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Pre-paid meters and household electricity use behaviours: evidence from Addis Ababa, Ethiopia

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Abstract

In low-income countries such as Ethiopia, pre-paid metering offers the potential to alleviate several typical challenges with traditional electricity billing systems, including high non-payment rate, pilferage and fraud, administrative and enforcement costs for utilities, and inflexibility and incongruence of bills with the irregular income flow of poorer consumers. Despite increasing adoption of pre-paid metering technology, few studies examine its impacts on household behaviour. This paper aims to fill this gap by examining impacts on electricity consumption, ownership of appliances, level of satisfaction, and cooking behaviour in Addis Ababa, the capital of Ethiopia. We employ propensity score matching and instrumental variable techniques to control for selection into pre-paid meters. Results indicate that pre-paid meter customers have significantly lower electricity consumption compared to post-paid users, and greater satisfaction with utility service. This technology also has a positive, but modest and statistically insignificant impact on total appliance ownership, and a positive and significant impact on ownership of energy-efficient lights. Furthermore, impacts are heterogeneous across customers: those who are more educated, who have higher income, and who do not share meters tend to reduce electricity use more. This evidence suggests the need for the utility to continue expanding the use of pre-paid meters and educating customers about their multiple advantages.

Key words: Electricity utility; Energy access; Propensity score matching; Instrumental variables; Satisfaction

JEL: L94; O13; Q41

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1 Introduction

Energy access is now prominent on the global development agenda, as reflected by its inclusion in the Sustainable Development Goals. However, recent attempts to increase access to electricity connections in low-income countries have created a set of new and complex challenges for utilities and consumers that collectively challenge sustainable development (McRae, 2015; Sievert and Steinbuks, 2020; Lukuyu *et al*., 2021). Among these concerns is low revenue generation for the utility or other providers, which relates both to low electricity use among those newly connected and to low collection rates among electricity consumers (Lukuyu *et al*., 2021; Blimpo and Cosgrove-Davies, 2019; Fobi *et al*., 2018). Empirical evidence shows that high non-payment rates often force utilities to restrict electricity supply (Golumbeanu and Barnes, 2013). Another major challenge is electricity theft, which impedes revenue collection and hence infrastructure maintenance (Blimpo and Cosgrove-Davies, 2019; Smith, 2004). In addition, the traditional, post-paid billing system is costly to maintain and makes it difficult to reduce pilferage and fraud (Tewari and Shah, 2003). For cash-constrained consumers, meanwhile, monthly bills are inflexible and incongruent with the typically irregular nature of their income flows (Jack and Smith, 2015).

Pre-paid metering is increasingly deployed in both the electricity and water sectors as an innovative approach to address problems of non-payment, as well as to remove the mismatch between consumer access to cash and consumption (Heymans *et al*., 2014; Jack and Smith, 2020). In sub-Saharan Africa (SSA) specifically, market forecasts suggest the greatest growth in electricity metering will come from pre-paid meters and that, by the end of 2034, the market value of prepaid electricity meters for SSA will grow by 234% (Northeast Group, 2014). South Africa was the first African country to introduce pre-paid meters in 1988, followed by Mozambique and Rwanda and, more recently, by Ethiopia, Nigeria, Angola, and Uganda (Esteves *et al*., 2016). In Ethiopia, the location of our study, the Ethiopia Electric Utility (EEU) Company, a single and state-owned utility, has faced persistent challenges relating to billing collection, customer complaints (Walta Media and Communications Corporate SC, 2021), and calls for aggressive expansion of access to electricity (MoWIE, 2019).[1] As part of the technological solution to these challenges, the utility is increasingly replacing post-paid meters with pre-paid alternatives. Both

[1] Due to problems collecting receivables from its customers, the EEU faces deficits. This has been responsible for delaying grid development and expansion of access to electricity for the remaining unconnected Ethiopian consumers. The EEU estimates these deficits currently amount to nearly US $100 million per year: https://www.rti.org/impact/expanding-electricity-services-and-energy-access-in-ethiopia.

utilities and policymakers in Ethiopia consider the installation of pre-paid meters to be one of the most critical tools for enhancing cost recovery (Tesfamichael *et al*., 2021).

Despite growing deployment and adoption of this technology, relatively few studies have rigorously examined its impacts on household electricity consumption and other outcomes, however, especially in developing countries (Jack and Smith, 2015; Jack and Smith, 2020). This paper aims to fill this gap, examining the impact of the introduction of pre-paid metering in Addis Ababa, Ethiopia. We use quasi-experimental methods and aim to address several related questions: what is the impact of pre-paid metering on households' electricity consumption? How does this system affect other related variables, such as appliance ownership and in particular cooking technology alternatives and energy-efficient devices? Is pre-paid metering related to customer satisfaction with the services provided by the utility?

The rest of the paper is organised as follows. The next section (Section 2) presents a brief review of the literature. Section 3 focuses on discussing the background on electric meter replacement in Ethiopia. Section 4 presents the sampling technique, the nature of the data, and descriptive statistics of selected variables. Section 5 discusses the empirical strategies. Section 6 presents the estimation results, and the last section (Section 7) concludes.

2. Brief literature review

The shift to pre-paid billing is expected to have various impacts on electric consumers. Some of these impacts relate to behavioural changes undertaken by consumers as a result of pre-payment, given the greater flexibility of this system (Arthur *et al*., 2010; Jack and Smith, 2015). Pre-payment also provides real-time information feedback about electricity consumption and its major drivers, which may increase consumer attention (Qiu *et al*., 2017). Previous work has documented considerable advantages of pre-paid metering for utilities, including higher revenue collection (Jack and Smith, 2020; Tewari and Shah, 2003; Trimble *et al*., 2016); reduction of non-technical losses, such as illicit connection and electricity theft (Kambule *et al*., 2018; Mwaura, 2012); improved customer service and satisfaction (Mwangia and Mangusho, 2017; O'Sullivan *et al*., 2004; Tewari and Shah, 2003); increased debt recovery (Tewari and Shah, 2003); reduction in disconnection and reconnection fees; and cash flow benefits from upfront payment (Tewari and Shah, 2003; The Allen Consulting Group, 2009).

Pre-paid metering also appears to induce energy saving, which can reduce pressure on limited transmission and generation capacity (Baptista, 2015; Jack and Smith, 2020; Kambule *et al*., 2018; Padam *et al*., 2018; Qiu *et al*., 2017). There is considerable evidence from high income countries on the general link between information feedback of the type provided by pre-paid metering and energy saving (Aydin *et al*., 2018; Blasch *et al*., 2019;

Darby, 2001; Lynham *et al*., 2016; Ramos *et al*., 2015). This literature highlights the heterogeneity of impacts across different circumstances, typologies of information feedback, and socioeconomic settings. Pre-paid metering, as one of the typologies providing more direct and continuous information (Darby, 2001), can play a particularly strong role in reducing energy consumption by offering uniquely relevant information to households on how their electricity consumption varies with the use of different appliances (Ayodele *et al*., 2017; Arawomo, 2017). Empirical evidence supports this prediction. For example, following a randomised phase-in of new pre-paid customers and observing consumption for four and a half years, Jack and Smith (2020) found a 14% reduction in electricity consumption in a sample from South Africa, which suggests such meters helped customers better understand and control electricity usage. Similar reductions have been observed in other developing country settings, e.g. among those receiving electricity consumption information in China (Du *et al*., 2017) and in Nigeria, where a study by Arawomo (2017) compared consumption data provided by meter readers and pre-paid meters and where a study by Ayodele et al. (2017) examined data from pre-paid meters alone.

This evidence notwithstanding, there is growing scepticism among researchers about the impact of pre-paid metering, particularly on low-income households. For example, this payment system has been criticised for effectively hiding the difficulties low-income households face due to disconnection of service (O'Sullivan *et al*., 2016; O'Sullivan *et al*., 2014; Colton, 2001). O'Sullivan *et al*. (2014) argue that a pre-payment system forces vulnerable households to engage in a 'dichotomous choice between self-rationing and self-disconnection'. Another study in Tanzania argues that cash-constrained prepaid meter users may tend to rely on biomass fuels in order to avoid sudden disconnection (Jacome and Ray, 2018).

We make three main contributions in this paper. First, in deploying a quasi-experimental evaluation approach to control for non-random selection into connection with pre-paid meters, we add to a small handful of rigorous, empirical evaluations of the impacts of pre-paid metering in low-income countries. As discussed above, most quantitative studies on metering reforms address smart meters in a developed country context; studies in the developing world tend to be qualitative in nature or pertain to middle-income developing economies. The small set of studies relating to pre-paid metering in Ethiopia (Akele, 2012; Getachew, 2018) focus solely on the management and service quality pertaining to the introduction of a pre-paid metering system. Second, we leverage a unique and rich household dataset to examine a broader set of impacts than those on electricity consumption alone. This allows us to disentangle how consumption savings come about and shed light on several hypothesised negative effects of pre-paid meters. In particular, we are able to determine whether appliance ownership patterns change, specifically considering the balance of domestic labour-saving appliances (e.g. refrigerators, irons, washing machines, cooking appliances), entertainment devices (e.g. TVs, radios), and lighting technologies (e.g. rechargeable batteries, CFL or LED bulbs).[2] We also examine the impact of pre-paid metering on customer satisfaction of those serviced by the EEU. Third, we consider the possibility of heterogeneous impacts on different households, which further elucidates the equity implications of such a payment system.

Finally, beyond these specific contributions, our paper is timely and relevant for the policy environment in Ethiopia. The EEU is currently investing in expansion of pre-paid metering technology. As such, this study will help facilitate the formulation and implementation of evidence-based policy and in identifying the possibilities for further improvements in its implementation. The study not only provides evidence on the role of pre-paid metering as a demand side management tool, but also contributes to a more robust dialogue on how electricity billing and payment modalities in developing countries affect consumer well-being and energy transition.

3 Status of electric meter replacement in Ethiopia

The EEU, the state-owned electric power distribution agency in Ethiopia, is responsible for the distribution and sale of all of the country's grid electricity. The EEU operates in 11 regions and 28 districts and through nearly 560 customer service centres (CSCs). Despite its considerable problems, post-paid billing was the company's standard method of bill collection until 2007, prior to the advent of new metering technology. This traditional billing system, which remains in place in most of the country today, creates numerous challenges for the EEU. First, it requires lengthy and inefficient revenue collection procedures in that meter reading must be completed by utility personnel making the rounds of neighbourhoods and towns, followed by the generation and delivery of customer bills and finally payment collection. Second, non-payment and late payment for the electricity service are common, and the company incurs a high cost for legal enforcement (i.e., collection of penalties and eventual disconnection). Third, this billing system is prone to a range of errors, which can lead to inappropriately high or low billing amounts (Akele, 2012). For these and other reasons, post-paid billing has long been considered problematic by the utility, and attempts to improve on billing and revenue collection remain a major challenge.

In response to these problems and to better manage electricity supply and demand, the EEU began experimenting with a pre-paid metering system since around 2008, hoping to improve service quality in the process (Akele, 2012;

[2] Other appliances, such as sewing machines, solar lanterns, fans, etc., are owned by only a small proportion of the sample (less than 1% each) and hence are ignored in this analysis.

Esteves *et al*., 2016; Getachew, 2018). The dissemination of pre-paid metering began with a pilot project in the *Gerji* area of the capital city, Addis Ababa, implemented in 2007 in collaboration with an Egyptian meter manufacturer. Encouraged by the success of this pilot project, the EEU began disseminating these meters to its customers in 2008 (Getachew, 2018). At present, out of a total of more than 2 million domestic customers, about half a million have pre-paid meters.[3] The company is still rolling out the intervention and has plans to gradually switch all existing residential and non-residential meters to a pre-payment system (Akele, 2012). In Ethiopia, EEU believes that these meters will reduce non-technical losses, improve understanding of energy use and facilitate planning, help overcome revenue recovery and administration challenges, reduce customer debt, and facilitate improvement of customer service quality (Getachew, 2018).

Pre-paid meters also include in-home displays that provide information to consumers. Customers top up their account by buying a fixed amount of electricity from a nearby payment centre. When there is a disconnection (almost always because consumers fail to top up their account, rather than because of voltage fluctuation), pre-paid customers must travel to the nearest centre to pay to reconnect their meter. It is up to the customer to recharge their account if they want to continue drawing electricity from the grid. There is no penalty for exhausting the balance. Meters give a warning (blinking red lights) when a customer's balance drops below 30 birr.[4] In addition, the meter allows for a small amount of consumption on credit even after the balance drops to zero. This feature gives a customer time to replenish their account and helps reduce the inconvenience arising from sudden disconnection.

Currently, all domestic customers in Ethiopia are eligible for meter replacement, but meter replacement has been implemented gradually over time. New customers or existing post-paid users who apply for a new meter today are automatically assigned to the pre-payment system. Some households apply for meter replacement because they want to switch to pre-paid meters. In other cases, households may request meter replacement due to technical problems with the old post-paid meter. The third group of pre-paid meter users is composed of those moving into new residences, including condominium areas and newly built houses. These various aspects of selection for new meters inform the empirical strategy discussed in Section 5.

[3] This information was retrieved from the Addis Fortune newspaper: https://addisfortune.news/electric-billing-gets-worse-before-it-gets-better/

[4] The Birr is the Ethiopian currency, with an exchange rate of US $1 ≈ 29 birr at the time of the survey (August 2019).

4 Sampling and data

4.1 Sampling

The sample for this study leverages the household Multi-Tier Framework (MTF) survey in Ethiopia administered by the World Bank as part of an international effort to better understand energy access in low- and middle-income countries.[5] The MTF survey was designed to provide a nationally representative survey covering both urban and rural households. We draw on the sample from the first round to conduct a second-round survey focusing entirely on the major urban enumeration areas included in the original survey.

This particular study is based on data collected in Addis Ababa, which is where meter replacements have been most extensive. The complete sample comprises 1,182 households.[6] To construct this sample, all households enrolled in the first-round MTF survey from Addis Ababa were included. More than 78% of the sampled households in Addis Ababa who were surveyed in 2016 were revisited in 2019. The remaining households (22% of the sample) could not be found, for reasons such as relocation. At the time of the 2016 survey, only 8.9% of households had pre-paid meters in Addis Ababa. These pre-paid users were also enrolled in 2019, but the sample size was deemed insufficient for assessing the impact of pre-paid meters on the various outcome indicators evaluated in this study.[7] To increase the sample size of the 'treatment' group, we also recruited an additional 400 households not enrolled in the first-round survey from a list of pre-paid meter customers. This strategy allowed us to obtain a sufficient number of observations to have confidence in estimates of the impact of pre-paid metering on household electricity consumption.

Specifically, these additional pre-paid meter customers were selected according to the following two-step procedure. First, we distributed the total sample of pre-paid customers (obtained from the EEU) into the four regions (North, South, East, and West) of Addis Ababa, and then selected one centre from each region using a simple random sampling method. Each region has, on average, nine centres, with a minimum of seven and a maximum of 10 centres per region. The total number of centres in Addis Ababa is 36. For the second stage, 100

[5] Details on the sampling procedure adopted in the first round can be found in Padam et al. (2018).

[6] After dropping households without electricity meters (shared households) and those with incomplete information, 1,030 households were used for analysis. The shared households were those without an electric meter and which did not pay their electricity consumption expenses to the EEU. Instead, they paid them to a landlord or meter owner. The form of payment could be inclusion in the house rent, payment of a fixed amount per month, or some other arrangement for sharing the monthly electricity consumption expense (Meles, 2020).

[7] This also makes it impossible to adopt the difference-in-difference (DID) estimation method, which requires longitudinal data to measure the impact of the 'treatment' by the difference between pre-paid and post-paid customers in the before–after difference in electricity consumption.

households were randomly selected from the list of all residential pre-paid meter customers in each of the selected centres in the four regions.

4.2 Descriptive statistics

The descriptive statistics show that 89.3% of the sampled households have a meter on the premises, while the remaining 10.7% are unmetered (i.e. they get electricity from their neighbours). Among the metered households considered in our analysis (N = 1,030), 56% are post-paid meter users, and the remainder are pre-paid subscribers. Meter sharing is commonplace in Addis Ababa: of the total sample households used in this empirical study, more than 26% share meters with their neighbours. This substantiates previous findings, which show meter sharing is widespread in Africa, and particularly in Ethiopia (Kojima *et al*., 2016; Meles, 2020).

Table 1 presents the demographic characteristics of survey respondents. As shown, 44% of households are female-headed.[8] At first glance, female-headed households appear less likely to have pre-paid meters than male-headed households. More than half of post-paid meter users and only 35% of pre-paid meter users are female-headed. Pre-paid meter users appear more likely to be currently married. In addition, pre-paid meter users tend to have a smaller household size, to have relatively younger respondents, and to have more years of schooling compared to post-paid meter users. The difference in terms of education may not be surprising, as those who are better educated may have a greater understanding of the benefits of the pre-paid meter system. Finally, more than 43% of post-paid meter users and about 62% of pre-paid customers live in their own home. This suggests that ownership of the dwelling may be one of the factors driving connection to the pre-paid system, which aligns with expectations given the way the new metering system is being rolled out, especially for newly constructed homes and neighbourhoods.

Table 1: Summary statistics of variables used in the analysis

Description of variables	Total (N=1053) Mean (1)	Post-paid (N=598) Mean (2)	Pre-paid (N=455) Mean (3)	Difference Mean (4=2-3)
Household size	4.80	4.90	4.68	0.22*
Presence of children under 5 (= 1)	0.30	0.25	0.36	-0.10**
Age of household head	51.38	54.47	47.32	7.15***
Sex of household head (= 1 if female)	0.44	0.50	0.36	0.14***
Years of schooling of head	7.52	6.43	8.94	-2.51***
Per capita monthly consumption expenditure (birr)	1910.5	1514.7	2430.7	-915.9***

[8] Similarly, the report prepared based on the 2016 MTF data shows 39.6% of households are female-headed in urban areas and 12% of households are female-headed in rural areas (Padam *et al*., 2018).

Marital status of household head (= 1 if married, 0 otherwise)	0.56	0.47	0.68	-0.21***
Dwelling ownership (= 1 if household owns house)	0.51	0.44	0.61	-0.17***
Number of rooms of dwelling	2.63	2.66	2.61	0.05
Meter sharing (= 1 if household shares meter)	0.24	0.24	0.24	-0.00
Household head unemployed (= 1 if unemployed)	0.21	0.24	0.18	0.05
Household head wage employed (= 1)	0.30	0.24	0.38	-0.14***
Household head self-employed (= 1 if self-employed)	0.21	0.19	0.24	-0.04
Household head's occupation other (= 1 if household head engaged in other types of employment)	0.28	0.33	0.20	0.13***
Walls of house made of wood and mud (= 1)	0.71	0.82	0.58	0.24***
Walls of house made of concrete (= 1)	0.25	0.15	0.38	-0.23***
Walls of house made of other (= 1)	0.04	0.04	0.04	-0.01
Distance of the HH from the nearest centre in km	5.37	4.40	6.65	-2.25***
Dwelling connected to grid after 2007 (= 1) [a]	0.47	0.19	0.82	-0.63***
Proportion of pre-paid meter owners in CSC'	0.20	0.17	0.25	-0.07***

Source: Authors' computation from survey, 2019; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$. CSC refers to customer service centres. [a] The sample size for the variable 'dwelling connected to grid after 2007' are 511 and 441 for post-paid customers and pre-paid users respectively.

4.3 Electricity consumption and income

Data on various measurements of the outcome variables—such as electricity consumption and expenditures; the type and number of appliance stock, such as lighting, housekeeping, and entertainment appliances; the type of main cooking and baking stoves; the use of efficient bulbs; and other additional information on the cooking behaviour of households and their level of satisfaction with the utility services—were collected by asking respondents about these in the survey. Households were asked about their electricity consumption (in kilowatt hours (kWh)) and about the bill they had paid for the month preceding the survey period (July 2019). This elicitation, based on recall, has several drawbacks. One is that the electricity consumption in the month immediately preceding the survey may not be a good representation of a household's actual electricity consumption pattern, due to seasonal or other variations. More importantly, obtaining an exact figure for electricity consumption from a survey is difficult for both post-paid and pre-paid customers, although the issues are distinct in each case. For pre-paid meter users, no bill is ever issued by the utility company. Instead, these consumers top up their meter whenever their account is out of credit. We calculated the monthly amount of electricity (kWh) consumed from the amount of money spent to top up their meter in the prior month, after deducting monthly service charges. Another challenge relating to pre-paid meters is that households do not top up at regular intervals, which makes it difficult to measure their exact monthly consumption. For post-paid meter users, bills are issued on a monthly basis but are subject to billing errors and complexities in amounts charged due to non-payment or arrears.

To address these issues, we complemented the survey data with billing data from the EEU covering the prior five years (2014-2018). The billing data for pre-paid customers were obtained from records based on actual recharge amounts purchased and were converted into monthly consumption amounts given the differing time intervals of such payments. Note we were only able to get such billing data for about 785 of the total sampled households (N = 1,030).[9] We then calculated the monthly average electricity consumption (kWh) and electricity spending from the billing data. The monthly averages were calculated from the total annual electricity consumption, accounting for any differences in the number of days covered by the bills. The average treatment effects were then estimated using monthly average electricity consumption as our main outcome variable. In addition, monthly electricity expenditure was used as a check on the robustness of our results.

Table 2 presents a summary of the key variables relating to electricity consumption and income. The average electricity consumption per month was 234.7 kWh,[10] higher than the average electricity consumption of 193 kWh per month found by the MTF survey for this particular subsample in 2016 (Padam *et al*., 2018). Similarly, average household spending on electricity for 2019 was 244.8 birr (US$ 8.5) per month, considerably higher than what was reported in 2016 for urban Ethiopia, 73.9 birr (US$3.384) per month (Padam *et al*., 2018). This increase in electricity spending is partly due to an increase in electricity consumption, and partly to a substantial upward tariff revision implemented in January 2019 that affected all consumers (pre-paid and post-paid). Based on the recall data, monthly electricity consumption for pre-paid meter users was lower than that of post-paid meter users, and this difference is statistically significant. Similarly, a simple means comparison reveals that pre-paid meter customers' average monthly electricity spending was 25.59 birr (US$ 0.9) lower than that of post-paid meter customers. On the other hand, simple mean comparison based on the utility data for the reduced sample indicates that pre-paid meter users have higher electricity consumption compared to post-paid meter users, although the difference is not statistically significant. However, as shown later in this paper, after accounting for the influence of other factors such as income and education, the estimates based on matching and multiple regression analysis,

[9] The remaining households did not match due to various inconsistencies in the survey and billing databases, especially relating to meter numbers. In cases where meter numbers did not match, we tried to match households based on the subscriber name in the billing data, but this was not always consistent either, as was the case for many renters or extended families. We have examined the distribution of missing data across the pre-paid and post-paid group and found it to be 29.6% and 22.9% respectively (Appendix 3A).

[10] The average electricity consumption is almost the same (256.2 kWh/month) when we exclude the 400 additional pre-paid households enrolled since the first round of the MTF survey in 2016. This suggests that those additional households do not have systematically different electricity consumption on average relative to the original sample.

shows that the impact of pre-paid meters on electricity consumption is negative and significant. Pre-paid meter users tend to have higher average monthly *per capita* expenditure and income compared to post-paid meter customers, however. This is in line with other literature, which finds a positive correlation between income and using pre-paid meters.

Table 2: Summary statistics for key outcome variables

	Full sample(1)		Post-paid(2)		Pre-paid(3)		Difference (2)-(3)
	N	Mean	N	Mean	N	Mean	Mean
Average monthly bill (birr)	1033	244.83	585	255.93	448	230.34	25.59**
Average monthly electricity consumption (kWh)	1031	234.74	583	240.74	448	226.92	13.82
Average monthly bill (based on utility data)	783	269.91	462	262.15	321	281.08	-18.93
Average monthly electricity consumption (kWh) (based on utility data)	783	265.97	462	262.15	321	271.45	-9.30
Appliance stock index	1053	0.93	598	0.82	455	1.06	-0.24***
Lighting appliance index	1053	-0.73	598	-0.64	455	-0.84	0.19*
Entertainment appliance index	1053	1.09	598	1.12	455	1.06	0.06**
Housekeeping appliance index	1053	0.34	598	0.33	455	0.36	-0.04**
Main bulb in house is energy-efficient	1044	0.83	593	0.82	451	0.86	-0.04**
Main cookstove is electric (=1)	1053	0.73	598	0.71	455	0.76	-0.05
Main baking stove is electric (=1)	1053	0.84	598	0.83	455	0.84	-0.01
Frequency of cooking (days per week)	1053	6.58	598	6.55	455	6.62	-0.07
Frequency of baking (days per week)	1053	1.74	598	1.75	455	1.72	0.03
Household satisfaction with the utility	1055	0.67	599	0.65	456	0.70	-0.04

Source: Authors' computation from survey, 2019. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The indices are constructed based on polychoric Principal Component Analysis.

5. Theoretical framework and estimation strategy

5.1 Conceptual framework

Pre-paid metering is believed to influence energy consumption via nudging, price effects, information provision, and costs of discontinuation (Qiu *et al.*, 2017). First, the information feedback channel arising from in-home displays and real-time feedback can encourage energy conservation. Frequent reminders about energy consumption among those who pay attention to the displays provide nudges that aid budgeting and are generally believed to reduce consumption, at least for those who are resource-constrained or conservation-minded. Second, information provided by pre-paid meters is more likely to be salient. In our context, even inattentive consumers receive reminders when their balance is depleted. Households are further incentivised to pay attention to their electricity consumption because not monitoring their balance entails significant inconvenience relating to disconnection. Thus, unless the recharge amounts are large and infrequent, it seems likely that consumers obtain additional and more salient information with this setup than they would with the typical post-paid system. Third, the prepaid program reduce consumption as future payments in the case of post-paid mechanism provide additional advantage due to discounting. However, this effect tends to be insignificant as the time interval is too short and the interest rate is small. Fourth, failure to top up a pre-paid account creates additional costs for the households relating to disconnection. For those who remain inattentive despite the additional information feedback, these disruptions will increase the relative cost of electricity, inducing both income and substitution effects. The latter may also result from the upfront nature of payments under the pre-paid system, which must be compared with the discounted future benefits of that energy consumption.[11]

Consistent with this framework, existing research has found that in-home-displays alone can induce energy conservation (Stinson *et al*., 2015). Still, this impact may vary across individuals and the way displays are designed, having been shown to depend on various factors like message framing (Schultz *et al*., 2015), the initial level and type of energy consumption (Matsukawa, 2018), and characteristics of the target population (Aydin *et al*., 2018; Krishnamurti *et al*., 2013). On the other hand, the pre-payment mechanism is expected to trigger behavioural change among electricity consumers due to changes in the timing of payment (Malama *et al*., 2014). For example, studies have observed an improvement in household budgeting, with many households also reporting that they ration credit when it is low, reduce electricity use and debt, and stop using electricity for energy-intensive activities like cooking (Malama *et al*., 2014). In our setting, information and payment timing mechanisms are relevant but cannot be identified separately, since all pre-paid customers also have access to in-house displays that provide feedback on energy consumption. Based on prior evidence, however, we expect the pre-paid billing system will tend to reduce electricity consumption.

We also examine the heterogeneous impacts based on different factors such as education, income, and meter sharing. We expect impacts would be greater, *ceteris paribus,* for those at the lower end of the income distribution, those who do not share meters, and those who are more educated (and perhaps understand information better).

[11] In our case, the period over which discounting occurred was relatively short, but previous research also shows that individuals tend to discount outcomes in the near future more compared to outcomes in the distant future, and that discount rates among those facing tight income constraints can be high (Frederick *et al*., 2002). This will reinforce income and substitution effects.

We also hypothesise an impact of pre-paid metering on the ownership of appliances and on the use of electric stoves since these consumers are perhaps more conscious of their consumption patterns and therefore better able to control their electricity use, as well as positive effects on customer satisfaction due to the enhanced reliability of their electricity service and on the use of energy-efficient bulbs that conserve energy.

5.2 Model specification

Our empirical analysis of the impact of pre-paid meters on various outcomes involves estimation of average treatment effects, accounting both for selection on observables and for selection on unobservables. To adjust for the former, we estimate the average treatment effect on the treated (ATT) using propensity score matching (PSM). To also account for the latter, we further implement an instrumental variable (IV) estimation approach.

Our primary interest is to estimate the average treatment effect of having a pre-paid meter on electricity consumption, satisfaction with electricity service, and ownership and use of various appliances, including electric stoves and energy-efficient light bulbs. The appliance category is also disaggregated into cooking, entertainment, lighting, and domestic labour-saving equipment groups. The treatment takes a binary value of $T_i = 1$ if household i is enrolled in the pre-payment programme, and $T_i = 0$ if household i is a post-paid customer. Let Y_i denote the outcome variable (e.g. monthly electricity consumption) of household i. This variable Y_i takes values of Y_1 and Y_0 for pre-paid (treatment) and post-paid (control) users respectively. Following Rosenbaum and Rubin (1983), the average treatment effect (ATE) is then defined as

$$ATE = E(Y_1 \,|T_i = 1) - E(Y_0 \,|\, T_i = 0) \tag{1}$$

Direct estimation of the above equation is problematic as the two groups are not directly comparable owing to the selection by various means (discussed in Section 4) into the pre-paid metering group. In such cases, the average difference in the outcome after treatment cannot be reasonably attributed to the treatment, since observable and unobservable pre-treatment differences may be partly responsible for the change in the outcome of interest. To address those problems, we apply PSM and IV methods.

5.2.1 PSM

In this approach, we assume that assignment into pre-paid metering is driven only by observed characteristics, in which case knowledge of the vector of these observed variables X_i is sufficient to identify the unbiased impact of the treatment on the outcome. Under this assumption, we estimate the average treatment effects on the treated using PSM based on observables. The idea is to create a control group that is statistically comparable to the pre-paid metering group and that approximates the counterfactual shown in Equation (1), because it is observationally comparable with the treatment group in terms of characteristics that are unaffected by the treatment (Caliendo and Kopeinig, 2008; Becker and Ichine, 2002). According to Rosenbaum and Rubin (1983), the propensity score, $\Pr\,(T_i = 1/X)$, is defined as the propensity of exposure to a particular treatment, given a set of observed covariates. Mathematically, the conditional probability that a household has a pre-paid meter, conditional on observed characteristics X, is given by:

$$P(X) = \Pr\,(T_i = 1|X_i) \qquad (2)$$

The validity of matching on propensity scores depends on two basic assumptions: i.e. *the overlap condition*, which requires that a sufficient number of observations in the treatment have corresponding untreated comparisons based on their propensity scores; and the *unconfoundedness* condition (also called conditional independence), which requires that, given the observed covariates X, outcomes are independent of the treatment assignment (Khandker *et al.*, 2010). If these assumptions are satisfied, the treatment assignment is said to be strongly ignorable, given the observed covariates X and given the propensity score $P(X)$. Under strong ignorability, units with the same propensity score but with a different treatment condition, can be used as treatment and control (Rosenbaum and Rubin, 1983), and the ATT is:

$$ATT = E(Y_1|T_i = 1, P(X)) - E(Y_0|T_i = 1, P(X) \qquad (1)$$

Our PSM analysis was implemented in Stata using the *psmatch2* module. Propensity scores were first obtained for each of 1,029 observations for which the survey data were complete and which had electricity connections (as discussed in Section 3), and then for the restricted sample with verifiable billing data. Table 3 reports the results of a logit specification used to estimate the probability shown in Equation (2) (columns 1 and 2). It displays the determinants of selection into having a pre-paid meter as a function of a number of household variables we believe are likely to affect the likelihood of using pre-paid metering technology.[12] Column 1 is for the complete sample, while column 2 is for the subsample for which we are able to match billing data. The signs and levels of significance of the variables in the first and second columns are generally consistent. Thus, these determinants do not appear sensitive to restricting the analysis to the sample for which we are able to verify billing data. Column 3 and 4 also show the first stage regression results for the IV specification that is described in further detail below.

[12] We have checked the results by including regional dummies representing utility districts and found that most of the results are qualitatively similar but differ in level of significance which may be due to reduced degrees of freedom as a result of large number of explanatory variables.

Most of the results are qualitatively similar. The results show that older people are less likely to use pre-paid meters, while married households are more likely to have them. Unlike the findings of Oseni (2015), households with high *per capita* consumption expenditure are more likely to have pre-paid meters, as are households who own their dwelling or whose dwellings have more rooms. Distance from the nearest utility centre is found to be positively and significantly associated with the probability of using a prepaid meter, which is intuitive regarding differential convenience of bill payment, as well as the manner in which pre-paid meters are rolled out (with greater use in newer and therefore outlying housing developments).

Table 3: First-stage regression estimates

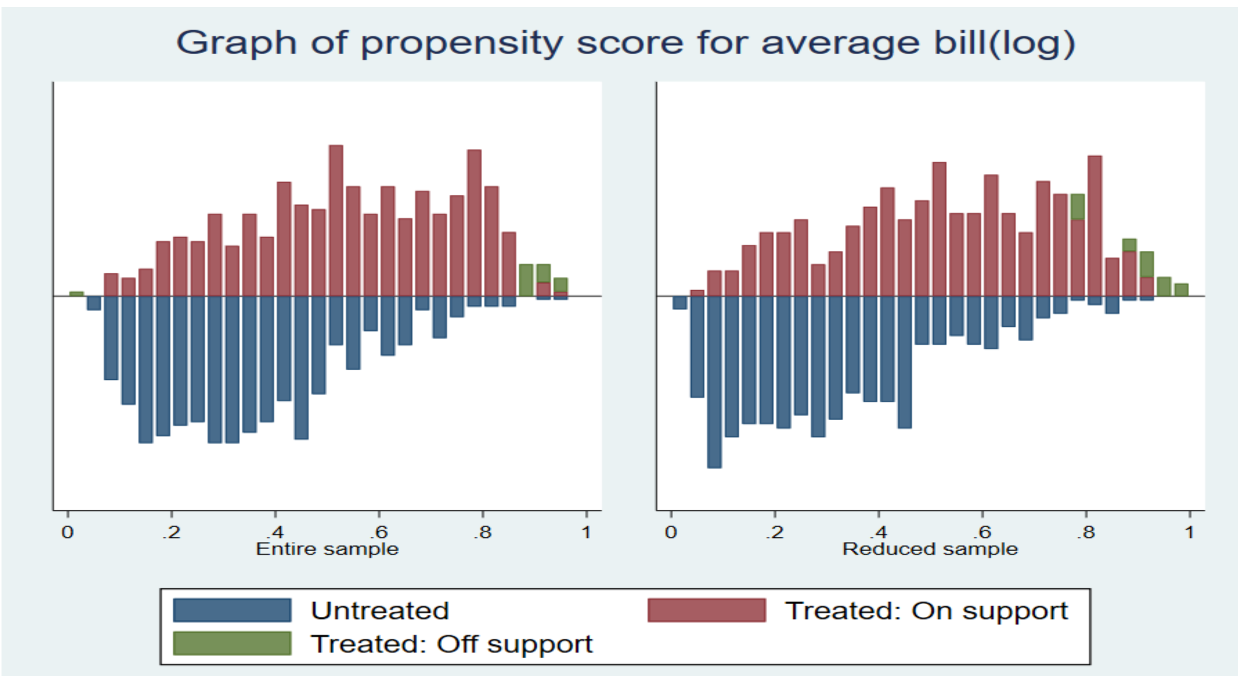
	Logit for PSM-Entire sample	Logit for PSM-reduced sample	Probit for IV-entire sample	Probit for IV-reduced sample
Household size	-0.02	-0.03	0.02	0.03
	(0.04)	(0.05)	(0.03)	(0.04)
Presence of children under 5	0.17	0.21	-0.00	-0.00
	(0.17)	(0.21)	(0.12)	(0.14)
Age of head	-0.02***	-0.02**	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.01)
Sex of head	0.15	0.04	0.32**	0.23
	(0.19)	(0.22)	(0.13)	(0.16)
Schooling of head	0.02	0.02	0.03**	0.03**
	(0.02)	(0.02)	(0.01)	(0.01)
Consumption expenditure (ln)	0.33***	0.37***	0.16**	0.19**
	(0.11)	(0.13)	(0.07)	(0.09)
Marital Status	0.85***	0.89***	0.45***	0.50***
	(0.18)	(0.22)	(0.13)	(0.16)
Dwelling ownership	0.83***	1.02***	0.32***	0.32**
	(0.16)	(0.19)	(0.11)	(0.13)
Number of rooms	-0.23***	-0.22***	-0.11***	-0.08
	(0.06)	(0.07)	(0.04)	(0.05)
Meter sharing	-0.21	-0.13	0.15	0.24*
	(0.17)	(0.21)	(0.12)	(0.14)
Head is wage employed	0.29	0.55**	0.05	0.26
	(0.22)	(0.27)	(0.16)	(0.19)
Head is self employed	0.07	0.15	-0.14	-0.17
	(0.23)	(0.28)	(0.16)	(0.19)
Head employed in other	-0.07	-0.05	0.01	0.02
	(0.22)	(0.27)	(0.15)	(0.18)
Walls made of wood and mud	-0.43	-0.38	-0.08	0.01
	(0.35)	(0.40)	(0.25)	(0.29)
Walls made of concrete	0.53	0.46	0.19	0.18
	(0.37)	(0.43)	(0.26)	(0.31)
Distance from nearest centre	0.04***	0.06***	0.01**	0.02
	(0.01)	(0.02)	(0.01)	(0.01)
Grid-connected after 2007			1.67***	1.81***

			(0.10)	(0.13)
Proportion of pre-paid in CSC			0.81***	0.93***
			(0.29)	(0.34)
_cons	-2.30**	-2.97**	-3.00***	-3.60***
	(1.03)	(1.22)	(0.73)	(0.88)
N	1050	779	987	736

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively; standard errors in parentheses

Furthermore, as depicted in Figure 1, there exists a sizeable region of common support between the two groups in both the full sample and the confirmed billing data subsample. Observations outside the common support region were dropped from further analysis.

Figure 1: Distribution of propensity scores



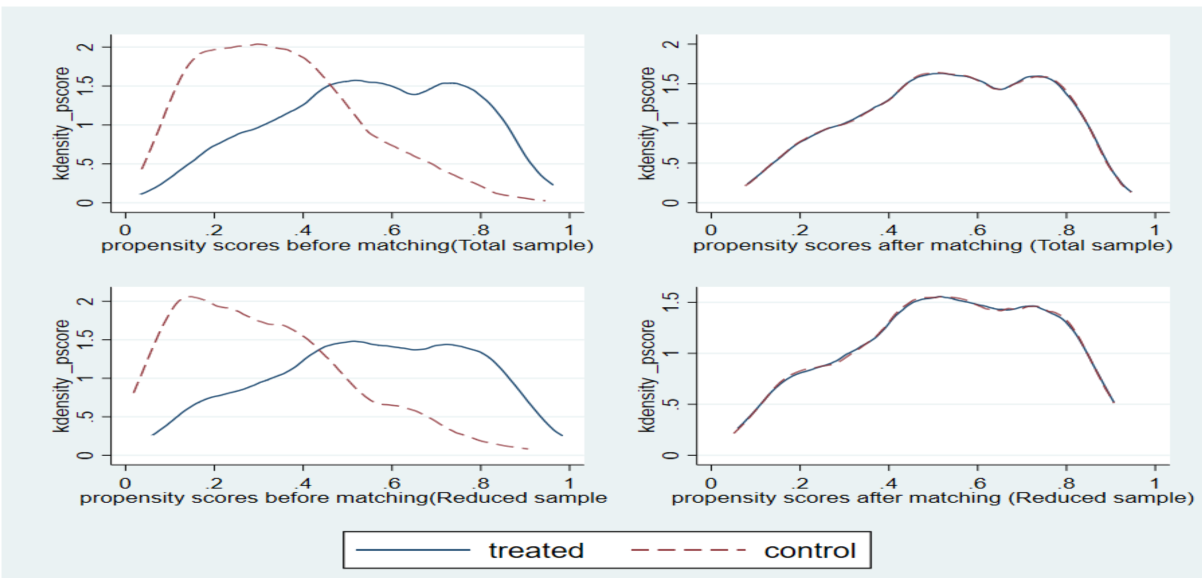
Note: 'Treated: on support' refers to observations in the pre-paid group that have a suitable comparison. 'Treated: off support' refers to the observations in the pre-paid group that do not have a suitable comparison.

To assess robustness across different specifications of the matching algorithm, we applied various commonly-used approaches: nearest-neighbour matching (NNM) with one, three, and five neighbours, kernel matching, and radius matching with three caliper levels (0.1, 0.05, and 0.01).[13] As suggested in the literature, there is no

[13] In this paper, we apply matching with replacement instead of matching without replacement, as the former allows a better match to be used more than once and reduces bias (Dehejia and Wahba, 2002). The latter, on the other hand, may increase bias but might improve

matching algorithm that dominates in all data situations and the choice of specific algorithms involves a trade-off between bias and efficiency (Caliendo and Kopeinig, 2008). In each case, following Rubin (2001), we estimate the standardised difference in the mean value (Rubin's B) and the variance ratio (Rubin's R) of the propensity score for pre-paid and post-paid meter users. Standardised differences greater than 20% are considered high (Rosenbaum and Rubin, 1985). The distributions of propensity scores (for the example of radius matching with a caliper level of 0.05) are shown in Figure 2. As shown, there is substantial reduction in the bias after matching. In other words, there is sufficient similarity on observables between households in the treatment group and those in the control group to allow appropriate comparisons, and the overlap condition is satisfied.[14]

Figure 2: Distribution of propensity scores before and after matching, for radius matching algorithm with caliper level of 0.05



the precision of the estimates. As discussed in Rosenbaum (1996), the results obtained based on matching without replacement may be sensitive to the order in which the treatment units are matched.

[14] As suggested in Rosenbaum and Rubin (1985), we examined the reduction in the mean absolute standardised difference between the pre-paid customers and post-paid customers before and after matching. The difference or bias is calculated for each covariate. In our case, the standardised mean difference for overall covariates used in the propensity score is less than 25% for most of the algorithms (Appendix 1). Furthermore, the p-values of the likelihood ratio tests show that the joint significance of the covariates was always rejected after matching in all matching algorithms. All the tests (low pseudo R2, low standardised bias, and high total bias reduction) suggest that PSM was successful in balancing the distribution of covariates between the two groups. We have undertaken these analyses for the various matching algorithms applied, and results are consistent across approaches. More details can be found in Appendix 1, and additional diagnostics are available upon request from the authors.

Of course, if unobserved factors affect selection into the use of pre-paid meters, the strong ignorability assumption required for PSM no longer holds, and the results from PSM will be biased (Rosenbaum, 1996). Indeed, the assignment of pre-paid meters in Ethiopia is likely to be affected by an array of observed and unobserved factors. As discussed further in the results, we check the robustness of our estimated results across various methods. First, we tested for the presence of hidden bias drawing from sensitivity analysis, as proposed by Rosenbaum (1996, 2002, 2005). Results were generally insensitive to small bias (for instance bias that would alter the odds of treatment assignment by 20% or so), but could be sensitive to larger bias. Furthermore, we complemented our analysis with IV estimation of average treatment effects, as described below.

5.2.2 IV estimation of average treatment effects

Following Wooldridge (2010) and Cerulli (2015), the IV estimation of treatment effects is given as follows. Let

$$Y = Y_0 + T(Y_1 - Y_0)$$

$$Y = \mu_0 + T(\mu_1 - \mu_0) + \nu_0 + T(\nu_1 - \nu_0) \qquad (4)$$

where $Y_0 = \mu_0 + \nu_0$, $Y_1 = \mu_1 + \nu_1$ and ν_0 and ν_1 are random components of Y_0 and Y_1 respectively. We further assume that the weak version of the conditional mean independence assumption does not hold, i.e.: $E(\nu_1|T, X) \neq E(\nu_1|X)$ and $E(\nu_0|T, X) \neq E(\nu_0|X)$

For parameter estimation, we further consider two scenarios. In the first scenario, we assume homogenous treatment effects, in which case Equation (4) becomes:

$$Y = \mu_0 + T(\mu_1 - \mu_0) + \nu_0 \qquad (5)$$

Suppose there is a vector of instruments Z that satisfies the conditions that Z is uncorrelated with $\nu_0 (E(\nu_0|X, Z) = E(\nu_0|X))$ and correlated with the treatment $(E(T|X, Z) \neq E(T|X))$. Under those conditions, the outcome equation and the latent selection functions are given by:

$Y_i = \mu_0 + T_i ATE + X\beta + u_i$ and $T_i = \rho + q_i\delta + \varepsilon_i$ respectively,

where $q_i = (X_i, Z_i)$ is an identification restriction and $E(\nu_0|X, Z) = E(\nu_0|X) = g(X\beta)$. The outcome equation cannot be consistently estimated due to the endogeneity of the treatment T_i. In such cases, IV regression estimated by probit and two-stage least squares provides consistent estimation of the outcome equation, irrespective of the correct specification of the selection model (Cerulli, 2015). The procedure is as follows. First, the predicted probability of treatment is estimated by estimating a probit model of the binary treatment as a function of a set of covariates *X* and instruments *Z*. Second, the predicted probabilities from the selection model are used to instrument for the treatment T_i, and two-stage least squares regression is applied to estimate the average treatment effect (Cerulli, 2015). Under the assumption of homogenous treatment effects, the average treatment effect (ATE) and average treatment effect on the treated (ATET/ATT) are equal.

In the second scenario, we assume there is a heterogeneous response to the treatment, which depends on covariates X, such that the ATE and ATET/ATT are not equal. In this case, the outcome equation becomes:

$$Y_i = \mu_0 + T_i ATE + X\beta_0 + (X - \mu_X)\beta + \varepsilon_i \tag{6}$$

Equation (6) can also be consistently estimated by applying probit–2SLS (Cerulli, 2015).

In order to estimate the IV regression, valid instruments are needed that have a direct effect on the use of pre-paid meters and only affect electricity consumption indirectly via the use of pre-paid meters. In other words, the instruments must first be correlated with the endogenous variables (switching to a pre-paid meter) and, second, they must not be correlated with the other unobserved factors that affect electricity consumption.

We identified two potential instruments from the survey and billing data collected from EEU. The first is the proportion of pre-paid meter customers to total customers in a given CSC. If there are more customers with pre-paid meters in a given centre, it is highly likely that information spread about the technology will induce other customers in the centre to switch to that system.[15] Centre-level dissemination should, however, be exogenous to individual household characteristics, so households residing in a centre with more pre-paid customers are more exposed to the technology and become better aware of it, and this differs from centre to centre.[16] We collected data on the number of pre-paid and post-paid meter customers in each of the 36 CSCs in Addis Ababa. The instrument at the centre level was then computed as follows:

$$Proportion\ of\ pre-paid\ customers\ = \frac{The\ number\ of\ pre-paid\ costomers}{Total\ number\ of\ customers}$$

The second instrument employed is a variable representing whether the customer's house was connected to the national grid after 2007 or not. From the household survey, households were asked about the number of years their house had been connected to the national grid. The intuition behind this instrument is that the distribution

[15] The correlation coefficient between pre-paid meter ownership and the proportion of pre-paid meter customers in a centre is 0.665, but the correlation coefficient between household electricity consumption and the proportion of pre-paid meter customers in a centre is -0.017, supporting our argument that it can be a valid instrument.

[16] Community-level proportions of this kind have been used as instruments in the literature. For example, Jung and Streeter (2015) used the average take-up rate of insurance in the community as a valid instrument for the endogenous variable 'enrolment of health insurance'.

of pre-paid meters in Addis Ababa started in 2007, and most newly built houses were automatically assigned to pre-paid electricity meters after that date. In addition, it is highly likely that older dwellings connected to the grid after 2007 were assigned to pre-paid electricity meters. Our first-stage regression result suggests the instruments are relevant, as they are significant at the 1% level (Table 3, column 3). Moreover, the signs and significance of variables in the IV probit generally appear similar to those for the first stage of the PSM model, with a few exceptions. This is expected, due to the inclusion of the two additional IVs (note that the IV estimation is only possible for the subsample with matched billing data, for which we can also identify the timing of the grid connection).

6 Estimation results

6.1 Average treatment effects using PSM

This section presents the effect of pre-paid metering on electricity consumption, appliance ownership, cooking behaviour, and household satisfaction with utility service, as derived from the PSM approach. The tables below present the average treatment effects on the treated (ATT), with bootstrapped standard errors. As shown, the use of pre-paid meters results in significantly lower electricity consumption. The estimation result shown in Table 4 shows that the effect ranges from 14% to 23%. Given that the outcome variable is in logarithmic form, prepaid customers have, on average, 13% to 20.5% lower electricity consumption per month compared to post-paid meter users. Alternatively, when the outcome is measured in terms of monthly spending on electricity, households with pre-paid meters have, on average, 19.7% to 26.6% lower monthly electricity spending compared to similar households with post-paid meters. Results show only minor differences [17] across the different matching algorithms (radius and kernel matching and NNM), which indicates results are robust to the specific PSM algorithm that is applied.

[17] Note the dependent variables are log transformed.

Table 4A: Estimates of average treatment effects: PSM results for the entire sample (using self-reported monthly electricity consumption)

Matching algorithm		Bill	kWh	App. Stock	Lighting App.	Entertainment App.	Housekeeping App.
Radius	Caliper=0.01	-0.27***	-0.18***	0.07	-0.12	-0.09**	-0.02
		(-0.07)	(-0.06)	(-0.06)	(-0.14)	(-0.04)	(-0.02)
	Caliper=0.05	-0.23***	-0.15***	0.07	-0.09	-0.08**	-0.02
		(-0.06)	(-0.06)	(-0.06)	(-0.13)	(-0.04)	(-0.02)
	Caliper=0.1	-0.22***	-0.14**	0.08	-0.13	-0.08**	-0.01
		(-0.06)	(-0.05)	(-0.06)	(-0.13)	(-0.04)	(-0.02)
Nearest neighbour (NN)	NN=1	-0.31***	-0.23**	0.08	-0.15	-0.07	0
		(-0.09)	(-0.1)	(-0.09)	(-0.17)	(-0.06)	(-0.03)
	NN=3	-0.29***	-0.22***	0.06	-0.08	-0.09**	-0.02
		(-0.08)	(-0.09)	(-0.07)	(-0.15)	(-0.04)	(-0.02)
	NN=5	-0.26***	-0.20***	0.07	-0.1	-0.09*	-0.02
Kernel		(-0.07)	(-0.07)	(-0.08)	(-0.15)	(-0.05)	(-0.02)
	BW=0.06	-0.23***	-0.15**	0.06	-0.09	-0.08**	-0.02
		(-0.06)	(-0.06)	(-0.06)	(-0.12)	(-0.04)	(-0.02)
N		1025	1024	1050	1050	1050	1050

Standard errors are in parentheses; *p< 0.10, **p< 0.05, ***p< 0.01

Table 4A: Continued

Matching Algorithms		Energy Eff. Bulb	Main cookstove	Main bakingstove	Cooking freq.	Baking freq	Satisfaction
Radius	Caliper=0.01	0.05	0.00	0.02	0.02	-0.01	0.11***
		(0.04)	(0.04)	(0.04)	(0.10)	(0.06)	(0.04)
	Caliper=0.05	0.05	0.01	0.03	0.00	-0.01	0.10**
		(0.03)	(0.03)	(0.04)	(0.09)	(0.06)	(0.04)
	Caliper=0.1	0.06*	0.01	0.03	0.00	-0.02	0.09**
		(0.03)	(0.03)	(0.04)	(0.09)	(0.06)	(0.04)
NN	NN=1	0.10**	0.02	0.02	-0.04	0.00	0.08
		(0.05)	(0.05)	(0.05)	(0.13)	(0.10)	(0.06)
	NN=3	0.07	-0.00	0.03	-0.02	-0.02	0.08
		(0.04)	(0.04)	(0.05)	(0.10)	(0.08)	(0.06)
	NN=5	0.07**	-0.01	0.02	-0.02	-0.02	0.10*
		(0.04)	(0.04)	(0.04)	(0.11)	(0.07)	(0.05)
Kernel	BW=0.06	0.05	0.00	0.03	0.00	-0.01	0.10**
		(0.03)	(0.03)	(0.03)	(0.09)	(0.07)	(0.04)
N		1041	1050	1050	1050	1050	1050

Standard errors are in parentheses; *p< 0.10, **p< 0.05, ***p< 0.01

We conducted a similar exercise for the sample with actual billing data (Table 4B). The ATT estimates for this reduced matched sample are higher than those based on survey-reported electricity consumption from the previous month (Table 4A). Depending on the specific matching algorithm used, the estimated impact of pre-paid meters (measured in kWh) is estimated to range from 22 to 28%. This shows that, on average, prepaid adopters have 19.8% to 24.4% lower electricity consumption than non adopters. Similarly, the estimated impact on electricity expenditure (measured in Ethiopian birr) ranges from 21% to 27% showing that prepaid adopters have on average 19% to 23.7% lower monthly electricity spending than non adopters..[18] Results are significant and similar, irrespective of the type of matching algorithm used.

These basic findings on energy consumption are in line with other findings from similar studies. For example, Jack and Smith (2015) found that households with pre-paid meters in Cape Town had 14% lower consumption of electricity. In a developed world context, a 12% reduction was found in Arizona in the United States (Qiu *et al*., 2017).

Table 4B: Estimates of average treatment effects: PSM on matched sample using metering information obtained from the billing data from EEU

Matching Algorithms		Bill from EEU	kWh from EEU
Radius	Caliper=0.01	-0.23**	-0.25***
		(0.09)	(0.09)
	Caliper=0.05	-0.23**	-0.25***
		(0.09)	(0.09)
	Caliper=0.1	-0.21**	-0.22**
		(0.09)	(0.09)
NN	NN=1	-0.27***	-0.28***
		(0.10)	(0.10)
	NN=3	-0.26***	-0.27***
		(0.09)	(0.09)
	NN=5	-0.26***	-0.27***
		(0.10)	(0.10)
Kernel	BW=0.06	-0.24**	-0.25***
		(0.09)	(0.09)
N		779	779

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

[18] The results show that effects on expenditure are lower with actual bills, but higher with survey data. The main reason for this might be the load-shedding in the city just before the survey period (previous months), which may affect household consumption behaviour.

Turning to the other outcome variables of interest, our first observation is that pre-paid metering has a positive, but modest and statistically imprecise influence on total appliance ownership. Further analysis by appliance type does not reveal statistically significant impacts on specific categories of entertainment, domestic labour-saving, or lighting devices. Thus, the overall effect may be slightly positive on ownership across all categories, but with clearly positive and significant impact only on the use of energy-efficient light bulbs, which is encouraging, as the promotion of such energy-saving devices is also a goal of the EEU. Pre-paid meters do not appear to have any meaningful impact on household cooking behaviour, as reflected by the number of cooking and baking episodes per week, or on the use of electric stoves.

Some literature, mostly qualitative, finds a link between customer satisfaction and pre-paid metering (Mahapatra and Golhar, 2018; Mwangia, and Mangusho, 2017; O'Sullivan *et al*., 2014; Chinomona and Sandada, 2014). Our analysis supports this interpretation. Depending on the matching methods, the level of satisfaction among pre-paid consumers is 9.0 to 11.0 percentage points higher than among post-paid customers. This suggests that, in addition to saving energy, pre-paid metering improves household perception of electricity service quality.

As discussed above, PSM reduces selection bias arising from observables but does not address unobservables, nor does it allow for a direct test of the influence of the latter. Ichino *et al*. (2008), therefore, suggest that estimation of causal effects through matching under the unconfoundedness assumption should be followed by sensitivity analysis to understand the degree of reliability of the derived estimates. Following Rosenbaum (2002), we computed the bounds test for sensitivity (see also DiPrete and Gangl (2004) for additional details). The associated values of Γ estimated using the *rbounds* test are presented in Appendix 4 for each estimate.[19] This sensitivity analysis indicates that our estimates are not sensitive to small biases but may be affected by moderate to large bias. To be specific, when the outcome is measured in terms of electricity consumption (kWh) per month, a hidden bias that alters the odds of treatment assignment by more than 15% could result in a change in our conclusion about the impacts of pre-paid meters. To further verify robustness of our estimates to such hidden bias, we supplement the matching analysis with the IV analysis (Section 6.3).

6.2 Heterogeneous impacts using PSM

The ATT estimates reported in Table 4A and 4B above assume homogeneous impacts of pre-paid meters, but these impacts may differ across different household types. For example, household electricity consumption

[19] For the weak version of conditional independence assumption (CIA), please see Gangl (2004)

behaviours, as well as their attention to new information, are variable, creating the possibility that pre-paid metering may also have differential impacts. Previous studies (e.g. Aydin *et al*., 2018; Bao and Ho, 2015) reveal that information provision can have heterogeneous impacts that vary according to household characteristics. In this section, we present the heterogeneous treatment effect of pre-paid metering on our outcomes of interest, as a function of several characteristics (income, education, and meter sharing).

Heterogeneous impacts across income groups (Table 5A) were analysed based on a median income cut-off. We find that electricity consumption decreases for both low-income and high-income groups with pre-paid meters, but that the effect is greater for higher-income households. This is consistent with evidence from prior studies, which found that higher-income groups who also consume more energy tend to have more scope for conservation.[20]

Table 5A: Heterogeneous impacts across income group

Matching Algorithms		Lower income		Higher Income	
		Bill	kWh	Bill	kWh
Radius	Caliper=0.01	-0.15	-0.09	-0.24**	-0.22**
		(0.11)	(0.09)	(0.10)	(0.09)
	Caliper=0.05	-0.17	-0.08	-0.28***	-0.24***
		(0.11)	(0.09)	(0.09)	(0.09)
	Caliper=0.1	-0.15	-0.07	-0.26***	-0.18**
		(0.10)	(0.08)	(0.08)	(0.08)
NN	NN=1:1	-0.02	-0.05	-0.26**	-0.22*
		(0.14)	(0.14)	(0.12)	(0.13)
	NN=1:3	-0.15	-0.07	-0.27**	-0.25**
		(0.13)	(0.12)	(0.11)	(0.10)
	NN=1:5	-0.17	-0.10	-0.28***	-0.22**
		(0.12)	(0.10)	(0.10)	(0.10)
Kernel	BW=0.06	-0.16	-0.08	-0.28***	-0.24**
		(0.10)	(0.08)	(0.10)	(0.10)
N		531	530	494	494

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

We next consider the role of education, estimating our model for subsamples differentiated based on the household head's level of education: more or less than the median number of years of schooling (eight years).

[20] We have also carried out a heterogeneous impacts analysis based on the reduced sample with verified billing data in the next section discussing the IV analysis. The results are similar.

Results indicate that pre-paid metering reduces electricity consumption, especially among households with relatively more educated heads (Table 5B). This is consistent with the idea that pre-paid metering may have a higher impact on households that are more aware of their electricity consumption. It should, of course, be acknowledged that such households may also have higher income and higher energy consumption (and, therefore, more potential for energy saving). The descriptive statistics also show that pre-paid meter customers are better educated than post-paid customers, although this variable is not strongly related to selection into pre-paid meters once we control for other factors (as shown in Table 3).

Table 5B: Heterogeneity across education (median education)

Matching Algorithms		Lower education		Higher Education	
		Bill	kWh	Bill	kWh
Radius	Caliper=0.01	-0.10	0.04	-0.23***	-0.20**
		(0.12)	(0.13)	(0.08)	(0.09)
	Caliper=0.05	-0.13	-0.05	-0.27***	-0.21***
		(0.10)	(0.12)	(0.08)	(0.08)
	Caliper=0.1	-0.13	-0.04	-0.25***	-0.18**
		(0.09)	(0.11)	(0.08)	(0.07)
NN	NN=1:1	-0.08	-0.09	-0.25**	-0.20*
		(0.17)	(0.15)	(0.11)	(0.11)
	NN=1:3	-0.17	-0.04	-0.25**	-0.21**
		(0.12)	(0.14)	(0.10)	(0.09)
	NN=1:5	-0.16	-0.02	-0.25***	-0.19**
		(0.13)	(0.12)	(0.09)	(0.08)
Kernel	BW=0.06	-0.13	-0.04	-0.27***	-0.21**
		(0.11)	(0.10)	(0.08)	(0.08)
N		475	473	550	551

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Finally, stratification of sample households by meter sharing (Table 5C) shows that pre-paid metering only significantly reduces electricity consumption among households that do not share meters. This result is expected, as households that do not share meters have higher *per capita* consumption than those that do share, and we have previously shown that higher-income households reduce electricity consumption more (Table 5A). The result is also consistent with the idea that meter sharing may dilute incentives to conserve electricity, even among those with pre-paid meters, and may diminish the information content of this type of metering system.

Table 6C: Heterogeneous impacts across income group[21]

Matching Algorithms		Do not share meter		Share meter	
		Bill	kWh	Bill	kWh
Radius	Caliper=0.01	-0.22***	-0.13*	-0.04	0.02
		(0.08)	(0.08)	(0.16)	(0.15)
	Caliper=0.05	-0.25***	-0.16**	-0.12	-0.06
		(0.08)	(0.07)	(0.11)	(0.11)
	Caliper=0.1	-0.23***	-0.14**	-0.11	-0.05
		(0.08)	(0.06)	(0.11)	(0.10)
NN	NN=1	-0.23*	-0.16	0.03	0.06
		(0.12)	(0.11)	(0.15)	(0.14)
	NN=3	-0.23**	-0.18*	-0.06	-0.02
		(0.10)	(0.10)	(0.14)	(0.13)
	NN=5	-0.27***	-0.19**	-0.10	-0.04
		(0.10)	(0.08)	(0.13)	(0.12)
Kernel	BW=0.06	-0.25***	-0.17**	-0.12	-0.06
		(0.07)	(0.08)	(0.13)	(0.10)
N		781	780	244	244

*Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01*

6.3 IV estimation of treatment effects

In this section, we relax the CIA underlying PSM to allow for selection on un-observables, using the IV estimation approach described in Section 5. Before proceeding to estimate the average treatment effects, we discuss various tests of endogeneity and identification. Based on Baum *et al*. (2007), we followed these steps. First, we tested for endogeneity of pre-paid metering, using the Wu–Hausman and Durbin–Wu–Hausman tests. As presented in Appendix 5, we reject the null hypothesis that metering is an exogenous regressor for both electricity consumption and expenditure. Second, we tested for the relevance of our proposed instruments (under identification) using Anderson's canonical correlation test. Results reject the null hypothesis that the equation is underidentified. Finally, the Sargan–Hansen test for overidentifying restrictions indicates that the instruments are valid. The results from these various tests support the use of these IVs to estimate the average impact of pre-paid metering on household electricity consumption.

[21] One of the challenges we faced was computing the actual electricity consumption of households sharing an electricity meter—that is, a household's relevant electricity consumption is the total metered electricity consumed by all shared households, minus the electricity consumed by all households sharing the meter. As the survey questionnaire does not have detailed information on those sharing a meter with the surveyed household, it is impossible to fully account for their electricity consumption.

The IV estimation was implemented using the probit–2SLS option of the Stata *ivtreatreg* command (Cerulli, 2014). Appendix 2 presents the covariates affecting household electricity consumption. Consistent with expectations, results indicate that larger households have higher average monthly electricity consumption, as do households with higher income. The results indicate that a 10% increase in average monthly *per capita* consumption expenditure (excluding spending on electricity) is associated with 1.5% increase in electricity consumption. In addition, households with a married head of household have higher monthly electricity consumption than those with a non-married household head.

As discussed in Section 5, the IV treatment effect was estimated under two separate assumptions. First, we assume a homogeneous response to the treatment—in other words, household response to the treatment is not affected by other characteristics. The estimated average treatment effects on the treated (ATT/ATET) are somewhat higher than those obtained from PSM, indicating that hidden bias may, if anything, reduce the ATT estimated using PSM (Table 6). Pre-paid meter customers are found to have about 23% lower monthly average electricity consumption and 5% lower average monthly spending on electricity, though the latter is not significant.

Table 6: IV–2SLS estimation of treatment effect (bootstrapped standard errors: number of replications = 100)

	Homogeneous treatment effects					Heterogeneous treatment effects				
	Bill	kWh	Bill from EEU	kWh from EEU	House keeping App.	Bill	kWh	Bill from EEU	kWh from EEU	House keeping App.
Average Treatment Effects on the treated(ATET)	-0.12	-0.04	-0.05	-0.23**	-0.25***	-0.12	-0.03	-0.05*	-0.25**	-0.26***
	(0.09)	(0.10)	(0.03)	(0.10)	(0.10)	(0.09)	(0.09)	(0.03)	(0.10)	(0.10)
Average Treatment Effects on the non treated (ATENT)						-0.13	-0.05	-0.06*	-0.19*	-0.20*
						(0.10)	(0.09)	(0.03)	(0.10)	(0.11)
Average Treatment Effects (ATE)						-0.12	-0.04	-0.06*	-0.21**	-0.22**
						(0.09)	(0.08)	(0.03)	(0.10)	(0.10)
No. of obs	966	965	987	736	736	966	965	987	736	736

Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

The average treatment effects (with bootstrapped standard errors) obtained from the model, allowing for heterogeneous treatment effects, are similar to those with a homogeneous response. The average difference in monthly electricity consumption increases very slightly to 25% and the magnitude of the effect on monthly electricity spending is the same but significant at 10%.

Table 7 presents the estimation results, assuming heterogeneity based on income, education, and meter sharing (as we did for the PSM). The main outcome variable is electricity consumption.[22] In addition, we examine the effect on other outcome variables, such as the main baking stove and the number of cooking days. Results again indicate that pre-paid metering impacts differ as a function of the level of education of the household head. Specifically, pre-paid meters reduce consumption most for households with heads who have more than the median years of schooling. Pre-paid meter households with more educated heads have a 25% lower monthly average electricity consumption than their post-paid counterparts. On the other hand, households with heads with fewer than the median years of schooling have an electricity consumption that is no different from that of the post-paid group.

We completed the same analysis for the two income categories: above and below the median income. Higher-income households with pre-paid meters seem to reduce electricity consumption by around 20.5%. Among the lower-income households, we find no statistical difference between the groups (pre-paid and post-paid customers), although the point estimates are similar to those in the higher-income group. The final analysis based on meter sharing shows that pre-paid meters have a larger effect on reducing electricity consumption for households that do not share meters. These results are largely consistent with those from the PSM.

Table 7: Heterogeneous treatment effects of pre-paid metering on electricity consumption (based on billing data)

	Income		Meter Sharing		Education level	
	Below med	Above med	No	Yes	Below median	Above media n
Bill from EEU	-0.27*	-0.22*	-0.25**	-0.16	-0.08	-0.29**
	(0.15)	(0.11)	(0.12)	(0.17)	(0.16)	(0.12)
kWh from EEU	-0.27	-0.23**	-0.26**	-0.17	-0.08	-0.30**
	(0.17)	(0.12)	(0.12)	(0.22)	(0.16)	(0.12)
Housekeeping App.	-0.08*	-0.03	-0.05	-0.04	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)	(0.04)

[22] We have checked whether the missing observations had any impact on our estimates. Results are shown in Appendix 3 and suggest missing data does not bias the estimation results.

Bill from survey	-0.18	-0.10	-0.16	-0.03	-0.07	-0.07
	(0.14)	(0.13)	(0.11)	(0.18)	(0.15)	(0.12)
kWh from survey	-0.09	-0.01	-0.07	0.03	-0.03	0.04
	(0.15)	(0.12)	(0.10)	(0.18)	(0.16)	(0.11)
N	501	464	728	237	449	516

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

6.4 Summary and relation to prior estimates in the literature

Overall, these results point to significantly lower electricity consumption among households with pre-paid meters relative to customers in the traditional post-paid billing system, using both PSM and IV specifications. The findings agree with previous work (for example Aliu, 2020; Ayodele *et al*., 2017; Jack and Smith, 2020; Qiu *et al*., 2017) showing that real-time feedback from pre-paid metering generally tends to reduce electricity consumption. Our estimates are somewhat higher than those from several previous rigorous causal impact studies (12%–13% from Jack and Smith (2020) and Qiu *et al*. (2017)) focusing on the more developed contexts of South Africa and the United States, where income constraints may bind to a lesser degree. However, one existing study from Nigeria has reported a greater difference in energy consumed (47%) between pre-paid and post-paid customers (Aliu, 2020).

In our setting, it is likely that the real-time feedback provided by pre-paid meters raises consumer consciousness of their own electricity consumption, especially among more educated households (Azila-Gbettor *et al*., 2015; Qiu *et al*., 2017), and allows them to understand the impacts of behaviours that reduce electricity consumption and expenditures. In addition to such real-time feedback, the nature of accounting for these costs and the timing of payment is also different for pre-paid meter users. Studies have found that pre-paid meter customers are more knowledgeable of the impacts of their electricity-related behaviours and feel they have more control over their consumption (Amnie, 2016).

Interestingly, our findings also suggest heterogeneous impacts along education, income, and meter sharing dimensions. Level of education is a major predictor of energy literacy (Brounen *et al*., 2013)[23]. It may also proxy for the capacity to monitor and make rational decisions based on the information provided by pre-paid meters. Households with better education tend to conserve more energy than their counterparts. Similarly, both PSM

[23] According to Brounen et al. (2013), energy literacy means consumers' ability to calculate the long-term impacts in terms of monetary and energy savings resulting from energy efficiency investments.

and IV estimations indicate that pre-paid metering more significantly reduces electricity consumption among higher-income households and those who do not share meters.

Unlike other similar studies on pre-paid metering, we also examined the impact of pre-paid metering on the ownership of appliances, the type of main cooking and baking stoves, the use of energy-efficient lights, and the frequency of baking and cooking days. We further analysed whether the use of pre-paid meters affects household satisfaction with the services provided by the utility. While pre-paid metering may have a modest positive impact on the ownership of total appliances, this result is not statistically significant or fully consistent across specifications, and pre-paid billing does not appear to have a significant impact on ownership of appliances in specific categories other than energy-efficient lights. Given that education and appliance ownership may not have a clear correlation pattern (Tesfamichael *et al*., 2021), it may not be surprising to see less of an impact of pre-paid metering on appliance ownership; moreover, while prepayment does appear to reduce consumption and expenses, increased appliance acquisition may not follow for highly budget-constrained households. Another key result of this study is that households with pre-paid meters are more satisfied with utility services. This is a new and important finding that lends support to the EEU's efforts to promote pre-paid meters.

7 Conclusion and policy implications

Pre-paid electricity metering is increasingly being adopted by many utilities and consumers around the world, but there is still relatively limited evidence of the impacts of such a system on the electricity consumption and wellbeing of households. In Ethiopia, for example, although the dissemination of pre-paid meters started more than a decade ago, its impact on electricity consumption has never been rigorously examined. This paper is an attempt to fill this gap. Using data collected from households in Addis Ababa combined with billing data obtained from the Ethiopian Electric Utility (EEU), we analysed the impact of pre-paid meters on household electricity consumption, using PSM and IV regression methods to better isolate causal impacts.

We find strong and consistent evidence that the pre-payment system significantly reduces household electricity consumption. Pre-paid meter users are found to have at least 13% lower monthly average electricity expenditure and 19% lower monthly average electricity consumption. Results are generally robust across different estimation methods, and across samples with and without verified billing data. In addition, our results indicate heterogeneous impacts along education, income, and meter sharing dimensions. Pre-paid meter households with heads who have more than the median number of years of schooling are found to reduce their electricity consumption substantially. Meanwhile, we find no significant differences between pre-paid and post-paid meter users from households with a head who has less than the median years of schooling. Greater and more consistent consumption reductions are also observed in households with more income and households that do not share meters.

Given these results, it appears that scaling up of pre-paid metering has the potential to reduce household electricity consumption substantially, and the impacts of such a change do not appear to be regressive. In other words, pre-paid metering does not have a disproportionately negative effect on consumption by lower-income households, which might be a particular concern given that such households already consumer relatively little electricity. This is vital for countries like Ethiopia, where increasing demand for electricity is a strain on existing generation capacity. Increased dissemination of pre-paid meters and the replacement of existing post-paid meters could save electricity and further enable efforts to expand electricity access, while incentivising energy conservation among higher status and consumption households. Furthermore, related empirical evidence shows that pre-paid metering can help improve cost recovery, one of the main challenges facing the EEU (Tesfamichael *et al*., 2021). It should also be noted that pre-paid metering may be even more effective when combined with efforts to improve energy literacy. This requires the efforts of the utility company to continue educating customers about the multiple advantages of pre-paid metering.

Further research is required to understand longer-term responses to pre-paid metering, especially for outcomes such as appliance ownership, using data collected over longer periods. It is unclear whether impacts on energy consumption persist, expenditure savings continue, and what the implications of those savings are for long-term energy-using technology adoption and behaviors, and our analysis does not explore such aspects. Additional investigation is warranted to consider more carefully the behavioural adjustments made by poor households that may suffer from particularly acute energy poverty (Kambule et al., 2019). Finally, the role of pre-paid metering in affecting the EEU's cost recovery efforts through addressing non-technical losses, revenue collection and other administrative burdens should be further explored.

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Appendix 1: Matching quality indicators

Panel A: Matching quality indicator for the entire sample

Sample	Matching Algorithm	Pseudo *R2*	*LR χ2(p-value)*	p>chi2	Mean standardized bias	Median Bias	Rubin's B	Rubin's R
Unmatched		0.16	219.92	0.00	30.60	31.10	98.5*	1.32
	Radius (0.01)	0.01	12.32	0.72	5.90	4.90	24.10	1.05
	Radius (0.05	0.01	9.04	0.91	4.20	4.30	20.40	1.17
Matched	Radius (0.1)	0.01	9.81	0.88	3.80	3.50	21.20	1.41
	NN (1:1)	0.02	22.52	0.13	6.8	4.8	32.2*	1.00
	NN (1: 3)	0.01	12.06	0.74	5.1	5	23.50	1.22
	NN (1: 5)	0.01	12.16	0.73	4.7	3.7	23.60	1.15
	Kernel	0.01	9.07	0.91	4.1	4.1	20.40	1.18

Panel B. Quality of the match for the reduced sample

Sample	Sample	Pseudo *R2*	*LR χ2(p-value)*	p>chi2	Mean standardized bias	Median Bias	Rubin's B	Rubin's R
Unmatched		0.19	197.00	0.00	35.40	39.30	109.7*	1.19
	Radius (0.01)	0.01	12.21	0.73	4.70	3.40	28.5*	0.94
	Radius (0.05	0.01	10.56	0.84	5.40	5.10	26.2*	0.89
Matched	Radius (0.1)	0.01	10.76	0.82	6.60	6.70	26.5*	1.07
	NN (1:1)	0.04	29.57	0.02	7.9	6.3	44.2*	0.89
	NN (1: 3)	0.01	11.46	0.78	4.9	4.3	27.4*	1.10
	NN (1: 5)	0.01	11.65	0.77	5.4	5.1	27.6*	0.93
	Kernel	0.01	10.64	0.83	5.4	4.8	26.3*	0.90

* if B>25%, R outside [0.5; 2]

Appendix 2: IV-2SLS estimation of average treatment effects

	Homogeneous treatment effects					Heterogeneous treatment effects				
	Bill	kWh	Bill from EEU	kWh from EEU	Housekeeping App.	Bill	kWh	Bill from EEU	kWh from EEU	Housekeeping App.
Prepaid metering	-0.12	-0.04	-0.05*	-0.23**	-0.25**	-0.12	-0.04	-0.06*	-0.21**	-0.22**
	(0.10)	(0.10)	(0.03)	(0.10)	(0.10)	(0.10)	(0.10)	(0.03)	(0.10)	(0.10)
Household size	0.10***	0.10***	0.02***	0.12***	0.12***	0.10***	0.09***	0.02***	0.12***	0.12***
	(0.02)	(0.01)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(0.02)	(0.02)
Presence of children under 5	0.21***	0.19***	0.03*	0.09	0.09	0.22***	0.20***	0.03	0.10	0.10
	(0.06)	(0.05)	(0.02)	(0.07)	(0.07)	(0.06)	(0.06)	(0.02)	(0.07)	(0.07)
Age of head	0.00	0.00	0.00***	0.00	0.00	0.00	0.00	0.00***	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sex of head	0.12*	0.09	0.05**	0.08	0.08	0.12*	0.08	0.05**	0.09	0.09
	(0.07)	(0.07)	(0.02)	(0.08)	(0.08)	(0.07)	(0.07)	(0.02)	(0.08)	(0.08)
Schooling of head	0.02**	0.02***	0.01***	0.01	0.01	0.01	0.01	0.01**	0.02**	0.02**
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Consumption expenditure (ln)	0.15***	0.15***	0.08***	0.15***	0.14***	0.18**	0.17**	0.08***	0.12*	0.12*
	(0.05)	(0.04)	(0.01)	(0.04)	(0.04)	(0.09)	(0.07)	(0.02)	(0.07)	(0.07)
Marital Status	0.22***	0.15**	0.05**	0.21**	0.21**	0.23***	0.15**	0.05**	0.20**	0.20**
	(0.07)	(0.07)	(0.02)	(0.08)	(0.08)	(0.08)	(0.07)	(0.02)	(0.08)	(0.08)
Dwelling ownership	0.08	0.04	-0.01	0.13**	0.13**	0.09	0.05	-0.01	0.13**	0.13**
	(0.06)	(0.06)	(0.02)	(0.06)	(0.06)	(0.07)	(0.06)	(0.02)	(0.06)	(0.06)
Number of rooms	0.10***	0.08***	0.04***	0.07***	0.07***	0.10***	0.09***	0.04***	0.07***	0.07***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Meter sharing	0.36***	0.32***	-0.03	0.37***	0.37***	0.16	0.15	-0.05*	0.27**	0.27**
	(0.06)	(0.06)	(0.02)	(0.07)	(0.07)	(0.12)	(0.11)	(0.03)	(0.12)	(0.12)
Head is wage employed	-0.05	-0.07	-0.04	-0.09	-0.09	-0.05	-0.07	-0.04	-0.06	-0.06
	(0.09)	(0.08)	(0.03)	(0.09)	(0.09)	(0.09)	(0.08)	(0.03)	(0.09)	(0.09)
Head is self employed	-0.13	-0.13	0.00	0.05	0.05	-0.13	-0.13	0.00	0.07	0.06
	(0.09)	(0.08)	(0.03)	(0.09)	(0.09)	(0.09)	(0.08)	(0.03)	(0.09)	(0.09)
Head employed in other	-0.11	-0.13	-0.04	-0.14	-0.14	-0.12	-0.14	-0.04	-0.13	-0.13
	(0.08)	(0.08)	(0.02)	(0.08)	(0.08)	(0.09)	(0.08)	(0.02)	(0.08)	(0.08)
Walls made of wood and mud	0.27**	0.27**	-0.00	0.16	0.15	0.27**	0.27**	-0.00	0.14	0.13
	(0.11)	(0.12)	(0.04)	(0.13)	(0.13)	(0.12)	(0.12)	(0.04)	(0.13)	(0.13)
Walls made of concrete	0.33***	0.34***	0.07	0.27*	0.26*	0.34***	0.35***	0.07	0.26*	0.25*

	(0.12)	(0.12)	(0.04)	(0.14)	(0.14)	(0.12)	(0.13)	(0.05)	(0.14)	(0.14)
Distance from nearest centre	0.00	0.00	0.00**	-0.00	-0.00	0.00	0.00	0.00**	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Hetero(lncons)						-0.07	-0.07	-0.01	0.09	0.08
						(0.13)	(0.11)	(0.04)	(0.13)	(0.13)
Hetero(metersharing)						0.44**	0.39**	0.06	0.22	0.23
						(0.18)	(0.17)	(0.06)	(0.21)	(0.21)
Hetero(schooling)						0.01	0.02	0.01	-0.03*	-0.03*
						(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Constant	2.56***	2.73***	-0.70***	3.04***	3.10***	2.43***	2.64***	-0.67***	3.13***	3.15***
	(0.42)	(0.38)	(0.12)	(0.42)	(0.42)	(0.64)	(0.58)	(0.16)	(0.53)	(0.53)
No. of obs	966	965	987	736	736	966	965	987	736	736

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix 3: Determinants of missingness

3A. Tabulation of missingness across metering

Missing	Prepaid metering		
	No	Yes	Total
Matched	462 (77.13)	321 (70.39)	783(74.22)
Missing	137 (22.87)	135(29.61)	272(25.78)
Total	599 100.00	456 100.00	1055 100.00

First row has *frequencies* and second row has *column percentages*

3B. Determinants of missingness (logit model: status = 1 if missing)

	Model 1	Model 2
Household size	0.0628	0.0616
	(1.46)	(1.22)
Children under 5	-0.384*	-0.330
	(-2.05)	(-1.64)
Age of household head	0.00887	0.0108
	(1.38)	(1.58)
Sex of head	-0.297	-0.199
	(-1.49)	(-0.95)
Years of Schooling of head	0.0038	0.00021
	(0.22)	(0.01)
Per capita consumption expenditure (log)	0.138	0.148
	(1.26)	(1.24)
Marital Status	-0.315	-0.309
	(-1.63)	(-1.51)
Dwelling Ownership	-0.264	-0.214
	(-1.58)	(-1.22)
Number of rooms of dwelling	0.0121	0.0811
	(0.23)	(1.33)
Metersharing	0.411*	0.386*
	(2.34)	(2.05)
Head is Wage employed (=1)	-0.117	-0.0563
	(-0.49)	(-0.22)

Head is Self-employed (=1)	0.0749	0.0873
	(0.30)	(0.34)
Head is Other employment type	-0.154	-0.135
	(-0.68)	(-0.57)
Wall of house made of wood and mud	0.497	0.507
	(1.18)	(1.12)
Wall of house made of concrete	0.677	0.829
	(1.55)	(1.78)
Distance from Utility Center	0.0694***	0.0724***
	(6.57)	(6.50)
Electricity meter is prepaid	0.288	0.464**
	(1.76)	(2.65)
Monthly electricity bill(log)		0.228
		(0.89)
Monthly electricity consumption in kwh (log)		-0.381
		(-1.46)
Appliance stock index		-0.161
		(-0.83)
Lighting appliance index		0.0483
		(0.69)
Entertainment appliance index		0.257
		(1.47)
Housekeeping appliance index		-0.223
		(-0.61)
_cons	-3.420**	-3.331**
	(-3.13)	(-2.72)
N	1050	1023

t statistics in parentheses , * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 4: Sensitivity analysis (Rosenbaum's bounds test): entire sample

		r bounds		Hodges-Leshmann point estimates		Confidence Interval (a=.95)	
Variable	Gamma	Upper Bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound
Bill	1.00	0.00	0.00	-0.24	-0.24	-0.32	-0.16
	1.05	0.00	0.00	-0.26	-0.23	-0.34	-0.14
	1.10	0.00	0.00	-0.28	-0.21	-0.36	-0.13
	1.15	0.00	0.00	-0.30	-0.19	-0.38	-0.11
	1.20	0.00	0.00	-0.31	-0.18	-0.39	-0.09
	1.25	0.00	0.00	-0.33	-0.16	-0.41	-0.08
	1.30	0.00	0.00	-0.34	-0.15	-0.43	-0.06
	1.35	0.00	0.00	-0.36	-0.13	-0.44	-0.05
	1.40	0.00	0.00	-0.37	-0.12	-0.45	-0.03
	1.45	0.00	0.01	-0.38	-0.11	-0.47	-0.02
	1.50	0.00	0.02	-0.40	-0.09	-0.48	-0.01
	1.55	0.00	0.03	-0.41	-0.08	-0.49	0.00
	1.60	0.00	0.06	-0.42	-0.07	-0.51	0.02
kWh	1.00	0.00	0.00	-0.16	-0.16	-0.24	-0.09
	1.05	0.00	0.00	-0.18	-0.15	-0.25	-0.08
	1.10	0.00	0.00	-0.19	-0.13	-0.27	-0.06
	1.15	0.00	0.00	-0.21	-0.12	-0.28	-0.04
	1.20	0.00	0.00	-0.22	-0.10	-0.29	-0.03
	1.25	0.00	0.01	-0.24	-0.09	-0.31	-0.02
	1.30	0.00	0.02	-0.25	-0.08	-0.32	0.00
	1.35	0.00	0.04	-0.26	-0.07	-0.33	0.01
	1.40	0.00	0.08	-0.27	-0.05	-0.35	0.02
Entertainment Appliance	1.00	0.00	0.00	-0.13	-0.13	-0.18	-0.08
	1.05	0.00	0.00	-0.14	-0.12	-0.19	-0.07
	1.10	0.00	0.00	-0.15	-0.11	-0.20	-0.06
	1.15	0.00	0.00	-0.16	-0.10	-0.21	-0.05
	1.20	0.00	0.00	-0.17	-0.09	-0.22	-0.04
	1.25	0.00	0.00	-0.18	-0.08	-0.23	-0.03
	1.30	0.00	0.01	-0.19	-0.07	-0.24	-0.02
	1.35	0.00	0.01	-0.20	-0.06	-0.25	-0.01
	1.40	0.00	0.03	-0.21	-0.05	-0.25	0.00
	1.45	0.00	0.06	-0.22	-0.04	-0.26	0.01

Note: We only run the sensitivity analysis for outcomes with statistically significant average treatment effects

B. Sensitivity analysis for the reduced sample

		r bounds		Hodges-Leshmann point estimates		Confidence Interval (a=.95)	
Variable	Gamma	Upper Bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound
Bill	1.00	0.00	0.00	-0.21	-0.21	-0.31	-0.10
	1.05	0.00	0.00	-0.23	-0.19	-0.33	-0.08
	1.10	0.00	0.00	-0.25	-0.17	-0.35	-0.06
	1.15	0.00	0.00	-0.26	-0.15	-0.37	-0.05
	1.20	0.00	0.01	-0.28	-0.13	-0.39	-0.03
	1.25	0.00	0.01	-0.30	-0.12	-0.41	-0.01
	1.30	0.00	0.03	-0.31	-0.10	-0.42	0.00
	1.35	0.00	0.05	-0.33	-0.09	-0.44	0.02
	1.40	0.00	0.09	-0.34	-0.07	-0.45	0.04
kWh	1.00	0.00	0.00	-0.22	-0.22	-0.32	-0.11
	1.05	0.00	0.00	-0.24	-0.20	-0.34	-0.09
	1.10	0.00	0.00	-0.25	-0.18	-0.36	-0.07
	1.15	0.00	0.00	-0.27	-0.16	-0.38	-0.06
	1.20	0.00	0.00	-0.29	-0.14	-0.40	-0.04
	1.25	0.00	0.01	-0.31	-0.13	-0.41	-0.02
	1.30	0.00	0.02	-0.32	-0.11	-0.43	-0.01
	1.35	0.00	0.03	-0.34	-0.10	-0.45	0.01
	1.40	0.00	0.06	-0.35	-0.08	-0.46	0.02

Appendix 5: Endogeneity and Identification tests

	Bill	kWh	App. Stock	Lighting App.	Entertainment App.	Housekeeping App.	Energy Eff. bulb
Prepaid metering	-0.15	-0.06	0.12	-0.37*	-0.13**	-0.05*	0.05
	(0.10)	(0.10)	(0.08)	(0.20)	(0.06)	(0.03)	(0.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	966	965	987	987	987	987	978
R-sq	0.22	0.21	0.38	0.07	0.33	0.26	0.03
Underidentification	303.26	302.78	304.64	304.64	304.64	304.64	306.03
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	216.67	216.27	216.09	216.09	216.09	216.09	218.38
Overidentification	0.02	0.04	0.68	0.01	3.53	1.84	0.00
p-value	0.88	0.84	0.41	0.93	0.06	0.17	0.95
Endogeneity	0.00	0.01	0.12	1.51	3.17	4.39	0.13
p-value	0.97	0.92	0.73	0.22	0.07	0.04	0.72

Continued

	Main cookstove	Main bakingstove	Cooking freq.	Baking freq	Satisfaction	Bill from EEU	kWh from EEU
prepaid_metering	-0.02	-0.03	-0.11	-0.07	0.02	-0.24**	-0.25**
	(0.05)	(0.05)	(0.17)	(0.10)	(0.06)	(0.11)	(0.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
="N""	987	987	987	987	987	736	736
R-sq	0.05	0.09	0.05	0.13	0.02	0.23	0.23
Underidentification	304.64	304.64	304.64	304.64	304.64	253.38	253.38
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	216.09	216.09	216.09	216.09	216.09	188.21	188.21
Overidentification	9.60	0.97	2.58	0.08	0.95	0.11	0.08
p-value	0.00	0.33	0.11	0.78	0.33	0.74	0.78
Endogeneity	0.28	2.70	2.39	0.46	1.23	3.89	3.93
p-value	0.60	0.10	0.12	0.50	0.27	0.05	0.05

Standard errors in parentheses; *, **, *** refers to P<0.1, P<0.05, P<0.01, respectively

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The views expressed in this Working Paper do not necessarily reflect the UK government's official policies.