To estimate wealth levels across Togo, we use data from Meta's Relative Wealth Index, a global geospatial database developed by Chi et al. (2022). This index combines household survey data with non-traditional sources like satellite imagery, cellular network data, topographic maps, and privacy-protected Facebook connectivity data. Machine learning algorithms predict relative wealth at a fine resolution of 2.4 km^2. Importantly, this data captures *relative* wealth within each country, enabling us to compare wealth across villages in Togo and distinguish between wealth and transaction costs. Since not every village directly corresponds to a wealth cell, we calculate the average wealth score for all cells within a 5 km radius of each village (Figure A8).

4.2 Estimation and Causal Inference

4.2.1 Event-Study Analysis of Subsidy Policy

The subsidy policy was announced in February 2019 and rolled out over six months, reaching different groups of districts at three different times (see Figure 1). This scattered rollout provides natural variation to evaluate the initial impact of the policy. The timeline for the phased rollout is as follows:

- *Group 1*: Early March 2019: Subsidy begins in 11 districts.
- *Group 2*: Early May 2019: Subsidy begins in an additional 13 districts.
- *Group 3*: Early July 2019: Subsidy begins in the final 12 districts.

The Government of Togo first proceeded to pilot the policy in specific districts with the lowest electrification rates (0-10%), then districts with 11-20% and finally with districts with 21-40%, based on data from 2016. Table A2 shows increasing baseline electrification rates across the three groups of districts, according to the 2016 government data.[11] Since the 2016 data was outdated by 2019, arbitrary considerations played a role in determining when each district received the subsidy, with the coordinator choosing some districts to receive the subsidy later, as they supposedly had greater access to the grid in 2019.

To estimate the policy's causal effect using this variation, we first test for pre-trends (see in later sections) and examine a baseline balance table of household characteristics and electricity behavior (see Table A3). Overall, the three district groups show limited baseline differences in terms of characteristics of pre-subsidy customers. While there are slight variations in income sources—Group 3 customers are less likely to work in agriculture (67%) and more likely to own a business (16%) compared to Groups 1 and 2—there are no major differences in previous energy sources, with low electricity access common across all groups. Pre-subsidy electricity behavior is also similar, though Group 3 customers are more likely to choose the premium kit and make a slightly higher number of payments.

We use an event-study design that exploits this staggered subsidy rollout to estimate the intention-to-treat (ITT) effects of subsidy eligibility. In our setting, pre-subsidy electrification levels differ across treatment cohorts, which could lead to treatment effect heterogeneity. A recent literature has highlighted various issues that arise with two-way fixed effects (TWFE) models in the presence of treatment effect heterogeneity across time and cohorts (Borusyak et al., 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021).[12] To address these potential issues, we follow Sun and Abraham (2021) and estimate dynamic ITT effects using their interaction-weighted (IW) estimator, which is robust to both treatment effect heterogeneity across cohorts and cross-lag contamination.

Extensive Margin Analysis

We begin by estimating the effect of subsidy eligibility on *SHS adoption* at the village level using the following specification:

[11] Since the data was provided in ranges, the midpoint of each range is used to calculate district averages. All districts in Group 1 are in the 0-10% range, hence there is a 5% mean with no standard deviation.

[12] In particular, Sun and Abraham (2021) shows that in a staggered treatment setting, where different groups become treated at different times, estimating dynamic treatment effects with a simple TWFE model has two problems. First, it can put negative weight on post-treatment treatment effects for some units. Second, the coefficient on a given lead or lag can be contaminated by effects from other periods, and observed pre-trends may result from treatment effect heterogeneity alone.

$$Y_{dt} = \lambda_t + \theta_v + \sum_{e \in \{1,2\}} \sum_{l=-3, \neq -1}^{3} \beta_e^l \mathbb{1}\{Sub_{vd} = e\} \cdot D_{vdt}^l + \epsilon_{vdt}. \tag{1}$$

Here, Y_{dt} represents the number of prospective customers who applied to purchase SHS in village v, located in district d, during month t. We focus on applicants rather than actual new customers to control for changes in supply of SHS panels. λ_t and θ_v are month and village fixed effects, respectively. $\mathbb{1}\{Sub_{vd} = e\}$ are dummy variables for whether village v in district d belongs to the first or second subsidy rollout cohort e (i.e., districts that became eligible in March and May, respectively). Following Sun and Abraham (2021), villages in the last set of districts to become eligible (Group 3) serve as the "last treated" control group. Lastly, $D_{vdt}^l = \mathbb{1}(t - Sub_{vdt} = l)$ are relative time indicators showing the number of periods l since village v became eligible for the subsidy at month t.[13] We cluster standard errors at the village level.

The parameters of interest are $\hat{\beta}^l = \sum_{e \in \{1,2\}} \omega_e^l \hat{\beta}_e^l$, with weights ω representing the sample shares of each cohort in the relevant periods. For $l \geq 0$, $\hat{\beta}^l$ captures the impact of the subsidy each month after its implementation as a weighted average of cohort-specific treatment effects. To obtain a "static" average ITT effect and associated standard error, we follow Sun and Abraham (2021) and take the average of the dynamic effects. Specifically, we test the null hypothesis that the following linear combination of coefficients equals zero:

$$H_0 : \frac{\sum_{l=0}^{3} \hat{\beta}^l}{4} = 0 \tag{2}$$

Our identification strategy relies on two key assumptions. First, the parallel trends assumption, which requires that, in the absence of the subsidy, the difference between the adoption rate of "treated" and "control" villages would have been constant over time (Angrist and Pischke, 2008). Second, we assume that the subsidy event was unpredictable or that, at the very least, there was no anticipatory behavior.[14]

Customer-Level Intensive Margin Analysis

To analyze how customers respond to the subsidy at the intensive margin—in terms of

[13] We exclude the pre-period $l = -1$ as is standard practice. We include three post-treatment periods, as all districts were eligible by July 2019, making it impossible to estimate treatment effects beyond this point.

[14] The linear trend in l is not identified with a scattered policy rollout. This issue arises because we cannot distinguish between a pure calendar fixed effect with an absence of causal effects versus actual causal effects combined with anticipation of treatment. However, we restrict the pre-trends in the specification, while keeping district fixed effects to still observe potential non-linear pre-trends.

payment frequency, average payment size, and electricity usage—we estimate a similar model to Equation (1) at the customer level:

$$Y_{idt} = \lambda_t + \eta_i + \sum_{e \in \{1,2\}} \sum_{l=-4, \neq -1}^{3} \beta_e^l \mathbb{1}\{Sub_{id} = e\} \cdot D_{idt}^l + \epsilon_{idt}, \tag{3}$$

where instead of village fixed effects θ_d we now have customer fixed effects η_i. We cluster standard errors at the customer level. Additionally, we impose two sample restrictions. First, to have a balanced panel across pre- and post-subsidy periods, we restrict the sample to customers who had adopted an SHS by November 2018, a few months before the subsidy became available. Second, we limit our analysis to customers who received the subsidy at least once by December 2019, five months after the staggered subsidy rollout reached all districts.[15] This yields a sample of 3,423 customers. To obtain the static average effect we follow the same procedure as with the village-level analysis, where we average the dynamic effects.

4.2.2 Heterogeneous Treatment Effects

To quantify the role of transaction costs in SHS adoption and payment decisions, we estimate the heterogeneous effects of the subsidy based on the level of pre-subsidy access to a mobile money agent. Using the mobile money agent location data described in Section 4.1, we calculate the distance of each village to the nearest mobile money agent in December 2018, three months before the subsidy was rolled out.[16] Rural Togolese villages are often sparsely populated, with households sometimes located several kilometers from the village centroid. For this reason, we define a village as having a mobile money agent if the distance between the centroid and the nearest agent is less than 3km. We check the robustness of our results to various distance cutoffs.

To estimate heterogeneous treatment effects on SHS adoption, we follow Sun and Abraham (2021) and adapt equation 1. Instead of having one single set of relative-time indicators, D_{vdt}^l, we now have two sets of indicators: one for villages with a mobile money agent ($M_v = 1$) an another for villages without an agent ($M_v = 0$):

[15] Given the limited subsidy outreach, we impose this restriction to ensure that our results are more representative of the population of customers who received the subsidy within a reasonable time frame after becoming eligible, even if not during the evaluation period.

[16] Say something about how we calculate it?

$$Y_{idt} = \lambda_l + \eta_v + \sum_{e \in \{1,2\}} \sum_{l=-3, l \neq -1}^{3} \beta^l_{e,0} \cdot 1\{Sub_{vd} = e\} \cdot D^l_{vdt} \cdot (1 - M_v) + \beta^l_{e,1} \cdot 1\{Sub_{vd} = e\} \cdot D^l_{vdt} \cdot M_v + \epsilon_{vdt} \tag{4}$$

The dynamic ITT effect for villages with and without a mobile money agent is captured by the parameters $\beta^l_{e,1}$ and $\beta^l_{e,0}$, respectively.[17] To estimate the differential effect of the subsidy by agent access, we test the null hypothesis of the following linear combination:

$$H_0 : \frac{\sum_{l=0}^{3} \hat{\beta}^l_1}{4} - \frac{\sum_{l=0}^{3} \hat{\beta}^l_0}{4} = 0 \tag{5}$$

Finally, we extend this analysis to examine payment frequency, average payment size, and electricity usage at the customer level, replacing village fixed effects with customer fixed effects and applying the same sample restrictions as in the event study (Section 4.2.1).

4.2.3 Event Study Analysis of Mobile Money Agent Expansion

We leverage the expansion of mobile money agents throughout the country, as outlined in Section 2.5, to estimate the causal effect of reduced transaction costs using an event-study design. Figure A4 shows that 101 villages without any previous mobile money agents received an agent at different times between September 2019 and December 2021. Crucially, the agent expansion stopped in March 2020 with the onset of COVID, and resumed in January 2021. Our event-study design exploits this abrupt halt in agent expansion, and compares villages that received an agent between September 2019 and April 2020 to villages that received one in 2021 (the "last-treated group"). The analysis period is thus September 2019 to December 2020.

Our analysis proceeds as follows. First, given our interest in estimating the impact of a reduction in transaction costs, we restrict the sample to villages that did not have an agent prior to receiving one through the expansion policy. Second, we conduct the analysis at the bimonthly instead of the monthly level for two reasons. First, the information we have are approximate months of agent arrivals. Second, our sample size is considerably smaller than for the subsidy analysis, thus aggregating outcomes to the bimonthly level smooths the data and reduces noise.

[17] As in equation 1, these are the weighted averages of cohort-specific treatment effects: $\beta^l_{e,1} = \sum_{e \in \{1,2\}} \omega^l_{e,1} \beta^{\hat{l}}_{e,1}$ and $\beta^l_{e,0} = \sum_{e \in \{1,2\}} \omega^l_{e,0} \beta^{\hat{l}}_{e,0}$.

We define a village as being treated by the expansion policy when an agent is introduced within a 3km radius. The staggered expansion generates five treatment cohorts that are treated at different bimonths; September 2019, November 2019, January 2020, March 2020 and January 2021. As with the analysis of the subsidy's impact, we exploit this phased rollout to implement Sun and Abraham (2021)'s IW estimator, where villages treated in 2019-2020 are the treated cohorts, and the villages treated in 2021 are the control group.

We estimate impacts on SHS adoption through the following equation:

$$Y_{vt} = \lambda_t + \phi_v + \sum_{e \in [1,4]} \sum_{l=-4, \neq -1}^{4} \beta_e^l \mathbb{1}\{Agent_v = e\} \cdot A_{vt}^l + \epsilon_{vt}, \tag{6}$$

where Y_{vt} is the number of SHS applications in village v in bimonth t, λ_t and ϕ_v are time and village fixed effects, respectively, and $\mathbb{1}\{Agent_v = e\}$ are dummy variables for village v belonging to treatment cohort e, where a cohort is defined by the bimonth in which it was first treated. Lastly, M_{vt}^l are relative-time indicators for village v to be l periods away from initial treatment. The parameters of interest are $\hat{\beta}^l = \sum_{e \in [1,5]} \omega_e^l \hat{\beta}_e^l$, with weights ω denoting the sample shares of each cohort in the relevant periods. To obtain a single static average effect and associated standard error, we follow the same approach as with the subsidy and test the null hypothesis that the average of the dynamic effects is equal to zero (Equation 2).

We also study intensive margin impacts on payment and consumption behavior by estimating an analogous equation at the customer level. We impose a balanced panel by restricting the sample to customers that had joined prior to January 2019, several months before the agent expansion policy.

5 The Role of Transaction Costs in Demand Estimates and Policy Impacts

5.1 The Impact of the Subsidy on Adoption

In this section, we analyze the phased rollout of the subsidy across districts to estimate its causal impact on solar adoption.

We first plot the evolution of solar adoption separately for each of the three district groups in Figure A9. We observe two key points: (1) the adoption rate increased dramatically in the short term, with new customer adoption rising by an average of 127% in the three months following the subsidy launch, and (2) there is no clear evidence that households in Groups 2 and 3 anticipated the subsidy in their districts. However, this graph does not allow us to directly distinguish between subsidy and time effects, as demand appears to be increasing over time in all three district groups before the subsidy.

To address this, we test Prediction 1 by estimating the causal impact of the subsidy. Figure 2 shows the β^l estimates from regression Equation (1), where the outcome variable is the number of monthly SHS applications per village. Overall, the adoption results are consistent with the predictions of our framework outlined in Section C.2. We find that the subsidy significantly increased adoption, leading to approximately 0.2 and 0.4 additional monthly applications in the first two months respectively, peaking at 0.6 additional applications in the third month. Table 1 shows that the average effect is 0.415 and is statistically significant at the 1% level. Given that the average pre-subsidy number of monthly applications in the control group was 0.249, these effects represent more than a doubling of adoption in the first four months, with an average increase of 167%. The statistically insignificant β^l estimates for the pre-subsidy periods suggest no pre-trends; the joint test that all pre-trends are different from 0 yields a p-value of 0.205. These findings are in line with those of Lang (2024a), which uses similar data.

Robustness and Confounders We then perform a series of robustness checks to rule out potential confounders: supply-side factors and information effects. First, we address the possibility of supply-side factors that may have differentially influenced adoption during the subsidy period. For example, the notion that increased adoption could be due to greater attention from the solar company on villages eligible for the subsidy compared to the control group. We present three arguments against this hypothesis. First, the solar company relies on local shops (approximately one shop per district), which are responsible for supplying their respective areas and operate independently. We observe no reduction in supply in control districts during the subsidy rollout, suggesting no reallocation of resources. Second, discussions with the solar company indicate that the observed impact is driven by increased demand, not by increased sales attention to the subsidy villages. Third, our adoption measure is based on the number of applicants, not connected customers. While supply issues might affect the number of connected customers, leading to installation delays, they are less likely to influence the number of applicants. Our results are consistent across both measures, and the lack of significant discrepancies between them suggests that supply-side effects are minimal.

Second, we address concerns that the increase in adoption might be driven by greater awareness of the SHS product rather than the price reduction itself. Information barriers are particularly relevant when assessing policy impacts, especially in rural areas of low-income countries where knowledge of new technologies is often limited. To investigate this, we collected detailed marketing campaign data from the solar company over time (bi-monthly) at the shop level. We found no significant increase in information campaigns during the subsidy launch; if anything, the number of campaigns decreased everywhere during the subsidy launch. We further discuss this issue in Appendix Section D where we explore the role of marketing campaigns and show that they do not appear to drive our results. However, this is one type of information campaign, and we cannot fully rule out the information channel potentially coming from public officials, which might have targeted treated areas first.

5.2 The Role of Transaction Costs in Adoption Decisions

To provide initial evidence that transaction costs significantly influence demand estimates and policy effectiveness, we investigate whether the impact of the subsidy on adoption varies depending on access to mobile money agents. As previously mentioned, payments for electricity must be made through a mobile money account. Given that rural customers predominantly transact in physical cash, mobile money agents play a crucial role in facilitating these payments. Consequently, customers in villages farther from an agent face higher transaction costs when paying their bills.

Prediction 3 states that the subsidy will have a greater impact on adoption in areas with lower transaction costs, as the affordability threshold for adoption is lower in these areas. We test this prediction by running the heterogeneous treatment effects specification specified in Equation 4. Table 1 shows that the adoption rate increases significantly more in villages with a mobile money agent relative to those without an agent. There was an increase in the number of monthly applications of 1.09 relative to 0.38 and this difference is statistically significant at the 5% level. Figure 3 shows how these differences increase over time, with no evidence of any significant pre-trends.

Robustness and Confounders We then perform a series of robustness checks to rule out potential confounders that might be associated with mobile money access: wealth, population density and differential subsidy access. Mobile money agents might be expected to be more prevalent in villages that are wealthier, more densely populated and with more customers successfully receiving the subsidy, all of which could be driving the heterogeneous treatment effects from Table 1. Wealth is a potential confounder as only relatively wealthy households can afford a SHS. Population density might matter as information about the SHS or the subsidy might spread more effectively in densely populated areas due to social learning or more targeted marketing campaigns. Moreover, proximity to mobile money agents could influence the likelihood of receiving the subsidy, in turn affecting SHS adoption, implying a different causal mechanism. Figure A3 shows that a significant number of eligible customers did not receive the subsidy, especially early in the rollout period. We compute the share of customers per village receiving the subsidy by December 2019, several months after subsidy rollout, and group villages based on this share. In Table A4, we show that there is no significant relationship between subsidy receipt and proximity to mobile money agents.

In Table 3, we examine whether the heterogeneous treatment effects with proximity to mobile money agents holds even within bins of potential confounders. Specifically, we split the sample into two based on whether village wealth, population density and village subsidy receipt is above or below the median. We then estimate the heterogeneous treatment effects by mobile money agent from equation 4 separately for each of the six bins. Across all of the bins in Table 3, the subsidy impact is consistently always higher for villages with a mobile money agent. Importantly, this holds especially true in the high wealth bins (Panel A), with a differential effect of 0.704 applicants which is slightly higher than our main effects. We also find that the mobile money heterogeneity is more pronounced for villages with low population density (Panel B). Unsurprisingly, as we have found no relationship between village subsidy receipt and having a mobile money agent, the heterogeneous treatment effects by village subsidy receipt bins (Panel C) are very similar to our main results, with the differences statistically significant at the 10%. Therefore, the heterogeneous treatment effects by mobile money is highly persistent across a range of subsamples.

5.3 The Impact of the Subsidy on Consumption and Payment Behavior

In this section, we examine how the subsidy affected payment behavior and electricity consumption among existing customers, highlighting the trade-offs imposed by transaction costs in the context of liquidity constraints. For our event-study analysis at the customer level, we restrict the sample to customers who had adopted an SHS by November 2018, a few months before the subsidy became available, and those who received the subsidy at least once by December 2019, five months after the staggered subsidy rollout reached all districts. We plot the dynamic ITT effects of the subsidy on monthly payment frequency, average payment size, and electricity consumption in Figure 4, as well as average effects in Table 4.

We find that customers responded to the subsidy by maintaining their consumption of electricity by reducing their number of payments, keeping their average payment size mostly unchanged. On average, the number of payments per month dropped by 0.38, approximately 18% of the country group mean of 2.07 (Column 1 from Panel A from Table 4). From Figure 4a, we see no evidence of pre-trends and that this sharp reduction in the payment frequency was immediate and persistent for the following three months. This persistence provides evidence that this change was intentional, as they could have easily changed to a different payment after the first couple of months with the subsidy (e.g. by maintaining the same number of payment days, but reducing the payment size accordingly). While our point estimates indicate a reduction in the average payment size of 0.85 days, this accounts for only around 4% of the control mean and is only marginally significant (Column 2 from Panel A from Table 4). The point estimates for electricity consumption are precisely around 0, implying no changing in their utilization rate (Column 3 from Panel A from Table 4). This is likely because the utilization rate, at around 90%, is already quite high.

In Panels B, C and D of Table 4, we see minimal heterogeneity in effects based on whether customers have a mobile money agent in the village. In both cases, customers strikingly react by reducing their payment frequency over other alternative payment plans with average treatment effects of -0.33 and -0.40 in villages with and without a mobile money agent respectively.

These results are consistent with Prediction 4 and align with the presence of high transaction costs for liquidity-constrained customers. As discussed in the conceptual framework (Section C.3), customers would prefer to make fewer payments (i.e., buy in bulk) to minimize transaction costs, but their liquidity constraints prevent them from borrowing to do so. The subsidy, by lowering the cost of electricity, partially alleviates these liquidity constraints, enabling more customers to have sufficient income at the time of purchase to buy in bulk.

fin

5.4 Policy Directly Reducing Transaction Costs

To further illustrate the importance of transaction costs in this context, we examine the impact of a direct reduction in these costs. We test this by assessing the impact of the mobile money agent expansion, detailed in Section 2.5, which occurred in late 2019, after the subsidy rollout. We apply a similar event-study methodology, outlined in Section 4.2.3, to analyze the effects for 101 villages.

We find that the introduction of a mobile money agent led to an increase in the number of SHS applications by 0.88, a sizable increase of 188% relative to the control group mean of 0.47 (Table 5). This positive result on adoption is consistent with Prediction 2. There is a small, but statistically insignificant increase in the probability of there being an applicant in the village; this suggests that the impacts of the mobile money agent expansion are through the intensive margins, with more applicants per village, rather than the extensive margin. Figure 5 shows that there is no evidence for any pre-trends, and that the effects are immediate and increasing over time, peaking at around one year after the introduction of the agent with an additional 2 applications. As the subsidy was already implemented nationwide by the time the mobile money agent expansion policy was introduced, we have no price variation to test for complementarity.

The large adoption impacts suggest that the introduction of mobile money agents must have reduced the effective electricity price significantly. We perform a back-of-the-envelope calculation to quantify this price reduction. We proceed in three steps:

1. For each village in our estimating sample, we calculate the reduction in distance to the nearest mobile money agent resulting from the expansion policy.[18] This yields a median reduction in distance of 4.9km.

2. We calculate the average number of payments customers in treated villages make each bimonth, prior to the expansion.

3. We compute the price reduction resulting from the reduction in distance by taking the product of four components: the median reduction in distance (obtained in 1), the median moto taxi price per km in rural Togo (obtained from our survey data of transport costs), the average number of payments each period (obtained in 2), all multiplied by two, since customers make round trips.

These calculations yield a reduction in the effective price of electricity of CFA 1,532. This represents a 34% price reduction relative to the effective electricity price customers faced prior to the expansion policy.[19] The relative price reduction is similar in magnitude to the 44% price reduction from the subsidy, which underscores the significance of transaction costs. This might explain why the adoption impact of the expansion policy

[18]We compute the difference between the distance to the nearest agent prior to the expansion policy—as measured by the government-provided agent location data—and the distance to the nearest agent after an agent is introduced to the village through the expansion policy.

[19]The effective electricity price prior to the expansion policy is defined as the subsidized electricity price plus transaction costs. To calculate the transaction cost, we follow the same approach as in our back-of-the-envelope calculation, replacing the median distance reduction (1) with the median distance to the nearest agent prior to the expansion policy.

is comparable to the effect of the subsidy, especially for the subsample of villages with a mobile money agent, where the subsidy increased the number of applicants by 190%.

Because part of our analysis period overlaps with the onset of COVID, one concern is that our effect estimates may partly reflect the impact of having a mobile money agent during a large economic shock. We have several reasons why we believe this is unlikely. First, news sources indicate that the economic impacts of COVID were far from instantaneous in rural parts of Togo. This is illustrated by the fact that we do not observe a "trend break" in SHS applicants until November 2020 (Figure A10). Second, we re-estimate the impact of mobile money agent introduction restricting the time period up to April 2020 instead of December 2020. Table A5 shows that the adoption effects are very similar, with a 149% increase in the number of SHS applicants. Given the smaller sample, the effect is imprecisely estimated, with a p-value of 0.12.

At the customer level, we find that there are no extensive margin impacts on the probability that a customer makes a payment, nor on their utilization rate (Table 6). While not statistically significant, there is a small increase in the number of payments of 16%, accompanied by average payment sizes that are 27% smaller. These results should be interpreted with caution due to the presence of pre-trends in some of the effects (Figure 6).

As discussed in Prediction 5 and Section C.3, in the absence of liquidity constraints, we would expect payment frequency to increase when it becomes relatively cheaper for customers to smooth their payments. However, when liquidity constraints are present, reducing transaction costs also has an offsetting effect; it alleviates the income constraint, allowing more customers to make bulk purchases. We interpret the null effects on payment frequency as consistent with this ambiguous effect and as additional evidence of an income effect from reducing transaction costs which puts downward pressure on the number of payments as customers are able to afford larger purchases of electricity.

6 Conclusion

Transaction costs in making bill payments play a crucial role in contexts with liquidity constraints and may undermine the effectiveness of policies aimed at providing essential services like electricity. In this study, we examine a context where these costs are particularly burdensome: survey data we collected reveals that transaction costs account for approximately 28% of the total cost of electricity in rural Togo, rising to 43% in the most remote regions (75th percentile). These high transaction costs significantly weaken the impact of subsidy policies designed to boost solar panel adoption rates.

We present four key pieces of evidence to support this conclusion. First, while the subsidy more than doubled electricity access, the increase in adoption is substantially larger in villages with mobile money agents. We attribute this to the high transaction costs in areas without nearby mobile money agents. This finding remains robust even after accounting for various confounders, including wealth disparities across villages. Second, the subsidy enables bulk purchases for existing customers by making it more affordable to reduce payment frequency. Third, the expansion of mobile money agents leads to a nearly threefold increase in adoption rates. Fourth, we find no statistically significant effects on payment frequency, indicating that the income effect partially offsets any potential increase in the number of payments as lower transaction costs enable bulk purchases.

These findings highlight the importance of addressing transaction costs to enhance the effectiveness of price reduction policies, especially in settings with high liquidity constraints. This has direct policy implications. We believe that two key features of this study—the analysis of two nationwide policies targeting electricity costs in different ways, combined with multiple data sources—contribute to the broader literature on market frictions that impede access to essential services in developing economies.

References

Abdullah, Sabah and P. Wilner Jeanty, "Willingness to pay for renewable energy: Evidence from a contingent valuation survey in Kenya," *Renewable and Sustainable Energy Reviews*, 2011, *15* (6), 2974–2983.

Africa Progress Panel, "Lights, Power, Action: Electrifying Africa," *Report*, 2017.

Aklin, M., P. Bayer, S.P. Harish, and J. Urpelainen, "Economics of household technology adoption in developing countries: Evidence from solar technology adoption in rural India," *Energy Economics*, 2018, *72*, 35–46.

Angrist, Joshua and Jorn-Steffen Pischke, "Mostly Harmless Econometrics: An Empiricist's Companion," *Princeton University Press*, 2008.

Berkouwer, Susanna B., Pierre Biscaye, Eric Hsu, Oliver Kim, Kenneth Lee, Edward Miguel, and Catherine Wolfram, "Money or Power? Choosing COVID-19 Aid in Kenya," *Energy Economics*, 2023, *127*, 107036.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting Event Study Designs: Robust and Efficient Estimation," *Working Paper*, 2021.

Breza, Emily and Cynthia Kinnan, "Measuring the Equilibrium Impacts of Credit: Evidence from the Indian Microfinance Crisis*," *The Quarterly Journal of Economics*, 05 2021, *136* (3), 1447–1497.

Burgess, Robin and Rohini Pande, "Do rural banks matter? Evidence from the Indian social banking experiment," *American Economic Review*, 2005, *95* (3), 780–795.

_, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan, "Demand for Electricity on the Global Electrification Frontier," *Working Paper*, 2023.

Burlig, Fiona and Louis Preonas, "Out of the darkness and into the light? Development effects of rural electrification," *Working Paper*, 2022.

Chaisemartin, Clément De and Xavier d'Haultfoeuille, "Two-way fixed effects estimators with heterogeneous treatment effects," *American Economic Review*, 2020, *110* (9), 2964–2996.

Chi, Guanghua, Han Fang, Sourav Chatterjee, and Joshua E Blumenstock, "Microestimates of wealth for all low-and middle-income countries," *Proceedings of the National Academy of Sciences*, 2022, *119* (3), e2113658119.

Devoto, Florencia, Esther Duflo, Pascaline Dupas, William Parienté, and Vincent Pons, "Happiness on Tap: Piped Water Adoption in Urban Morocco," *American Economic Journal: Economic Policy*, May 2012, *4* (4), 68–99.

Dinkelman, Taryn, "The Effects of Rural Electrification on Employment: New Evidence from South Africa," *American Economic Review*, 2011, *101* (7), 3078–3108.

Duflo, Esther, "The Economist as Plumber," *American Economic Review*, May 2017, *107* (5), 1–26.

Fink, Günther, B. Kelsey Jack, and Felix Masiye, "Seasonal Liquidity, Rural Labor Markets, and Agricultural Production," *American Economic Review*, November 2020, *110* (11), 3351–92.

Fonseca, Julia and Adrien Matray, "The Real Effects of Banking the Poor: Evidence from Brazil," Technical Report, National Bureau of Economic Research 2022.

Gertler, Paul, Brett Green, and Catherine Wolfram, "Digital Collateral," *The Quarterly Journal of Economics*, 01 2024, *139* (3), 1713–1766.

Goodman-Bacon, Andrew, "Difference-in-Differences with Variation in Treatment Timing," *Journal of Econometrics*, 2021.

Government of Togo, "Togo electrification strategy," *Report*, 2016.

Grimm, Michael, Luciane Lenz, Jorg Peters, and Maximiliane Sievert, "Demand for Off-Grid Solar Electricity: Experimental Evidence from Rwanda," *Journal of the Association of Environmental and Resource Economists*, 2020, *7.*

GSMA, "Mobile Connectivity Index," 2021.

Jack, Kelsey and Grant Smith, "Charging Ahead: Prepaid Metering, Electricity Use and Utility Revenue," *American Economic Journal: Applied Economics*, 2020, *12* (3), 134–68.

Jack, William and Tavneet Suri, "Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution," *American Economic Review*, 2014, *104* (1), 183–223.

Khandker, Shahidur, Hussain Samad, Asaduzzaman M, and Mohammad Yunus, "The Benefits of Solar Home Systems: An Analysis from Bangladesh," *World Bank Policy Research Working Papers*, 2013.

Kpemoua, Palakiyem, "Analyse de l'impact de l'energie electrique sur la croissance economique du Togo," *Working Paper*, 2016.

Lang, Megan, "Decentralized Markets for Electricity in Low-Income Countries," *Working Paper*, 2024.

— , "The Role of Market Frictions in Demand for Prepaid Electricity," *Working Paper*, 2024.

Lee, Kenneth, Edward Miguel, and Catherine Wolfram, "Does Household Electrification Supercharge Economic Development?," *Journal of Economic Perspectives*, 2020, *34* (1), 122–44.

— , — , and — , "Experimental Evidence on the Economics of Rural Electrification," *Journal of Political Economy*, April 2020, *128* (4).

Lipscomb, Molly, Mushfiq Mobarak, and Tania Barham, "Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil," *American Economic Journal: Applied Economics*, 2013, *5* (2), 200–231.

Moneke, Niclas, "Can Big Push Infrastructure Unlock Development? Evidence from Ethiopia," *Working Paper*, 2020.

Rud, Juan Pablo, "Electricity provision and industrial development: Evidence from India.," *Journal of Development Economics*, 2012, *97* (2), 352–367.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

Suri, Tavneet, "Selection and comparative advantage in technology adoption," *Econometrica*, 2011, *79* (1), 159–209.

— , "Mobile Money," *Annual Review of Economics*, 2017, *9*, 497–520.

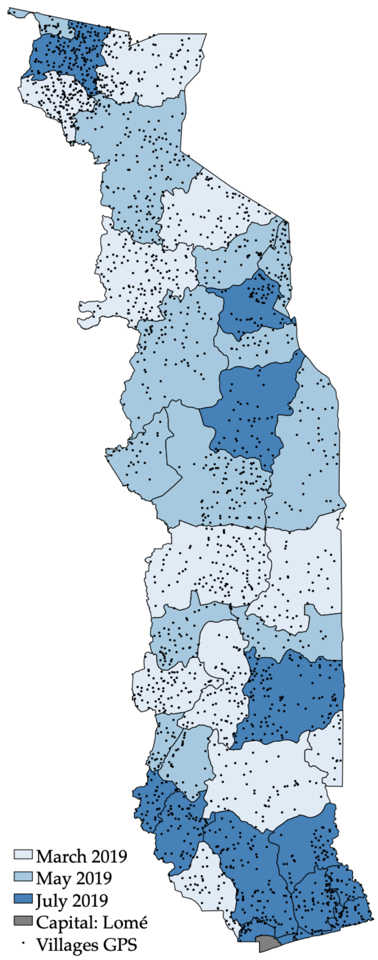
van de Walle, Dominique, Martin Ravallion, Vibhuti Mendiratta, and Gayatri Koolwal, "Long-Term Gains from Rural Electrification in Rural India," *World Bank Economic Review*, 2017, *31* (2), 385–411.

World Bank, "Grid Solar Market Trends Report 2020," *WB Group Lighting Global Program - International Finance Corporation*, 2020.

World Bank Group, "The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution," *Report*, 2017.

Figures and Tables

Figure 1: Districts of Togo by Subsidy Launch Date

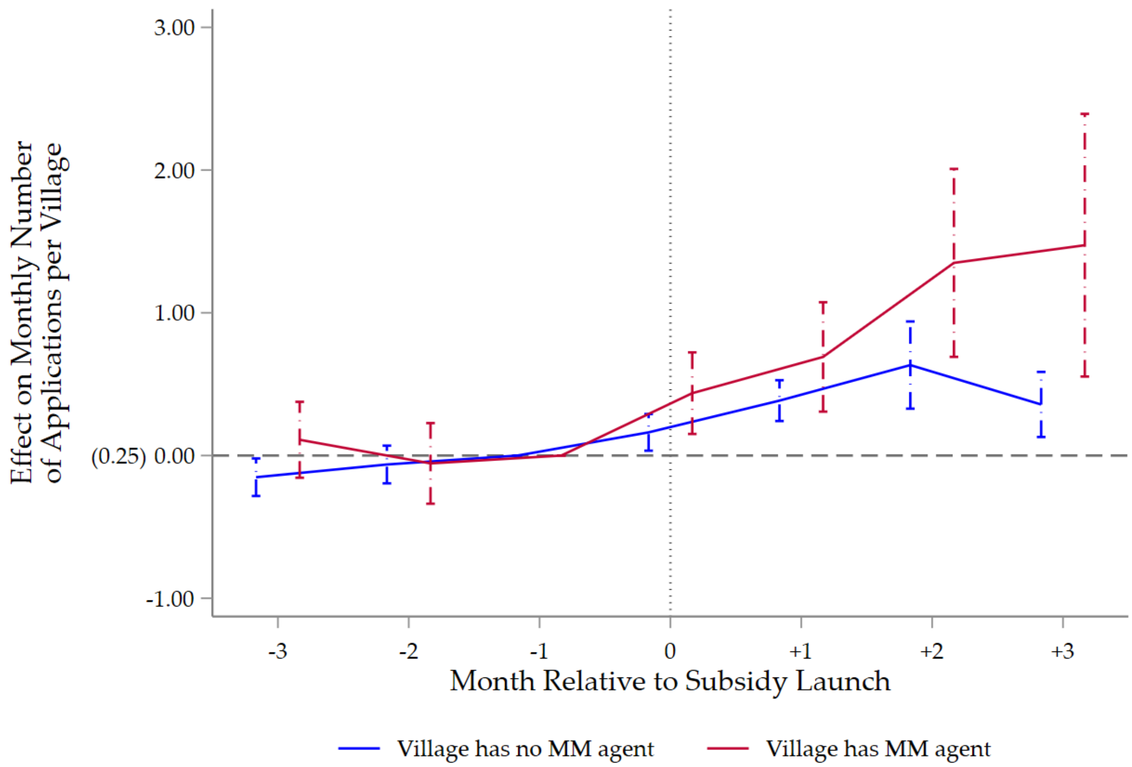


Notes: The figure illustrates the spatial distribution of subsidy program rollout across Togo's districts. Districts shaded in the lightest hue represent the first phase, where the program launched in March 2019. Districts in a slightly darker shade indicate the second phase, beginning in May 2019. The darkest shaded districts correspond to the final phase, initiated in July 2019.

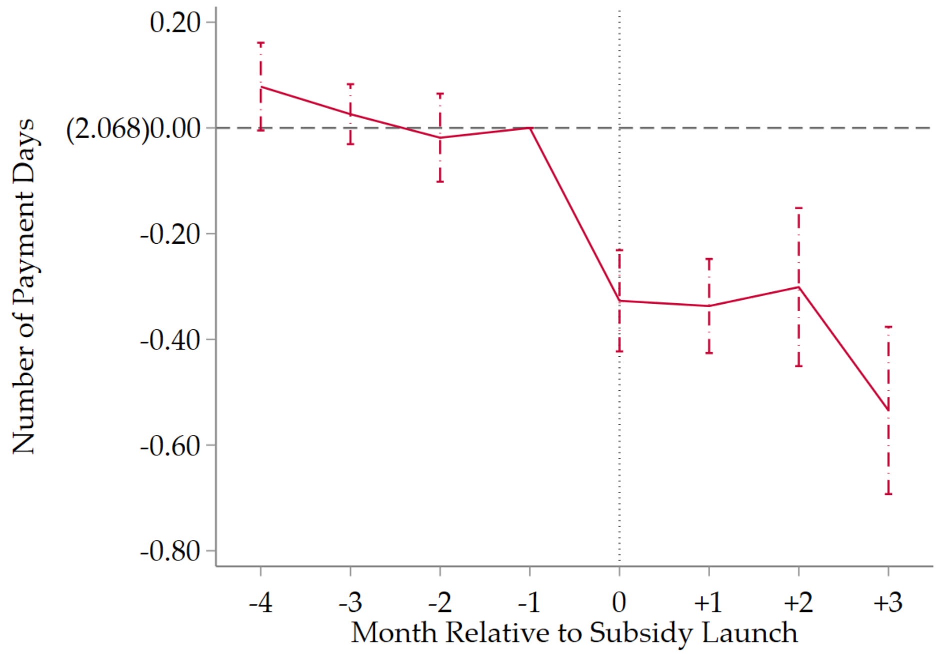
Figure 2: Subsidy Impact on SHS Adoption

Notes: This figure displays village-level dynamic ITT effects of subsidy eligibility on solar home system (SHS) adoption, estimated by equation 1, following Sun and Abraham (2021). Our empirical strategy compares villages in districts that launched the subsidy in March and May 2019 (treatment group) to villages in districts that launched it in July 2019 (control group). The outcome variable is the number of SHS applications per month in each village. The number in parentheses at the point (0,0) denotes the mean value of the outcome in the control group prior to subsidy launch. The dashed vertical lines are 95% confidence intervals using standard errors clustered at the village level. Table 1 aggregates the dynamic effects into a single average effect.

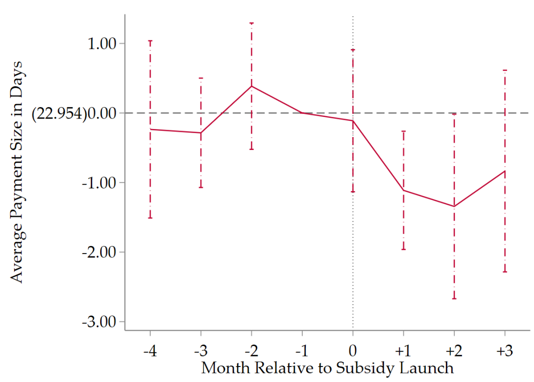
Figure 3: Heterogeneous Subsidy Impacts on SHS Adoption by Mobile Money Agent Access



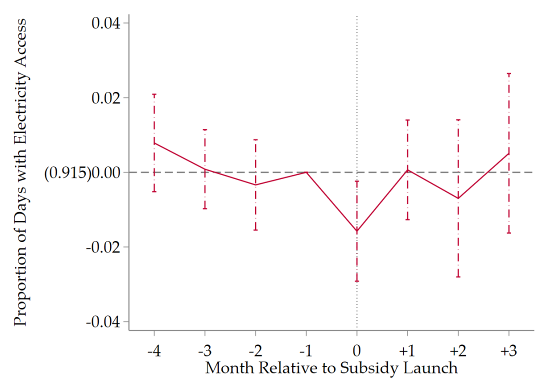
Notes: This figure displays village-level heterogeneous ITT effects of subsidy eligibility on solar home system (SHS) adoption, estimated by equation 4 , following Sun and Abraham (2021). Our empirical strategy compares villages in districts that launched the subsidy in March and May 2019 (treatment group) to villages in districts that launched it in July 2019 (control group). The subsidy's impact for villages that had a mobile money agent prior to subsidy launch is shown in red, and the impact for villages without an agent in blue. The outcome variable is the number of SHS applications per month in each village. The number in parentheses at the point (0,0) denotes the mean value of the outcome in the control group prior to subsidy launch. The dashed vertical lines are 95% confidence intervals using standard errors clustered at the village level. Table 1 aggregates the dynamic effects into a single average effect and tests whether it differs between villages with and without a mobile money agent.



(a) Reduction in payment frequency



(b) Negligible reduction in payment size



(c) No change in share of days with electricity

Figure 4: Subsidy Impacts on Customer Payments and Consumption

Notes: This figure displays customer-level dynamic ITT effects of subsidy eligibility on monthly electricity payment and consumption behavior, estimated by equation 3, following Sun and Abraham (2021). Our empirical strategy compares customers in districts that launched the subsidy in March and May 2019 (treatment group) to customers in districts that launched it in July 2019 (control group). To ensure a balanced panel, the sample is restricted to customers that had joined by November 2018, a few months before subsidy launch. Panel a) displays impacts on payment frequency, defined as the number of days per month in which a customer paid for electricity. In panel b) the outcome is the average size of each payment made that month. The size of each payment is measured in terms of the number of days of electricity purchased. The outcome equals zero if no payment was made that month. In Panel c) the outcome is the proportion of days in the month in which the customer had access to electricity. The number in parentheses at the point (0,0) denotes the mean value of the outcome in the control group prior to subsidy launch. The dashed vertical lines are 95% confidence intervals using standard errors clustered at the customer level. Table 4 aggregates the dynamic effects into a single average effect, and tests whether the impacts differ by pre-subsidy mobile money agent access.

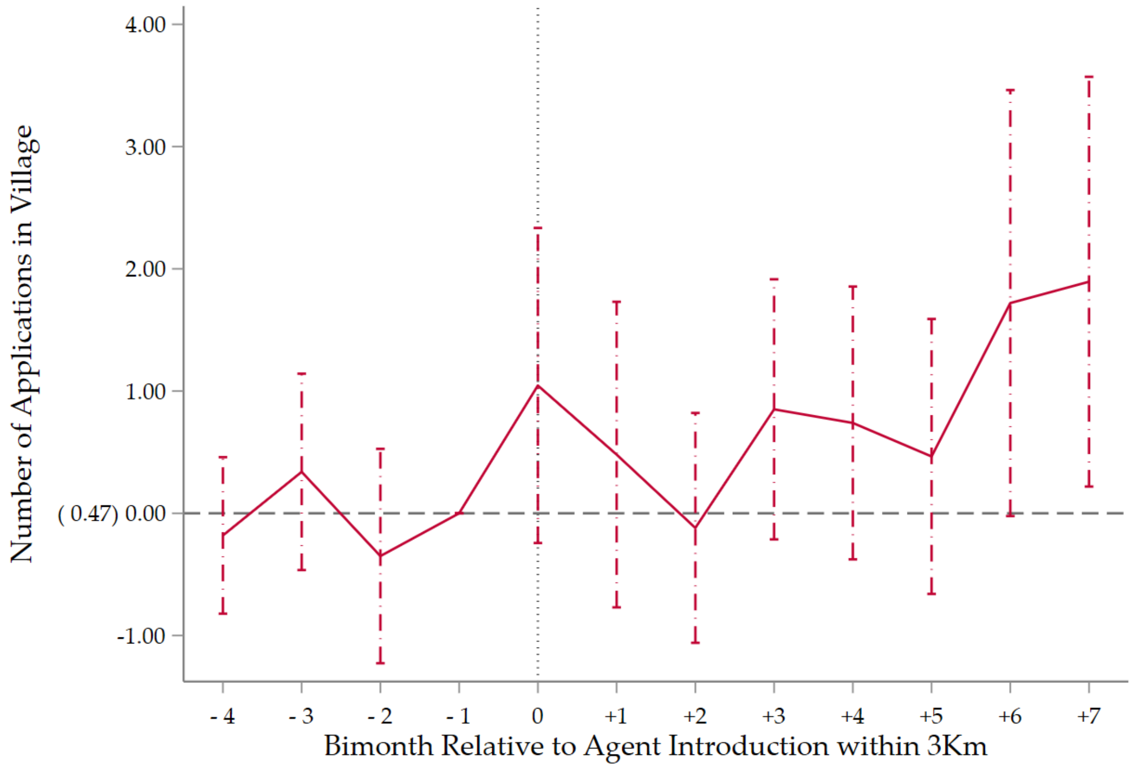
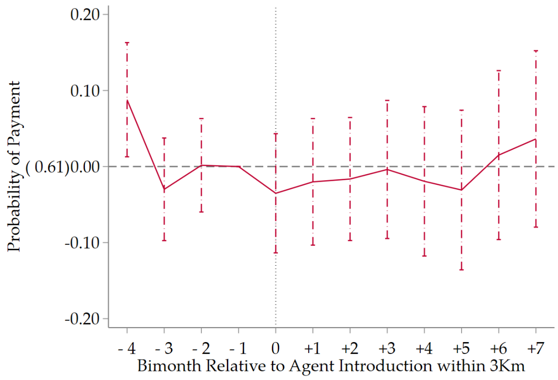
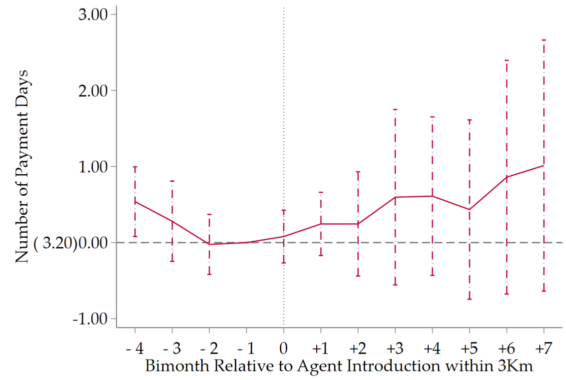


Figure 5: Mobile Money Agent Expansion Impacts on SHS Adoption

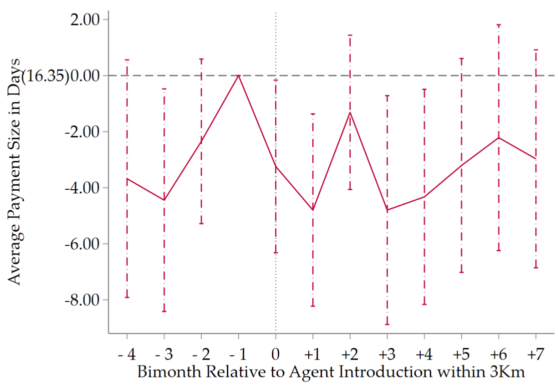
Notes: This figure displays village-level ITT effects of having a mobile money agent introduced in the village, on solar home system (SHS) adoption, estimated by equation 6, following Sun and Abraham (2021). Our empirical strategy compares villages that received a mobile money agent between September 2019 and March 2020 through the agent expansion policy described in section 2.5, to villages that received an agent in later, in 2021, due to an abrupt halt caused by COVID. The analysis is conducted at the bimonthly frequency. The outcome variable is the number of SHS applications per bimonth in each village. The number in parentheses at the point (0,0) denotes the mean value of the outcome in the control group prior to the launch of the agent expansion policy. The dashed vertical lines are 95% confidence intervals using standard errors clustered at the village level. Table 5 aggregates the dynamic effects into a single average effect.



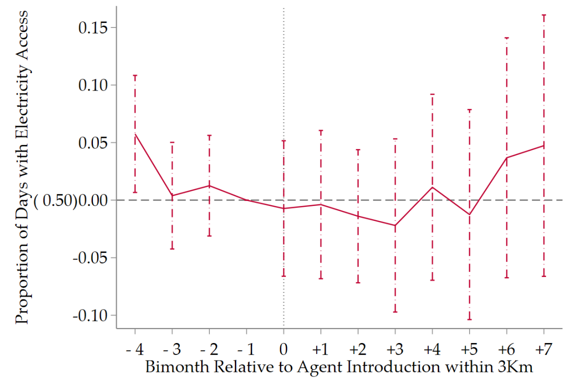
(a) No effect on probability of payment



(b) Small positive effects on payment frequency



(c) No effect on payment size



(d) No effect on share of days with electricity

Figure 6: Mobile Money Agent Expansion Impacts on Payments and Consumption

Notes: This figure displays customer-level ITT effects of having a mobile money agent introduced in the village, estimated by equation 6, following Sun and Abraham (2021). Our empirical strategy compares customers in villages that received a mobile money agent between September 2019 and March 2020 through the agent expansion policy described in section 2.5, to customers in villages that received an agent later, in 2021, due to an abrupt halt caused by COVID. The analysis is conducted at the bimonthly frequency. Panel a) displays the results for a binary outcome variable equal to one if the customer made any payment in the bimonthly period. Panel b) displays impacts on payment frequency, defined as the number of days per bi-month in which a customer paid for electricity. In panel c) the outcome is the average size of each payment made that bi-month. The size of each payment is measured in terms of the number of days of electricity purchased. The outcome equals zero if no payment was made that month. In Panel d) the outcome is the proportion of days in the bi-month in which the customer had access to electricity. The number in parentheses at the point (0,0) denotes the mean value of the outcome in the control group prior to the launch of the agent expansion policy. The dashed vertical lines are 95% confidence intervals using standard errors clustered at the village level. Table 6 aggregates the dynamic effects into a single average effect and tests whether it differs between villages with and without a mobile money agent.

Table 1: Subsidy Impacts on SHS Adoption

	(1)	(2) By Mobile Money Agent Access		
		(a)	(b)	(c)
	All Villages	Has Agent	No Agent	Difference
Monthly SHS Applications	0.415***	0.988***	0.385***	0.603***
	(0.069)	(0.217)	(0.085)	
Control Mean	0.278	0.521	0.252	
Effect relative to control mean	149%	190%	153%	
P-val: pre-periods = 0	0.205	0.468	0.077	
Number of villages	2,686	517	1,704	
Observations	18,802	3,619	11,928	

Notes: This table displays village-level ITT effects of subsidy eligibility on solar home system (SHS) adoption, defined as the number of monthly SHS applications in the village. Our empirical strategy compares villages in districts that launched the subsidy in March and May 2019 (treatment group) to villages in districts that launched it in July 2019 (control group).
Column (1) shows the average ITT effect for the full sample of villages. We obtain this in two steps, following Sun and Abraham (2021): first, we estimate the dynamic ITT effects with equation 1. Second, we obtain the average effect and associated standard error by testing the null hypothesis that the average of the dynamic effects equals zero (equation 2).
Columns (2) (a) (b) display the average effect in villages with and without a mobile money agent. We obtain these by estimating equation 4, which yields a set of separate dynamic effects for each subgroup, and then. aggregating them into an average effect using the same procedure as in equation 2. Column (2) (c) tests the hypothesis that the difference in treatment effects between villages with and without mobile money agents is zero.
The control mean corresponds to the mean of the outcome in the control group prior to subsidy launch. To asses parallel pre-trends, we report the p-value of the joint test that the coefficients in all pre-periods equal zero. Standard errors, clustered at the village level, shown in parentheses. *, ** and ***, denote significance at the 10, 5 and 1% level, respectively.

Table 2: Ruling out Alternative Explanations for Subsidy Impacts

Heterogeneity Bin:	(1) Top 20^{th} Percentile	(2) Bottom 80^{th} Percentile	(3) Difference
Panel A) By Village Wealth			
Monthly SHS Applications	0.921***	0.607***	0.313
	(0.300)	(0.115)	(0.315)
Control Mean	0.485	0.347	
Effect relative to control mean	190%	175%	
P-val: pre-periods = 0	0.895	0.125	
Number of villages	326	1,305	
Observations	2,282	9,135	
Panel B) By Population Density			
Monthly SHS Applications	0.093	0.446***	-0.353
	(0.196)	(0.083)	(0.209)
Control Mean	0.267	0.237	
Effect relative to control mean	35%	188%	
P-val: pre-periods = 0	0.664	0.450	
Number of villages	435	1,744	
Observations	3,045	12,208	
Panel C) By Village Subsidy Receipt			
Monthly SHS Applications	0.407***	0.417***	-0.010
	(0.072)	(0.082)	(0.103)
Control Mean	0.224	0.255	
Effect relative to control mean	182%	164%	
P-val: pre-periods = 0	0.493	0.161	
Number of villages	531	2,155	
Observations	3,717	15,085	

Notes: This table displays heterogeneous village-level ITT effects of subsidy eligibility on solar home system (SHS) adoption, defined as the number of monthly SHS applications in the village. Our empirical strategy compares villages in districts that launched the subsidy in March and May 2019 (treatment group) to villages in districts that launched it in July 2019 (control group). Each panel estimates heterogeneous effects by a potential confounder correlated with mobile money agent access. For each confounder, we define a binary variable that equals one if the village is in the top 20% of the distribution of the confounding variable, and zero otherwise. We then estimate heterogeneous treatment effects by this variable using equation 4. Panel A uses a geospatial index of village wealth Chi et al. (2022). Panel B uses population density within a 3km radius around each village, based on geospatial population density estimates from *WorldPop*. Panel C uses the share of customers in each village receiving the subsidy in the first few months of subsidy launch. Columns (1) and (2) display the average effects for villages in the top 20% and bottom 80% of the confounder. Column (3) tests the hypothesis that the difference in treatment effects between villages with and without mobile money agents is zero (equation 5). The control mean corresponds to the mean of the outcome in the control group, within each heterogeneity bin, prior to subsidy launch. To asses parallel pre-trends, we report the p-value of the joint test that the coefficients in all pre-periods equal zero. Standard errors, clustered at the village legel, shown in parentheses. *, ** and ***, denote significance at the 10, 5 and 1% level, respectively.

Table 3: Heterogeneous Subsidy Impacts within Bins of Potential Confounders

	High Wealth			Low Wealth		
Panel A) By Village Wealth	Has Agent	No Agent	Diff.	Has Agent	No Agent	Diff.
Monthly SHS Applications	1.266***	0.562***	0.704**	0.971***	0.512***	0.459
	(0.326)	(0.130)	(0.343)	(0.364)	(0.182)	(0.392)
Control Mean	0.561	0.373		1.135	0.365	
Effect relative to control mean	226%	151%		86%	140%	
P-val: pre-periods = 0	0.870	0.707		0.707	0.142	
Number of villages	310	504		104	713	
Observations	2,170	3,528		728	4,991	

	High Population Density			Low Population Density		
Panel B) By Population Density	Has Agent	No Agent	Diff.	Has Agent	No Agent	Diff.
Monthly SHS Applications	0.610*	0.309***	0.301	1.053***	0.377**	0.677**
	(0.334)	(0.113)	(0.347)	(0.317)	(0.151)	(0.342)
Control Mean	0.475	0.296		0.453	0.196	
Effect relative to control mean	128%	104%		232%	192%	
P-val: pre-periods = 0	0.112	0.920		0.920	0.196	
Number of villages	234	656		184	724	
Observations	1,638	4,592		1,288	5,068	

	High Subsidy Receipt			Low Subsidy Receipt		
Panel C) By Village Subsidy Receipt	Has Agent	No Agent	Diff.	Has Agent	No Agent	Diff.
Monthly SHS Applications	1.041***	0.467***	0.574*	1.142***	0.443***	0.699*
	(0.330)	(0.124)	(0.340)	(0.349)	(0.153)	(0.375)
Control Mean	0.708	0.271		0.521	0.329	
Effect relative to control mean	147%	172%		219%	135%	
P-val: pre-periods = 0	0.428	0.261		0.261	0.006	
Number of villages	195	606		260	810	
Observations	1,365	4,242		1,820	5,670	

Notes: This table tests whether the heterogeneous adoption effects by mobile money agent access hold within bins of potential confounders. The outcome variable is the number of monthly SHS applications in the village. Our empirical strategy compares villages in districts that launched the subsidy in March and May 2019 (treatment group) to villages in districts that launched it in July 2019 (control group). Each panel splits the sample by above/below median values of the confounder and estimates heterogeneous treatment effects by mobile money agent access within each bin, following equation 4, The first two columns under each subheading display the average effect in villages with and without mobile money agent, respectively. The third column tests the hypothesis that the difference in treatment effects between villages with and without mobile money agents is zero. The confounder in Panel A is a geospatial index of village wealth Chi et al. (2022). Panel B uses population density within a 3km radius around each village, based on geospatial population density estimates from *WorldPop*. Panel C uses the share of customers in each village receiving the subsidy in the first few months of subsidy launch. The control mean corresponds to the mean of the outcome in the control group, within each heterogeneity bin, prior to subsidy launch. To asses parallel pre-trends, we report the p-value of the joint test that the coefficients in all pre-periods equal zero. Standard errors, clustered at the village legel, shown in parentheses. *, ** and ***, denote significance at the 10, 5 and 1% level, respectively.

Table 4: Subsidy Impacts on Customer Payments and Consumption

	(1) Number of Payments	(2) Average Payment Size (in days)	(3) Utilization Rate
Panel A) Average Effect			
Subsidy impact	-0.375***	-0.851*	-0.004
	(0.053)	(0.493)	(0.007)
Control Mean	2.068	22.954	0.915
Effect relative to control mean	-18%	-4%	-0%
P-val: pre-periods = 0	0.131	0.597	0.351
Number of customers	3,423	3,423	3,423
Observations	21,322	21,322	21,322
Panel B) Customers with Mobile Money Agent in Village			
Subsidy impact	-0.329***	-0.972	-0.005
	(0.069)	(0.616)	(0.010)
Control Mean	2.952	16.940	0.929
Effect relative to control mean	-11%	-6%	-1%
P-val: pre-periods = 0	0.335	0.798	0.799
Number of customers	1,262	1,262	1,262
Observations	8,006	8,006	8,006
Panel C) Customers without Mobile Money Agent in Village			
Subsidy impact	-0.399***	-0.813	-0.003
	(0.057)	(0.547)	(0.008)
Control Mean	2.386	19.412	0.911
Effect relative to control mean	-17%	-4%	-0%
P-val: pre-periods = 0	0.186	0.415	0.138
Number of customers	2,153	2,153	2,153
Observations	13,260	13,260	13,260
Panel D) Heterogeneous Impact: β in Panel B - β in panel C			
Subsidy impact	0.070	-0.159	-0.002
	(0.063)	(0.604)	(0.010)

Notes: This table displays customer-level ITT effects of subsidy eligibility on electricity payment and consumption. Our empirical strategy compares customers in districts that launched the subsidy in March and May 2019 (treatment group) to customers in districts that launched it in July 2019 (control group). To ensure a balanced panel, the sample is restricted to customers that had joined by November 2018.

Panel A shows the average ITT effect for the full sample of villages. We obtain this in two steps, following Sun and Abraham (2021): first, we estimate the dynamic ITT effects with equation 3. Second, we obtain the average effect and associated standard error by testing the null hypothesis that the average of the dynamic effects equals zero (equation 2).

Panels B and C display the average effect in villages with and without a mobile money agent, respectively. We obtain these by estimating equation 4, which yields a set of separate dynamic effects for each subgroup, and then aggregating them into an average effect using the same procedure as in equation 2.

Panel D tests the hypothesis that the difference in treatment effects between villages with and without mobile money agents is zero.

The control mean corresponds to the mean of the outcome in the control group prior to subsidy launch. To asses parallel pre-trends, we report the p-value of the joint test that the coefficients in all pre-periods equal zero. Standard errors, clustered at the village legel, shown in parentheses. *, ** and ***, denote significance at the 10, 5 and 1% level, respectively.

The outcomes in columns (1) - (3) are: payment frequency, defined as the number of days per month in which a customer paid for electricity; the average size of each payment; the proportion of days each month in which the customer had access to electricity. s

Table 5: Mobile Money Agent Expansion Impacts on SHS Adoption

	(1) SHS Applications	(2) $\mathbb{1}\{\text{Any SHS Application}\}$
Agent Arrival	0.884**	0.148
	(0.451)	(0.090)
Control Mean	0.47	0.29
Effect relative to control mean	188%	51%
P-val: pre-periods = 0	0.328	0.207
Number of villages	101	101
Observations	1,212	1,212

Notes: This table displays village-level ITT effects of having a mobile money agent introduced in the village, on solar home system (SHS) adoption, estimated by equation 6, following Sun and Abraham (2021). Our empirical strategy compares villages that received a mobile money agent between September 2019 and March 2020 through the agent expansion policy described in section 2.5, to villages that received an agent in later, in 2021, due to an abrupt halt caused by COVID. The analysis is conducted at the bimonthly frequency and the ITT effects are estimated from the period September 2019 - December 2020. We obtain the static average effect by averaging the dynamic effects, as in equation 2. The outcome variable in column (1) is the number of SHS applications per bimonth in each village. The outcome variable in column (2) is a dummy variable that equals one if the village had any SHS applicants in the bimonth. The control mean corresponds to the mean of the outcome in the control group prior to mobile money agent expansion. To asses parallel pre-trends, we report the p-value of the joint test that the coefficients in all pre-periods equal zero. Standard errors, clustered at the village level, shown in parentheses. *, ** and ***, denote significance at the 10, 5 and 1% level, respectively.

Table 6: Mobile Money Agent Expansion Impacts on Customer Payments and Consumption

	(1) Number of Payments	(2) Made a Payment	(3) Average Payment Size (in days)	(4) Utilization Rate
Agent Arrival	0.511	-0.009	-2.670**	0.004
	(0.452)	(0.043)	(1.185)	(0.036)
Control Mean	3.20	0.61	9.91	0.50
Effect relative to control mean	16%	-1%	-27%	1%
P-val: pre-periods = 0	0.023	0.006	0.038	0.037
Number of customers	632	632	632	632
Observations	7,584	7,584	7,584	7,548

Notes: This table displays customer-level ITT effects of having a mobile money agent introduced in the village, on payment and consumption behavior, estimated by equation 6, following Sun and Abraham (2021). Our empirical strategy compares customers in villages that received a mobile money agent between September 2019 and March 2020 through the agent expansion policy described in section 2.5, to customers in villages that received an agent in later, in 2021, due to an abrupt halt caused by COVID. The analysis is conducted at the bimonthly frequency. We obtain the static average effect by averaging the dynamic effects, as in equation 2. The outcome variable in column (1) is a binary outcome variable equal to one if the customer made any payment in the bimonthly period. Column (2) displays impacts on payment frequency, defined as the number of days per bi-month in which a customer paid for electricity. In column (3), the outcome is the average size of each payment made that bi-month. The size of each payment is measured in terms of the number of days of electricity purchased. The outcome equals zero if no payment was made that month. Column (4) shows impacts on the proportion of days in the bi-month in which the customer had access to electricity. The control mean corresponds to the mean of the outcome in the control group prior to mobile money agent expansion. To asses parallel pre-trends, we report the p-value of the joint test that the coefficients in all pre-periods equal zero. Standard errors, clustered at the village level, shown in parentheses. *, ** and ***, denote significance at the 10, 5 and 1% level, respectively.

Appendix

Table of Contents

A Appendix Figures **43**

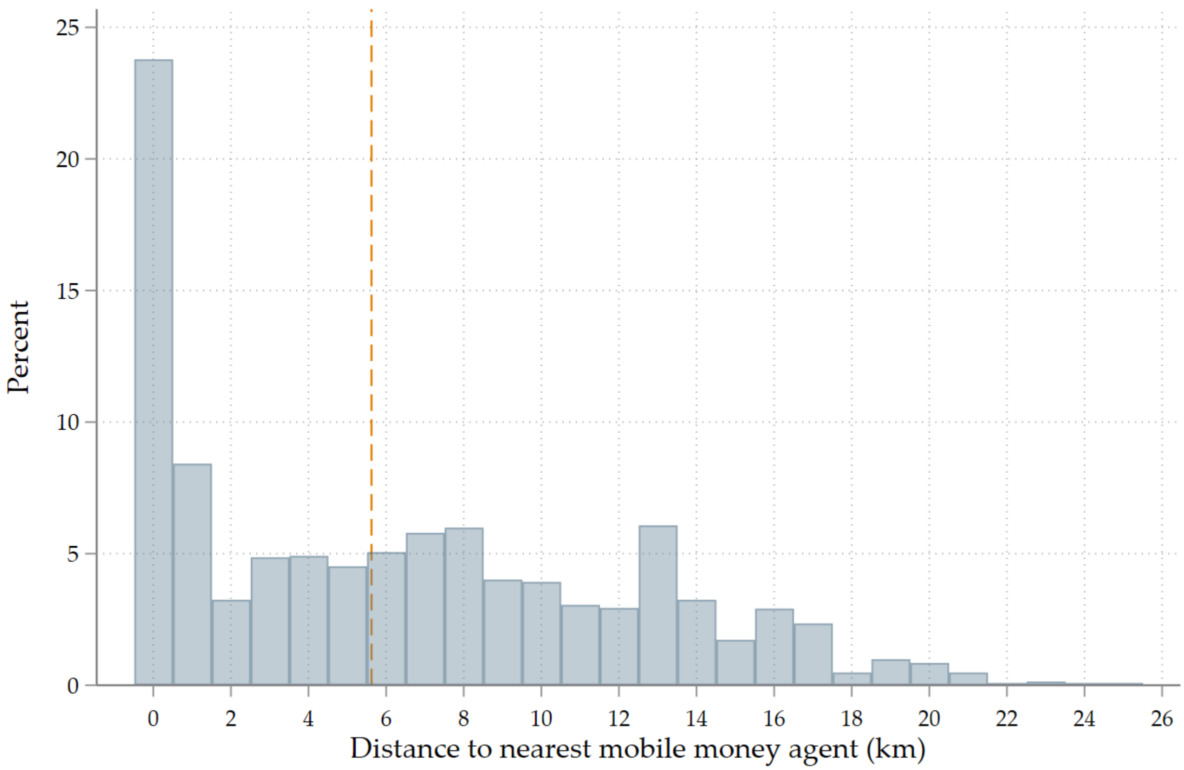
B Appendix Tables **53**

C Conceptual Framework **57**
- C.1 Setup 57
- C.2 Adoption 59
- C.3 Frequency of Payments for Electricity 60
  - C.3.1 Liquidity-Unconstrained Households 60
  - C.3.2 Liquidity-Constrained Households 61
- C.4 Deriving Properties of the Income Threshold for Purchasing in Bulk 63

D Information Campaigns **66**

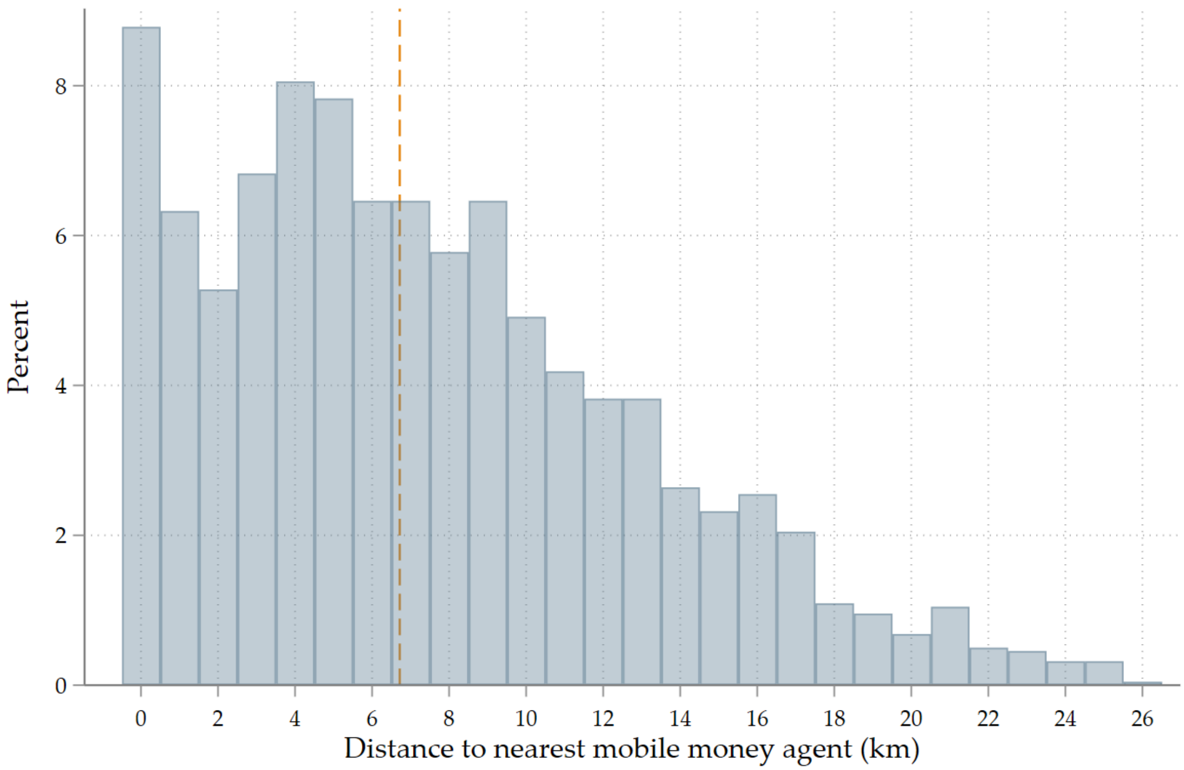
A Appendix Figures

Figure A1: Distance to Nearest Mobile Money Agent Before the Subsidy



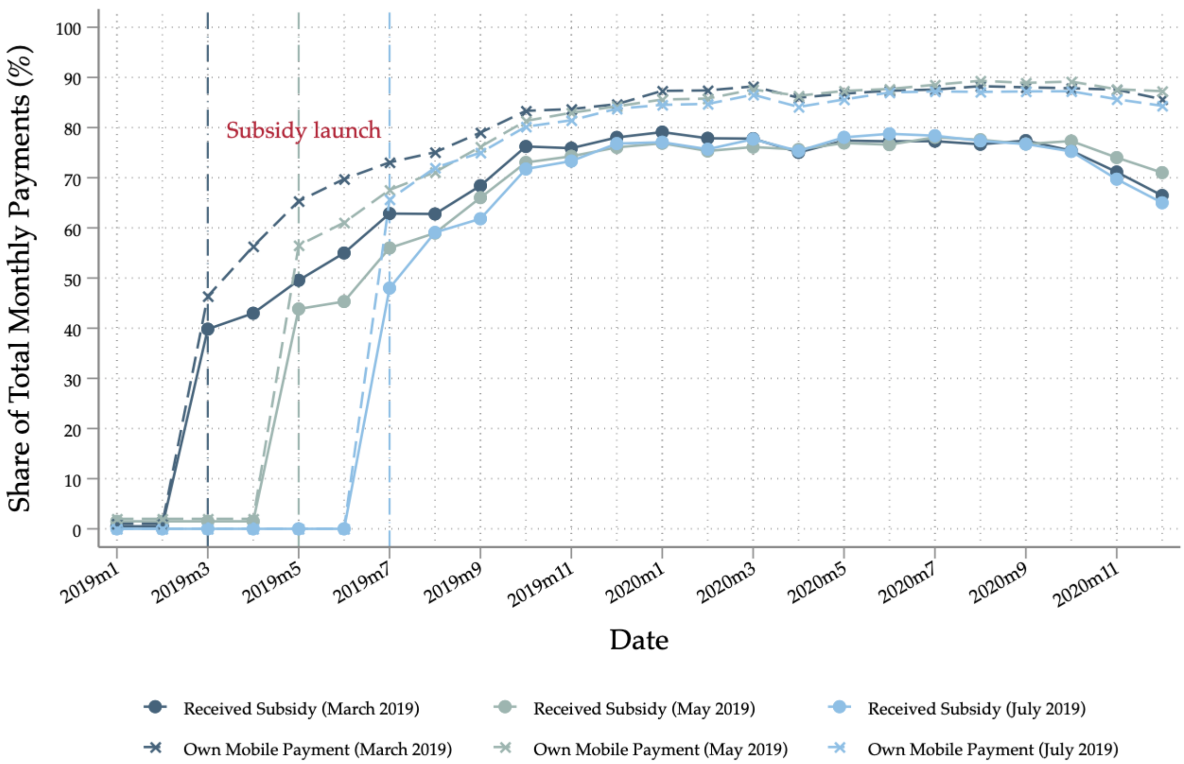
Notes: This figure plots the distribution of customers' distance to the nearest mobile money agent in January 2019, two months before the subsidy was rolled out. To calculate the distance to the nearest mobile money agent, we combine data from the Togolese government, detailing the longitude and latitude of all mobile money agents in the country from 2010 to 2024, on a monthly or yearly basis, with the coordinates of villages in our sample.

Figure A2: Distance to Nearest Mobile Money Agent Across all Villages



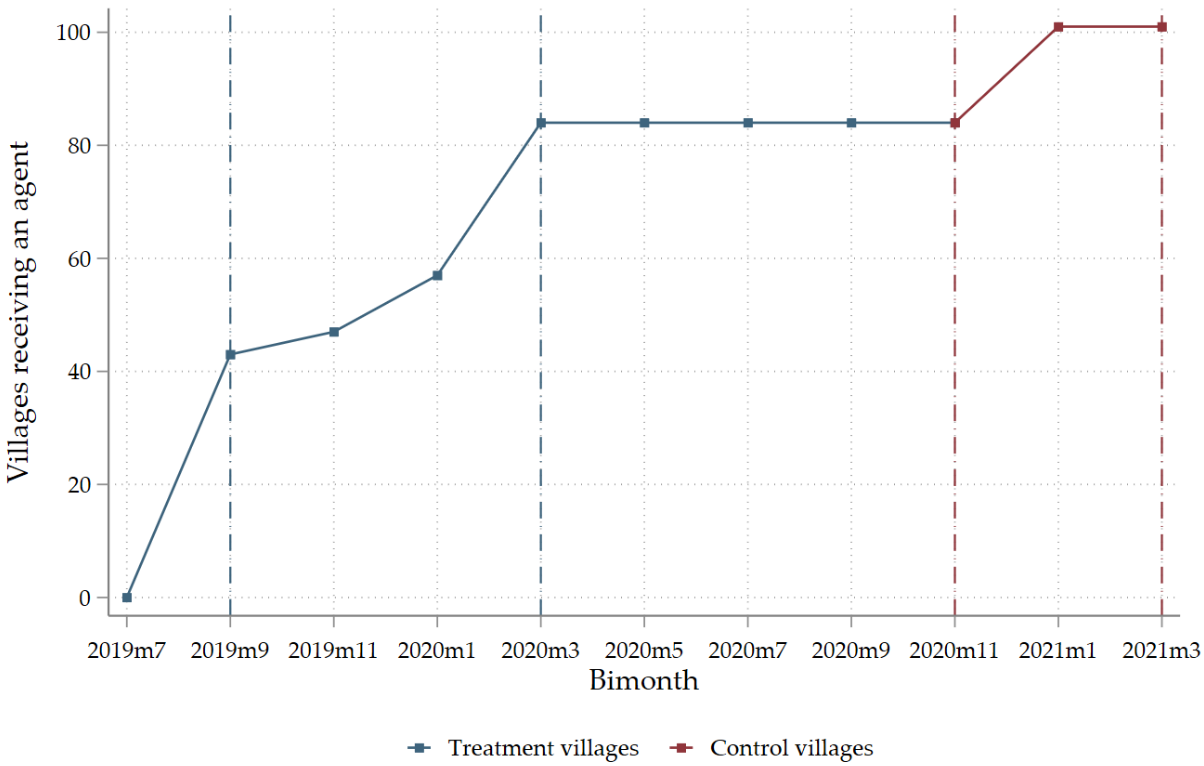
Notes: This figure plots the distribution of village distance to the nearest mobile money agent in January 2019, two months before the subsidy was rolled out. This includes the entire universe of villages we observe in our data at any point. To calculate the distance to the nearest mobile money agent, we combine data from the Togolese government, detailing the longitude and latitude of all mobile money agents in the country from 2010 to 2024, on a monthly or yearly basis, with the coordinates of villages in our sample.

Figure A3: Subsidy Receipt and Payment using Own Mobile, by Subsidy Launch Date



Notes: This figure plots the proportion of total payments (i) receiving the subsidy and (ii) paying using their own personal phone (a precondition to receiving the subsidy) by subsidy rollout group (the first set of districts implemented the subsidy in March 2019, a second group in May 2019 and the last group in July 2019, as outlined in Section 4.2.1). The limited take-up of the subsidy is discussed in Section 2.4.

Figure A4: Mobile Money Agent Expansion



Notes: This figure plots the evolution of the number of villages with a mobile money agent within 3km, due to the expansion campaign described in Section 2.5. The first wave of the expansion took place between September 2019 and April 2020.

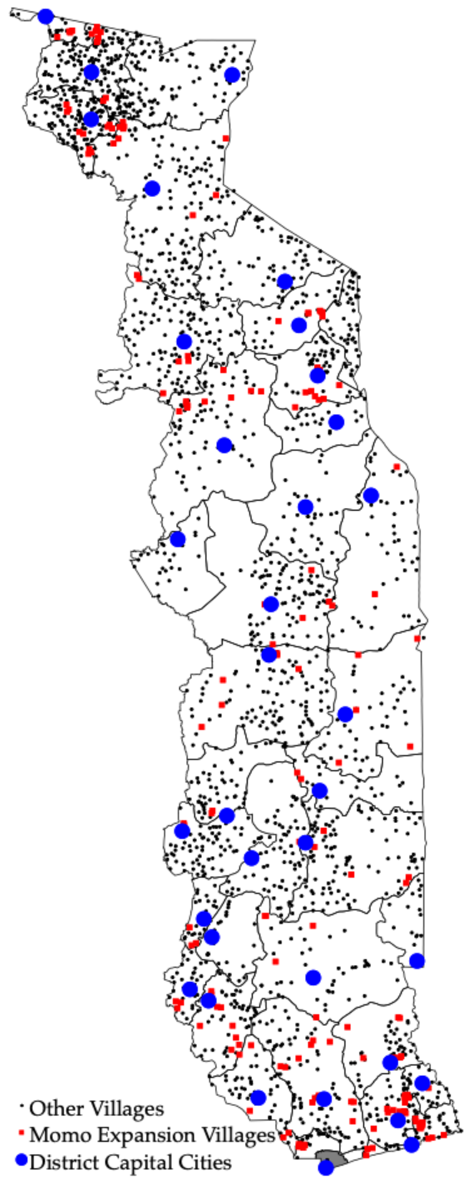
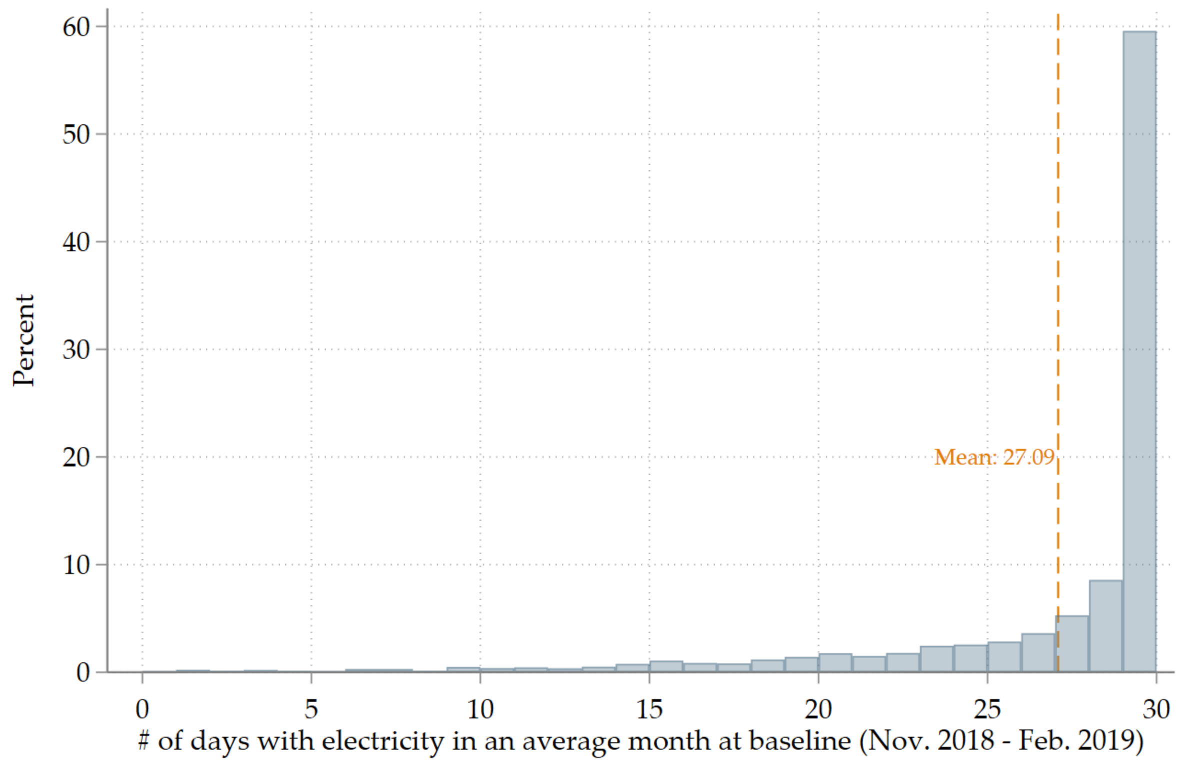


Figure A5: Map of Mobile Money Agent Expansion

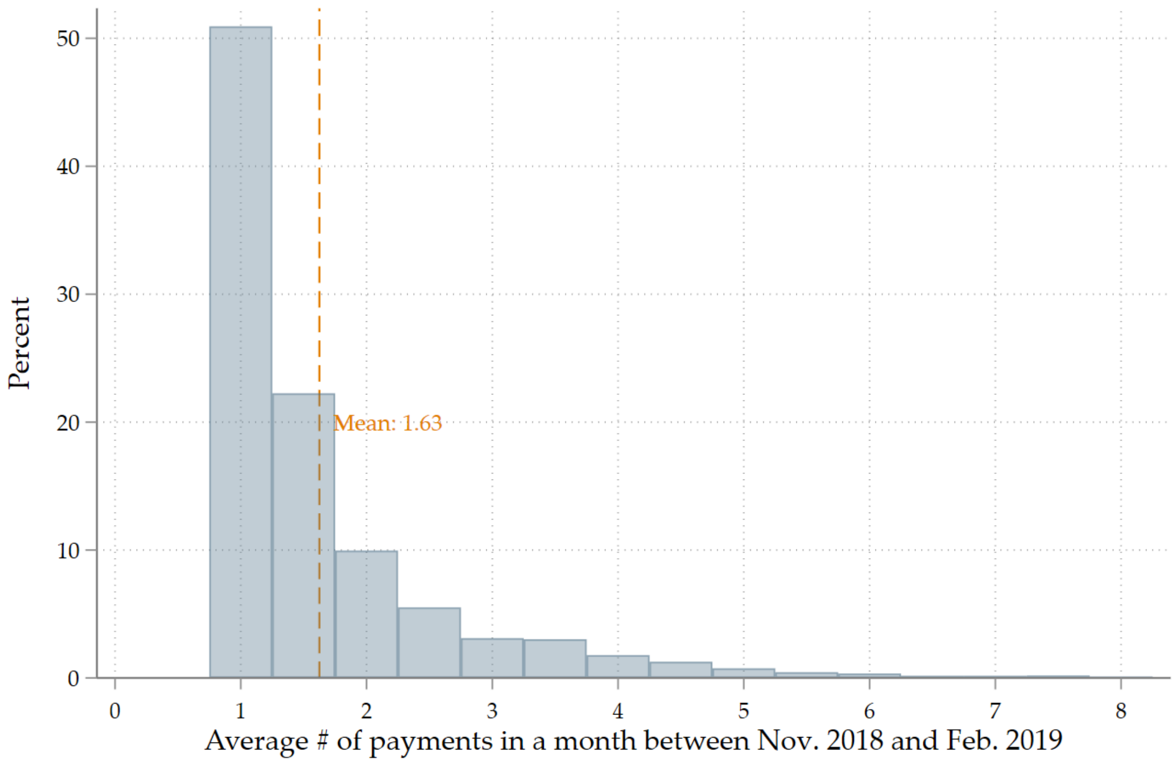
Notes: This map shows the spatial distribution of the mobile money agent expansion described in Section 2.5. The red dots represent the locations of villages that received a mobile money agent within 3km as a result of the expansion policy. We leverage the scattered nature of the expansion in our identification strategy described in section 4.2.3.

Figure A6: Histogram of Days of Electricity Consumed per Month at Baseline



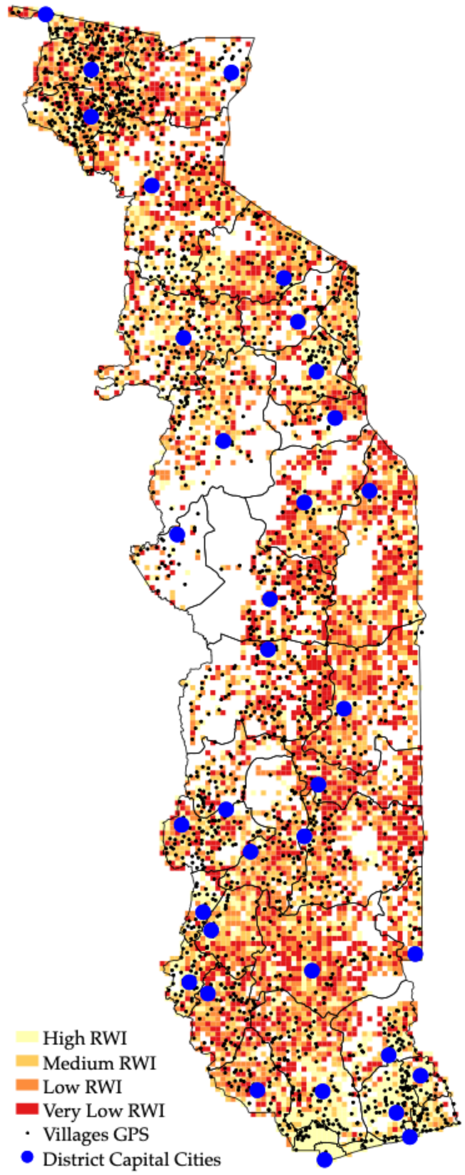
Notes: This histogram plots the distribution of the number of days in each month that a customer has electricity. The sample is restricted to existing customers by December 2018.

Figure A7: Histogram of Number of Payments per Month at Baseline



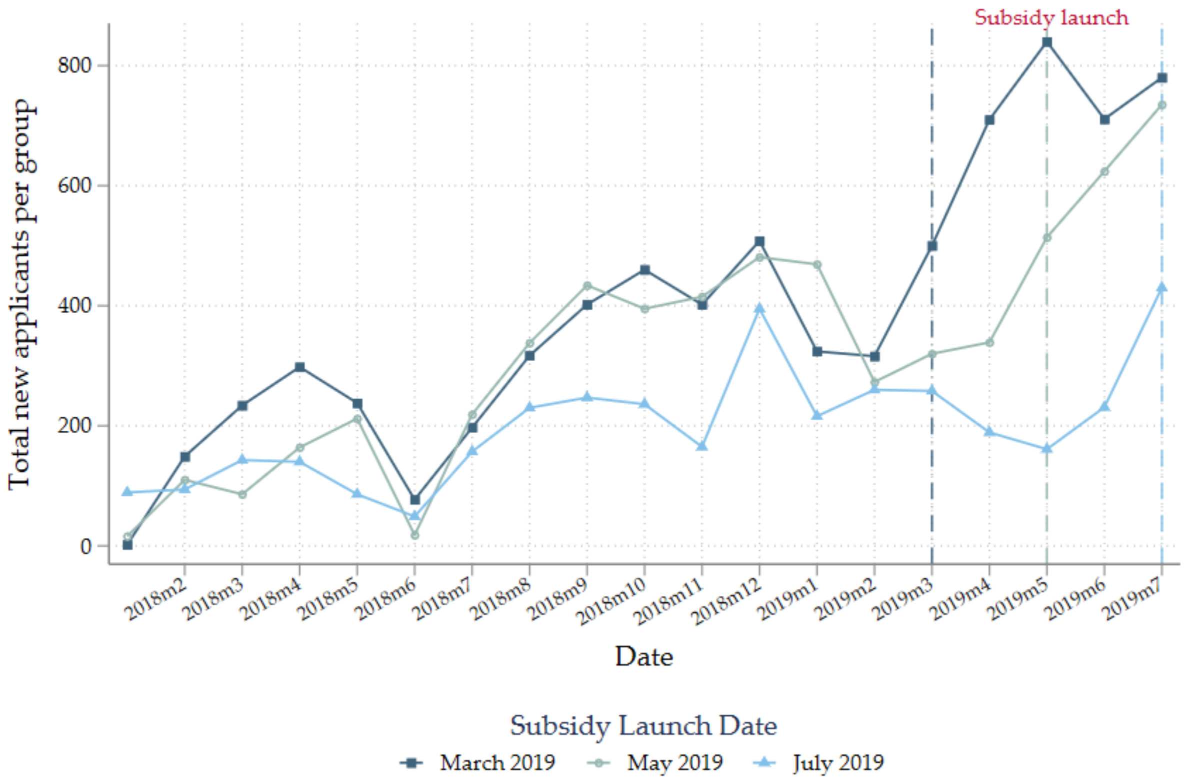
Notes: This histogram plots the distribution of the number of payments customers make each month. The sample is restricted to existing customers by December 2018.

Figure A8: Map of Relative Wealth Index across Togo



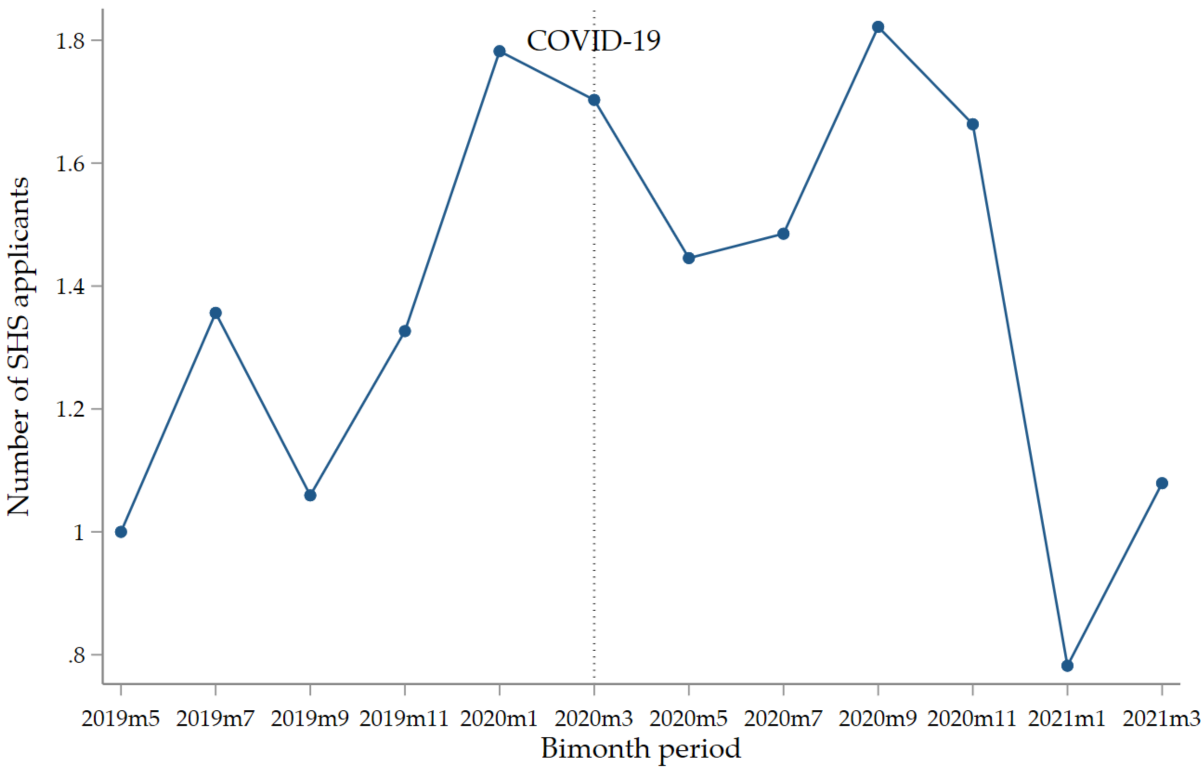
Notes: This map shows the spatial distribution of relative wealth in Togo, as measured by Meta's Relative Wealth Index. This is a global geospatial database based on Chi et al. (2022) which combines household survey data with non-traditional data sources (including satellite imagery, cellular network data), as described in Section 4.1.

Figure A9: New applicants in subsidized and un-subsidized districts



Notes: This figure plots the total number of new SHS applicants by subsidy rollout group. The first set of districts implemented the subsidy in March 2019, a second group in May 2019 and the last group in July 2019, as outlined in Section 4.2.1.

Figure A10: SHS Applications and COVID-19



Notes: This figure plots the total number of new SHS applicants in villages used in the analysis of the mobile money agent expansion policy, described in Section 2.5. These are villages that received a mobile money agent through the expansion policy at different points between September 2019 to March 2020 (the 'treatment villages"), and in 2021 ("control group villages").

B Appendix Tables

Table A1: Summary Statistics Pre- and Post-Subsidy Customers

	(1) Pre-subsidy (February 2019)	(2) Post-subsidy (May 2020)	(3) Test of Difference
Panel A. Demographics			
HH's age at adoption	40.71	39.80	(-3.36***)
	(11.26)	(11.75)	
Female-headed Households (%)	1.60	2.48	(2.03*)
	(12.54)	(15.56)	
Customer income: agriculture (%)	77.53	70.54	(-3.16***)
	(41.74)	(45.59)	
Customer income: own biz (%)	9.86	14.51	(3.43***)
	(29.81)	(35.22)	
Customer income: employee (%)	10.53	11.47	(1.59)
	(30.69)	(31.87)	
Customer income: other (%)	2.08	3.48	(2.98***)
	(14.28)	(18.33)	
Panel B. Previous Energy Sources			
Any Electricity Sources (%)	2.22	1.34	(-1.82*)
	(14.74)	(11.48)	
Solar (%)	1.27	0.68	(-1.63)
	(11.21)	(8.20)	
Grid (%)	0.44	0.36	(-0.74)
	(6.62)	(5.95)	
Generator (%)	0.51	0.30	(-1.58)
	(7.12)	(5.50)	
Flashlight (%)	44.01	26.56	(-4.57***)
	(49.65)	(44.17)	
Kerosene/Lantern/None (%)	52.75	71.46	(5.03***)
	(49.93)	(45.16)	
Panel C. Electricity Behavior			
Basic Kit (Light+Charger) (%)	27.53	39.04	(6.91***)
	(44.67)	(48.79)	
Plus Kit (Above+Radio) (%)	29.48	20.64	(-4.19***)
	(45.60)	(40.47)	
Premium Kit (Above+TV) (%)	42.99	40.32	(-1.49)
	(49.51)	(49.06)	
Number of Payment Days	1.65	1.94	(6.12***)
	(1.41)	(1.76)	
Average Payment Size (in days)	28.02	16.49	(-14.82***)
	(26.36)	(12.33)	
Utilization Rate (%) (%)	90.98	87.96	(-5.66***)
	(20.31)	(22.07)	
Number of Customers	4322	11523	

Notes: The table summarizes the characteristics of the consumers available in our data, for demographic variables (Panel A), energy sources (Panel B) and electricity behavior (Panel C). Column (1) show the mean values of each variable for customers who joined by February 2019. before the subsidy. and who received the subsidy by December 2019. Column (2) shows the mean values for all customers who had joined by May 2020, nearly a year after the subsidy. Standard deviations in brackets. The third column shows the t-stat of the difference between the baseline and endline group of consumers, where the following OLS regression equation, controlling for district fixed effect, is performed: $Y_i = \beta May2020 + District_i + \epsilon_i$, with standard errors clustered at the district-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Balance Table Across Groups of Districts - Government Data

	(1) Group 1	(2) Group 2	(3) Group 3	(4) F-stat ANOVA	(5) N	All districts
Electrified households (%)	5.00	16.54	23.18	(26.37***)	35	15.00
	(0.00)	(6.58)	(7.83)			(9.39)
# of districts	11	13	11			35

Notes: The table summarizes the electrification rates of the districts within the three groups. This is based on data collected in 2016 from the Government of Togo (data is unavailable for one out of thirty-six districts). The first three columns show the mean values of the district averages for each of the three groups of districts treated at different times, with standard deviations in parentheses. The electrification rates are provided by the Government in ranges, and so the midpoint of the range is used for each district average (all districts in Group 1 have electrification rates between 0 and 10%, hence the 5% mean with no standard deviation). The fourth column shows the F-stat of the one-way analysis-of-variance (ANOVA) model to test for differences in means across the three groups. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Balance Table Across Groups of Districts

February 2019	(1) Group 1	(2) Group 2	(3) Group 3	(4) F-stat ANOVA	(5) N	All districts
Panel A. Demographics						
HH's age at adoption	40.25	39.92	41.64	(1.74)	36	40.59
	(2.63)	(2.79)	(1.62)			(2.46)
Female-headed Households (%)	0.74	1.44	3.35	(5.45***)	36	1.86
	(1.21)	(1.56)	(2.79)			(2.22)
Customer income: agriculture (%)	83.04	77.22	66.88	(2.50*)	36	75.55
	(15.21)	(17.59)	(19.60)			(18.37)
Customer income: own biz (%)	8.13	10.20	15.71	(2.35)	36	11.40
	(8.22)	(8.66)	(9.28)			(9.07)
Customer income: employee (%)	7.28	10.14	14.58	(1.82)	36	10.75
	(6.49)	(8.54)	(11.86)			(9.50)
Customer income: other (%)	1.56	2.44	2.83	(0.71)	36	2.30
	(2.08)	(2.80)	(2.82)			(2.59)
Panel B. Previous Energy Sources for Lighting						
Any Electricity Sources (%)	2.53	1.46	2.38	(0.51)	36	2.09
	(3.66)	(2.28)	(2.50)			(2.80)
Solar (%)	1.26	0.91	1.23	(0.11)	36	1.12
	(2.43)	(2.09)	(1.64)			(2.01)
Grid (%)	0.79	0.07	0.75	(2.27)	36	0.52
	(1.15)	(0.17)	(1.22)			(0.99)
Generator (%)	0.47	0.49	0.40	(0.02)	36	0.45
	(0.78)	(1.26)	(0.95)			(1.00)
Flashlight (%)	48.04	42.22	50.57	(0.28)	36	46.78
	(29.42)	(29.83)	(26.08)			(27.92)
Kerosene/Lantern/None (%)	48.44	55.49	46.32	(0.36)	36	50.28
	(26.82)	(30.60)	(27.04)			(27.80)
Panel C. Electricity Behavior						
Basic Kit (Light+Charger) (%)	28.32	29.93	22.86	(0.66)	36	27.08
	(14.45)	(21.25)	(8.90)			(15.78)
Plus Kit (Above+Radio) (%)	25.60	32.16	20.83	(1.46)	36	26.38
	(16.47)	(20.36)	(11.49)			(16.86)
Premium Kit (Above+TV) (%)	46.08	37.91	56.31	(2.59*)	36	46.54
	(24.14)	(19.51)	(16.83)			(21.13)
Number of Payment Days	1.60	1.53	1.90	(4.44**)	36	1.67
	(0.33)	(0.27)	(0.36)			(0.35)
Average Payment Size (in days)	35.90	30.79	26.11	(1.57)	36	30.79
	(21.94)	(8.27)	(3.74)			(13.46)
Utilization Rate (%)	91.81	92.29	92.54	(0.11)	36	92.23
	(3.77)	(4.29)	(3.28)			(3.72)
# of districts	11	13	12			36
# of consumers per district	154	115	94			120

Notes: The table summarizes the characteristics of customers who joined by February 2019, before the subsidy, and who receive the subsidy at some point by December 2019. Panel A displays demographic, population, and past energy sources variables, and Panel B electricity behavior variables. The first three columns show the mean values of the district averages for each of the three groups of districts treated at different times. This is measured at baseline, before the subsidy intervention in February 2019, with standard deviations in parentheses. The fourth column shows the F-stat of the one-way analysis-of-variance (ANOVA) model to test for differences in means across the three groups. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Relationship between Subsidy Receipt and Mobile Money Agent Proximity

	Subsidy received within the first two months			
	(1)	(2)	(3)	(4)
Momo Agent Within 3km of the Village	0.032	0.038	0.037	0.029
	(0.044)	(0.043)	(0.039)	(0.039)
Constant	0.671***	0.623***	0.688***	0.629***
	(0.037)	(0.041)	(0.034)	(0.039)
Cohort Fixed Effects	No	Yes	No	Yes
Cohorts	1 & 2	1 & 2	All	All
R-squared	0.001	0.015	0.001	0.019
Observations	565	565	750	750

Notes: Regressions of an indicator variable for receiving the subsidy within the first two months of eligibility on pre-subsidy access to a mobile money agent within 3km. Sample restricted to customers used in the heterogeneity analysis (i.e., they either had an agent within 3km or eventually received one between June-December 2019). First two columns include customers that became eligible for the subsidy in March and May 2019. The last two columns include all customers. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Adoption impacts of mobile money agent introduction, omitting COVID period

	(1)	(2)
	SHS Applications	$\mathbb{1}\{$Any SHS Application$\}$
Agent arrival	0.698	0.122
	(0.448)	(0.096)
Control Mean	0.47	0.29
Effect relative to control mean	149%	42%
P-val: pre-periods = 0	0.326	0.205
Number of villages	101	101
Observations	808	808

Notes: This table re-estimates the results in Table 5, but stops the analysis period at April 2020, instead of December 2020. The table displays village-level ITT effects of having a mobile money agent introduced in the village, on solar home system (SHS) adoption, estimated by equation 6, following Sun and Abraham (2021). Our empirical strategy compares villages that received a mobile money agent between September 2019 and March 2020 through the agent expansion policy described in section 2.5, to villages that received an agent in later, in 2021, due to an abrupt halt caused by COVID. The analysis is conducted at the bimonthly frequency. We obtain the static average effect by averaging the dynamic effects, as in equation 2. The outcome variable in column (1) is the number of SHS applications per bimonth in each village. The outcome variable in column (2) is a dummy variable that equals one if the village had any SHS applicants in the bimonth. The control mean corresponds to the mean of the outcome in the control group prior to mobile money agent expansion. To asses parallel pre-trends, we report the p-value of the joint test that the coefficients in all pre-periods equal zero. Standard errors, clustered at the village level, shown in parentheses. *, ** and ***, denote significance at the 10, 5 and 1% level, respectively.

C Conceptual Framework

We develop a stylized framework to provide intuition for the role of transaction costs and liquidity constraints in adopting SHS and in choosing the optimal frequency of electricity payments. This framework provides us with five key predictions.

C.1 Setup

The environment consists of a continuum of ex-ante identical households, indexed by $i \in [0,1]$, with two time periods, indexed by $t = 1, 2$. Each household draws a level of exogenous income y^i from a common distribution F (we also denote $\bar{F} = 1 - F$ and assume that F is twice differentiable, denoted by f and f')[20]. A household will choose to adopt a solar home system (SHS) if the benefits from current and future electricity consumption exceed the costs:

$$V(SHS) = \begin{cases} V(1), & \text{if } SHS = 1 \\ 0, & \text{if } SHS = 0. \end{cases} \tag{1}$$

For simplicity, as in Lee et al. (2020b), a household's lifetime utility is normalized to 0 in the absence of a solar home system; this implies that households always prefer to have electricity if they can afford it. Given the setting in this paper, we assume that households do not have access to alternative forms of electricity, which means that their decision to become electrified is limited to adopting a SHS. Therefore, in this framework, a household will adopt if it is sufficiently wealthy, which will depend on its income (y^i), the price per unit of electricity (p) and the fixed transaction cost (τ) per electricity payment. For simplicity, we ignore the downpayment cost of adoption here.[21]

A household's is conditional on choosing an optimal payment plan in order to purchase its *inelastic* demand for electricity and maximize its consumption. Each household ranks its consumption decisions and payment plans according to the utility it accrues from consumption. Following adoption, the household's problem is as follows:[22]

$$V(1) = \max_{(c_1,c_2,d_1,d_2)\in\mathbb{R}^+\times\mathbb{R}^+\times\mathbb{N}_0\times\mathbb{N}_0} u(c_1) + \beta u(c_2) \quad \text{subject to} \tag{2a}$$

$$a_{t+1} = (1+r)a_t + y - c_t - \mathbb{1}\{d_t > 0\}(pd_t + \tau) \tag{2b}$$

$$e_t = e_{t-1} - 1 + d_t \tag{2c}$$

$$e_t > 0, \quad (a_0, e_0) = (0, 1) \qquad \forall t = 1, 2. \tag{2d}$$

At the start of each period, households receive their exogenous income, y, a stock of

[20]Each household belongs to a village v. For simplicity, we assume that each village has the same income distribution.

[21]The downpayment is not affected by the subsidy policy we study and is relatively small compared to the value of the solar home system.

[22]Subscripts are used to denote time t while superscripts are used to denote household i, although we suppress the i for simplicity.

assets, a_t, and any interest earned on these assets at the rate of r. They then choose both consumption, c_t, and the number of days of electricity to purchase, d_t. The households rank consumption and payment plans according to a time-separable utility function, $u(\cdot)$, which is non-negative, increasing and concave in consumption ($u'(\cdot) > 0$ and $u''(\cdot) < 0$), with a discount factor, β. The stock of electricity is e_t, the price for one unit of electricity is p, and whenever the household makes a payment there is a fixed transaction cost of τ.

The law of motion for assets (Equation (2b)) is standard and we assume that households can either save, which will pay out $(1+r)$ next period, or borrow at the cost of $(1+r)$. The law of motion for the stock of electricity (Equation (2c)) states that electricity today is one less than electricity yesterday, plus any days of electricity purchased today. Lastly, there are positivity constraints on the stock of electricity (Equation (2d)). This latter constraint imposes that households are not deciding how much electricity to consume, but rather how to optimally purchase their stock of electricity. Thus the framework assumes that electrification is an extensive margin decision and that once households decide to purchase a solar home system, they desire to maintain a positive stock of electricity. We therefore do not explicitly model the utility of electricity consumption relative to other consumption, as this is not the margin of interest in our study.

In the first period, the household inherits no stock of electricity (or assets) and therefore must make a purchase. The household must then choose to either purchase only one unit of electricity in this period and then make a second payment in the following period (incurring transaction costs twice), or purchase two units of electricity in this period and none in the following period (incurring transaction costs only once). The household is essentially faced with two decisions: to either purchase in bulk, with $d^B = (2, 0)$, or spread their payments, with $d^S = (1, 1)$. We denote n, the number of payments that each household makes, which is a function of p, τ, and y with:

$$n = n(p, \tau, y) = \mathbb{1}\{d_1 > 0\} + \mathbb{1}\{d_2 > 0\}. \tag{3}$$

Given the simple setting of the framework, we can denote the indirect utility function for each payment plan $d = (d_1, d_2)$ as a function of the number of payments, n, with $v(n^*)$ where $n^* = 1$ if the household buys in bulk with $d^* = (2, 0)$ and $n^* = 2$ if the household spreads their payments with $d^* = (1, 1)$, conditional on the households choosing their consumption optimally.

Finally, we also introduce liquidity-constraints, where households are unable to borrow against their future income. The following subsections will describe settings with and without liquidity constraints to highlight their role in our framework. Formally, we also introduce the assumption that households face an additional non-negativity constraint on their asset stock:

$$a_t \geq 0. \tag{4}$$

This section proceeds in two parts. First, we consider the adoption decision of households. Secondly, we characterize the solution and determine the optimal frequency of payments for electricity.

C.2 Adoption

A necessary cutoff condition for adoption is that the household has enough income y^i to purchase electricity. This means that households must be able to purchase a total of two days of electricity across the two time periods, and that they must be able to purchase at least one day of electricity in the first time period. If the household's income allows them to purchase one day of electricity today, given that households earn identical exogenous income y at the start of each period, this condition also implies that they will be able to purchase electricity in the subsequent period. In the absence of liquidity-constraints, a household can also borrow against their future income to purchase in bulk. Therefore, household i will adopt if they satisfy the following affordability constraint:

$$y^i > \min\left\{p + \tau, \frac{1+r}{2+r}(2p+\tau)\right\}. \tag{5}$$

If households face a liquidity constraint, the second option of borrowing against future income is ruled out and the adoption decision simplifies to:

$$y^i > p + \tau. \tag{6}$$

In our analysis, we simplify the adoption process such that households adopt when they can afford to, namely that the affordability constraint is indeed an adoption constraint[23]. Therefore, the proportion of households that satisfy the adoption constraint is determined by $1 - F(p+\tau) = \bar{F}(p+\tau)$. The framework predicts that **levels of adoption are lower in the presence of liquidity constraints**, as they prevent households with incomes between $p + \tau$ and $\frac{1+r}{2+r}(2p+\tau)$ from adopting.

We make three assumptions on the price of electricity, transaction costs, and income distribution, namely that: (i) the income distribution F is unimodal, (ii) only relatively wealthy households are able to adopt (those with incomes above the mode, denoted by $\bar{y}_{\text{mode}}$), and (iii) the reduction in price induced by the subsidy is not sufficiently large to shift the adoption threshold to households with incomes below the mode. These conditions describe the setting in this paper, where most households in a village are relatively homogeneous with a large majority working in agriculture, only a relatively small fraction of households in each village are able to afford a solar home system, and, in response to the subsidy, demand increases substantially but not overwhelmingly (especially because of the unaltered downpayment cost). Formally, these are assumptions require that:

$$F \text{ is unimodal} \quad \text{and} \quad \bar{y}_{\text{mode}} < p + \tau. \tag{7}$$

We characterize three predictions of the framework in the presence of liquidity constraints.

Price reductions increase adoption.

Transaction cost reductions increase adoption.

[23] We could extend the framework and formally introduce the utility of electricity to compare the tradeoffs between consumption and electricity. In this case, households would also factor their optimal payment plan, outlined in Section C.3, into their adoption decision. This would imply a tighter adoption threshold but does not substantially change our main predictions.

For the Predictions 1 and 2, we have that **levels of adoption are decreasing in price and transaction costs**[24]. This is because the adoption constraint (Equation (6)) is linear in price and transaction costs such that reductions in p and τ will make the solar home system more affordable to prospective households:

$$\frac{\partial \bar{F}(p+\tau)}{\partial p} = \frac{\partial \bar{F}(p+\tau)}{\partial \tau} = -f(p+\tau) < 0. \tag{8}$$

There are complementary adoption effects of reducing price and transaction costs: price reductions in villages with low transaction costs should have higher effects on adoption than in villages with high transaction costs.

For Prediction 3, we have that **the impact on adoption in response to a price reduction will be higher in areas with low transaction costs relative to those with high transaction costs**[25]. The intuition is that in villages with low transaction costs, more households will be closer to the adoption threshold, such that a reduction in price will result in a larger proportion of households crossing the adoption threshold, compared to households in villages with high transaction costs. This follows from a unimodal F and that adoption occurs for relatively wealthy households (Equation (7))[26]. Therefore, this complementarity is identified by the positive cross partial derivative:

$$\frac{\partial^2 \bar{F}(p+\tau)}{\partial p \partial \tau} = -f'(p+\tau) > 0 \tag{9}$$

This third prediction highlights how policies that reduce prices and policies that reduce transaction costs are complementary in this setting, where transaction costs are relatively high and households are liquidity-constrained. Specifically, reducing transaction costs will enhance and amplify the impact of the subsidy on adoption, and thus rural electrification efforts. The framework therefore predicts that the treatment effect of price reductions will vary with baseline transaction costs.

C.3 Frequency of Payments for Electricity

After a household adopts a solar home system, it must determine the optimal number of payments to make for its electricity. We first describe behavior in liquidity-unconstrained settings and then detail how this changes with the introduction of liquidity constraints.

C.3.1 Liquidity-Unconstrained Households

In a setting without any liquidity constraints, the household's budget constraint equates the present value of consumption to the present value of income net of electricity purchases:

[24] This assumes income is held constant.

[25] Assuming the same income distribution across these areas.

[26] The unimodal assumption implies that the probability density function $f(\cdot)$ is decreasing for incomes above the modal income such that $f'(\cdot)$ is negative. Our prediction is therefore symmetric, as it is reversed if, instead, adoption has already occurred for households with incomes below the mode.

$$c_1 + \frac{c_2}{1+r} = \begin{cases} y - (2p+\tau) + \dfrac{y}{1+r}, & \text{if } n = 1 \\ y - (p+\tau) + \dfrac{y-(p+\tau)}{1+r}, & \text{if } n = 2. \end{cases} \quad (10)$$

An interior solution satisfies the Euler equation for consumption: $u'(c_1^*) = \beta(1+r)u'(c_2^*)$. We further assume that $\beta(1+r) = 1$, which is standard and implies that $c^* = c_1^* = c_2^*$: households will perfectly smooth consumption. The decision then becomes whether to purchase electricity in bulk in the first period, or smooth payments across both periods. This problem then simplifies to choosing the payment plan that maximizes the present value of income, net of electricity purchases. If a household purchases in bulk, its net income is lower today than tomorrow and so it will borrow against tomorrow's income. If a household spreads its payments, it will simply consume its net income in each period. The intuition for this tradeoff is straightforward as a household will choose to purchase in bulk only if the interest earned on making one less payment, $p\,r$, is less than having to incur an additional transaction cost, τ, tomorrow. The optimal payment plan is as follows:

$$n^* = \begin{cases} 1, & \text{if } p\,r < \tau \\ 2, & \text{otherwise.} \end{cases} \quad (11)$$

The framework makes two predictions in the absence of liquidity constraints: First, **a reduction in price will reduce the number of payments** because it becomes more cost effective to purchase in bulk as the price of electricity lowers. Second, **a reduction in the transaction cost will increase the number of payments** because as it becomes more cost effective to spread payments as the transaction cost for each payment becomes lower. Formally, we have that[27]:

$$\frac{\Delta\, n^*}{\Delta\, p} \geq 0 \quad \text{and} \quad \frac{\Delta\, n^*}{\Delta\, \tau} \leq 0. \quad (12)$$

The main insight here is that, without liquidity constraints, policies that reduce the price of electricity and that reduce the transaction cost for each electricity payment will result in opposite effects, and thus an ambiguous total effect on payment behavior.

C.3.2 Liquidity-Constrained Households

Suppose now that households are liquidity-constrained and are unable to borrow against their future income. The optimality implication of this constraint is that the Euler equation will not always bind. There are two income ranges that we must consider in this case. First, households whose incomes are below the bulk payment amount, $y^i \in (p+\tau, 2p+\tau]$, will be unable to purchase in bulk and must spread their electricity payments. Households that can afford to purchase in bulk, $y^i > 2p+\tau$, face a clear tradeoff. If they purchase in bulk, they will consume less today and more tomorrow (failing to satisfy the

[27]We ignore affordability constraints for an interior solution, as consumption must be positive (see Equation (5)).

Euler equation with equality) but will only incur the transaction cost once. If they spread their payments, they will have perfectly smooth consumption (satisfying the Euler equation with equality) but must incur a second transaction cost.

Liquidity constraints therefore have two key impacts on household behavior. First, they impose a *contemporaneous-income constraint* for households that do not have enough first-period income to buy in bulk and are unable to borrow against future income. Second, they also impose a standard *consumption-smoothing constraint*, which applies particularly to households with relatively higher incomes who can afford to buy in bulk. For these households, it is less appealing to buy in bulk (than in the unconstrained world) because they unable to borrow against future income to optimally smooth their consumption.

Formally, the optimal payment plans are as follows:

$$n^* = \begin{cases} 1, & \text{if } v(1) \geq v(2) \\ 2, & \text{otherwise} \end{cases} \tag{13a}$$

$$v(1) = u(y - [2p + \tau]) + \beta u(y) \tag{13b}$$

$$v(2) = u(y - [p + \tau]) + \beta u(y - [p + \tau]). \tag{13c}$$

Let us denote the threshold level of income that a household will choose to purchase in bulk by $y_B(p, \tau) \geq 2p + \tau$[28]. This threshold exists because liquidity constraints prevent customers from borrowing against future income. Households with incomes below this threshold will spread payments and those above will purchase in bulk. The optimal payment plan will now depend on the relative position of a household's income y^i to this threshold income $y_B(p, \tau)$.

Assuming that the unconstrained optimum is to purchase in bulk ($p\, r < \tau$) and additionally that households have decreasing absolute risk aversion, then $y_B(p, \tau)$ exists and is unique. Moreover, this income threshold, $y_B(p, \tau)$, is increasing in p but the relation is ambiguous for τ, with the following inequalities[29]:

$$\frac{\partial y_B(p, \tau)}{\partial p} > 1 \quad \text{and} \quad \frac{\partial y_B(p, \tau)}{\partial \tau} < 1. \tag{14}$$

We characterize two predictions of the framework.

Price reductions decrease payment frequency.

Transaction cost reductions have an ambiguous effect on payment frequency.

For Prediction 4, it is clear that reductions in price mean that more households can afford to purchase in bulk, thus alleviating the *contemporaneous-income constraint*. Furthermore, for those households already able to purchase in bulk, reductions in price also make it possible to smooth consumption to a greater extent (in the absence of borrowing), alleviating the *consumption-smoothing constraint* and making it more appealing to purchase in bulk. These indirect effects amplify the direct effects outlined in the liquidity-

[28] This threshold may be larger than $2p+\tau$ as the disutility from non-smooth consumption may dissuade some households from purchasing in bulk even if they can afford to.

[29] Appendix Section C.4 for proofs and additional exposition for these claims.

unconstrained setting; price reductions thus unambiguously reduce the number of payments, as in the case for liquidity-unconstrained households.

For Prediction 5, reductions in transaction costs, however, have a more ambiguous effect. On the one hand, as in the liquidity-unconstrained case, lower transaction costs make it less costly to make multiple payments and smooth consumption. On the other hand, lower transaction costs alleviate the *contemporaneous-income constraint*, as more households can afford to buy in bulk (in the absence of the ability to borrow against future income). As such, the presence of liquidity constraints means that, depending on the magnitudes of these relative effects, a reduction in transaction costs can actually decrease the number of payments.

The directional effect of a price reduction on payment frequency is the same as in the setting without liquidity constraints, as both direct and indirect effects move in the same direction. However, reducing transaction costs can have a counter-intuitive effect due to the presence of liquidity constraints. Even though the transaction cost reduction makes it cheaper to smooth consumption, this can be outweighed by the alleviation of the contemporaneous-income constraint as more households have enough first-period income to afford to buy in bulk.

These predictions show that the presence of liquidity constraints can, under certain conditions, lead to the counter-intuitive prediction of a decline in frequency when transaction costs are lowered. For this to hold, it must be the case that transaction costs are relatively large such that the contemporaneous-income constraint is sufficiently restrictive. The frictions in this environment can also drive complementarity between reductions in price and reductions in transaction costs.

C.4 Deriving Properties of the Income Threshold for Purchasing in Bulk

In the theoretical framework outlined in Section C.3, we are interested in deriving the properties of $y_B(p,\tau)$, the income threshold above which adopting households will optimally choose to purchase their electricity in bulk. In the liquidity-unconstrained setting, the solution is trivial as, if $p\,r < \tau$, all households will purchase in bulk provided that they can afford to adopt, such that $y_B(p,\tau) = \min\left\{p+\tau, \frac{1+r}{2+r}(2p+\tau)\right\}$. In the liquidity-constrained setting, there is no closed form solution but we can still derive first and second order partial derivatives for $y_B(p,\tau)$. Let us define $I(p,\tau,y)$ as the net utility of purchasing in bulk relative to the utility from spreading payments; this function is equal to 0 when evaluated at y_B:

$$I(p,\tau,y_B) = u(y_B - (2p+\tau)) + \beta u(y_B) - (1+\beta)u(y_B - (p+\tau)) = 0. \tag{15}$$

First we prove existence and uniqueness of y_B and identify sufficient conditions. It is helpful to note that this problem can also be conceptualized through an analogous lottery problem. After scaling the total utility function by $\frac{1}{1+\beta}$, the two period time-separable utility function becomes a von Neumann–Morgenstern utility function. Now, we define the option to purchase in bulk as investing in a risky asset R that with probability $\frac{1}{1+\beta}$ yields $-(2p+\tau)$ and with probability $\frac{\beta}{1+\beta}$ yields 0, and we define the option to spread payments as investing in a safe asset with a certain outcome of $c = -(p+\tau)$. The expected utilities of $y + R$ and $y + c$ represent the same preferences as before but scaled by $\frac{1}{1+\beta}$:

$$E[u(y+R)] = \frac{1}{1+\beta}u(y-(2p+\tau)) + \frac{\beta}{1+\beta}u(y), \tag{16a}$$

$$E[u(y+c)] = u(y-(p+\tau)). \tag{16b}$$

Therefore, at y_B we have that $E[u(y_B+R)] - E[u(y_B+c)] = 0$, which is equivalent to finding $I(p,\tau,y_B) = 0$. In this risk conceptualization, the income threshold y_B is the level of wealth at which the household is indifferent between choosing the risky asset and the safe asset. As we have assumed that the household is risk averse from a concave utility, a necessary condition for the existence of y_B is that the expected payoff from the risky asset R must be higher than the safe asset. Formally, we have that:

$$E[R] > c \iff -\frac{1}{1+\beta}(2p+\tau) > -(p+\tau) \iff \frac{1-\beta}{\beta}p < \tau \iff p\,r < \tau. \tag{17}$$

The last expression holds because of the assumption that $\beta(1+r) = 1$. This is the identical condition that was derived in the liquidity-unconstrained setting (Equation (11)). The assumption that it is optimal to purchase in bulk in a liquidity-unconstrained setting is necessary for households to potentially choose to purchase in bulk in a liquidity-constrained setting. Otherwise, the household would never choose the risky asset or to purchase in bulk. Therefore, existence of $y_B(p,\tau)$ depends on focusing on parameter values for which it would be optimal to purchase in bulk in an unconstrained world: $p\,r < \tau$.

We make one additional assumption about the utility function: the household has decreasing absolute risk aversion (DARA) preferences. If we define $\rho_A = -u''(c)/u'(c)$ as the coefficient of absolute risk aversion, then DARA implies that:

$$\frac{d\rho_A}{dc} < 0 \iff u''(c)u''(c) < u'(c)u'''(c). \tag{18}$$

The implication of Equation (18) is that the household becomes less risk averse against additive changes in income when their income increases. Thus, the risk premium associated with the risky asset (for a fixed R) decreases with income. Therefore, at some income level, the household's coefficient of absolute risk aversion will be sufficiently low such that it will choose to invest in the risky asset or, in our context, to purchase in bulk. This proves the existence of y_B.

An additional and important implication of this result is that, if the household prefers $y + R$ to $y + c$ for some level of income $y = y_1$, then the household must also prefer the risky asset at any higher level of wealth $y = y_2 > y_1$. Importantly, this proposition implies that there is a unique income threshold, y_B, because for all incomes above this threshold, the household will always prefer the risky asset and thus always prefer to purchase in bulk. Therefore, there is only a single crossing point, proving the uniqueness of y_B.

In order to derive the partial derivatives of $y_B(p,\tau)$ with respect to price and transaction costs, we apply the implicit function theorem. We have that the income threshold is unambiguously increasing in p, while the income threshold is ambiguous in τ with the following bounds:

$$\frac{\partial y_B(p,\tau)}{\partial p} > 1 \quad \text{and} \quad \frac{\partial y_B(p,\tau)}{\partial \tau} \begin{cases} < 0, & \text{if } I_\tau > 0 \\ = 0 & \text{if } I_\tau = 0 \\ \in (0,1), & \text{if } I_\tau < 0. \end{cases} \tag{19}$$

The proof is as follows. We have defined $I(p, \tau, y_B) = 0$ and if $I_y \neq 0$ at this point, we can express $y_B = h(p, \tau)$ where the first order derivatives are:

$$\frac{\partial y_B(p,\tau)}{\partial p} = h_p = -\frac{I_p}{I_y} \quad \text{and} \quad \frac{\partial y_B(p,\tau)}{\partial \tau} = h_\tau = -\frac{I_\tau}{I_y}. \tag{20}$$

We have the following first order partial derivatives for $I(p, \tau, y_B)$:

$$I_p = -2u'(y_B - (2p+\tau)) + (1+\beta)u'(y_B - (p+\tau)), \tag{21a}$$
$$I_\tau = -u'(y_B - (2p+\tau)) + (1+\beta)u'(y_B - (p+\tau)), \tag{21b}$$
$$I_y = u'(y_B - (2p+\tau)) + \beta u'(y_B) - (1+\beta)u'(y_B - (p+\tau)). \tag{21c}$$

Assuming that the utility function is strictly increasing and concave and that $\beta \in (0,1)$, we can conclude that for positive values of p and τ, the following relationships hold:

$$-I_p > I_y > -I_\tau \quad \text{and} \quad I_y > 0 > I_p. \tag{22}$$

The proof for these inequalities is as follows. We have that $u'(y_B - (2p+\tau)) > u'(y_B - (p+\tau)) > u'(y_B) > 0$. First, $I_p + I_y = -u'(y_B - (2p+\tau)) + \beta u'(y_B) < 0$. Second, $I_y + I_\tau = \beta u'(y) > 0$. Third, $I_p < 0$ because $u'(y_B - (p+\tau)) < u'(y_B - (2p+\tau))$ and $1 + \beta < 2$. Fourth, at the solution for $I(p, \tau, y_B) = 0$, we have earlier shown that y_B is unique and that for all income levels above y_B, the household will always prefer to purchase in bulk such that $I(p, \tau, y_B + \epsilon) > 0$ for $\epsilon > 0$. Similarly, for income levels below y_B, the household will always prefer to spread payments such that $I(p, \tau, y_B - \epsilon) < 0$. Therefore, by taking the limit as $\epsilon \to 0$, we have that it must be that $I_y > 0$. Given these conditions, we have proved that $h_p > 0$ and so the income threshold is unambiguously increasing in p. h_τ, however, is ambiguous depending on the sign of I_τ. Furthermore, given the strict inequalities in Equation (22), this also means that h_p is bounded below by 1 and h_τ is bounded above by 1 which concludes the proof for Equation (19).

D Information Campaigns

One might expect the subsidy impact to be partly influenced by information campaigns, conducted both by the solar company and the government. To partly address this concern, we use the company's data to measure the sensitivity of the subsidy's impact to the information campaigns.

The data analyzed is aggregated at the store level and focuses on marketing campaigns conducted by the solar provider. Each store (a total of 22) is assigned to at least one district, in which it is responsible for all information campaigns. This gives us data for campaigns in a total of 29 districts. Inevitably, within each district, different villages will be targeted differently by these campaigns. Unfortunately, we do not have access to such granularity in the data, and therefore much of our analysis can only be conducted at the district level.

We separate the campaigns into three categories: (i) market, which involves proactive outreach in large market areas; (ii) radio, which includes radio advertisements and shows; and (iii) other campaigns, which combine festivals, children targeted campaigns, and door-to-door outreach. Figure 11 shows the number and type of information campaigns conducted during each bi-month period, whilst Table 6 records the percentage of District x Bi-months during which each campaign occurred. Market visits and radio campaigns are the most frequently employed. Given the variation in Figure 11, one might suppose that the introduction of the subsidy would have been accompanied by additional information campaigns that could act as a potential confounder on the estimated impact of the subsidy. Columns (2) and (3) of Table 6 show the proportion of District x Bi-months for each information campaign for the two-month periods before and after the subsidy launch in each district. These averages are not significantly different from each other, which suggests no significant change in the extent of information campaigns during subsidy launch, apart from the proportion of districts receiving radio ads, which declined at the 10% significance level.

Generally, we find no significant change in the extent of information campaigns during subsidy launch[30] and no significant impacts of the campaigns on customer and village adoption, both before and after the subsidy.

The limited impact of the information campaigns might however be attributed to the lack of granularity in the data available. As discussed above, the data is at the store level, and our analysis assumes that each store covers the entire district(s) assigned to it. In reality, each store is only likely to run campaigns in a subset of villages within each district. Ideally, more granular data would enable us to exploit this variation within districts, which might provide greater insight into the specific impact of the campaigns. It must also be noted that this data relates to specific marketing campaigns undertaken by the solar company and not the broader work done by the government to raise general awareness about the subsidy.

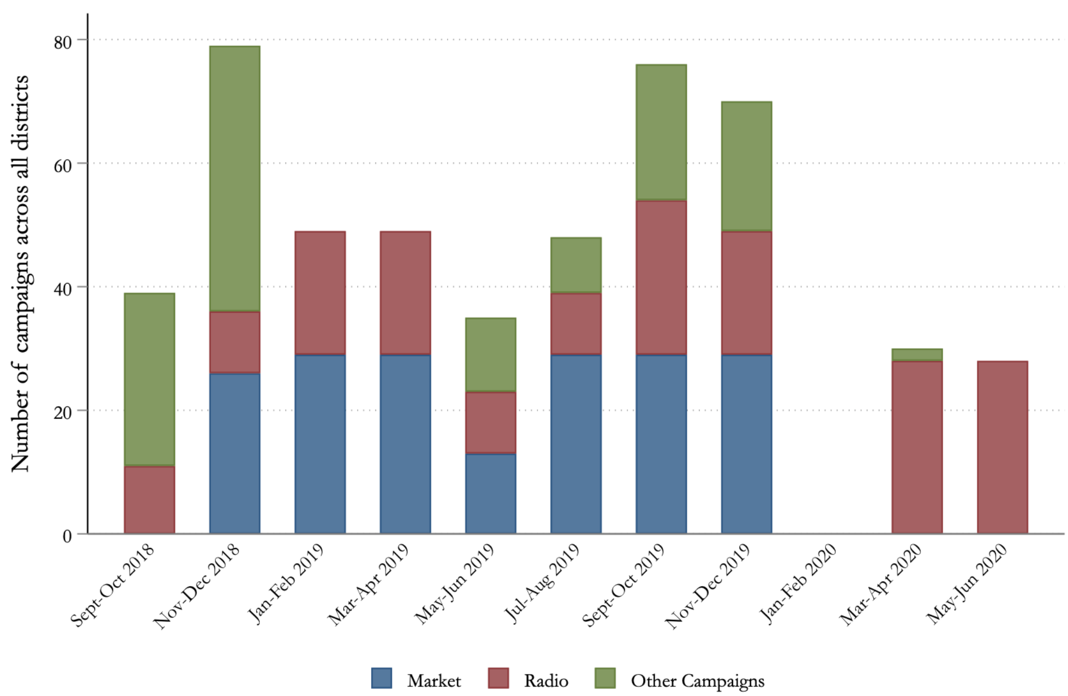
[30] Apart from the proportion of districts receiving radio ads, which declined at the 10% significance level.

Table 6: Percentage of District x Bi-months targeted by marketing campaigns

	(1) September 2018 - May 2020	(2) 2 months pre-subsidy	(3) 2 months post-subsidy	(4) T-stat difference
Market	55.76	73.33	83.33	(1.14)
	(49.74)	(44.98)	(37.90)	
Radio	55.15	56.67	50.00	(-1.86*)
	(49.81)	(50.40)	(50.85)	
Other campaigns	33.86	17.24	20.69	(-0.33)
	(47.40)	(38.44)	(41.23)	
N	319	29	29	

Notes: The table summarizes the proportion of districts targeted by various marketing campaigns across each bi-month period. The first column shows this proportion over the full sample period (September 2018 - May 2020). The second and third columns show the proportion in the two months pre- and post- subsidy launch (these specific months vary by prefecture). The fourth column shows the t-stat of the difference between the two months pre- and post-subsidy, where the following OLS regression equation is performed $Y_i = \beta Post-Subsidy + \epsilon_i$, with standard errors clustered at the district-level (with the sample restricted only to two months pre- and post- subsidy launch). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 11: Number of District-level Information Campaigns



Notes: This figure describes the number and types of information campaigns conducted by the solar company around the time of the subsidy launch.