Does prepaid metering make a difference in electricity consumption? Evidence from Bangladesh

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Abstract

Developing country like Bangladesh has been facing huge revenue losses due to technical failure, non-payment of electricity bills, electricity theft and corruption. To reduce these problems, Bangladesh government has implemented pre-paid electricity metering system through the state-owned electricity distributing companies across different cities. Using a unique customer-level monthly electricity consumption data from July, 2017 to June, 2018, this study explores the impact of pre-paid electricity metering on customer monthly electricity consumption in Dhaka city. Employing difference-in-difference model, we find that customers reduce their monthly electricity consumption by 47 kWh or 24 percent when they switched from post-paid electricity metering system to pre-paid metering. Moreover, we show that pre-paid metering has larger effect on the customers monthly electricity consumption who are in the lower tariff life-line group compare to the upper tariff line samples. Based on our findings, this study suggests some policy implications to the government.

1. Introduction

Power and energy are a very important asset for any country in the world. Because the overall development and progress of the country depends on the proper production and supply of electricity. In connection to that, over the last few decades globally the developing and emerging countries are playing a major role in increasing their electricity production and supply capacity to meet rising demand for electricity consumption (Wolfram et al., 2012). Therefore, the capital investment for developing new electricity plant and broadening electricity access has increased wide scale in recent years as well (World Economic Outlook, 2013).

Over the past few years Bangladesh has substantially expanding its access to electricity and electricity generating capacity across the country as well. However, on the ground the economy has been facing huge revenue loss through system loss, non-payment of electricity bills, electricity theft and corruption. In fact, the standard exiting post-paid electricity bill collection system works manually, which provides a subtle scope of non-payment, electricity theft and corruption opportunity. Therefore, to reduce system loss, electricity theft and corruption, increase 100% electricity bill collection and amplify the satisfactory electricity service, Bangladesh government implemented pre-paid electricity metering in some selected area of Dhaka city in 2016.

Pre-paid electricity meter provides a smart technological solution to control non-payment problem, electricity theft and corruption. It is a special kind of meter which run in a debit basis i.e. customer purchase upfront and load the amount into their electricity meter. Each time a unit of electricity use automatically deduct the money from loaded amount in the meter, and when the money is exhausted, the meter stops to provide power supply. To resume the power supply customer have to recharge the meter again.

Globally pre-paid meter is very popular in developed countries like USA, UK, Japan, Canada, Germany and so on. However, recently pre-paid metering system caught an attention in developing countries government policy in order to maximise the electricity revenue. A recent research shows that greatest expansion of pre-paid electricity meter is now happing in some South Asian and African countries such as Bangladesh, India, South Africa, Rwanda, Kenya and so on (Jack and Smith, 2016). While the pre-paid meter is becoming popular across the countries, but there remains dearth of literature to test its impact on the customer electricity consumption and government revenue generation.

Therefore, this study explores the effect of pre-paid metering on customer monthly electricity consumption in Dhaka city. To examine the fact, we design an impact evaluation of customers' electricity billing data, which is obtained from the Dhaka Electric Supply Company Limited (DESCO). For this research, we consider two DESCO provided electricity regions Ramna and Khilgaon in Dhaka city. In Ramna region DESCO have not implemented pre-paid metering yet, whereas in Khilgaon DESCO implemented pre-paid metering from January, 2018. For analysing the impact of pre-paid meter on customers' monthly electricity consumption, we retrieved monthly customer level electricity billing panel data from July, 2017 to June, 2018. In this case, a sample of Ramna areas customers are considered as a control group and Khilgaon as treatment group. Using Difference-in-Difference techniques, we find that customers' monthly electricity consumption falls when they switched from post-paid electricity metering to pre-paid system.

The remained of the paper is laid out as follows. In section 2, we provided a sketch of existing literature on pre-paid meter and electricity consumption. Section 3, provides a detail information about pre-paid electricity meter in Bangladesh. Section 4, entails the sample design and data details. Section 5, presents the empirical specifications. Section 6 and 7 presents the results and series of robustness checks and finally Section 8 draws conclusion and policy implications.

2. Past research

A rich literature documents explores the different aspects of electricity pricing on electricity consumption across the world and most of them are predominantly on developed economies. These literatures are largely focused on attention and information intervention in households' economic decision making i.e. energy consumption (Salle, 2014, Allcott and Taubinsky, 2015, Houde, 2018). Using randomize control trails in California, Fowlie et al. (2018) show that the default effect largely reduces the peak electricity consumption in response to the dynamic time-varying electricity price.

In connection with that evidence, Gillan (2018) find that the dynamic electricity pricing has significant impact on electricity consumption of those households use automation system in USA.

The evidence of pre-paid metering in developing and emerging countries context is very rare. So far, our extensive literature survey, we found few rigorous empirical evidence from South Africa. Using South African customer-level pre-paid electricity metering data, Jack and Smith (2016) find that pre-paid electricity metering reduce the customers' electricity use by 12 to 15 percent, vis-à-vis help to overcome the revenue recovery challenges. McRae (2015) shows the dynamic pricing and heterogeneous effect of metering on household utility and welfare in Colombia. On the other hand, using South African water billing data Szabo and Ujhelyi (2015) explore that providing extra information type intervention intensify the bill payment rate than taxing on non-payment. Besley and person (2013) show that non-payment of electricity bill and tax dodging exacerbate the revenue generation in most of the developing countries.

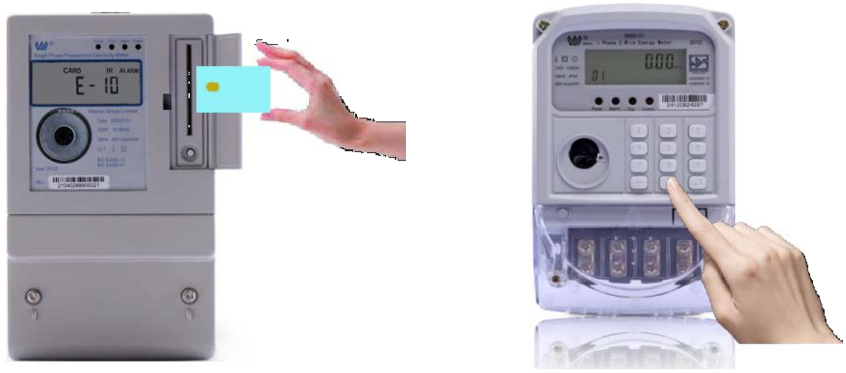
However, from our extensive literature review, we find dearth of literature which accounts for the impact of pre-paid metering on electricity consumption. Therefore, to fill this research gap into literature, this study examines the impact of pre-paid electricity metering on customers' monthly electricity consumption in Dhaka city, Bangladesh.

3. Background

3.1 Pre-paid electricity meter

In Bangladesh pre-paid electricity meter has first implement in some selected area in Dhaka city by DESCO in 2016 with a view to reduce non-technical electricity losses, maximum electricity bill collection and better service to customers'. The post-paid electricity billing and pre-paid electricity vending data measures electricity use in different ways. Pre-paid electricity metering system is a smart-card/key-pad based electricity bill payment mechanism, where customer purchase upfront and load the amount into their electricity meter. After recharging the meter, it displays available amount by which customer can consume the electricity kWh units. As long as positive balance remains the electricity flows and when balance reaches to zero, the power automatically disconnects. In post-paid system electricity billing information calculated daily average electricity use from time t to $t-1$, while in pre-paid metering system electricity bill charge based on the electricity use from time t to $t+1$. There are two types of pre-paid meter prevails in Dhaka city that provide to the customer based on their preferences: (a) smart card type meter and (b) key-pad type meter (Figure 1).

Figure 1: Existing electricity per-paid metering system in Dhaka city



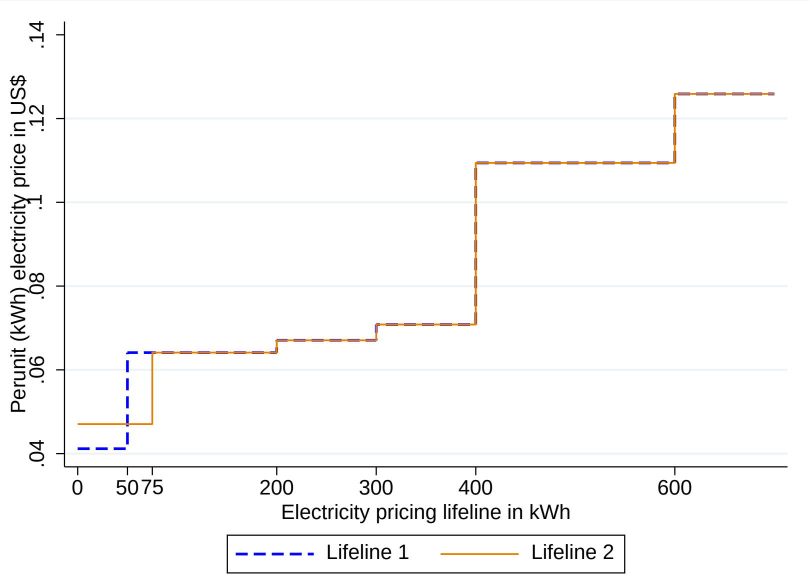
(a) Smart card meter (b) Key-pad meter

[Source: Dhaka Power Distribution Company Limited[1]]

3.2 Electricity tariff rate

In Bangladesh, the Energy Regulatory Commission (ERC) sets the price of electricity. It was formed in 2003, passing the Bangladesh Energy Regulatory Commission Act. Latest price of electricity was rescheduled by Bangladesh Energy Regulatory Commission in 2017. Based on the ERC electricity price schedule, the companies involved in power generation and supply like DESCO sets the retail electricity tariff life-line is 6 fold. Figure 2 depicts the increasing block retail electricity tariff schedule for July, 2017 to June, 2018. This tariff schedule starts two different lower tariff life-line price (1) the customer who consumes electricity less or equal to 50 kWh monthly will pay 3.5 BDT (=US$ 0.04) and (2) the customer who consumes electricity less or equal to 75 kWh monthly will pay 4 BDT (=US$ 0.05)

Figure 2: DESCO provided electricity tariff schedule in July, 2017 to June, 2018



[Source: Dhaka Electric Supply Company Limited[2] (DESCO) administrative data]

[1] http://www.dpdc.gov.bd/

[2] https://www.desco.org.bd/bangla/

4. Sample design and data

In this section, we describe the sample design and summary statistics of the data.

4.1 Sample design

Our sample consists of 7,954 customers' monthly electricity billing data from two different suburb (Ramna and Khilgaon) of Dhaka city over July, 2017 to June, 2018. In January, 2018 DESCO implemented pre-paid smart electricity metering in Khilgaon region. Therefore, we have collected pre-paid metering intervention data from January to June, 2018 of this region. In our study design Ramna area's customers are considered as a controlled group and Khilgaon as a treatment group. For the analysis, we consider sufficient number of months before and after implementing pre-paid meter, which is mandatory to design the impact evaluation of a program. In this study, we consider first 6 months i.e. July-December, 2017 as a baseline period and 6 months i.e. January-June, 2018 in treatment period. The detail sample design shows in Table 1.

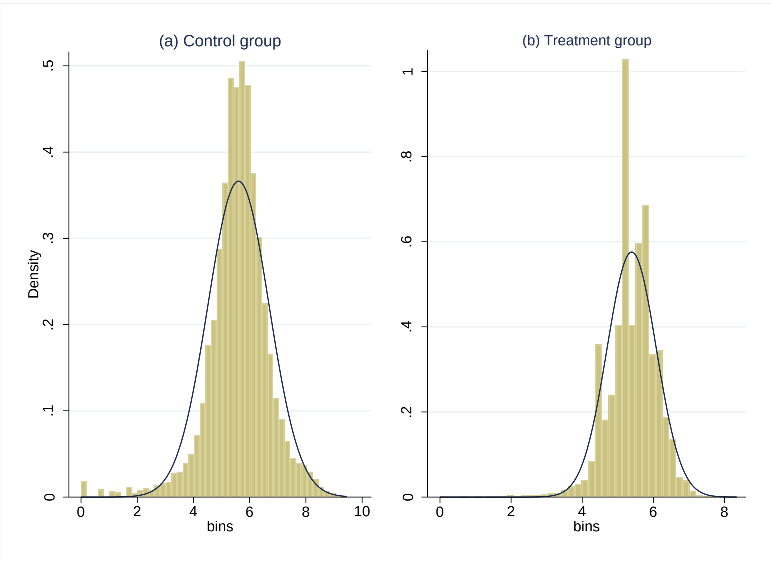
Table 1: Sample design

Time	Control (post-paid)	Treatment (pre-paid)	Total
Before (2017 July-Dec)	No pre-paid meter (31,860; 2,655)	No pre-paid meter (15,864; 1,322)	(47,724; 3,977)
After (2018 Jan-June)	No pre-paid meter (31,860; 2,655)	P re-paid meter (15,864; 1,322)	(47,724; 3,977)
Total	(63,720; 5,310)	(31,728; 2,644)	(95,448; 7,954)

Note: Number of observations; number customers are in parenthesis

Figure 3 plots the sample distribution of the log of monthly electricity consumption between control groups who are post-paid metering customer only and treatment group who previously use post-paid meter and switched to pre-paid meter from July, 2017 to June, 2018. In panel (a) the control samples consists of 63,720 observations of 5,310 customers, while in panel (b) the treatment group contained 31,728 observation in those of 2,644 customers. The figure 2 shows that the distribution of both sample groups is very similar.

Figure 3: Distribution of log of monthly electricity consumption



4.2 Data description

The data of this paper is obtained from Dhaka Electric Supply Company Limited[3] (DESCO) under a non-disclosure agreement. We assembled a 12-month panel of post-paid and pre-paid electricity metering transactions using DESCO's customer database which starts from July, 2017 to June, 2018.

4.2.1 Customer's electricity billing data

In Dhaka city, DESCO authorized meter readers collect the customers' electricity billing information in every month following a specific time schedule. They write the readings on the meter card which is stored on the customer's side and write the readings in the meter reading book which is stored in the DESCO office and billed accordingly. At the end of every month customer receive a single electricity bill sheet prepared by DESCO office that includes customers details information (e.g. name, location, meter number and so on), electricity kWh use, demand charge, electricity price, value-added-tax (VAT), bill payment date, late payment date with penalty etc.

For this study we collect customers' post-paid billing information from two different DESCO distributed electricity area (1) Ramna and (2) Khilgaon. In Ramna area DESCO has not been implemented pre-paid electricity metering yet, therefore this area's customers are considered as a controlled group for this study, whereas In Khilgaon region DESCO implemented pre-paid electricity metering from January, 2018, which is our treatment group. We retrieved Raman area's customer's post-paid electricity billing data for 12 months period from July, 2017 to June, 2018. Similarly, Khilgaon area's customer's post-paid electricity billing data collected from July to December, 2017 and the pre-paid metering vending data from January-June, 2018.

4.2.2 Summary statistics

Considering the above dataset, we construct a strongly balance panel data, where the unit of observation is the customer who use electricity for their house by monthly electricity billing information. In our case, our total sample consists of 7,954 customers over 12 months period, therefore total panel observations are 95,448 (7,954×12) among them 63,720 (5,310×12) and 31,728 (2,644×12) are control and treatment group respectively.

[3] https://www.desco.org.bd/bangla/

Table 2a: Summary statistics

Variables	(1) Mean	(2) SD	(3) Min.	(4) Max.
Full samples				
Number of observation	95,448	-	-	-
Number of customers	7,954	-	-	-
Log of monthly electricity consumption (kWh)	5.202	1.626	0	9.451
Log of monthly electricity bill	6.882	1.625	0	11.51
Life line tariff	3.283	1.577	1	6
Control groups				
Number of observation	63,720	-	-	-
Number of customers	5,310	-	-	-
Log of monthly electricity consumption (kWh)	5.361	1.560	0	9.451
Log of monthly electricity bill	7.141	1.163	0	11.51
Life line tariff	3.480	1.634	1	6
Treatment groups				
Number of observation	31,728	-	-	-
Number of customers	2,644	-	-	-
Log of monthly electricity consumption (kWh)	4.884	1.707	0	8.344
Log of monthly electricity bill	6.363	2.196	0	10.68
Life line tariff	2.889	1.373	1	6

In Table 2a and 2b reports detail summary statistics of our control and treatment samples. Column (1), (2), (3) and (4) summarize mean, standard deviation, minimum and maximum value of three main variables considered for this study (log of monthly electricity consumption (kWh), log of monthly electricity bill and tariff life line) respectively in Table 2a. Table 2b shows the detail summary statistics of the considered variable for before and after implementation of pre-paid metering in the perspective of study samples. The monthly electricity consumption data was measured in kWh and monthly electricity bill was priced in Bangladesh Taka (BDT). For the simplification of our analysis, we converted the level data into natural logarithmic form. The electricity tariff life-line data generated based on the DESCO ordered retail electricity pricing rate for the fiscal year 2017 to 2018 (see Figure 1).

Table 2b: Summary statistics

	Before post-paid metering (July-December, 2017)			After post-paid metering (January-June, 2018)		
VARIABLES	N	Mean	SD	N	Mean	SD
Number of observation	47,724	-	-	47,724	-	-
Number of customers	3,977	-	-	3,977	-	-
Log of monthly electricity consumption (kWh)	-	5.226	1.390	-	5.178	1.831
Log of monthly electricity bill	-	6.927	1.175	-	6.838	1.973
Life line tariff	-	3.154	1.483	-	3.413	1.656

4.2.3 Baseline balance

Table 3 provides further evidence of baseline difference of the treatment and control group. Column (1) and (2) shows the control and treatment groups average monthly electricity consumption, electricity bill and tariff life-line before implementing pre-paid metering (i.e. in the period of July-December, 2017). Column (3) reports the *t*-statistics for mean difference of those variables between control and treatment groups. The result indicates that there is a significant mean difference of all the variables between two groups in the baseline period, which is statistically significant at 1% level. Comparing in both groups, control group customers mean electricity consumption, electricity price and tariff life-line is higher than the treatment group samples. Therefore, it indicates a strong evidence that our control and treatment group are random.

Table 3: Baseline difference

	(1) Control group	(2) Treatment group	(3) Mean difference
Monthly electricity consumption (kWh)	389.20	250.76	138.43***
	(3.39)	(1.42)	(4.91)
Monthly electricity bill	1881.71	1376.91	504.79***
	(14.81)	(11.01)	(22.38)
Life line tariff	3.25	2.95	0.30***
	(0.008)	(0.10)	(0.014)

Note: *** p<0.01; standard errors in parentheses

5. Empirical strategy

This research estimates a difference-in-difference (DID) techniques using monthly customer level panel data from the post-paid and pre-paid metering period to identify the effect of adopting pre-paid metering on customer-level electricity consumption. The main DID model specifies in the following form:

$$y_{it} = \beta + \tau(prepaid_{it} \times time_t) + \gamma \; traiff_{it} + \phi_i + \alpha_t + \epsilon_{it} \qquad (1)$$

Where y_{it} measures monthly electricity consumption (kWh) for customer i in month t. The equation controls for electricity tariff lifeline indicator as $traiff_{it}$, ϕ_i for customer specific fixed effects, while α_t for the time fixed effects as calendar month and billing year (i.e. month-year). The main variable of interest of this model is the effect of $(prepaid_{it} \times time_t)$. $prepaid_{it}$ is an indicator variable that implies customer i had adopted pre-paid electricity meter during month t. $time_t$ is also an indicator that explains in time when pre-paid meter had implemented. Therefore, the treatment effect of $(prepaid_{it} \times time_t)$ is capture by τ, which implies the average treatment effect (ATE) of being use pre-paid meter in the period of pre-paid meter implementation event on customers' electricity consumption. ϵ_{it} is the error term. We estimate two sets of DID regression based on equation (1). First set, DID estimates based on level ordinary least squares (OLS) and second set based on panel fixed effects (FE) techniques. Both estimates run separate regression based level data (y_{it}) and log transformed $ln(y_{it})$ for simplification of our interpretation. The standard error of this model is clustered at the customer-level. We relax parallel trend assumption for our DID specification because using a fairly long time-series of the cross-section observations.

For robustness check first, we estimate equation (1) considering heterogeneous treatment groups based on the different electricity tariff life line offered by DESCO (see Figure 1). Second, we estimate DID using propensity score matching (PSM) techniques. The average treatment effect on treated (ATT) of PSM is estimated as follows:

$$\begin{aligned}\tau_{ATT} = E\{y_{i,after} - y_{i,before}|time = 1, p(X)\} \\ - E\{y_{i,after} - y_{i,before}|time = 0, p(X) = 1|time = 1\}\end{aligned} \tag{2}$$

Where, τ_{ATT} is estimated based on the common support of $p(X)$ which indicates the probability of assignment to pre-paid (i.e. treatment) conditional on post-paid (pre-treatment) variables. There are several matching techniques prevails in literature (e.g. nearest neighbour matching, IPW, IPWRA and so on). However, for the robustness checks, we employ the most commonly used kernel-based propensity score matching methods using `psmatch2` command in Stata16.

6. Main results

In this section presents the empirical results that capture the effects of switching from post-paid to pre-paid electricity metering on customer monthly electricity consumption kWh. Using a strongly balance panel dataset, we estimate DID estimator presents in equation (1).

Table 4 reports the estimates of the ATE of switching to pre-paid meter on both level and log electricity kWh consumption. Each column (1)-(4) of the table reports the coefficient estimates from different specification i.e. OLS and FE and all include tariff life-line as a control variable. In column (1) and (3) estimates equation (1) based on OLS similarly (2) and (4) estimates based on panel FE estimators.

In first two columns, we consider outcome variable in level and in right two columns outcome variable is the log form. The OLS coefficient in column (1) indicate that average monthly electricity consumption falls by 39 units during the pre-paid time period as a result of switched to a per-paid metering system, which is statistically significant at 1% level. Column (2) shows the estimated coefficient-based panel fixed effect model controlling for month-year fixed effects. The result indicates that average treatment effect of pre-paid metering decline monthly electricity consumption by 47 unit.

Table 4: Impact of prepaid metering on customers electricity consumption

	(1)	(2)	(3)	(4)
	monthly electricity use kWh		ln(monthly electricity use kWh)	
VARIABLES	OLS	FE	OLS	FE
Prepaid×time	-39.502***	-47.043***	-0.181***	-0.241***
	(3.714)	(2.610)	(0.010)	(0.009)
Constant	153.582***	148.774***	1.174***	1.442***
	(10.509)	(5.324)	(0.035)	(0.029)
Total Observations	95,448	95,448	95,365	95,365
Number of customers	-	7,954	-	7,954
R-squared	0.358	0.552	0.882	0.809
Fixed Effects	no	month, year	no	month, year

Note: In each model we controlled electricity tariff life-line. Robust standard errors in parentheses. Standard error is clustered on customer level; *** p<0.01, ** p<0.05, * p<0.1

The results in column (3) indicates that average monthly electricity consumption reduce by 18%, while controlling month-year fixed effect this corresponds to a decline to 24%. All the estimated coefficients are statistically significant at 1% level. The estimated result is persistent considering different estimator, which indicated switching into pre-paid metering significantly reduce customers' monthly electricity consumption. As the panel FE estimates is statistically robust than OLS, therefore, the implications of the result is that providing customers' the opportunity to switching into pre-paid meter leads to an average reduction of customer level electricity use by 24% (0.24 log points) or 47 units.

7. Robustness checks

In this part, we investigate the sensitivity of our main results based on equation 1. For doing that we employ several alternative techniques to check for robustness of our main coefficient of interest. First, we check the customer-level heterogeneity based on different DESCO electricity tariff life-line samples.

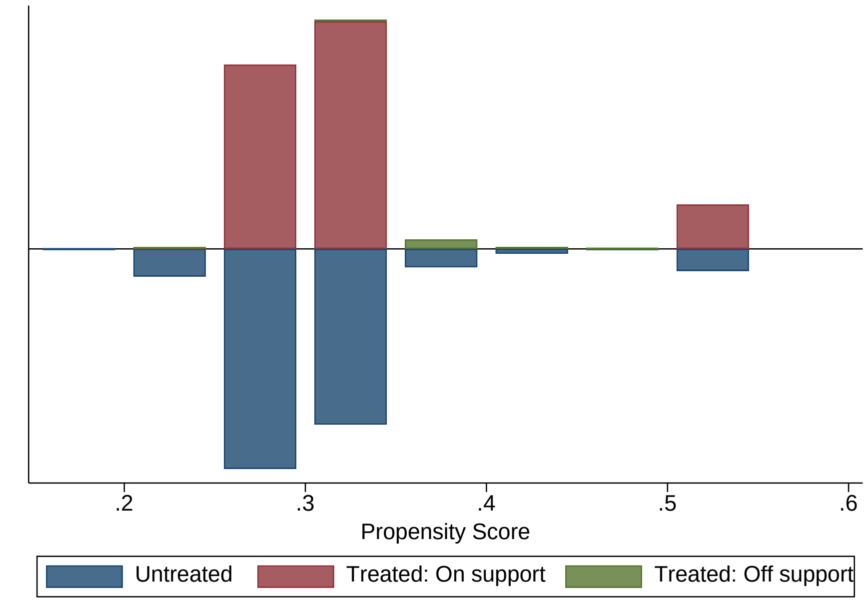
Table 5: Heterogeneous treatment effects on customers' electricity consumption

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	FE	FE	FE	FE	FE	FE
Prepaid×time	-1.976***	-0.074***	-0.007	-0.033***	-0.045***	-0.171***
	(0.113)	(0.010)	(0.005)	(0.004)	(0.006)	(0.024)
Constant	1.574***	4.982***	5.534***	5.868***	6.208***	7.120***
	(0.052)	(0.006)	(0.003)	(0.002)	(0.003)	(0.005)
Total Observations	9,493	29,891	17,942	12,900	12,442	12,697
Number of customers	2,775	5,637	5,433	4,695	3,875	2,482
R-squared	0.183	0.153	0.098	0.050	0.093	0.470
Fixed Effects	month, year	month, year	month, year	month, year	month, year	month, year

Note: Robust standard errors in parentheses. Standard error is clustered on customer level; *** p<0.01, ** p<0.05, * p<0.1

Table 5 reports the estimated effects of pre-paid metering on average monthly electricity consumption kWh by different electricity tariff life-line sub-group. The reported results estimated based on panel fixed effects with controlling for month-year fixed effects. The estimated coefficient in each column (1)-(6) of Table 5 show the negative impact on customers' monthly electricity consumption. This indicates our estimated results are reasonably stable and not suffers from outliers or other assumptions typically used for variables construction. The results also find that pre-paid metering has larger effect on the customer monthly electricity consumption who are in the lower tariff life-line group compare to the upper tariff line samples.

Figure 4: Propensity score distribution and common support for propensity score estimation



Next, we estimate DID in matching samples using kernel-based propensity score matching (PSM) technique. Figure 4 plots the distribution of propensity scores and common support. The figure depicts that there is a very little off support between treatment and control group. Therefore, it indicates that untreated and treated groups are well matched under the common support condition.

The effect of prepaid metering on customer monthly electricity consumption estimated based on kernel-based PSM techniques reported in Table 6. The results indicate that switching to pre-paid electricity metering reduce monthly electricity consumption by 12%, which is statistically significant at 1% level. The sign and magnitude of the PSM results is about to similar with our main estimated results reported in Table 4. Therefore, we can conclude that our estimated result is robust in terms of coefficient sensitivity, which implies that pre-paid metering reduces the customer electricity use. The reason could be, as customers are paying upfront of their electricity bill which is increasing their awareness money spending and level of electricity consumption.

Table 6: Estimated effects of prepaid metering on customers' electricity consumption

	ATT estimator using kernel matching common support comparison			
	Treatment	Control	Difference	t-stat
ATT	4.923	5.037	-0.117***	-9.74
	-	-	(0.011)	-
Common support	30,803	63,720	-	-

Note: ATT implies average treatment effect on treated; *** p<0.01; standard errors in parentheses

8. Conclusion and policy implications

To improve the revenue cycle, load and demand management, electricity theft, increase the quality of customer service and reduce non-payment of electricity bills, Bangladesh government has set up prepaid metering across the country. However, the benefits of the pre-paid meter are mostly anecdotal. Therefore, our study explores the impact of pre-paid electricity metering on customer monthly electricity consumption in Dhaka city. Our dataset is unique, which tracks the customers' monthly electricity billing information in both their post-paid and pre-paid electricity consumption period. Using Difference-in-Difference techniques, this study finds that customers' monthly electricity consumption falls when they switched from post-paid electricity metering to pre-paid system by 18 to 24 percent. Our results are validated through the battery of robustness checks. The main policy implication of our findings are: as prepaid metering increases customers' energy use consciousness, therefore consumer will more likely shifts into energy saving device. Hence, government should implement the prepaid metering not only for electricity but also for water and gas utilities across the country. In addition, to reduce the peak hour electricity demand, government could implement the dynamic pricing for efficient electricity demand and load management.

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