Prepayment and Electricity Usage in Temperature Extremes: Implications for Energy Poverty and Climate Justice*

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Abstract

Prepayment systems, though benefiting utilities' revenue recovery, could impose additional burdens on disadvantaged households. This paper provides novel evidence on how prepaid metering affects households' electricity-temperature relationship. Leveraging a novel dataset on 150,000 customers billing record in Bangladesh, we find that households' electricity consumption becomes remarkably less responsive to temperature after they are enrolled in prepayment systems. Larger effects are documented among households with lower wealth or education levels. Prepaid households tend to engage in mental accounting on their electricity consumption especially during hot seasons. Our results implies that prepaid metering might have unintended impact on energy poverty and climate justice.

Keywords: Prepayment, Electricity Consumption, Temperature, Climate Justice
JEL Codes: L94, O13, O33, Q41, Q54, Q56

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1 Introduction

As a technological solution to non-payment in billing systems, prepaid meters are increasingly deployed by the electric utility sectors in both developed and developing countries. Previous studies have documented considerable advantages of prepaid metering, including higher energy savings and increased revenue recovery (Jack and Smith, 2015, 2020; Qiu, Xing and Wang, 2017; Beyene et al., 2022). However, there is growing concern about the equity consequences of prepaid metering and its impact on energy poverty, particularly among disadvantaged households (Kambule and Nwulu, 2021). Prepayment systems can impose additional burdens on poor people. Consumers in debt or with intermittent income might face disconnections of service if they are temporarily unable to purchase credits. Low-income households may also under-utilize electricity, ultimately returning to consumption of suboptimal fuels, like biomass or Kerosene, with relatively lower costs.

Energy insecurity associated with prepaid metering can be exacerbated during temperature extremes under climate change. Households rely on energy-intensive heating or cooling technologies to adapt to cold or hot weather. The potential high energy bills can be a financial burden for low-income households, who may end up with insurmountable energy debt and lose access to energy services due to non-payment. With prepayment systems, households are forced to engage in self-control and to shrink their energy consumption to avoid auto-disconnections. As a result, these households might have limited adaptive capacity to temperature extremes and become more vulnerable to temperature-related harms. Despite emerging evidence on consumption and revenue recovery, little is known about whether prepaid metering will disproportionately affect poor households and to what extent can limit their capacity for climate adaptation.

In this paper, we examine how prepayment impacts household electricity consumption in response to temperature extremes and investigate the distributional effects on households' climate adaptation capacity in Bangladesh, one of the most vulnerable countries to climate change. Studying this question is empirically difficult for two main reasons. First, the utility's decision to deploy prepaid meters could be endogenously determined by region-specific or customer-specific characteristics that are correlated with electricity consumption patterns, such as historical records on revenue recovery or bill non-payment. Second, obtaining granular data on household electricity consumption across wide climate zones is notoriously difficult, especially in developing countries.

We overcome these challenges by exploiting two sources of exogenous variation – the staggered introduction of prepayment systems and temperature. From 2015, electric utility companies started switching from postpaid to prepaid systems in large-scale across the major urban areas in Bangladesh. By 2020, almost one-third of urban households have been enrolled in the prepayment system. The implementation of prepayment was a mandatory program by the government. The rollout process of prepaid meters to different locations was mainly determined by administrative capacities, which therefore provides plausible exogenous variations across locations and over time. Therefore, we employ a difference-in-differences (DiD) design to estimate the impact of prepayment on the electricity-temperature relationship. Conceptually, we compare, in terms of how electricity consumption responds to temperatures, among households in the postpaid group to those in the prepaid group before and after the implementation of prepayment. Our regression models include a rich set of fixed effects and interaction terms to flexibly control for time-invariant or household-invariant differences in the electricity-temperature relationships.

Our empirical analyses take advantage of a novel dataset on administrative electricity billing record for residential customers from five districts of Bangladesh: Dhaka, Chittagong, Khulna, Bagherhat, Shatkhira and Pirojpur. The data contains 10 million observations on monthly electricity consumption from January 2014 to November 2019 for a random sample of 150,000 households. We supplement this data with prepaid metering switching dates from the electric utility companies, socioeconomic and demographic information from the census, and weather variables from the Bangladesh Meteorological Department.

We begin by confirming the electricity-temperature response function and the impact of prepayment on electricity consumption within a single model. Consistent with central results of prior studies, additional days with hot temperatures lead to a significant increase in electricity consumption in the current billing period. In addition, we document over 15% decline in household electricity usage after they switch to a prepayment billing system.

Next, we explore how prepayment changes the electricity-temperature relationship by adding an interaction term of the prepayment indicator and a flexible function of monthly temperature measures. We find that the implementation of prepayment remarkably mitigates the relationship between hot temperatures and electricity usage. Household energy spending becomes much less responsive to extreme weather after prepaid metering. The results survive a series of robustness checks that address confounding factors or use alternative measurements of monthly weather patterns. More importantly, heterogeneity analysis suggests that this effect is more pronounced among poor households who now have almost muted spending responses, and among regions with a hot historical climate. The differential impacts on poor and rich households imply an energy poverty gap, which could be explained by foregone space cooling during hot weather. We are now collecting household survey data, and in the future steps, we plan to investigate how prepaid metering affects household appliance adoption and other expenditures during hot temperatures.

Taken together, these results provide novel evidence on how prepaid metering disproportionately affects poor households and limits their adaptation capacity to hot temperatures under climate change. We contribute to the literature on energy poverty and climate justice, which we show could be exacerbated by prepayment systems under extreme weather (Longden et al., 2021; Barreca, Park and Stainier, 2022; Doremus, Jacqz and Johnston, 2022). Our findings imply that the implementation of prepayment systems, though benefiting utilities' revenue recovery, could impose huge burdens on disadvantaged households especially among temperature extremes, leaving them exposed to higher climate-related risks.

2 Institutional Background

2.1 Climate Crisis in Bangladesh

As a country, Bangladesh contributes only 0.56% of the global greenhouse gas emissions. The average person in Bangladesh emits 0.5 metric tons of CO_2 per year, which is much lower compared to developed countries. Despite the tiny proportion of carbon emissions, Bangladesh – with low elevation, high population density and weak infrastructure – ranks the seventh of countries most vulnerable to climate devastation (Eckstein, Künzel and Schäfer, 2021).

Although Bangladesh has made substantial efforts and investments in climate adaptation, it continues to face severe and increasing climate risks. Climate change intensifies extreme weather events, like heat waves and flooding, which bring remarkable damages to the economy. During 2000 – 2019, Bangladesh encountered $3.72 billion in economic losses and witnessed 185 extreme weather events due to climate change. By 2050, a third of agricultural GDP could be lost and 15 to 30 million Bangladeshis could become internal climate migrants and be displaced from coastal areas (World Bank Group, 2022). Severe flooding could cause a 9 percent reduction in GDP. These climate-related costs are expected to rise over time, compounded by higher heat, humidity, and health impacts. Evolving climatic conditions also pose a threat to physical and mental health, negatively affecting human capital and productivity. Due to extreme heat induced by global warming, Bangladesh loses 7 billion working hours in a year (Parsons et al., 2021).

Poor and vulnerable populations will be hit by climate change the hardest. Disadvantaged people have limited resources to invest in adaptation to extreme weather events. Consequently, heat waves, sea level rise, powerful cyclones and devastating floods destroy the lives and livelihoods of the poorest people. Rural families in Bangladesh are estimated to be spending $2 billion annually to avoid or recover from climate damages (Eskander and Steele, 2019).

2.2 Prepaid Metering

As a smart technological solution, prepaid electricity metering can address non-payment problems, reduce system losses, avoid electricity thefts, and improve load management. Prepaid meters operate on a debit basis. Customers should purchase credits upfront and load the amount into their electricity meters. The available credits will be automatically deducted from the meters when there is electricity usage. Once the money is exhausted, the electricity will be automatically disconnected. To resume power supply, households need to top up the meter again with credits.

Bangladesh's large-scale implementation of prepaid metering started in 2015. Electricity distribution companies replaced existing postpaid system with prepaid electricity meters among urban households. Figure 1 shows the share of households enrolled in prepayment over time on a monthly basis. Prepaid metering expanded rapidly since 2017, reaching around 40% of total share of households in our sample by late 2019.

The staggered rollout of prepaid meters at different locations followed a random implementation process, which therefore provides plausible exogenous variations. According to discussions with DESCO, DPDC, BPDB, WZPCL, Power Division, and MPENR officials, the implementation of prepaid metering does not depend on any household or location specific characteristics. Rather, they considered their own administrative capacity, e.g., how easy and hassle-free to implement the prepaid metering in a particular area, when determining the rollout process.

This metering replacement is not voluntary. Once utilities start to deploy prepaid meters at a certain distribution area, all of the residents in that region are forced to switch to the prepaid system. Households are usually given notice two weeks in advance that their electricity will be disconnected and the existing postpaid meter will be replaced by a prepaid one. Since this is a mandatory program by the government, households do not have an option to opt-out. Utility records also suggest that, once the meter replacement starts in a region, all of the residents in that area will be covered in a short period, which mitigates the concern of potential spillovers. More details about prepaid metering rollout are provided in Appendix A1.

2.3 Temperature, Prepayment, and Electricity Consumption

The relationship between temperature and electricity consumption has been studied extensively in the literature across different countries (Longden et al., 2021; Auffhammer, 2022). In general, electricity usage has a positive link with temperature. However, extreme temperatures can significantly impact electricity use for poor households. In particular, it incurs additional economic stress that often led to electricity disconnection (Barreca, Park and Stainier, 2022; Cicala, 2021).

Recent literature found that prepayment can influence households to use less electricity (Allcott and Mullainathan, 2010; Jack and Smith, 2020; Das and Stern, 2020).The behavioral economic theory suggests that when households use a prepayment system in their consumption plan they pay more attention to tracking their consumption or payment than a postpaid system (Gourville and Soman, 1998; Chen, Kök and Tong, 2013; Hochman, Ayal and Ariely, 2014; Tiefenbeck et al., 2019). In relation to that, when households use prepaid meter in their electricity consumption, they consider several factors, such as transaction costs, risk of auto-disconnection, credit constraints and budgeting.

Evidence also suggests that both energy insecurity and energy saving caused by extreme temperatures may have fatal effects on health (He and Tanaka, 2023; Cicala, 2021). Poor people who are unable to afford adequate cooling during hot summers may be at increased risk for heatstroke, and other heat-related illnesses. Moreover, extreme temperatures can impact work productivity.

3 Data

The empirical analysis draws on three unique datasets obtained from several sources, including the universe of residential customer electricity monthly billing information, prepaid vending information, and socio-economic information of census regions. We synthesise all these dataset and construct a balanced panel of household-level monthly electricity billing record from January 2014 to November 2019, resulting in a total of over 10 million observations. This section briefly describes the main data sources, construction of variables, and sample selection. We provide more details in Appendix A2.

3.1 Electricity Consumption and Prepaid Metering

The residential customer monthly electricity consumption data is extracted from four major utility in Bangladesh: Dhaka Electricity Supply Company Limited (DESCO), Dhaka Power Distribution Company Limited (DPDC), Bangladesh Power Development Board (BPDB) and West Zone Power Distribution Company Limited (WZPDCL) whose territory encompassed approximately 50 percent of total Bangladeshi urban residential customers (Power Division, 2021). This administrative dataset includes details of monthly electricity use and payment records for the full population of residential households in Dhaka, Chittagong, and Khulna regions from January 2014 to November 2019. We extract a random sample of 150,000 households and obtain their information on unique ID, location, electricity consumption, demand charge, electricity bill (BDT), tariff type, sanction load, bill cycle, meter phase, distribution location and feeder location. Data on prepaid meter switching date for each household are obtained from the corresponding electricity distribution companies' vending information.

3.2 Weather

The weather data comes from the National Centers for Environmental Information at the National Oceanic and Atmospheric Administration (NOAA). We use Global Surface Summary of the Day (GSOD) product that is derived from the Integrated Surface Hourly (ISH) dataset. GSOD reports global station-level weather data on a daily basis since 1929. We extract data from the 63 stations covering Bangladesh from 2014 to 2019. The data contains geographic location of each weather station and daily summaries on temperature, precipitation, dew point temperature, and wind speed. Figure B1 shows the weather stations in Bangladesh and our sample districts.

The electricity consumption data and weather data are merged by year, month, and sub-districts (i.e., upazila), the smallest administrative geographic unit available for each household. We transform weather data from the station to sub-district level using an inverse-distance weighting method. Specifically, we calculate the weighted average of weather measures from the stations located within a 100km radius of each sub-district's centroid. The weights are defined as the inverse distance between each station and the centroid.

3.3 Demographics

To obtain households socio-economic and demographic information, we matched each household's electricity feeder location with nine-digit administrative unit in the 2011 Bangladesh Census (BBS, 2011). This census data includes mean household size, housing quality, electricity access, poverty ratio, education achievement and many other variables.

3.4 Descriptive Evidence

The final merged sample is a balanced panel from January 2014 to November 2019 with 150,000 households from 96 subdistricts in Bangladesh. It has over 10 million observations. Summary statistics for electricity consumption and weather variables are provided for all households over all months in our sample in Table 1. Household average monthly electricity consumption is 290 kWh, corresponding to 1,667 BDT billed amount. Due to the hot climate, the average monthly temperature in our sample region is 80°F.

Figure B2 shows the distribution of daily average temperature and monthly total precipitation in our sample regions. We assign these temperatures into a series of 5°F temperature bins and plot in Figure B3 the distribution averaged across regions and years in our sample. The height of each bar represents the number of days in a year with daily average (or maximum) temperature falling in each temperature bin. On average, over 200 days in a year have daily average temperature above 80°F. As illustrated in Figure B4, the regions in our sample, especially the southwest districts, experience a substantial number of hot days.

Box plots of daily average temperature, precipitation, electricity consumption, and bills over each calendar month are presented in Figure 2. The average daily temperature rises and maintains at a level above 80°F from April to September. These months also have lots of precipitations. Similarly, household electricity consumption increases remarkably during these hot months.

4 Empirical Strategy

The rollout process of meter replacement in Bangladesh provides plausible exogenous variations across locations and over time in terms of the electricity bill payment method. Therefore, we employ a difference-in-differences (DiD) design to study the causal impact of prepayment on the relationship between temperature and household electricity consumption. We first estimate the direct effect of prepayment and temperature using one regression model, and then explore the change in electricity-temperature response function by adding interaction terms.

4.1 Basic Model

We begin by investigating the direct effect of both prepayment and temperature on household electricity consumption in a single econometric model. Our unit of analysis is the household-year-month. The following equation describes the regression model, with subscripts i and t representing household and time.

$$\ln q_{it} = \alpha \text{Prepaid}_{it} + \beta' \mathbf{g}(\text{Temp}_{it}) + \gamma' \mathbf{X}_{it} + \phi_i + \delta_{y(t)} + \tau_{m(t)} + \varepsilon_{it}. \tag{1}$$

The outcome of interest q_{it} is the electricity consumption (kWh) or billed amount (BDT). The dummy variable Prepaid_{it} is an indicator for whether household i has enrolled in prepaid metering at time t. The vector $\mathbf{g}(\text{Temp}_{it})$ is some function that aggregates daily temperatures to the monthly level. We consider two forms of $\mathbf{g}(\cdot)$ in the following analysis: monthly average temperature; a vector of temperature bins measuring whether the monthly average temperature falls into a specific temperature interval. In the main specification, we estimate models that include two indicators for whether the monthly average temperature falls into 80-85°F or above 85°F. The reference group is the months with average temperature below 80°F. We also test models that contain more temperature bins to flexibly estimate the nonlinear temperature effect.

We add a vector of control variables, $\mathbf{X}_{it}$, which vary across households and months. They include quadratic functions of monthly precipitation, dew point, and wind speed. To account for unobservable confounding factors, we control for household fixed effects ϕ_i to capture time-invariant differences across households. Since both electricity consumption and temperature exhibit substantial seasonality, We also include year fixed effects $\delta_{y(t)}$ and calendar month fixed effects $\tau_{m(t)}$. We do not control for year-by-month fixed effects to avoid absorbing too much weather variation. In robustness checks, we add region-specific year and calendar month fixed effects to allow differential seasonality across regions. Lastly, ε_{it} is the idiosyncratic error term. Standard errors are clustered at the feeder line level.

The first coefficient of interest is α that captures the average treatment effect of prepayment on household electricity consumption. The identification of α requires the parallel trends assumption for a DiD design: trends in electricity consumption would have been similar between prepaid households and postpaid households in the absence of the treatment. We provide support of this assumption by estimating an event study model and showing no differential trend prior to the prepaid meter rollout.

The second coefficient of interest is β that describes how electricity consumption changes in response to temperature. The identifying assumption is that, within a household, weather realizations are uncorrelated with other unobserved determinants of electricity consumption. Conditional on year and month fixed effects and other controls, weather realizations on generally considered to be random.

4.2 Interaction Model

To identify the interaction effect between prepayment and temperature, we leverage a DiD design to estimate how prepayment affects the electricity-temperature relationship. The specification is described below.

$$\begin{aligned}\ln q_{it} &= \beta'\mathbf{g}(\text{Temp}_{it}) + \eta'\text{Treat}_i \times \mathbf{g}(\text{Temp}_{it}) + \theta'\text{Prepaid}_{it} \times \mathbf{g}(\text{Temp}_{it}) \\ &\quad + \kappa_i \times \text{Prepaid}_{it} + \gamma'\mathbf{X}_{it} + \phi_i + \delta_{y(t)} + \tau_{m(t)} + \varepsilon_{it}. \qquad (2)\end{aligned}$$

This interaction model is distinct from the basic model in three ways. First, we introduce two interaction terms: (1) between the indicator for whether a household is ultimately enrolled in prepayment and the temperature function ($\text{Treat}_i \times \mathbf{g}(\text{Temp}_{it})$), which controls for fixed differences in the electricity-temperature relationship between the treatment group (i.e., households ultimately enrolled in prepayment) and the control group (i.e., households in postpaid system for the whole sample period); and (2) between the prepayment dummy and the temperature function ($\text{Prepaid}_{it} \times \mathbf{g}(\text{Temp}_{it})$). Second, in addition to previous weather controls, we fully interact these weather variables with the treatment group dummy and the prepaid indicator. This allows the effect of other weather conditions to vary across groups and treatment periods. Third, we control for heterogeneity in the prepayment effect across all households by including the interaction between household fixed effects and the prepaid indicator ($\kappa_i \times \text{Prepaid}_{it}$). Adding this term is to make sure the electricity consumption of different households with different payment methods is normalized to the same level during the months with the reference temperature category. We consider alternative time fixed effects in robustness checks.

The coefficient of interest in Equation (2) is θ. It captures the change in electricity-temperature relationship from before to after prepaid metering, relative to the change in electricity-temperature relationship among households who are never enrolled in prepayment at all. The additional identification assumption requires that the rollout of prepaid metering is independent of the electricity-temperature relationship, conditional on our control region. Since we are relying on random weather shocks, there is little reason to be concerned that temperature variation is related to the deployment of prepaid meters. Nonetheless, we show that estimates of the direct effect of prepayment and temperature are stable across versions of Equation (1), where both treatments are included and each is included separately.

Analogous to a standard DiD approach, another identifying assumption is that, in the absence of prepaid metering, the electricity-temperature relationship should exhibit similar trends between the treatment and control group. In later analyses, we separately estimate the electricity-temperature relationship for the control group and the treatment group during different event time windows to provide support for this assumption.

5 Results

5.1 Direct Effect of Prepayment and Temperature

5.1.1 Basic Model

Table 2 presents the results of the most basic models. In the top panel, we use the log of electricity consumption as the outcome variable, and all models include the set of weather controls and fixed effects described in Equation (1). These models vary in whether and how the effects of each treatment (i.e., prepayment and temperature) are incorporated.

Column (1) starts with a simple model that regress electricity consumption on the prepaid indicator, excluding all temperature variables. The coefficient estimate indicates that prepaid metering reduces household electricity consumption by 12.2%. Relative to the mean electricity usage of 290 kWh, this corresponds to a 35 kWh decrease in monthly consumption. Column (2) reports estimate from a simple model for the effects of temperature on electricity consumption, excluding any measures of prepaid metering. The coefficient estimate suggests that, an 1°F rise in monthly average temperature leads to an 1% increase in household electricity consumption. The statistical power is extremely high for all estimates in columns (1) and (2), which is important for the estimation of interaction effects that follow.

In column (3), we include both the prepaid indicator and temperature in a single regression model. The coefficient estimates are almost identical to those from the simple models where only one of the treatment variables is included. The result reassures that the variation used to identify the effects of prepayment and temperature on electricity consumption are independent of each other. Therefore, the identification of interaction effects in the following analyses is unlikely to be confounded by some unaddressed interdependence.

The estimates in columns (4) and (5) use models where the single temperature variable is replaced by two indicators for whether the monthly average temperature falls into 80-85°F or is above 85°F. The results here reveal the nonlinear effect of temperature, i.e., electricity consumption increases more during hotter months. The coefficient estimates indicate that, relative to the months with average temperature below 80°F, electricity consumption increases by 8.2% (10.2%) during the months with average temperature at 80-85°F (above 85°F). The bottom panel, with the log of electricity bill as the outcome variable, yields similar results.

5.1.2 Dynamic Effects and Nonlinear Effects

We then estimate more flexible models that include event dummies of prepaid metering rollout to trace the dynamic effect and include more temperature category indicators to better capture the nonlinear temperature effect. Figure 3 shows the estimates of the single-month event dummies relative to the initial rollout of prepaid metering. These estimates provide more details on the dynamic effect of prepayment. Prior to the rollout of prepaid metering, there is no meaningful difference in the trend of electricity consumption between the treatment group and the control group. After prepaid metering, we see an immediate and remarkable decline in household electricity consumption, and the effect persists one year later.

Figure 4 presents flexible estimates of temperature effects from the model with six 2°F temperature bins. We aggregate the bins with temperature below 75°F or in 75-80°F to guarantee sufficient sample size in those categories. The results characterize the nonlinear effect of temperature on electricity consumption. Relative to months with average temperature below 75°F, household electricity consumption increases dramatically in hotter months. In particular, there is a sharp jump in electricity consumption when monthly average temperature is above 80°F.

5.1.3 Heterogeneous Effect of Prepayment by Monthly Temperature

On average, prepaid metering leads to a remarkable decline in household electricity consumption. An interesting question is whether the effect of prepaid metering differs across months with various temperature levels. To explore the heterogeneous effects, we add in Equation (1) interactions between the prepaid indicator and the temperature bins. The left panel of Figure 5 plots the coefficient estimates and their corresponding 95% confidence intervals for electricity consumption from households with prepaid versus postpaid metering during months with different temperature levels. We consider months with average temperature below 75°F as the reference group and hence the other estimates are relative to the electricity consumption during the reference months.

We document consistent negative effect of prepaid metering on electricity consumption under all temperature levels. Prepaid households' electricity-temperature response during 80-88°F months becomes flatter. During months with temperature below 80°F, prepaid households consume remarkably less electricity compared to those postpaid households. In addition, prepaid households' electricity consumption during the 80-88°F months is at a similar level of postpaid households' consumption during months with cooler weathers.

5.2 Effect of Prepayment on Electricity-Temperature Relationship

We have shown that prepaid metering significantly reduces the level of household electricity consumption under all temperature conditions. In this section, we explore how prepaid metering affects the electricity-temperature response function. We start with showing graphical evidence using one group of households who are enrolled in prepaid metering in the same month. Then, we estimate the interaction model to formally identify the changes in electricity-temperature relationship and explore the heterogeneous effects by household consumption and education levels. Lastly, we explore the bunching features in household's electricity consumption distribution and investigate how prepaid metering intensifies bunching.

5.2.1 Graphical Evidence

To demonstrate how prepaid metering could affect the electricity-temperature relationship and to illustrate our identification strategy, we plot the electricity consumption of households who are enrolled in prepaid metering in January 2018 (henceforth the 2018m1 group) and households who are never enrolled during our sample (i.e., the control group) in Figure 6. The coefficient estimates for different monthly temperature bins come from separate regressions with household and year fixed effects using one group of households over either the pre-2018 or post-2018 period.[1]

Before 2018, the electricity-temperature response functions are virtually similar between these two groups of households. After 2018 when households in the 2018m1 group had been enrolled in prepaid metering, their electricity-temperature relationship becomes significantly flatter. In contrast, the electricity-temperature response of households in the control group does not change much. These results provide clear evidence that prepaid metering makes household electricity consumption less responsive to temperature. This graph also intuitively illustrates the key idea of our strategy to identify the causal impact of prepayment on household electricity consumption responses: comparing the electricity-temperature relationship between households in the treatment group and control group and before and after prepaid meter rollout.

5.2.2 Main Results

Motivated by the graphical evidence, we estimate the interaction model in Equation (2) to explore the effect of prepayment on the electricity-temperature response function. Table 3

[1]We do not include calendar month fixed effects to avoid absorbing too much variation in monthly temperature, as we are using sub-samples for the pre-2018 and post-2018 period separately.

shows the corresponding results. All columns include household-specific treatment dummies, year fixed effects, and calendar month fixed effects. Column (1) presents estimates of the model using monthly average temperature. The coefficient on the Tavg$\times$Prepaid interaction captures the change in the effect of temperature on electricity consumption that can be attributed to prepaid metering. It yields a negative and statistically significant estimate, suggesting that prepaid metering reduces the effect of 1°F increase in average temperature on electricity consumption by 40%. In column (2), we measure the temperature using two bins (80-85°F and >85°F) to better capture the nonlinearity. The reference group is electricity consumption during months with average temperature below 80°F. Similarly, we find that prepaid metering significantly flattens household electricity-temperature response. Larger effect is documented in months with hotter temperature. Specifically, after prepaid metering, households consume 25% less electricity during months with temperature in 80-85°F and 45% less electricity during months with temperature above 85°F. In the last two columns, we estimate the effect using electricity bills (BDT) as the outcome variable and find similar results.

To better characterize the shape of the electricity-temperature response function and study how it is affected by prepaid metering, we estimate a more flexible model with six temperature bins that indicate whether the monthly average temperature falls into a specific interval. Figure 7 plots the coefficient estimates of these temperature bins and their 95% confidence intervals for the postpaid households (in gray) and prepaid households (in blue), respectively. Consistent to our previously findings, households' electricity consumption becomes in-responsive to temperature changes after prepaid metering. For postpaid households, their electricity consumption sharply increases when monthly temperature is above 80°F and rises dramatically with temperature. In contrast, for prepaid households, we show an almost flat relationship between electricity and temperature when it is below 86°F, and the electricity consumption slightly increases after that. These results indicate that, after prepaid metering, households are likely to conserve or under-utilize electricity even in hot days, which might limit their adaptation capacity to extreme temperatures.

In Figure B7, we also separately plot the coefficient estimates for households in the treatment group over the period prior to prepaid meter rollout. Their pre-treatment electricity-temperature response function is virtually similar to households in the control group who are never enrolled in prepayment during our sample period. This result provides further support that our identified change in electricity-temperature relationship is mainly attributed to prepaid metering, rather than other differences between these two groups of households.

Next, we test whether there are differential trends in electricity-temperature responses between these two groups of households prior to the prepaid metering. In a similar spirit of the event study framework, we separately estimate the electricity-temperature relationship for households in the control group and the treatment group during various event time windows. Specifically, for households in the treatment group, we divide the sample into five time windows relative to the initial month of meter replacement: over 36 months ago (<-36), 1-36 months ago ([-36,-1]), 0-18 months later ([0,18]), and over 18 months later (>18). Each time window contains at least 18 months to guarantee sufficient sample size and weather variations for the estimation of electricity-temperature response. Figure 8 shows the coefficient estimates and their 95% confidence intervals. For the months prior to the prepaid meter rollout (i.e., <-1), the electricity-temperature relationship of households in the treatment group is comparable to that of the control group. After prepaid metering, treated households' electricity consumption starts becoming less responsive to temperature changes, and their electricity-temperature relationship becomes much flatter 18 months later.

5.2.3 Robustness Checks

We consider a series of alternative model specifications to check the robustness of our findings. Table 4 presents the results for electricity consumption. In column (1), we control for region-specific year and calendar month fixed effects to account for local shocks or differential seasonality across regions that might confound our identification. Along this line, to capture the potentially different seasonal electricity consumption patterns between the treated households and control households within a region, we add group-specific year and calendar month fixed effects in column (2). In column (3), we estimate a more flexible model that controls for individual-level seasonality in electricity consumption using the household-specific calendar month fixed effects. Lastly in column (4), to address the concern that our estimated change in electricity-temperature response could be attributed to other shocks that are common to all households over time, e.g., the improvement in electricity distribution infrastructure, we add interactions between temperature variables and year dummies in the regression. We also perform similar robustness checks using electricity bills as the outcome in Table 5. In general, our conclusion still hold.

5.2.4 Heterogeneous Effects

The effect of prepayment on electricity-temperature responses could vary across households with different demographic or socio-economic characteristics. To explore the heterogeneous effect, we estimate the model in Equation 2 separately for households with different baseline electricity consumption levels or education achievements. Table 6 reports the coefficient estimates. The first four columns show the results for electricity consumption while the last four columns show the results for electricity bills. We model the temperature function using monthly average temperature in Panel A while using temperature bins in Panel B.

We first consider the heterogeneity by baseline electricity consumption level, which can be considered as a proxy for household wealth. Households in our sample are classified into two groups based on whether their average monthly electricity consumption in 2014 (i.e., prior to the start of prepaid metering) is above or below the median. We find that the coefficient estimates of the temperature function itself exhibit similar values across these two groups. However, the estimates of those interaction terms yield much smaller magnitude for households whose baseline electricity consumption is above the median. The results indicate that the electricity-temperature responses of households with originally high electricity consumption are less affected by prepaid metering, compared to households with originally low electricity consumption.

Next, we explore how the effect differs across households with different education levels. We are not able to observe household-level education background directly but instead leverage subdistrict-level average education achievement using the 2011 Bangladesh census. Based on the census data, we calculate the percentage of adults who have at least completed primary education in each subdistrict, and then classify our sample regions into two groups based on whether their average primary education achievement rate is above or below the median. The results suggest that, regions with higher education achievement rates witness a larger effect of prepayment on flattening household's electricity-temperature responses.

Figure 9 shows the heterogeneity analysis using flexible models with six temperature indicators. Panel A plots the results by baseline consumption level, where we see an almost completely flat electricity-temperature relationship for prepaid households that are in the low consumption group. The electricity consumption of households with high baseline consumption, though becomes less responsive to temperature after prepaid metering, is still steeper that the low-consumption households. In Panel B, we demonstrate that regions with lower average education level witness a larger effect of prepayment on flattening household electricity-temperature responses. Combining these results, we show that vulnerable households, that are poor or less-educated, are affected by prepaid metering in a greater extent. Their electricity consumption becomes much in-responsive to temperature increase after they are enrolled in prepayment systems. Therefore, prepaid metering could exacerbate the energy insecurity and climate injustice problems by limiting poor households' electricity consumption and lowering their adaptation capacity to mitigate damages from extreme weather events.

5.2.5 Bunching in Electricity Consumption

To provide some insights on the underlying mechanisms, we explore how prepaid metering changes in the bunching patterns in the distribution of household's electricity consumption during different seasons. Both the prepaid and postpaid households face the same nonlinear tariff structure. There are six tariff blocks divided by the electricity consumption at 75, 200, 300, 400, and 600 kWh (see B5).

In Figure 11, we plot the distribution of electricity consumption for three subsamples: (i) households in the control group who are never enrolled in prepayment over our sample period; (ii) households in the treatment group for the period prior to the prepaid meter replacement; and (iii) households in the treatment group for the period after the prepaid meter replacement. We find that, the distribution of electricity consumption is virtually smooth, even around those tariff structure cutoffs, for control households or treated households in the postpaid period. In sharp contrast, we see a lot of bunching in the distribution of electricity consumption for treated households in the prepaid period. This figure provides suggestive evidence that, after prepaid metering, households tend to engage in mental accounting regarding their electricity consumption to avoid triggering a higher tariff level.

In Figure 12, we further break down the distribution of electricity consumption for households in the treatment group into four subsamples, depending on whether they are currently in prepaid versus postpaid system over the summer (April to September) versus winter (October to March) season.[2] The top panels show that, the distribution of electricity consumption is quite smooth during both seasons when households are still using the postpaid system. After they are enrolled in prepayment, the distribution pattern changes dramatically with more bunching. In particular, the bunching pattern becomes even more intensified during summer seasons, when households expect to consume more electricity and therefore pay more attention to their bills.

6 Conclusion

Though considered as a technological solution to bill non-payment, prepayment systems could disproportionately affect poor people and induce them to under-utilize electricity, which might ultimately make them vulnerable to extreme environmental conditions. This paper provides novel estimates on the effect of prepaid metering on households electricity-temperature responses. We find that households' electricity consumption becomes remarkably less responsive to temperature changes. The effect is larger among households with lower wealth or education levels. Our mechanism analyses reveal that prepaid households tend to engage in mental accounting and conserve electricity usage especially in hot seasons. Our findings suggest that, prepaid metering can bring huge burdens to disadvantaged households especially during temperature extremes, which further limits their adaptation capacity to mitigate weather-related damages and exacerbate the climate injustice issue.

[2] In Figure B8, we show similar results when classifying months by whether their average temperature is above versus below 85°F.

References

Allcott, Hunt, and Sendhil Mullainathan. 2010. "Behavior and energy policy." *Science*, 327(5970): 1204–1205.

Auffhammer, Maximilian. 2022. "Climate Adaptive Response Estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption." *Journal of Environmental Economics and Management*, 114: 102669.

Barreca, Alan, R. Jisung Park, and Paul Stainier. 2022. "High Temperatures and Electricity Disconnections for Low-Income Homes in California." *Nature Energy*, 7(11): 1052–1064.

Beyene, Abebe D., Marc Jeuland, Samuel Sebsibie, Sied Hassen, Alemu Mekonnen, Tensay H. Meles, Subhrendu K. Pattanayak, and Thomas Klug. 2022. "Pre-Paid Meters and Household Electricity Use Behaviors: Evidence from Addis Ababa, Ethiopia." *Energy Policy*, 170: 113251.

Chen, Li, A Gürhan Kök, and Jordan D Tong. 2013. "The effect of payment schemes on inventory decisions: The role of mental accounting." *Management Science*, 59(2): 436–451.

Cicala, Steve. 2021. "The incidence of extreme economic stress: Evidence from utility disconnections." *Journal of Public Economics*, 200: 104461.

Das, Debasish K, and David Stern. 2020. "Pre-paid metering and electricity consumption in developing countries." EEG Energy Insight, Oxford Policy Management.

Doremus, Jacqueline M., Irene Jacqz, and Sarah Johnston. 2022. "Sweating the Energy Bill: Extreme Weather, Poor Households, and the Energy Spending Gap." *Journal of Environmental Economics and Management*, 112: 102609.

Eckstein, David, Vera Künzel, and Laura Schäfer. 2021. "The Global Climate Risk Index 2021." Bonn: Germanwatch.

Eskander, Shaikh, and Paul Steele. 2019. "Bearing the Climate Burden: How Households in Bangladesh Are Spending Too Much." IIED, London.

Gourville, John T, and Dilip Soman. 1998. "Payment depreciation: The behavioral effects of temporally separating payments from consumption." *Journal of Consumer Research*, 25(2): 160–174.

He, Guojun, and Takanao Tanaka. 2023. "Energy saving may kill: evidence from the Fukushima nuclear accident." *American Economic Journal: Applied Economics*, 15(2): 377–414.

Hochman, Guy, Shahar Ayal, and Dan Ariely. 2014. "Keeping your gains close but your money closer: The prepayment effect in riskless choices." *Journal of Economic Behavior & Organization*, 107: 582–594.

Jack, B. Kelsey, and Grant Smith. 2015. "Pay as You Go: Prepaid Metering and Electricity Expenditures in South Africa." *American Economic Review*, 105(5): 237–241.

Jack, Kelsey, and Grant Smith. 2020. "Charging Ahead: Prepaid Metering, Electricity Use, and Utility Revenue." *American Economic Journal: Applied Economics*, 12(2): 134–168.

Kambule, Njabulo, and Nnamdi Nwulu. 2021. "Prepaid Electricity Meters and Energy Poverty—Lessons from South Africa." *The Deployment of Prepaid Electricity Meters in Sub-Saharan Africa* Vol. 759, 55–76. Cham:Springer International Publishing.

Longden, Thomas, Simon Quilty, Brad Riley, Lee V. White, Michael Klerck, Vanessa Napaltjari Davis, and Norman Frank Jupurrurla. 2021. "Energy Insecurity during Temperature Extremes in Remote Australia." *Nature Energy*, 7(1): 43–54.

Parsons, Luke A., Drew Shindell, Michelle Tigchelaar, Yuqiang Zhang, and June T. Spector. 2021. "Increased Labor Losses and Decreased Adaptation Potential in a Warmer World." *Nature Communications*, 12(1): 7286.

Qiu, Yueming, Bo Xing, and Yi David Wang. 2017. "Prepaid Electricity Plan and Electricity Consumption Behavior." *Contemporary Economic Policy*, 35(1): 125–142.

Tiefenbeck, Verena, Anselma Wörner, Samuel Schöb, Elgar Fleisch, and Thorsten Staake. 2019. "Real-time feedback promotes energy conservation in the absence of volunteer selection bias and monetary incentives." *Nature Energy*, 4(1): 35–41.

World Bank Group. 2022. "Bangladesh Country Climate and Development Report." World Bank, Washington, DC.

Figures and Tables

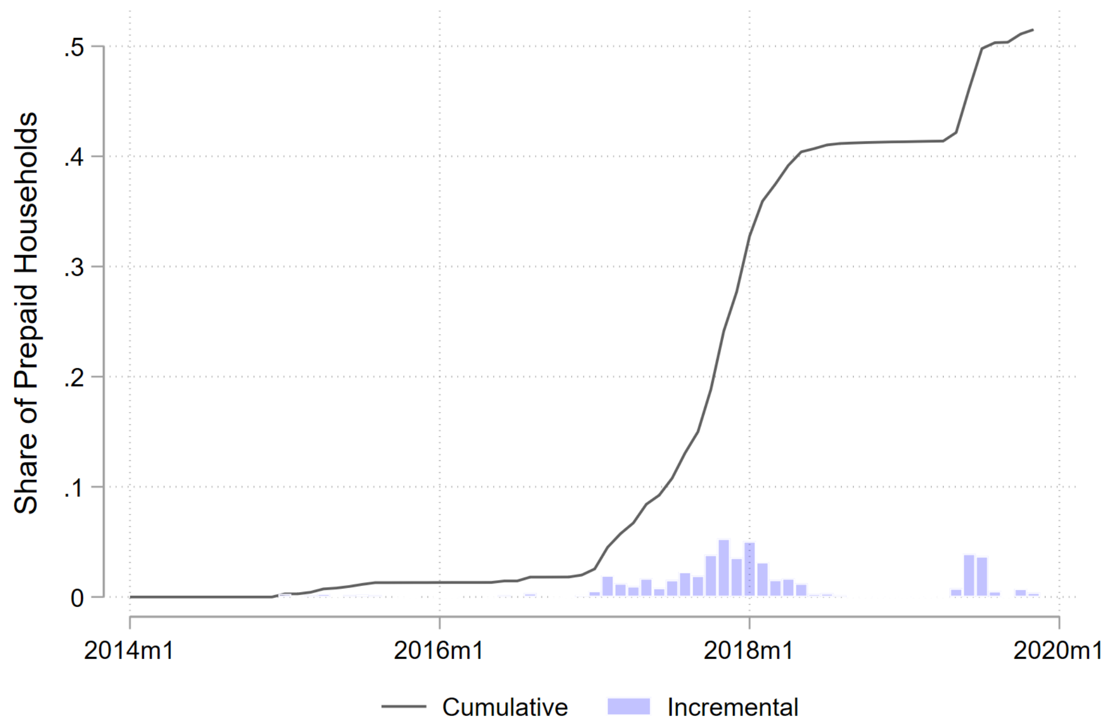
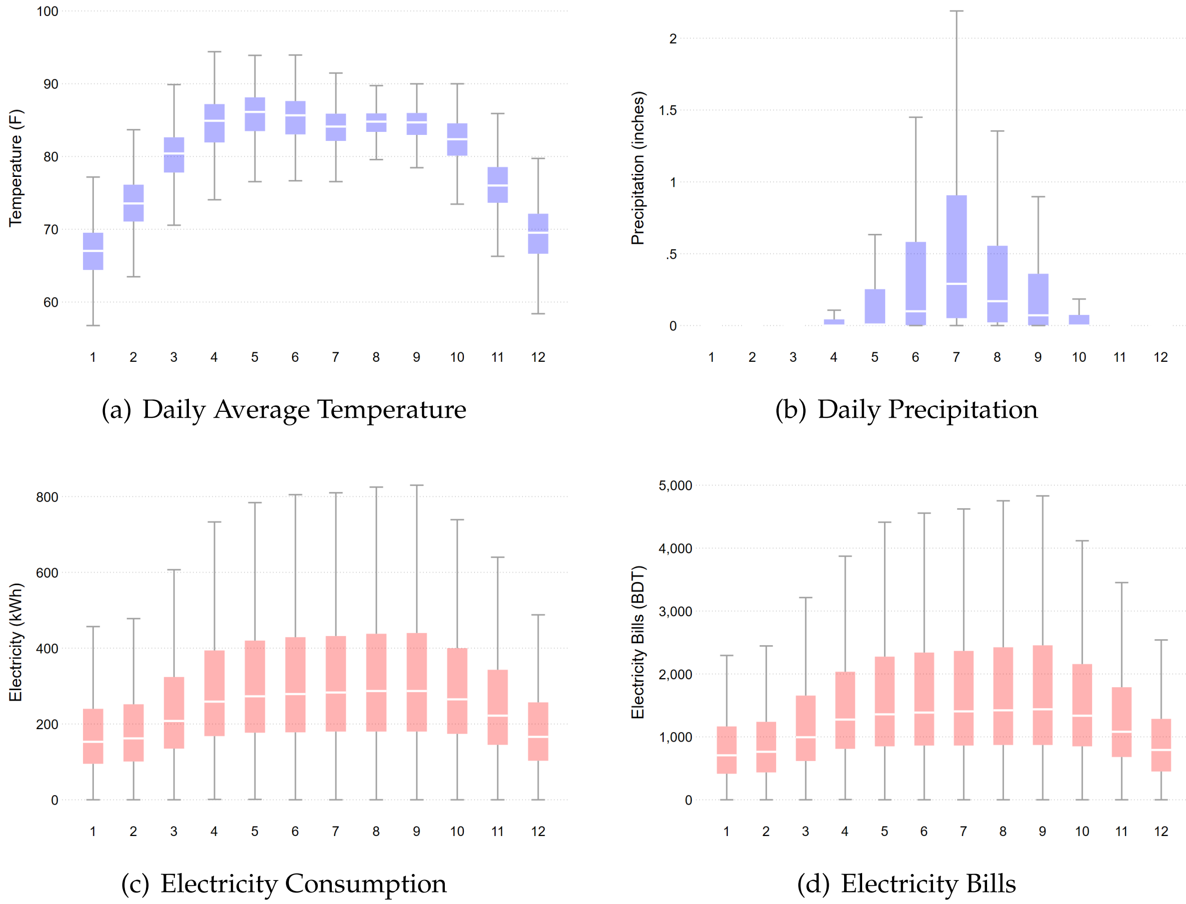


Figure 1: Rollout of Prepaid Metering

Notes: Figure shows the rollout of prepaid metering on a monthly basis.



(a) Daily Average Temperature

(b) Daily Precipitation

(c) Electricity Consumption

(d) Electricity Bills

Figure 2: Monthly Patterns of Weather and Electricity Consumption

Notes: Figure shows the box plots of daily average temperature, daily precipitation, electricity consumption, and electricity bills over calendar months.

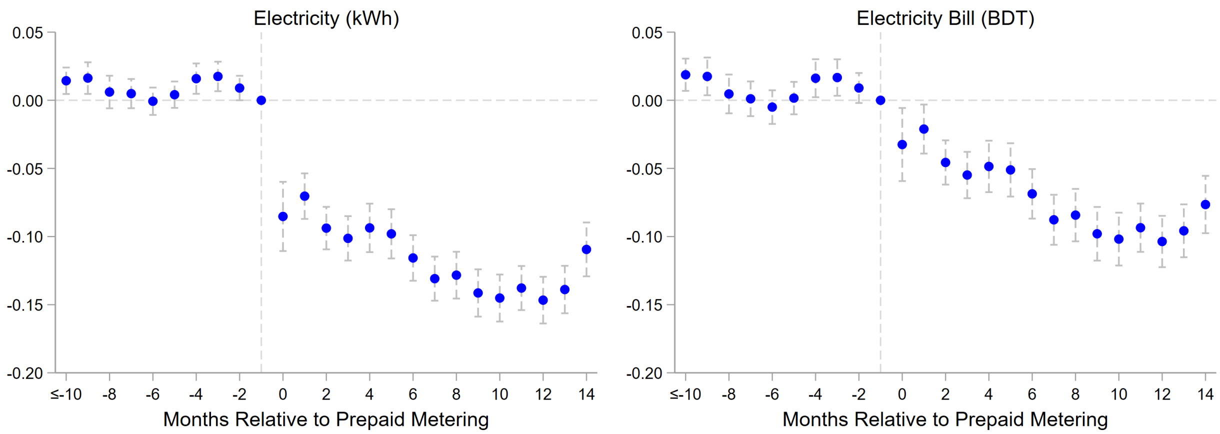


Figure 3: Dynamic Effect of Prepayment on Electricity Consumption

Notes: Figure shows the coefficient estimates and their corresponding 95% confidence intervals for the event dummies. One month prior to the prepaid metering is considered as the reference group and their coefficients are normalized to 0.

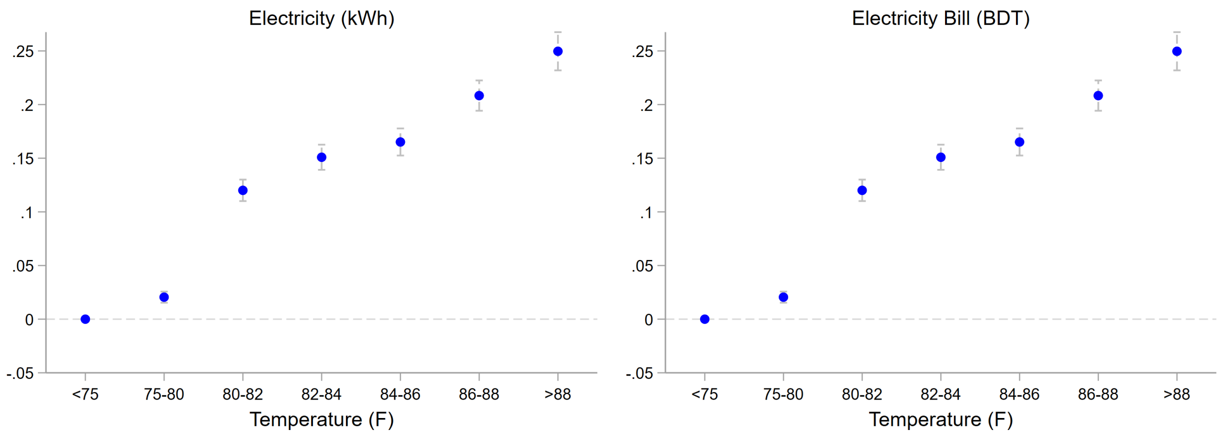


Figure 4: Relationship between Electricity Consumption and Temperature

Notes: Figure shows the coefficient estimates and their corresponding 95% confidence intervals for temperature bins. Months with average temperature below 75°F is considered as the reference group and their coefficients are normalized to 0.

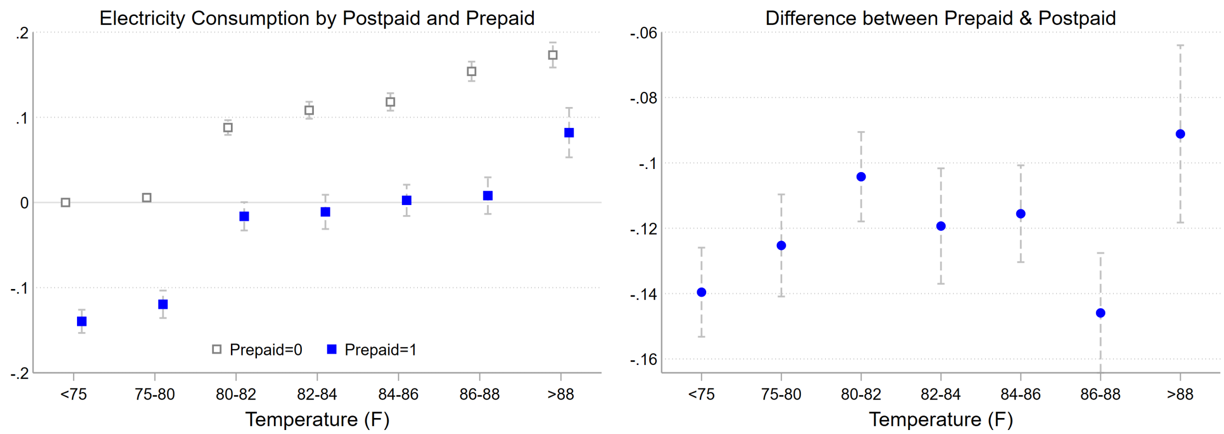


Figure 5: Heterogeneous Effect of Prepayment by Monthly Temperature

Notes: Figure shows the coefficient estimates and their corresponding 95% confidence intervals for temperature bins. In the left panel, electricity consumption of postpaid households during months with average temperature below 75°F is considered as the reference group and the coefficient is normalized to 0.

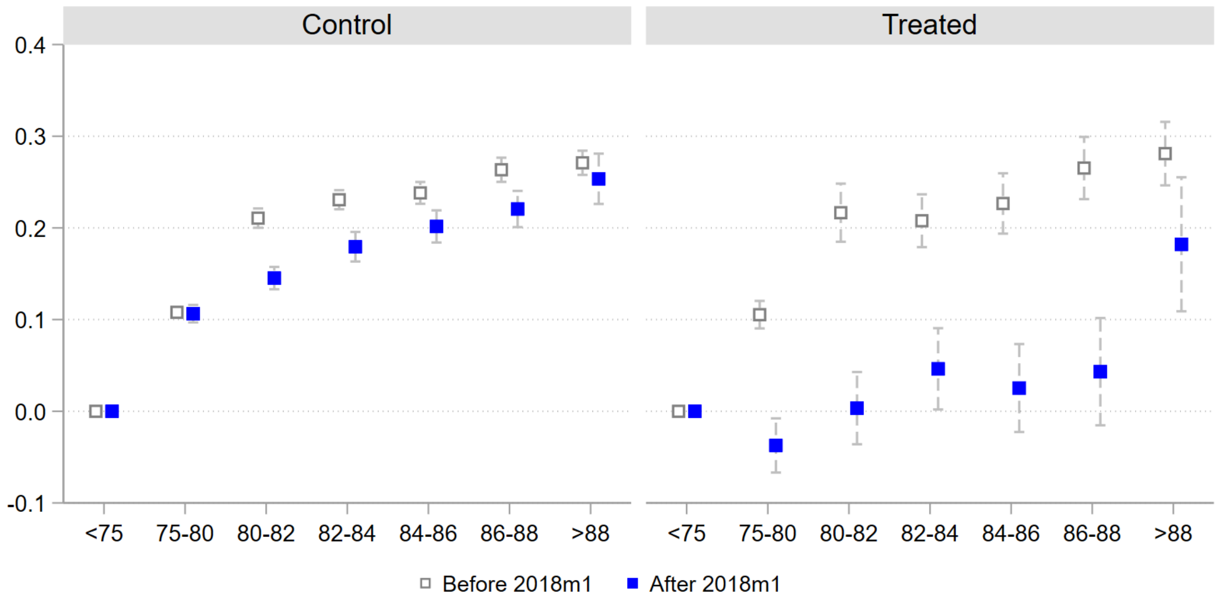


Figure 6: Electricity Consumption by Group and Temperature for the 2018-Jan Wave

Notes: Figure shows the coefficient estimates and their corresponding 95% confidence intervals for temperature bins.

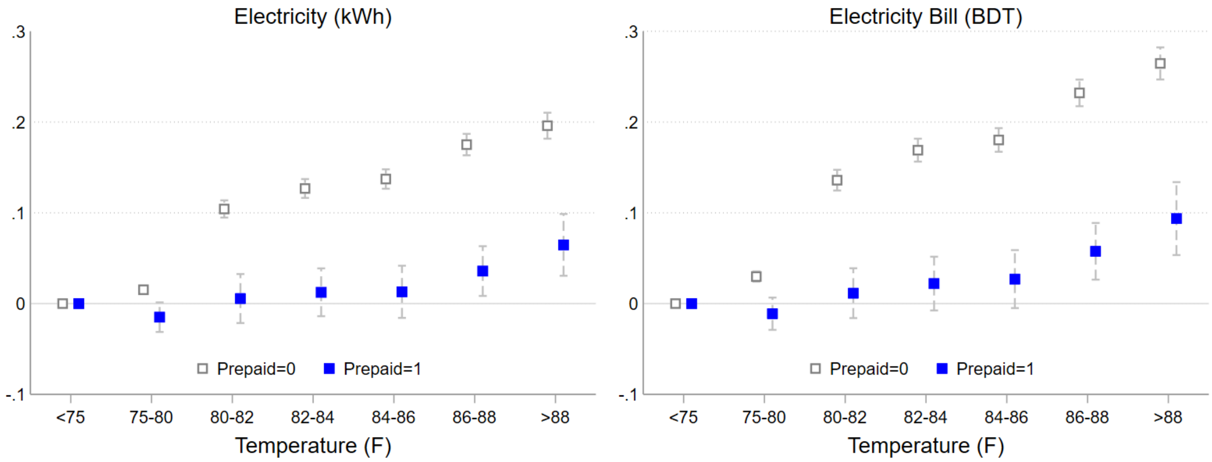


Figure 7: Effect of Prepayment on Electricity-Temperature Relationship

Notes: Figure shows the coefficient estimates and their corresponding 95% confidence intervals for temperature bins.

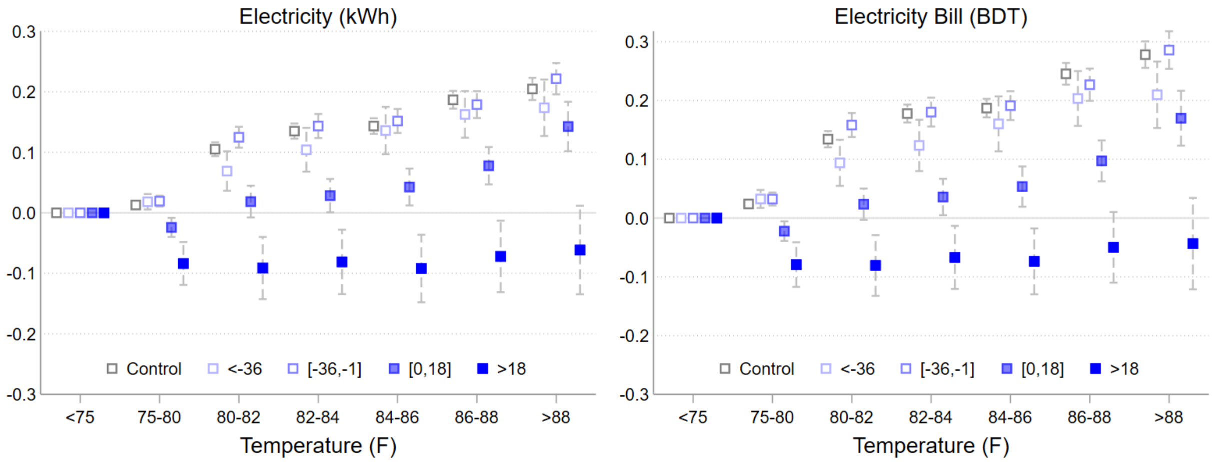
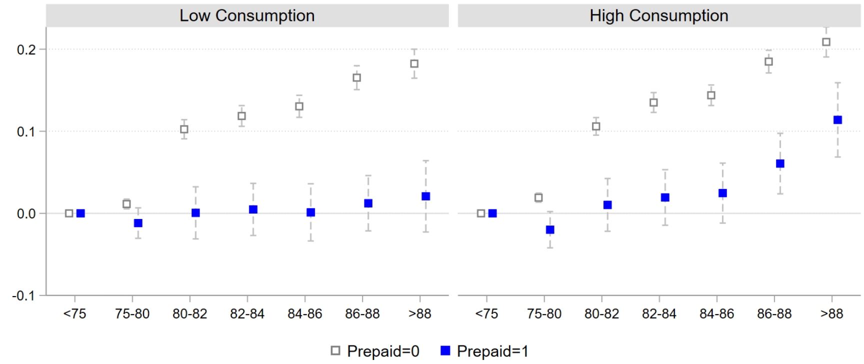
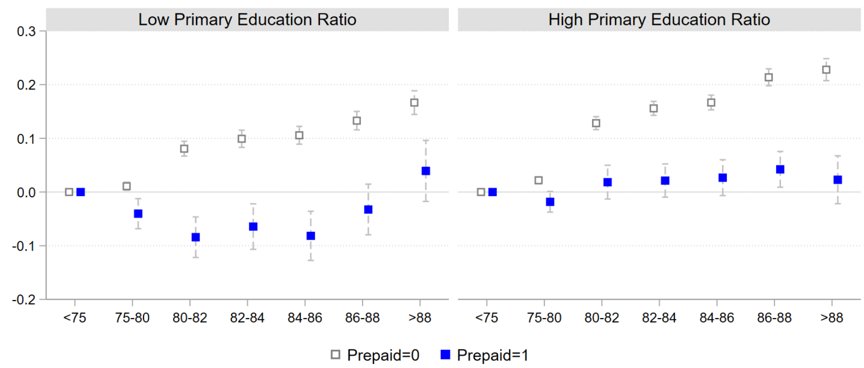


Figure 8: Dynamic Effect of Prepayment on Electricity-Temperature Relationship

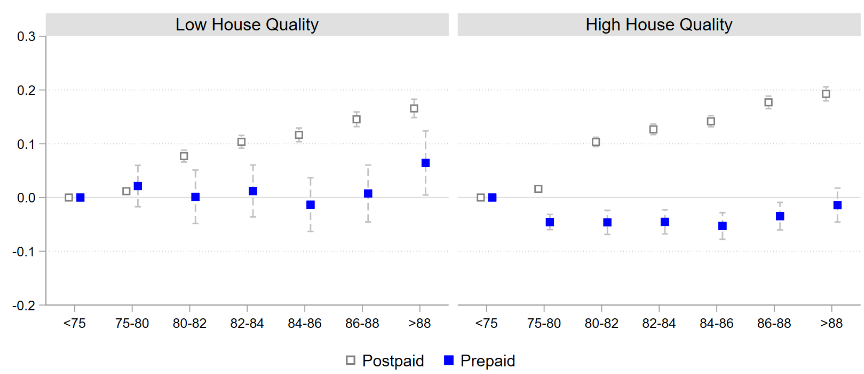
Notes: Figure shows the coefficient estimates and their corresponding 95% confidence intervals for temperature bins.



(a) By Electricity Consumption



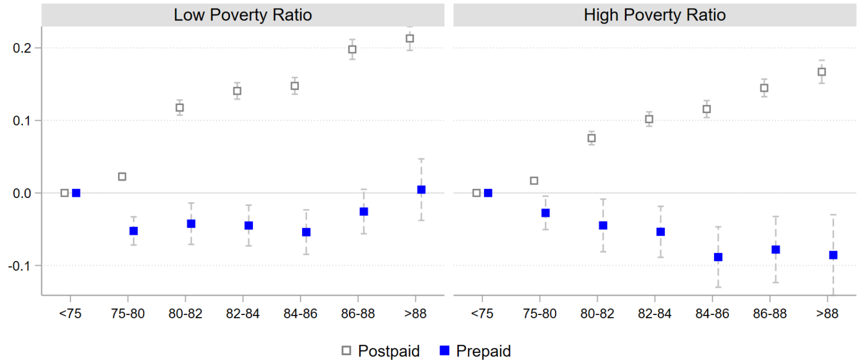
(b) By Education



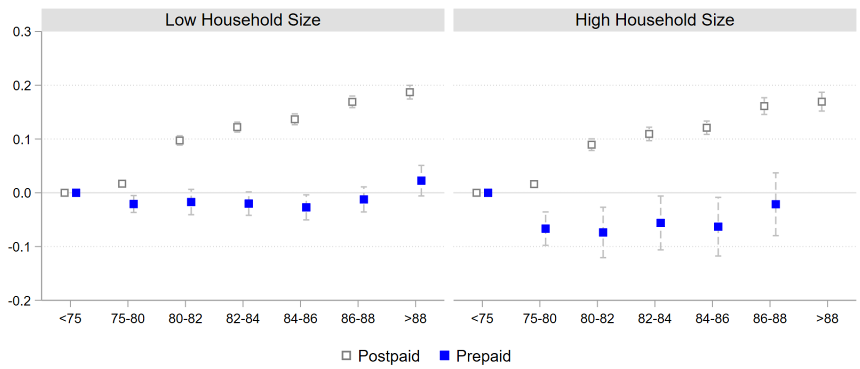
(c) By House Quality

Figure 9: Heterogeneous Effect of Prepayment on Electricity-Temperature Relationship

Notes: Figure shows the coefficient estimates and their corresponding 95% confidence intervals for temperature bins.



(a) By Poverty Ratio



(b) By Household Size

Figure 10: Heterogeneous Effect of Prepayment on Electricity-Temperature Relationship – cont'd

Notes: Figure shows the coefficient estimates and their corresponding 95% confidence intervals for temperature bins.

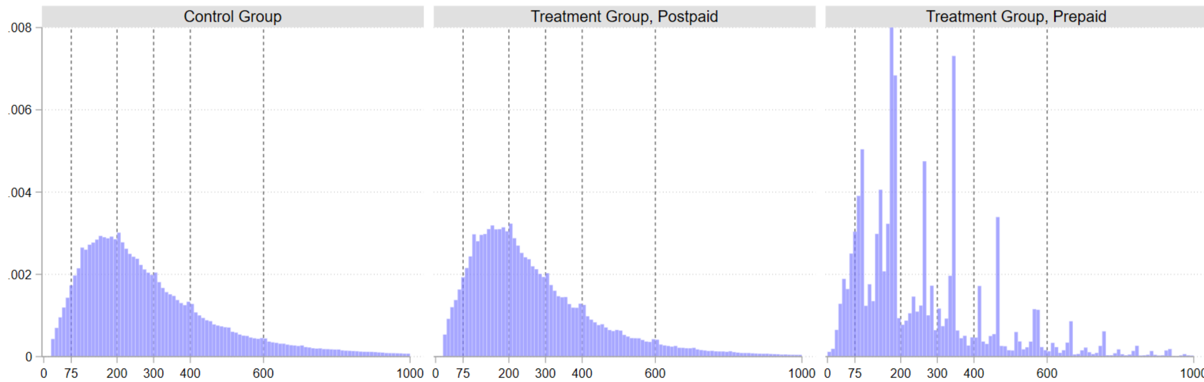


Figure 11: Distribution of Electricity Consumption by Group & Payment Method

Notes: Figure shows the distribution of electricity consumption by different groups of households enrolled in postpaid versus prepaid systems.

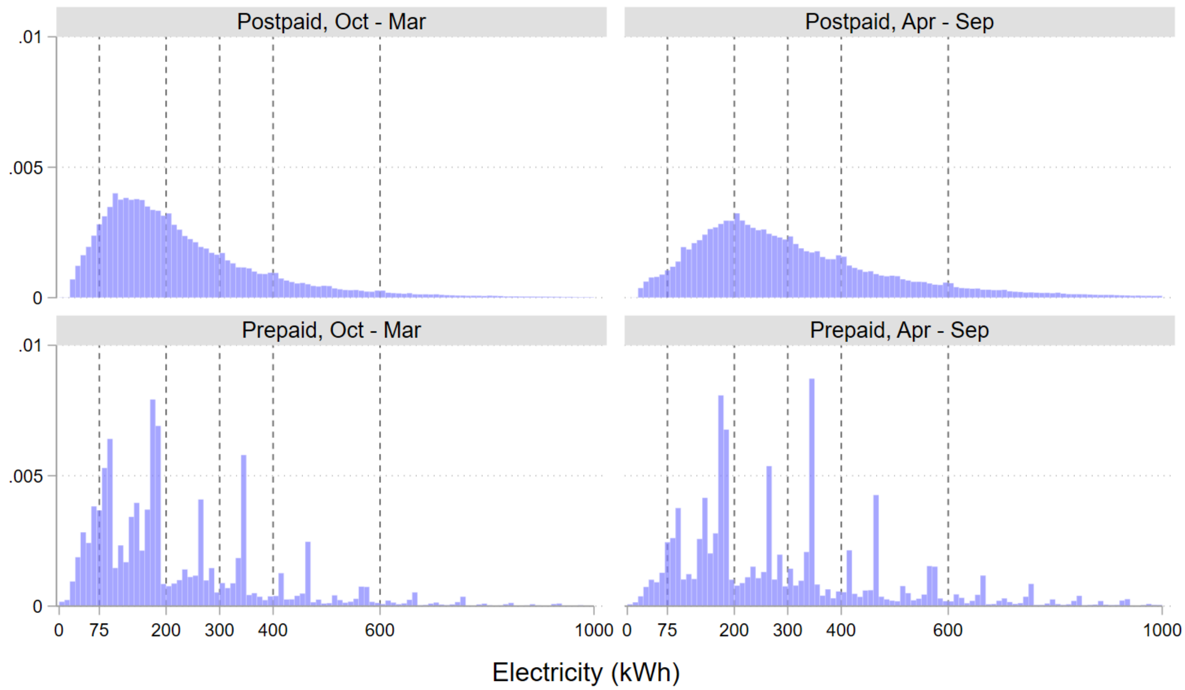


Figure 12: Distribution of Electricity Consumption by Payment Method & Season

Notes: Figure shows the distribution of electricity consumption for households in the treatment group by payment method and season.

Table 1: Summary Statistics

Variables	N	Mean	SD	Min	Median	Max
Electricity Consumption (kWh)	10,650,000	290	221	00	233	3,000
Electricity Bill (BDT)	10,650,000	1,667	1,805	0,000	1,138	189,509
Monthly Average Temperature (F)	10,650,000	79.9	6.3	61.8	82.3	90.4
Monthly Maximum Temperature (F)	10,650,000	88.1	5.1	74.4	89.7	99.5
Precipitation (inch)	10,650,000	0.2	0.3	0.0	0.1	2.1
Dew Point (F)	10,650,000	70.3	8.1	52.7	73.8	80.9
Wind Speed (knot)	10,650,000	2.8	1.7	0.1	2.4	10.6

Notes: The last five columns show the mean, standard deviation, minimum, median, and maximum of each variable.

Table 2: Effects of Prepayment and Temperature on Electricity Consumption

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Electricity Consumption (kWh)					
Prepaid	-0.122***		-0.122***		-0.123***
	(0.007)		(0.007)		(0.007)
Tavg		0.010***	0.010***		
		(0.000)	(0.000)		
80-85F				0.082***	0.086***
				(0.003)	(0.003)
$>$ 85F				0.102***	0.107***
				(0.004)	(0.004)
Dep. Var.: Electricity Bill (BDT)					
Prepaid	-0.083***		-0.083***		-0.084***
	(0.007)		(0.007)		(0.007)
Tavg		0.015***	0.015***		
		(0.001)	(0.001)		
80-85F				0.099***	0.102***
				(0.004)	(0.004)
$>$ 85F				0.127***	0.130***
				(0.005)	(0.004)
Weather Controls	✓	✓	✓	✓	✓
HH FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Observations	10,650,000	10,650,000	10,650,000	10,650,000	10,650,000

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Effect of Prepayment on Electricity-Temperature Relationship

Dep. Var. (in logs)	Electricity Consumption		Electricity Bill	
	(1)	(2)	(3)	(4)
Tavg	0.010***		0.015***	
	(0.001)		(0.001)	
Tavg × Prepaid	-0.004***		-0.006***	
	(0.001)		(0.001)	
80-85F		0.087***		0.107***
		(0.004)		(0.005)
$>$ 85F		0.118***		0.146***
		(0.005)		(0.006)
80-85F × Prepaid		-0.022***		-0.040***
		(0.007)		(0.009)
$>$ 85F × Prepaid		-0.054***		-0.074***
		(0.009)		(0.010)
Weather Controls	✓	✓	✓	✓
HH-Treatment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
Observations	10,650,000	10,650,000	10,650,000	10,650,000

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Robustness Checks for Electricity Consumption

Dep. Var. (in logs)	Electricity Consumption			
	(1)	(2)	(3)	(4)
A. Average Temperature				
Tavg	0.015***	0.012***	0.016***	0.011***
	(0.000)	(0.001)	(0.001)	(0.001)
Tavg $\times$ Prepaid	-0.003***	-0.006***	-0.007***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
B. Temperature Bins				
80-85F	0.091***	0.094***	0.081***	0.060***
	(0.003)	(0.004)	(0.004)	(0.005)
$>$ 85F	0.124***	0.126***	0.115***	0.134***
	(0.004)	(0.005)	(0.004)	(0.005)
80-85F $\times$ Prepaid	-0.016***	-0.030***	-0.021***	-0.024***
	(0.006)	(0.007)	(0.007)	(0.007)
$>$ 85F $\times$ Prepaid	-0.043***	-0.064***	-0.054***	-0.052***
	(0.008)	(0.009)	(0.009)	(0.009)
Weather Controls	✓	✓	✓	✓
HH-Treatment FE	✓	✓	✓	✓
Year FE			✓	✓
Month FE				✓
Subdistrict-Year FE	✓			
Subdistrict-Month FE	✓			
HH-Month FE			✓	
Temperature-Year Control				✓
Group-Year FE		✓		
Group-Month FE		✓		
Observations	10,650,000	10,650,000	10,650,000	10,650,000

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Robustness Checks for Electricity Consumption

Dep. Var. (in logs)	Electricity Bill			
	(1)	(2)	(3)	(4)
A. Average Temperature				
Tavg	0.021***	0.017***	0.022***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Tavg $\times$ Prepaid	-0.006***	-0.008***	-0.009***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)
B. Temperature Bins				
80-85F	0.111***	0.112***	0.100***	0.110***
	(0.004)	(0.005)	(0.004)	(0.006)
$>$ 85F	0.153***	0.154***	0.142***	0.191***
	(0.005)	(0.006)	(0.005)	(0.007)
80-85F $\times$ Prepaid	-0.033***	-0.049***	-0.038***	-0.030***
	(0.007)	(0.009)	(0.008)	(0.009)
$>$ 85F $\times$ Prepaid	-0.061***	-0.084***	-0.071***	-0.064***
	(0.009)	(0.010)	(0.010)	(0.011)
Weather Controls	✓	✓	✓	✓
HH-Treatment FE	✓	✓	✓	✓
Year FE			✓	✓
Month FE				✓
Subdistrict-Year FE	✓			
Subdistrict-Month FE	✓			
HH-Month FE			✓	
Temperature-Year Control				✓
Group-Year FE		✓		
Group-Month FE		✓		
Observations	10,650,000	10,650,000	10,650,000	10,650,000

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Heterogeneous Effect on Electricity-Temperature Relationship

	By Consumption		By Education		By Poverty		By House Quality		By Household Size	
	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. ln(Electricity Consumption)										
Tavg	0.009***	0.009***	0.005***	0.013***	0.014***	0.007***	0.008***	0.010***	0.008***	0.012***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tavg $\times$ Prepaid	-0.009***	0.003	-0.005***	-0.001	-0.002	-0.017***	-0.013***	-0.005***	-0.009***	0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)
B. ln(Electricity Bills)										
Tavg	0.014***	0.015***	0.010***	0.019***	0.020***	0.013***	0.012***	0.015***	0.014***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tavg $\times$ Prepaid	-0.011***	0.002	-0.008***	-0.003*	-0.004**	-0.018***	-0.015***	-0.006***	-0.011***	0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Observations	5,283,820	5,508,535	5,283,820	5,508,535	6,151,156	4,641,199	4,310,552	6,481,803	7,310,302	3,482,053

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Online Appendices: Not for Publication

A Additional Information

A1 Prepaid Metering Rollout

Prepaid metering in Bangladesh began in 2005 with two pilot projects in Dhaka and Chittagong, utilising a completely independent (proprietary) systems. This project did not materialise at that time due to several challenges with central management system. Later, in 2013, under the supervision of Bangladesh Government's Power Division, Bangladesh Power Development Board signed a MoU with all utilities to introduce unified prepaid metering system (UPMS). As a result, in early 2014, three utilities BPDB, DPDC and DESCO launched UPMS pilot project in five major cities. Finally, in March 2015, utilities started implement in large-scale across the major urban areas in Bangladesh. By the end of 2016, about 3% urban households were replaced to the new system. From the beginning of 2017, a substantial prepaid metering replacement occurred. By the end of November 2019, the last month for which I obtained DESCO and DPDC households electricity billing and vending information, a total of 43% of households had switched from postpaid to prepaid metres in Dhaka city. By 2020, nearly one-third of Bangladeshi urban households switched into prepaid system and in Dhaka city this rate is around 43%.

The utilities administrative documents revealed that several bureaucratic stages have been followed to assign the prepaid meter at the utility's sales and distribution level: (i) tilities submit their yearly prepaid meter implementation plan to the Power Division of Bangladesh Government; (ii) Power Division submit the plan and cost estimates to the MPENR for placing to the Executive Committee of the National Economic Council (ECNEC); (iii) after ECNEC approval, the distribution companies top management and administrative body call for tender to purchase the prepaid meter and assigned a sales and distribution location conditions on the availability of required meter, technical and administrative capacity; (iv) distribution companies also set meeting with local government and administrative body about their implementation plan of prepaid meter in that area. Finally, after assessing all the technical capabilities, skilled workforce, administration difficulties and political factors, the utility's administration approve the location for the final rollout.

A2 Data Details

The postpaid billing data include information on households unique ID, location, unit of electricity (kWh) use, demand charge, value-added-tax (VAT), monthly electricity bill, tariff type, Sanction load, bill cycle, electricity meter phase, electricity distribution location and feeder location.

The prepaid vending data includes all the households specific information mentioned in postpaid billing data along with households prepaid vending system records such as amount recharge, meter rent, rebate and so on. Most importantly, the data contains detailed recharge information specifically for recharge date with time and recharge frequency in a calendar month. This dataset also contain the prepaid households monthly average electricity use (kWh) variable that calculated6 by the respective utility using the block pricing system from the recharge information.

We merged the two administrative dataset and construct a strongly balance panel from the raw population data, where the unit of observation is the customer who use electricity for their house by monthly electricity billing and vending information. After cleaning the raw population data, finally I set a balanced panel of 768,380 households over 71 months period, therefore total panel observations become 54,554,980 among them 29,847,193 and 24,707,787 are in postpaid (control group) and switched from postpaid to prepaid system (treatment group) respectively. Data on prepaid meter switching dates are obtained from the respective electricity distribution companies vending information.

B Additional Tables and Figures

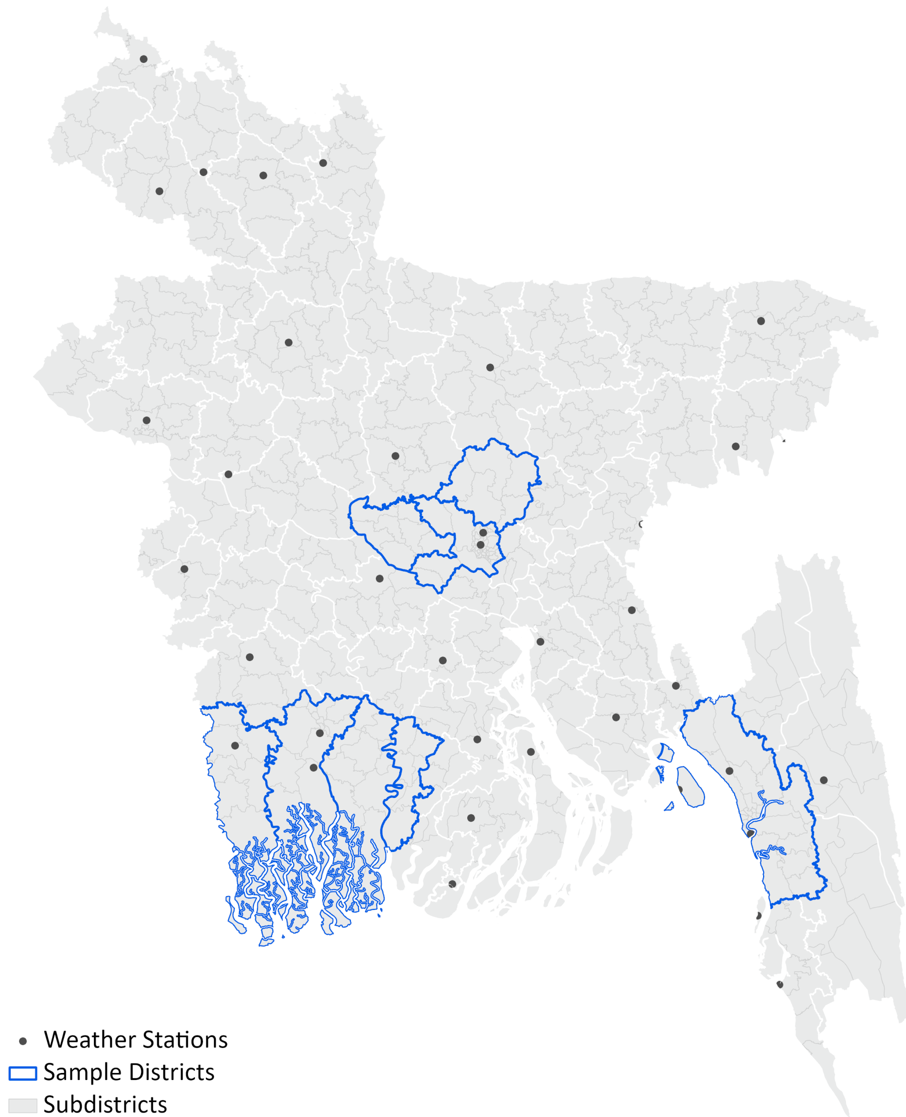
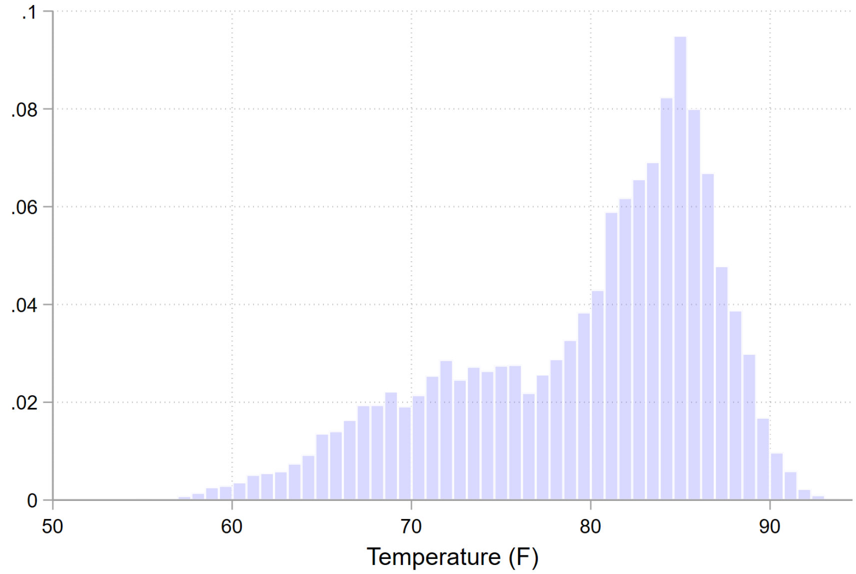
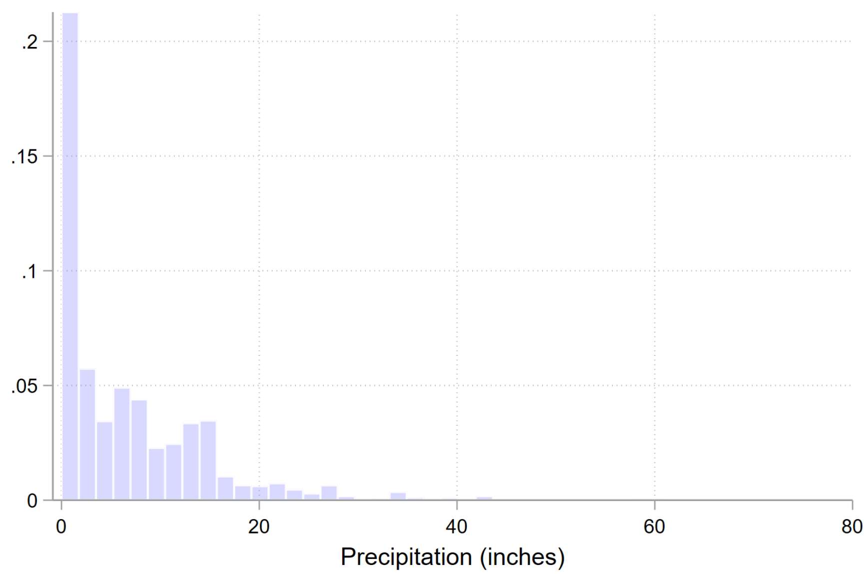


Figure B1: Weather Stations and Sample Districts

Notes: The map shows NOAA weather stations and our sample districts.



(a) Daily Average Temperature



(b) Monthly Precipitation

Figure B2: Distribution of Daily Temperature and Precipitation

Notes: Figure plots the distribution of daily temperature and monthly precipitation for the sample districts over 2014-2019.

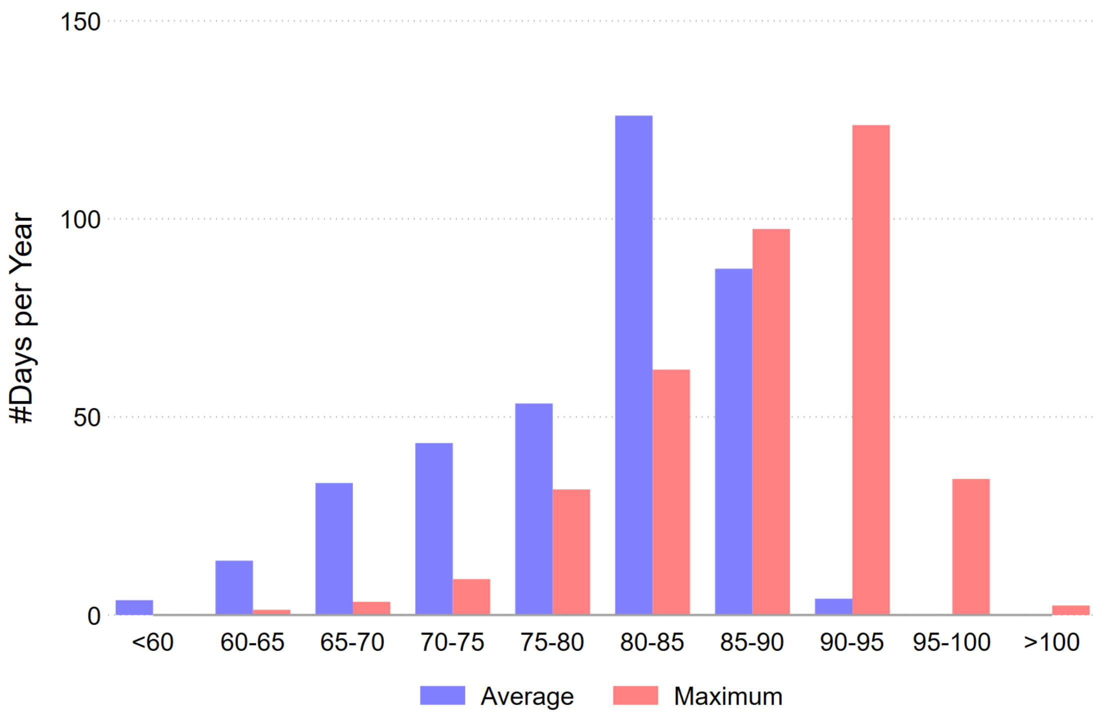
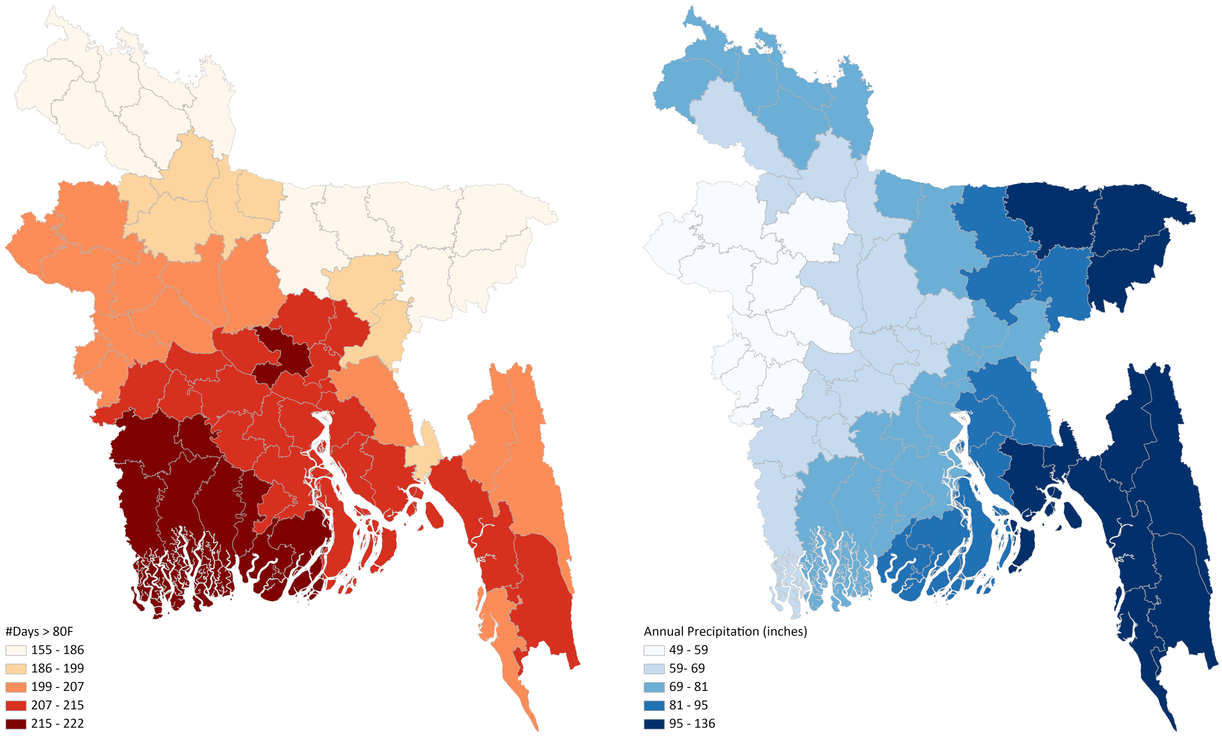


Figure B3: Daily Temperature Distribution

Notes: Figure plots the number of days per year with daily temperature falling into a certain interval.



(a) #Days with Average Temperature > 80F (b) Annual Precipitation

Figure B4: Geographic Distribution of Temperature and Precipitation

Notes: The map plots geographic distribution of annual temperature and precipitation measures at the district level.

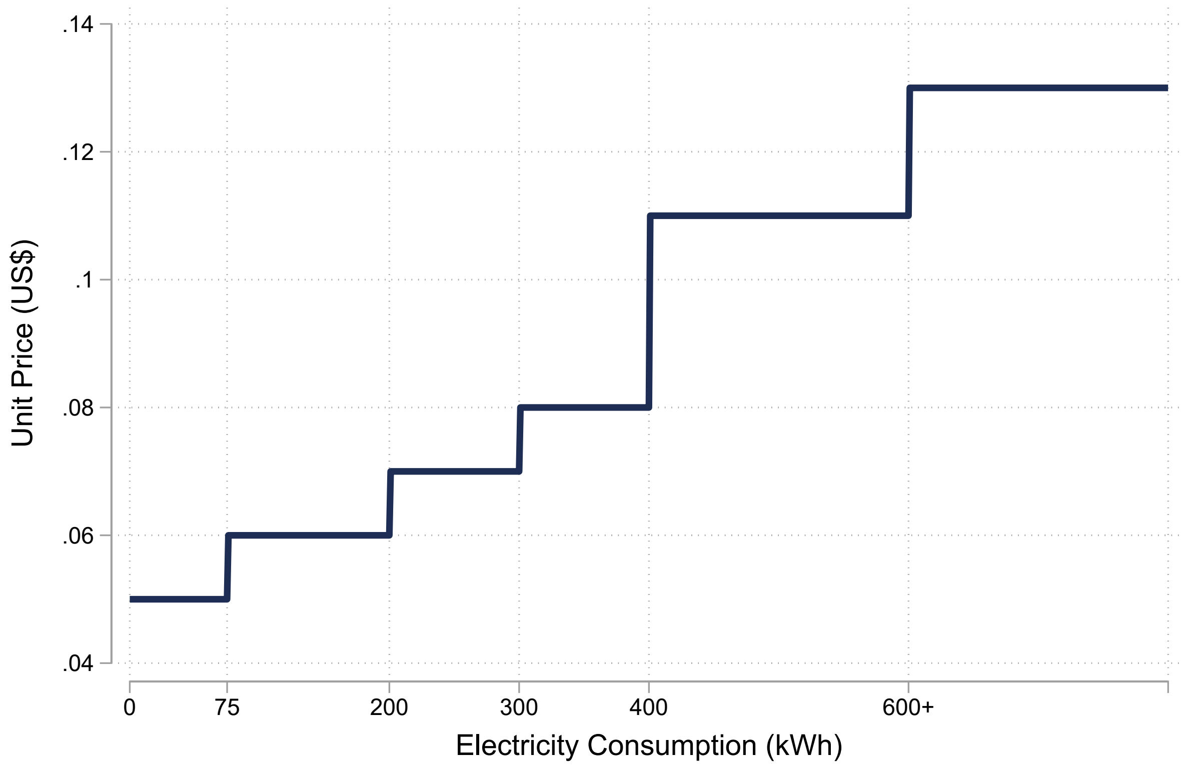


Figure B5: Residential Electricity Tariff Structure

Notes: Figure depicts the residential customers per kWh electricity price in a nonlinear price schedule.

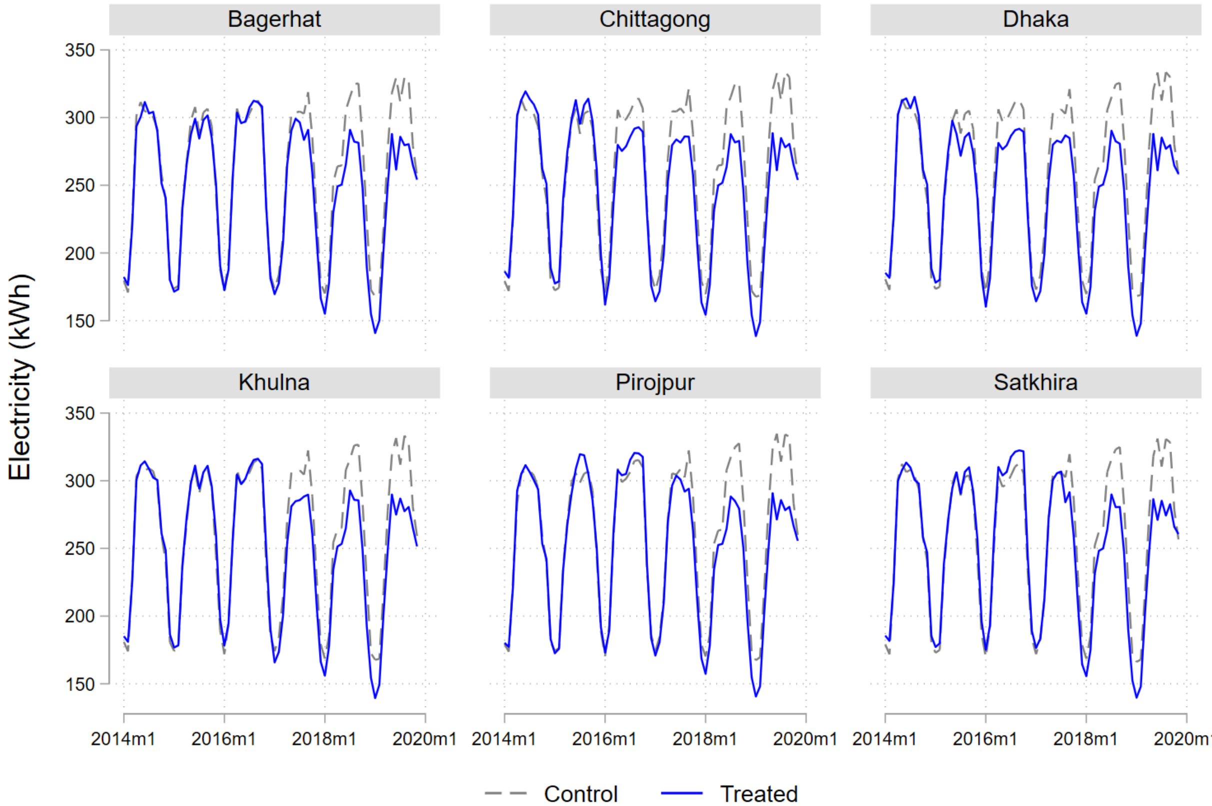


Figure B6: Monthly Electricity Consumption Patterns by Household Group

Notes: Figure plots the average electricity consumption (kWh) in each month for the treated and control households separately in each district.

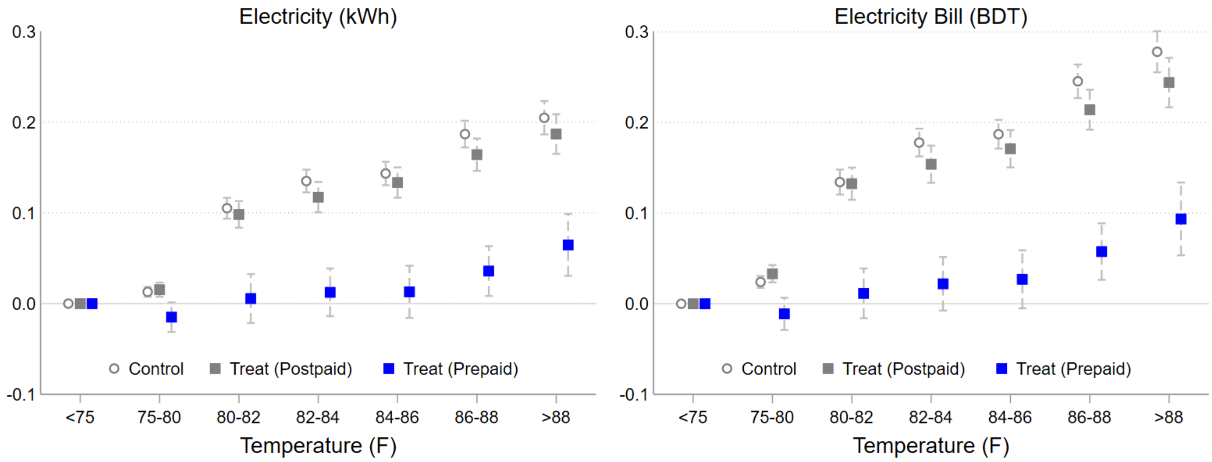


Figure B7: Electricity-Temperature Response Function by Group and Payment Method

Notes: Figure plots the coefficient estimates and their corresponding 95% confidence intervals.

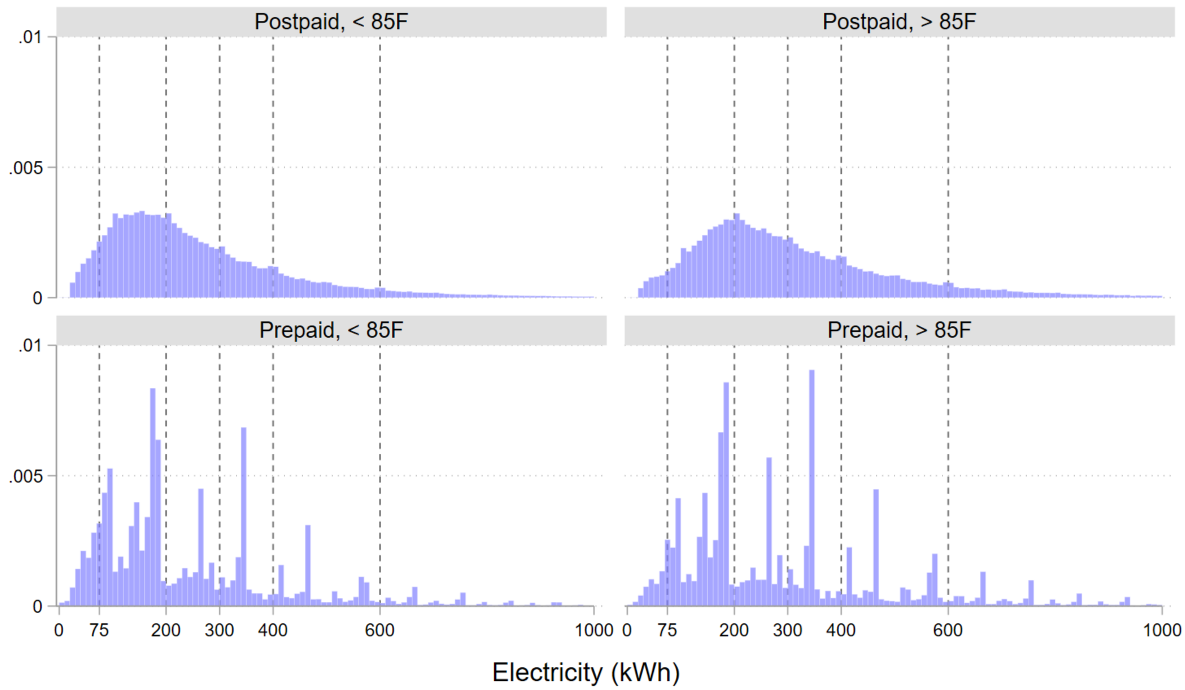


Figure B8: Distribution of Electricity Consumption by Payment Method & Temperature

Notes: Figure shows the distribution of electricity consumption for households in the treatment group by payment method and season.