Charging ahead: Prepaid metering, electricity use and utility revenue*

B. Kelsey Jack†
Grant Smith‡

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Abstract

The standard approach to recovering the cost of electricity provision is to bill customers monthly for past consumption. If unable to pay, customers face disconnection, the utility loses revenue, and the service provision model is undermined. A possible solution to this problem is prepaid metering, in which customers buy electricity upfront and use it until the prepaid amount is consumed. We use data from Cape Town, South Africa to examine the effects of prepaid electricity metering on residential consumption and electric utility revenue and costs. Over 4,000 customers on monthly billing were involuntarily assigned to receive a prepaid electricity meter, with exogenous variation in the timing of the meter replacement. Electricity use falls by about 13 percent as a result of the change in meter type, a decrease that persists for the following year. The decrease in revenue to the municipal electric utility is more than offset by lower revenue recovery costs, on average, though results vary by customer type. Poorer customers and those with a history of delinquent payment behavior offer the greatest net revenue gains when switched to a prepaid meter. These findings point to an important role for metering technologies in expanding energy access for the poor.

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†Department of Economics, Tufts University

‡Department of Economics, University of Cape Town

1 Introduction

The use of lights measured from space to proxy for economic activity (Henderson et al. 2011) drives home the importance of electricity for development. Much of the global increase in electricity consumption in coming decades is forecast to come from developing countries (Wolfram et al. 2012), and capital investment for new electrification has grown in recent years (WEO 2013). However, on the ground, expanding access to electricity introduces new challenges for service providers and for households. The standard model for recovering the costs of electricity provision is a postpaid metering system in which a customer receives a bill for consumption over the past month. For poor, liquidity constrained customers, finding resources to pay the bill, which is not only a substantial share of income but also varies from month to month, presents a major challenge. At the same time, enforcing bill payment is costly to the utility, and politically infeasible in many settings. To minimize losses, utilities may avoid connecting poor households in the first place.[1]

Prepaid electricity meters offer a technological solution to the non-payment problem. These meters, which operate on a debit basis, are increasingly common in both developed and developing counties. For example, in the United States, utilities in 34 states offer some type of prepayment plan for electricity, where they are used both to address non-payment and as a demand side management strategy (Drehobl 2017). The greatest expansion in prepaid metering, however, is happening in the developing world, where new electrification is fueling the demand for the meters. South Africa was an early adopter of prepaid electricity metering during the phase of rapid electrification following the end of apartheid, when electricity was rolled out to poor and rural communities (Gaunt 2005; Bekker et al. 2008; Dinkelman 2011; van Heusden 2012). Market forecasts suggest that the greatest growth in electricity metering in Sub-Saharan Africa will come from prepaid meters, which will dominate the electricity metering market in Africa by 2020 (Northeast Group 2014). Prepaid metering is

[1] In practice, access is often limited by connection fees, which impose an upfront cost that may be prohibitively high for poor households and small businesses (Golumbeanu and Barnes 2013; Lee et al. 2016b,a). On many common tariff structures, customers using small amounts of electricity each month are more costly to supply for reasons that go beyond the risk of non-payment. First, if recurring costs such as meter reading and bill processing are recovered out of consumption charges, then low levels of consumption are less likely to cover these costs. Second, on increasing block tariffs, low consumption results in a lower average marginal price for electricity.

also expanding into the water sector (Heymans et al. 2014).[2] In spite of the growing interest in prepaid metering to improve revenue recovery, we are unaware of any prior studies that combine credible causal estimates of customer behavior with utility cost numbers to evaluate whether prepayment does, in fact, improve the financial viability of supplying low income customers.

We partner with the municipal government in Cape Town, South Africa to generate new evidence on the impact of prepaid metering on two main sets of outcomes. First, we ask how transitioning customers from postpaid monthly billing to prepaid metering affects electricity use. Second, we examine the implications for the electric utility's bottom line. We observe monthly electricity use and payment behavior over a four and a half year period for 4,245 residential customers in a mandatory meter replacement project in Cape Town. The timing of meter replacement is randomly ordered across 27 geographic areas, and we follow customers for over a year following the replacement. The combination of involuntary replacement and exogenous timing allows us to recover a clean causal estimate of the impacts of prepaid metering that avoids selection into metering type. Prepaid metering affects numerous aspects of consumption, which precludes a clear accounting of consumer welfare in our setting. Our focus, in this paper, is on estimating consumption and payment responses as an input to the electric utility's revenue and cost calculations.

We find that customers reduce their electricity use when switched from postpaid monthly bills to prepaid electricity metering by 1.9 to 2.1 kWh per customer per day, or 12 to 15 percent.[3] The reduction persists for the year following the switch, and is robust to a number of alternative specifications. The largest reductions come from high consumers, but also poorer customers and those who are frequently delinquent in their postpaid bill payments. For more delinquent customers, the switch to prepaid metering represents a particularly dramatic transition away from the leniency of a weakly enforced monthly bill.[4] On average,

[2]The prepayment model has parallels in other technologies. For example, some argue that the rapid rise of mobile phones in Africa is due in part to their reliance on prepayment, which allowed poor users with unpredictable incomes to control their usage and avoid debt.

[3]For comparison, the reductions associated with non-price demand side management strategies are on the order of 1-2 percent (e.g., Allcott 2011). Our results are more consistent with reductions under critical peak pricing, which raise prices during peak demand episodes by up to 600 percent (Wolak 2011; Jessoe and Rapson 2014).

[4]Our utility partner is not unique in its lenience enforcing bill payment. Kojima and Trimble (2016) estimate that the total annual value of uncollected electricity bills is 0.17 percent of national GDP on average in Sub-Saharan Africa. South Africa is relatively effective in its collection rates. Some of the lack of billing enforcement can be attributed to the high cost of disconnecting and reconnecting a customer, which is roughly double the average bill total.

customers pay their postpaid bill around 100 days after consumption, or 40 days after payment is due. Mechanically, the prepaid meter forces payments to occur before consumption, and payment arrives almost 3 months sooner as a result of the switch to prepaid metering.[5]

The estimated decrease in consumption results in a corresponding decrease in the amount owed to the utility of around 7 USD per customer per month, and saves the utility around 3 USD in kWh supply costs.[6] However, better revenue recovery, lower recovery costs, and payments that arrive around 3 months sooner, on average, tip the balance in favor of prepaid electricity meters from the utility's perspective. Specifically, around 2 percent of bills are never paid on postpaid monthly billing, so the decrease in what customers owe the utility is partially offset by a greater likelihood that the amount owed is eventually recovered. In addition, the utility avoids the costs of meter reading and bill preparation, and the high costs of enforcement through disconnection.[7] All together, the changes in revenue and supply costs, along with the lower billing and revenue recovery costs –which we together refer to as the returns from prepaid metering relative to postpaid billing – is enough to offset the fixed costs of the prepaid meter over a period of seven years.[8] Accounting for changes in electricity use is important: assuming customer behavior remains fixed increases the projected returns from prepaid metering (relative to postpaid billing) to roughly three times the number we estimate.

The outcome of the utility's cost-benefit comparison depends on the type of customer, as well as features of the electric utility's cost environment.[9] Specifically, we observe relatively higher relative returns from switching lower and poorer users (based on average postpaid consumption and property values, respectively) to prepaid meters. In addition, customers that typically paid their postpaid bills late, carry outstanding debts or had a history of meter disconnections all generate substantially higher payoffs from the switch to prepaid metering

[5]Note that the timing of when payment arrives relative to consumption on a prepaid meter depends on customer purchasing patterns. Specifically, less frequent purchases mean that a customer pays for electricity further in advance of consumption, assuming consumption occurs over the entire time interval between purchases.

[6]All values are reported in 2014 real values, based on an exchange rate of 11.45 ZAR/USD.

[7]As discussed in footnote 1, these recurring monthly costs are proportionately high relative to revenue for low consumers, who also tend to be poorer. We calculate a break-even consumption level of 880 kWh per month: customers with consumption below that level incur lower recurring administrative costs (meter reading and bill preparation versus vendor fees) on a prepaid meter.

[8]We calculate the profit from prepaid metering relative to postpaid billing even though the utility may not be a profit maximizer. Rather than taking a stand on the utility's objective function, we focus on the relative payoff from each metering type as a way of aggregating changes in both revenue and costs.

[9]Our cost-benefit analysis focuses on the per-customer recurring (monthly) costs of electricity provision, and ignores fixed system-wide costs such as infrastructure development and maintenance.

than their more reliable counterparts. The electric utility actually loses money by switching customers who usually pay their bills on time or carry no outstanding debts. We also compare the relative returns from prepaid metering across different assumptions about administrative costs and observe that higher marginal electricity costs (holding tariffs constant) increase returns from prepaid metering, because the reduction in consumption creates less of a loss in settings where the average kWh is less profitable to the utility. Higher interest rates also increase the advantage of prepaid metering over postpaid billing.

Together, these results indicate that prepaid electricity metering can help overcome revenue recovery challenges, particularly for the types of customers that are most costly to the electric utility on a monthly billing model. While these customers benefit from lenient enforcement of bill payment, they also generate an externality on other customers by undermining the revenue base necessary for infrastructure expansion and maintenance. Prepaid metering makes substantial progress in narrowing the net revenue gap between richer and poorer customers in our sample, with implications for expanding electricity access in other settings. While the point estimates from our setting may be difficult to generalize, the heterogeneity that we observe suggests that prepaid metering will be relatively more beneficial to the electric utility in settings with a more delinquent customer base, a smaller profit margin per kWh or higher borrowing costs than Cape Town. Focusing on existing customers in the City of Cape Town presents a high hurdle for prepaid metering to show positive returns. Unlike in many developing countries, electricity in Cape Town is well managed, with revenue in excess of costs in most years (City of Cape Town 2016). Electricity losses are low and problems of bill payment delinquency and non-payment are comparatively minor. Furthermore, this setting allows us to focus on the impacts of prepaid metering in an environment free from confounds associated with new connections or unreliable supply, though the results may, of course, differ from impacts on previously unelectrified customers.

Our results highlight the importance of considering the customer response to a change in metering technology. We speculate that a number of mechanisms may underlie the changes in consumption that we observe. First, prepaid meters enforce payments automatically and so increase the experienced price of electricity relative to postpaid metering (even though tariffs remain the same), particularly where enforcement is lax. Second, by forcing customers to pay in advance, prepaid metering may affect expenditure patterns. On the one hand, postpaid billing provides a form of credit and helps smooth income. On the other hand, savings constraints together with variable monthly bill totals may lead to debt accumulation by credit constrained customers on postpaid billing. Third, the change from postpaid to prepaid metering transfers some transaction costs from the utility (meter reading, billing) to the customer (purchasing, monitoring consumption). Finally, a number of informational and behavioral differences characterize the change from postpaid to prepaid metering. For example, in-home displays provide feedback on usage, more frequent purchases make expenditures more salient, and the prepaid system offers a form of self- and intra-household control. A clean accounting of these mechanisms, and their implications for customer welfare, is outside the scope of this study, and offers an important topic for future work.

Our findings offer the first evidence on the impact of prepaid metering in a developing country context, where they are rapidly becoming the standard technology for new electricity connections. Existing work on the effects of prepaid electricity metering is scarce, and consists largely of descriptive studies (Tewari and Shah 2003; Baptista 2013). A recent paper on the largest prepaid metering program in the United States, the Salt River Project, found reductions in consumption of around 12 percent per month after customers voluntarily switch to prepaid metering (Qiu et al. 2016). The authors rely on a matching design to compare prepaid and postpaid customers, and do not calculate payoffs to the utility. We are not aware of any other plausibly causal evidence on prepaid electricity metering impacts.[10]

We also contribute to a small but growing body of literature on utility metering and revenue recovery in developing countries. For example, in a recent paper, McRae (2015) documents the heterogeneous impacts of metering (as opposed to a fixed monthly fee) on household welfare and utility revenue in Colombia. In a study of water bill payment in South Africa, Szabó and Ujhelyi (2015) show that an information intervention increases bill payment rates. More generally, non payment of bills and taxes undermines revenue generation in developing countries, and is often associated with challenges monitoring and enforcing tax payments (Gordon and Li 2009; Besley and Persson 2013). A growing number of empirical studies on taxation show that increasing information for monitoring or changing the incentives associated with enforcement can increase revenue (Kumler et al. 2013; Carrillo et al. 2014; Pomeranz 2015; Khan et al. 2016). Our results echo the conclusions in the taxation literature that innovations that shift the enforcement burden onto the payee may improve revenue even in settings where detection and enforcement might otherwise be difficult.

The paper proceeds as follows. In the next section, we provide background on prepaid electricity meters and on the study setting. Section 3 describes the data set and the empirical

[10]Gans et al. (2013) study the effect of a change in the meter interface that provides prepayment customers in Ireland with additional feedback about real-time usage. The change in feedback occurs for customers already on prepayment meters and therefore does not provide an independent estimate of the effect of prepayment on usage.

strategy, Section 4 presents the empirical results, and Section 5 calculates the costs and benefits to the utility. The final section concludes.

2 Background and context

We begin with a general description of prepaid electricity metering before turning to some of the specifics of our setting, including electricity tariffs and billing in the City of Cape Town and details of meter replacement program that we study.

2.1 Prepaid electricity meters

Prepaid electricity meters work on a debit basis: customers purchase electricity and load it on to their meter. As long as the meter has a positive balance, current flows through it into the home. Once the balance reaches zero, the current is interrupted. Prepaid meters display the number of units (kWh) remaining on the meter, and many have features to inform the customer when the balance is getting low, such as colored or blinking lights or an audible alert; they are also generally located within the dwelling in a visible and easy-to-reach place. Contrast this with what we refer to as postpaid metering. On a conventional postpaid meter, customers consume electricity and periodically have their meter read by an employee of the electric utility. Bills are sent based on cumulative consumption as recorded by the meter reader and customers typically have an additional grace period before their bill is due. The physical meters used in most postpaid systems are located outside of the home, and display consumption in a way that is difficult for the consumer to access and understand.[11]

Prepaid electricity metering is attractive to the electric utility for few reasons. First, it generates revenue in advance of consumption and cuts down on non-payment or late payment of electricity bills, though the latter will depend on how tightly bill payment is enforced on a postpaid system. Second, it eliminates the need to send meter readers to physically inspect meters or implement disconnections, and therefore addresses shirking or bribery, in addition to labor costs and safety concerns in many settings. Third, it eliminates preparing and mailing monthly bills and processing incoming payments. These last two

[11]Recent innovations with in-home displays and dynamic pricing have begun to change the information feedback on some postpaid systems (e.g., Jessoe and Rapson (2014)). Smart metering systems offer some of the same benefits as prepaid meters, such as lowering the costs of enforcing payment for electricity and automating meter reading. They tend to be more expensive than prepaid meters (roughly 3 times the hardware cost alone), however, and rely on more sophisticated grid and communication infrastructure.

benefits to the utility are achieved by transferring some of the transaction costs to the customer. The prepaid system is not without costs to the electric utility, however. There is a substantial initial cost of developing a vending network to track and charge customers.[12] Vendors typically earn a commission on sales of prepaid electricity, which may be passed on to the consumer or deducted from revenue to the utility (the latter in our setting). Prepaid electricity meters may also affect theft, which is unlikely to be an important factor in our setting.[13]

Customers purchase prepaid electricity from physical or electronic vendors, including supermarkets, small shops and kiosks, ATMs, gas stations, and online or via mobile phone. On the vending system used in Cape Town, the customer provides a meter number and the monetary value or number of kWh that they would like to purchase. The vending system issues an encrypted, meter-specific code based on the kWh purchased that the customer enters into a keypad on the physical meter. The meter itself does not communicate directly with the grid.[14] See Appendix figure A.1 for an example of receipts from Cape Town. Over time, prepaid metering technology has improved, both for reliability and theft prevention. The prepaid meters that we study are known as split prepaid meters, because the actual meter is located outside the home in a locked kiosk, with only the display and keypad inside of the home. Communication between the meter and the in-home display is by wire or radio frequency. This design minimizes the risk of tampering and allows the utility to perform maintenance more easily.

Prepaid metering is expanding across Africa and South Asia. Already widespread in Nigeria, Rwanda, Kenya, Uganda, Zambia and elsewhere, it is poised to become the dominant metering technology in Africa (Northeast Group 2014). Prepaid meters are also found in developed countries including New Zealand, the UK and Northern Ireland. A number of small scale programs are active in the United States (see Qiu et al. (2016), for example).

[12]How sophisticated this needs to be depends on the tariff structure. Under an increasing block tariff, cumulative purchases need to be tracked over the calendar month via a centralized server. We discuss this in the context of Cape Town's tariffs below.

[13]Generally, prepaid meters are used to combat theft because innovation in the technology have made it more difficult to tamper with the meter. However, theft may also increase if customers shift from nonpayment to illegal connections.

[14]This description covers the most common type of prepaid metering systems at this point in time. Earlier generations of prepaid meters were coin-operated or relied on a physical card or key. The technology used by the City of Cape Town is the STS system, developed in South Africa in the 1980s. It is currently used for most prepaid systems around the world.

2.2 Electricity in Cape Town, South Africa

In 1990, as South Africa began the transition to democracy, less than a third of South Africans had access to electricity. By the end of that decade the figure had doubled (Bekker et al. 2008), and by 2011 roughly 80 percent of South African households were electrified (IEA 2013). This extremely rapid expansion of electrification was facilitated in part by the introduction of prepaid electricity metering, which helped manage revenue recovery for previously unelectrified households (Bekker et al. 2008). In the City of Cape Town, where we focus, electrification rates in formal settlements are over 99 percent.

The national state-owned utility, Eskom, owns and operates most generation sources, as well as the national grid. It sells power in bulk to municipalities, including Cape Town, which pay time of use rates that vary by time of day and month of the year. The City of Cape Town supplies power to roughly 80 percent of residents of the city (the rest are supplied by Eskom), around 450,000 (75 percent) of whom are on prepaid metering.

The City of Cape Town did not charge a fixed service fee in the years we study, so the increasing block tariffs are set to cover both fixed and variable costs of electricity supply.[15] The tariffs charged on the prepaid meter are the same as on postpaid metering. On a prepaid meter, customers move up the tariff blocks based on cumulative purchases during the calendar month; the tariff resets on the first of each month. Over most of the study years, two tariffs are used. Residential customers that consume below a threshold quantity of electricity in a 12 month rolling window are on what is referred to as a "Lifeline" tariff, which provides free electricity for up to the first 60 kWh of consumption in a calendar month. Customers not on the Lifeline tariff are charged on a comparatively flat increasing block tariff ("Domestic" tariff). Figure 1 shows the tariffs for 2014-15 in 2014 USD. Tariffs for the other years in our data are shown in Appendix Figure A.2. Tariffs are updated each July.

Customers of the City of Cape Town historically received individual bills for each service (water, electricity, refuse removal, etc.) from the City. Over the last decade, customers have been shifted to a consolidated billing model, which includes all utilities on a single bill. In our sample, roughly two-thirds of customers received a consolidated bill prior to the switch to prepaid metering. A sample consolidated bill is shown in Appendix Figure A.3. We discuss the implications of consolidated billing for our results in subsequent sections.

[15]In other words, the average marginal price exceeds the average marginal cost, and the difference is used to cover maintenance, new infrastructure and other fixed operating costs, including both per-customer and system-wide fixed costs. This also means that lowering consumption will reduce revenue more quickly than it reduces costs.

2.3 Meter replacement program

In late 2014, the City of Cape Town initiated a program to replace postpaid meters with prepaid meters in selected areas. Suburbs with a low penetration of postpaid meters and a low average property value were targeted, with the idea that eliminating the final few postpaid meters from these areas would cut out entire meter reading routes.[16] The project consisted of a pilot followed by two stages of implementation. Stage 1 targeted 2,251 postpaid meters in a single suburb called Mitchell's Plain between November 2014 and February 2015, with successful replacement of over 90 percent of the targeted meters. Stage 2 targeted 1,994 postpaid meters spread across 14 different parts of the City between February and April 2015. Replacement rates were lower in the 2nd stage, because compliance became voluntary beginning in April 2015.

The meter replacement program proceeded as follows. A contractor hired to complete the meter replacements worked in geographically contiguous groups of customers identified by the City of Cape Town. Based on customer addresses, the contractor first delivered notices to targeted households informing them that they would have their postpaid meter replaced with a prepaid meter. The program was not widely publicized so this notice would have been the first time most customers learned of the program. Customers were instructed to call to schedule an appointment. The letter described a time window for scheduling and informed customers that if they had not scheduled an appointment within 15 days, their electricity would be disconnected. This window was eventually extended for an additional 15 days. When a customer called, the scheduling window available to them was determined by the order of their geographic group and by contractor availability. Customers were disconnected from electricity for a couple of hours, at most, while thier individual meters were replaced. Most meter replacements in a group occurred over a period of a few days and involved multiple contractor teams. We discuss how this process is used in our empirical design in Section 3.3.

[16]Though we do not observe the reasons that customers on prepaid metering prior to the project were switched, reasons include moves, debt write offs, new construction, and self selection. While the customers remaining on postpaid billing in these neighborhoods may not be representative, whether they are likely to be more or less sensitive to their metering technology than customers switched earlier is not obvious. We compare average electricity consumption between project customers and those in the same neighborhood but already on prepaid metering in Section 3.3.2.

2.4 Neighborhood characteristics

Our sample consists of 2,251 customers from the suburb of Mitchells Plain and 1,994 customers from 14 other areas in Cape Town (see the map in Appendix figure A.5). We describe the characteristics of the neighborhoods in our study, based on the 2011 South African census.[17] We begin by describing the Stage 1 sample in Mitchells Plain, a lower to middle income neighborhood in the Cape Flats area of Cape Town. During apartheid it was designated as a colored area, and residents were largely excluded from higher paying jobs and received less access to education as a result of apartheid policies.[18] Average monthly income is less than 300 USD for 42 percent of Mitchells Plain residents, which is close to the average for the City of Cape Town. The median household spends 8-10 percent of its monthly income on electricity. Unemployment rates among working age adults are around 32.5 percent, which is higher than the City average. Electrification is nearly universal: 99 percent of the 38,403 households in the 2011 census used electricity for lighting. Nearly all households (92 percent) in Mitchells Plain live in formal dwellings and owner occupancy rates are high.[19]

Customers in Stage 2 of the project are located in areas that are similar to Mitchells Plain on most dimensions. The other areas are, on average, slightly poorer than Mitchells Plain: unemployment was 35 percent, on average, in 2011, and 51 percent of households had monthly incomes below 300 USD. Electrification rates and formal property rights are high, like in Mitchells Plain. Overall, rates of electricity use are high in the study sample relative to low income consumers in other developing countries. Household survey data from project participants in Mitchells Plain indicate that the average household owns a refrigerator, an electric hot water heater and a television, and cooks and heats using electricity.

3 Data, study design and empirical strategy

3.1 Data

We obtain data from the City of Cape Town's billing system and prepaid vending system under a non-disclosure agreement. Here, we summarize key features of the data. Appendix

[17]Unless otherwise indicated, all figures are the authors' own calculations from Statistics South Africa's Census 2011 Community Profile data sets (version 1 from DataFirst - https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/517/get_microdata) and the small area layer GIS data set for this census (available, upon request, from Statistics South Africa).

[18]"Colored" is a designation for people of mixed ethnic origin in the South African census.

[19]Specifically, 88 percent of program participants surveyed in Mitchells Plain report owning their home.

A.2 contains further details on dataset and variable construction.

3.1.1 Billing data

The City of Cape Town follows a consolidated billing model for most customers (65 percent of our sample at the time of the program), and provides a single bill that covers electricity, water, refuse, sewerage, property taxes and debts (see Appendix Figure A.3 for a sample bill). Bills are sent to customers approximately every 30 days and bills are due 25 days after the posting date. Electricity charges are based on physical meter readings taken every 25 to 35 days. We use meter reading dates to construct an average daily kWh per month variable that assumes a constant rate of consumption per day between meter readings. We then take the average across all days in the month, some of which may have come from different bills. We also construct a measure of the corresponding amount owed for consumption in each month, based on the tariff schedule.

The bill also indicates the date and value of any payments made since the last bill. We use this information to construct measures of the days after consumption that a bill is paid off based on cumulative payments, and an indicator for late payments. We construct three other measures of delinquency. First, we calculate the share of all monthly bills on postpaid metering that were paid past the due date. Second, we construct an indicator for whether the customer had multiple outstanding bills at the end of the panel. Third, we construct a measure of whether a customer was ever disconnected while on postpaid metering, and include the cost to the City of disconnecting and reconnecting the customer in our benefit cost analysis.

3.1.2 Prepaid vending data

The prepaid vending system records electricity purchases. We use transaction dates to construct an average daily kWh variable that assumes a constant rate of consumption per day between transactions. We then take the average across all days in the month, some of which may have come from different transactions. This averaging assumes that customers are not accumulating electricity credit on their meter. As with the postpaid billing data, we also construct a measure of the corresponding amount owed in month, based on the tariff schedule. We calculate the days between consumption and payment (which will be ≤ 0) using the purchase date and the midpoint of the days before the next purchase.

3.1.3 Average marginal cost of supply and revenue recovery costs

We obtain data on the average marginal cost of electricity supply from the City of Cape Town. The City purchases electricity from Eskom, the national provider, at tariffs that vary by time of day and month of the year.[20] We use the city-wide monthly average price per kWh paid to Eskom as our average marginal cost of supply measure (see Appendix figure A.4). The Electricity Department has an estimated loss rate of 11.25 percent, which includes both technical and non-technical losses, which we assume both meter types equally. Prepaid electricity vendors receive approximately 0.002 USD per kWh sold, or around 1.5 percent of the average marginal price observed in our data, which is deducted from the revenue remitted to the City. We also gather information from the Electricity Department on other administrative costs associated with revenue recovery on postpaid billing, including the average per-customer meter reading and bill preparation costs.

3.2 Electricity outcomes across metering types

The billing data and prepaid vending data measure electricity in different ways. As described above, the billing data are used to construct a daily average between bill t and $t-1$, while the prepaid dataset is used to construct a comparable measure between transaction t and $t+1$. The constructed average daily consumption per month removes differences in the frequency of observations across the dataset.

Given that the prepaid metering system records transactions, rather than actual consumption, the comparability of the measures across systems deserves further discussion. A key assumption in transforming expenditures into a measure of average daily consumption is that customers are not accumulating unused electricity on their meter. Three observations suggest that this is reasonable. First, the increasing block tariff structure provides an incentive not to accumulate unused electricity since tariffs reset on the first of the month as discussed above. Second, customers tend to purchase very small amounts of electricity, very frequently: the median purchase size is 19 kWh or around 30 ZAR (2.6 USD), and the median purchase frequency is every 3 days (see Jack and Smith (2015) for further discussion of purchasing patterns in this context). Finally, while the prepaid technology might lead

[20] Roughly 45 percent of Cape Town's electricity purchases from Eskom are charged on time of use tariffs, with peak prices that are 3 to 4 times non-peak prices during the high demand season and around 50 percent higher than non-peak prices during the low demand season. Most of the seasonal variation is associated with with peak prices. The other 55 percent of purchases are not charged on time of use, so prices vary only by month of the year. We use the record of the average cents per kWh paid to Eskom, recorded monthly, provided to us by the City.

to greater smoothing if customers have a tight monthly budget constraint, we note that the within-customer coefficient of variation of our preferred constructed average daily kWh measure is very similar for prepaid and postpaid observations (0.24 for postpaid and 0.21 for prepaid) and even more similar when the outcome is in logs (0.11 versus 0.10). The assumption that customers are not accumulating unused electricity on their meter may be most difficult to satisfy in the month or two following the meter replacement as customers build up a minimum balance on their meter. Our main analysis drops the month of meter replacement. We show an event-study style analysis that shows how electricity use evolves in the months following the meter replacement.

More generally, the transformation of expenditure data into a measure of consumption is a common challenge in studies of household demand. In the case of prepaid electricity, we construct a monthly measure of consumption based on a mean (median) purchase frequency of 12.6 (9.5) times per month. Over 95 percent of customers make at least one purchase every month on prepaid metering. While a number of econometric methods have been advanced for estimating latent demand based on less frequent purchases (e.g., Kay et al. (1984); Blundell and Meghir (1987)), the high frequency of observed expenditures together with the administrative nature of our data allows us to make the simplifying assumption that monthly expenditures and monthly consumption converge.

3.3 Study design

We collaborated with the City of Cape Town to randomize the phase in of the meter installation program. Groups of around 150 adjacent customers were randomized in two separate waves, one for each of the meter replacement stages. First, in Mitchell's Plain (stage 1), we imposed a grid over a map of all targeted customers, and aggregated cells until around 150 adjacent customers formed a randomization group. Thirteen groups were identified and their order was randomized. Second, targeted customers in the other suburbs (stage 2) were aggregated in a similar process, but used pre-existing suburb definitions to assign customers to groups. The second stage included 14 groups, which were also randomly ordered. Thus, the final design consists of 27 groups, with separate random assignment within the first and second groups. A map of the randomization groups is shown in Appendix figure A.5.

3.3.1 Potential confounds

Three details of implementation present potential confounds. We discuss these in turn, anticipating the robustness checks that we perform in Section 4.1.2. First, when the City installs a new meter, it is defaulted into the Domestic tariff. If the meter should be assigned to Lifeline tariff, the change has to be manually entered into the billing or vending system. Because of the volume of meter replacements around the time of the project, there were some delays in restoring the Lifeline tariff to customers who had received it prior to the switch. Specifically, 981 of the 1,335 customers on Lifeline in the month before the switch were put on to the Domestic tariff for at least a portion of the month following the switch. The majority of these cases were corrected within three months of the switch, however, some lasted considerably longer, and some may indicate a permanent tariff change for the customer. Anecdotally, few customers noticed the change, and we have no reason to believe that it would have affected other customers via media reports, for example. A tariff change that coincides with the switch to prepaid metering presents an obvious confound to identifying the effects of the meter on electricity use. We control for erroneous tariffs in all of our analyses, and drop these customers altogether in a robustness check. Our analysis of heterogeneous treatment effects also shows separate results for Domestic tariff customers, who were unaffected by the tariff error.

Second, as described above, around two-thirds of customers receive a consolidated bill for all utilities (electricity, water and sewerage) prior to the meter replacement program. As a result, some of the effects of the meter replacement program may be due to the transition away from consolidated billing, which may, for example, raise the salience of electricity costs independent of the metering technology. In practice, differences in the postpaid experience on a consolidated bill versus a separate electricity bill is minimal: the consolidated bill contains all of the information about consumption, tariffs and total amount owed for electricity that is provided under separate billing. The types of customers customers who receive separate bills prior to the program are different from those on consolidated billing: they use less electricity, have older accounts with the City and are less likely to be located in Mitchells Plain (Stage 1). The response of these customers to prepaid metering may therefore differ from the sample average for numerous reasons. Nonetheless, we implement a robustness check that omits customers on consolidated billing prior to the meter replacement program.

Third, around the same time as the meter replacement program, the City of Cape Town implemented several months of rolling blackouts (loadshedding) to manage supply shortages. These involuntary outages may lead to a reduction in electricity use that is unrelated to prepaid metering. We obtain data on the hours of loadshedding and other outages per month for each substation serving Mitchell's Plain, where meter installations were most likely to overlap with the period of relatively intense loadshedding. Beginning in November 2014, substations in Mitchell's Plain experience an average of 1 to 1.5 hours of load shedding per month, or around 0.04 percent fewer hours of electricity supply (see Appendix figure A.6). We construct controls for the average hours per month of outage across all Mitchell's Plain substations, and control for them in a robustness check.[21] We also perform robustness checks that include comparison households outside of the project sample who were subject to loadshedding but not meter replacements.

3.3.2 Study sample

The final sample for analysis is based on the lists of targeted customers used in the randomization. Table 1 shows characteristics of the sample. We observe 4,245 customers, with a median of 54 monthly observations per customer, 16 of which are from a prepaid meter. On average, customers use around 16 kWh of electricity per month prior to the program, and owe around 52 USD per month for electricity. Over half of their bills are paid late, and it takes an average of around 100 days to pay after the date of consumption. Twenty-six percent of customers have multiple outstanding unpaid bills at the end of the panel and 21 percent were ever disconnected as a means of enforcing bill payment. The median property value is around 27,000 USD and 31 percent of customers are on the subsidized tariff at the time of the program.

Because the meter replacement program targeted the subset of households not already on prepaid metering in the neighborhoods targeted through the project, we cannot use consumption levels on postpaid metering to evaluate the representativeness of our sample. Instead, we compare electricity use following the switch to prepaid metering among project customers to use by customers outside of the project. Relative to other customers in the neighborhoods involved in the study, the project sample is less likely to be on a Lifeline tariff and use slightly more electricity on average. Once on a prepaid meter, project customers consume roughly 0.8 kWh per day more than customers not in the project, conditional on being on a Lifeline tariff, and around 1 kWh per day less, conditional on being on a Domestic tariff.

[21] We do not obtain the data for the suburbs in stage 2 of the meter replacement program. The loadshedding schedule was similar across suburbs and adhered to fairly closely.

3.4 Empirical strategy

We observe electricity and other billing outcomes for a customer i in each month-year t. To identify the effect of a switch from postpaid metering to prepaid metering on outcome y_{it}, we estimate:

$$y_{it} = \alpha + \beta prepaid_{it} + \tau_t + tariff_{it} + \eta_i + \epsilon_{it} \tag{1}$$

where $prepaid_{it}$ indicates the share of month t that customer i received electricity through a prepaid meter, τ_t are time fixed effects (either month-year or separate calendar month and billing year), $tariff_{it}$ is a time varying Lifeline tariff indicator, and η_i are customer fixed effects.[22] Our main results exclude the switch month, resulting in a binary measure of *prepaid*. Standard errors are clustered at the customer level. As a robustness check, we compute t-statistics based on standard errors clustered at the randomization group level. Under the assumption that prepaid metering is uncorrelated with ϵ_{it}, conditional on time and customer fixed effects, β identifies the causal impact of prepaid metering on outcome y_{it}. We also estimate the effect of prepaid metering over time through an event study style analysis that recovers a separate treatment effect for each month pre- and post- receiving the prepaid meter.

While meter replacement was involuntary, the actual meter replacement date may not be not exogenous to electricity consumption. First, there is a non-trivial amount of non-compliance, particularly in stage 2 of the project. Second, the timing of replacement even within the assigned windows may be determined by factors correlated with electricity use, such as customer work schedules or resistance to the replacement. In exceptional circumstances, customers were allowed to make appointments outside of the assigned replacement window. Third, in practice, the length of time that the contractor spent in each group was determined by the difficulty in scheduling all appointments. Our primary instrument for assignment to a prepaid meter is therefore the first date on which the contractor has more than one team working in the randomization group, which corresponds to the start of the scheduling window. As an alternative, we also use the date on which the first households in the group received a notification (maildrop) about the project.

Figure 2 summarizes the two instruments, and the actual switching patterns. The randomization groups are ordered on the vertical axis, with the Mitchell's Plain groups (stage

[22] We also add an indicator for months affected by the errors updating the Lifeline tariff in the months following the meter switch.

1) corresponding to groups 1-13. The circles indicate the timing of the first letters delivered in the group. The squares show the first date on which the contractor was performing installations in the group, and the triangles indicate the median switch date among those who ever switched, with the share ever switched printed on the figure. As the figure illustrates, letter deliveries followed the random ordering of the groups very closely, particularly during stage 1 of the program. The contractor dates are also consistent with the randomized order, though they occasionally deviate, particularly toward the end of the program. We use the contractor date as our main instrument since it most accurately reflects the exogenous determinant of take up. We show results using the group order and mailing dates as instruments in robustness checks. Given the higher compliance rates overall and the better adherence to the randomization, we report our main results for Mitchells Plain alone in a robustness check. The IV estimates estimate the local average treatment effect of prepaid metering by using the assignment variables as instruments for receiving a prepaid meter.

Recovering the causal effect of prepaid metering, either through the OLS or IV estimates, requires that the actual order or assigned (randomized) order of meter replacements is uncorrelated with unobserved time-varying factors that affect electricity consumption. Time invariant customer characteristics are absorbed in the customer fixed effects used in all analyses. Appendix table A.1 shows the correlation between pre-switch customer characteristics (prior to November 2014) and the assigned group order (column 2), the assigned switch date, based on the contractor instrument (column 3), the actual switch date (column 4) and whether the customer was ever switched (column 5). The small number of groups included in the randomization results in a lack of balance on property value (and therefore other characteristics, presumably), which would be of greater concern if the data did not allow for household and time fixed effects. We examine pre-program residuals for "parallel trends" after removing month-year and household fixed effects from the relationship between average daily kWh and month, prior to the program. We plot the average residual within each randomization group for the 34 months leading up to the start of the program and observe relatively flat trends that do not differ substantially across groups (see Appendix figure A.7). Appendix figure A.8 also plots monthly average daily kWh for the project sample and a comparison group of postpaid customers elsewhere in the City, and shows parallel trends in the months preceding the project start.

4 Results

We start by showing the impact of switching to a prepaid meter on electricity use. Second, we turn to heterogeneity in the treatment effects by customer characteristics and behavior prior to the replacement program. Finally, we estimate impacts on variables that inform the benefit cost analysis, including amount owed and payment patterns.

4.1 Electricity use

Figure 3 plots the median daily average consumption in each month and the share of targeted customers switched to prepaid metering. The figure clearly shows the strong seasonal pattern of consumption, which peaks in the South African winter, when many customers use electricity to heat their homes. The drop in usage that coincides with the prepaid metering program is clearly visible in the figure.

Table 2 shows the regression coefficients from OLS regressions (columns 1 and 2) and 2SLS regressions using the contractor date instrument (columns 3 and 4). The outcome in Panel A is average kWh/day and in Panel B is the log of average kWh/day. Columns 1 and 3 show the results with separate month and year fixed effects and columns 2 and 4 use month-year fixed effects. The OLS coefficients (columns 1 and 2) indicate that average daily usage fell between 2.12 and 2.15 kWh (Panel A), depending on the specification. This corresponds to a decline of between 13.3 and 13.9 percent (Panel B). The IV and OLS results are generally similar in magnitude. The first stage on the IV regressions is – unsurprisingly – very strong (F-statistic $>$ 1000). The reduction is precisely estimated in all specifications.[23] Appendix table A.2 shows the results restricted to the Mitchells Plain phase of the project (stage 1), where compliance was highest.

4.1.1 Persistence

We next provide suggestive evidence of impacts over time. We set the month prior to the switch as time 0 and estimate separate coefficients for each month following the switch (the switch month is omitted).[24] Figure 4 plots the resulting coefficients. Overall, the reduction

[23] We also construct t-statistics based on standard errors clustered at the randomization group level. For our main specifications, we perform 1000 iterations of the wild cluster bootstrap procedure (see Cameron et al. 2008), none of which generate t-statistics below the value without clustering, implying a p-value of $<$0.0001.

[24] We include month and billing year fixed effects, and cluster standard errors at the customer level, but omit the customer fixed effects used elsewhere in the analysis. Note that we cannot simultaneously control

persists for the first year on prepaid metering. If anything, the point estimates appear to decline over time. Note that customers that do not switch meter types are not included in the event study results.

4.1.2 Robustness checks

To examine the robustness of our estimate of the effect of prepaid electricity metering on electricity use, we repeat the analysis above with alternative specifications, including different instruments and a difference in difference design that includes comparison customers not part of the meter replacement program. As shown in Appendix table A.3, the coefficient remains reasonably stable, implying that the results are not driven by outliers or by the assumptions used in variable construction.[25] Appendix figure A.8 shows the descriptive consumption plot underlying the main difference in difference specification (column 4).[26] Next, we examine the robustness to alternative sample restrictions and manipulations of the outcome variable, and again see little difference in the point estimates (see Appendix table A.4). Finally, we implement three robustness checks designed to test remaining concerns about the implementation issues discussed in Section 3.3.1; we control for loadshedding, exclude Lifeline customers that received the incorrect tariff when their meter was replaced and omit the two-thirds of customers on consolidated billing prior to the program. Results change little for the first two tests and are somewhat smaller for the one-third of customers not on consolidated billing (see Appendix table A.5). Note that customers receiving a separate electricity bill prior to the program use less electricity than the average customer and may differ in numerous other ways; the smaller treatment effect in column 4 need not imply that the change from consolidated billing is an important part of our overall finding (see Section 3.3.1 for further discussion). Finally, we conduct a placebo test that reassigns the switch date and the instrument to one year prior to its actual occurrence and observe a small and insignificant coefficient on the prepaid indicator (see Appendix table A.5, column 4).

for time and household fixed effects and identify the event study coefficients, so we omit household fixed effects from the specification.

[25] Differences across the coefficient on the alternative instruments is unsurprising given that the marginal customer is likely to differ depending on which instrument is used. Nevertheless, the results are qualitatively similar across all instruments.

[26] Note that neither of the comparison samples are ideal. The sample of postpaid comparison customers (column 4) comes from other parts of the city since all postpaid customers in the project neighborhoods were targeted for meter replacement. The sample of prepaid comparison customers is drawn from the same neighborhood but provides a different counterfactual: what consumption would have been if project customers had always been on prepaid metering.

4.2 Heterogeneous treatment effects

We preview the heterogeneity that we will return to in the benefit cost analysis (Section 5), by examining impacts by observable customer characteristics. We re-estimate equation (1), interacting the prepaid indicator with month and billing year fixed effects with each binary heterogeneity measure, summarized in Table 3.[27] Columns 1 and 2 show the OLS effect on average daily kWh and columns 3 and 4 show the results instrumenting for the switch date with the first date the contractor worked in the group. We show the total effect for each subgroup in columns 1 and 3 and the difference (i.e. the coefficient on the interaction term) in columns 2 and 4. We also report the number of customers and the postpaid average daily kWh for each sub-group. We show the results in levels and report pre-switch average consumption by subgroup in the column labeled Mean and describe the proportional responses by characteristic. We also provide the same analysis with the outcome in logs in Appendix table A.6. The signs and significance patterns are very similar whether we analyze the results in levels or logs. The pairwise correlations between the heterogeneity variables is shown in Appendix Table A.7.

We begin with customer tariffs at the time of the program. On average, Lifeline customers use less electricity per month than Domestic customers, and pay less per kWh (see Figure 1). The first two rows Table 3 show results by tariff prior to the switch. Domestic customers cut back significantly more than do Lifeline customers. Proportional to their average consumption on postpaid, the reduction by domestic customers is also larger, at around 12 percent relative to a reduction of around 10 percent for Lifeline customers. Domestic customers also tend to consume more electricity than do Lifeline customers; unsurprisingly, when we split the sample into above and below median postpaid consumption, we see similar results, with larger absolute (and proportional) reductions among the larger consumers. To examine whether these two sets of results are simply capturing differences by wealth levels – Lifeline customers and below median consumers also tend to be poorer (Appendix Table A.7) – we split the sample by property value, which is the wealth proxy that we observe in the data. We divide customers according to the valuation used for many other anti-poverty programs in the City of Cape Town (300,000 ZAR based on the 2012 valuation, which corresponds to around 29,000 USD2014). We see larger reductions among low property value customers, both in levels and proportional to their average consumption on postpaid metering.

Next, we examine responses by three measures of delinquency. First, customers that pay

[27] We focus on the specification that includes separate month and year fixed effects because the prepaid coefficient may not be well identified within month-year for all sub-groups.

more than the median number of bills late (more than 58 percent) prior to the program reduce their consumption by more than do customers who tend to pay their bills on time. Next, customers with multiple outstanding unpaid bills at the end of the panel, and those that experienced disconnection at some point as a means of payment enforcement both show similar reductions to customers with a better history of payment (if anything, they are slightly less responsive). These last results are particularly relevant for considering the payoffs to the utility from switching customers from postpaid to prepaid billing, which we turn to in the next section.

4.3 Payment behavior and cost of supply

We turn from these impacts on kWh/day to the measures that will feed into the utility's cost-benefit analysis, specifically, the amount owed by the customer, the cost of supply and the timing of customer payments. The outcomes we show here exclude administrative costs such as bill preparation, which we include in the benefit cost analysis and explain in the next section. Summary statistics for each of these outcomes prior to the meter replacement program are shown in Table 1.

Effect on amount owed per month Electricity is priced on an increasing block tariff, which means that reductions in consumption may lead to proportionally larger reductions in the amount owed from customers whose reduction crosses a tariff step, or proportionally smaller (zero) reductions for customers that only consume their free electricity allowance on either meter type. We estimate the impact of prepaid metering on the amount owed for consumption in a month (Table 4, column 1).[28] Customers owe 6.8 USD less per month on prepaid metering. This corresponds to a reduction of around 13 percent each month relative to the average amount owed on postpaid metering (see Table 1).

Effect on marginal supply cost The utility purchases electricity from the national electricity company based on prices that vary with time of day and month of the year. While we do not observe the time of the day of consumption, we do observe the month of the year. Reductions in consumption are most valuable if they occur in June, July and August, when the utility pays a higher average marginal cost per kWh (see Appendix figure A.4). We estimate separate treatment effects on the average kWh/day for each calendar month, and

[28]This amount owed variable is calculated based on a month-level version of our main average kWh measure, multiplied by the customer's marginal price on each tariff block.

plot the results in Figure 5. These indicate that the largest reductions occur in the months when per kWh costs to the utility are highest. Column 2 of Table 4 shows the impact on the average marginal cost of supply, calculated by multiplying the utility's average marginal cost in the month by the customer's total kWh in the month. The point estimates indicate a 2.8 to 2.9 USD per customer per month reduction (column 2), which is considerably below the reduction in amount owed reported in column 1.

Payment timing The customer response to prepaid metering consists both of the quantity of electricity consumption and when it is paid for. Mechanically, prepaid metering moves the payment date from after consumption to before consumption. In addition, the billing cycle adds a delay of around 60 days to the time between when a postpaid metering customer consumes the average kWh in a month and when payment is due for that kWh. As discussed in Section 3.1, our measure of payment timing is calculated as the days between when consumption occurs and when payment arrives to the utility. Column 3 of Table 4 shows the impact on the days between consumption and payment. Prepaid metering results payment that arrives 75 (OLS) to 85 (IV) days sooner. Note that this measure of payment timing excludes payments that never arrive; i.e. average payment timing excludes bills that are eventually written off.

5 Costs and benefits to the utility

We calculate the costs and benefits of the meter replacement program for the City of Cape Town, based on our empirical estimates and administrative cost records. We then examine heterogeneity and implications for other settings.

5.1 Returns from the meter replacement program

We write down a simplified expression for the present value of revenue net of recurring costs for monthly electricity supply under each metering type $m = \{pre, post\}$:[29]

[29] These calculations avoid a more complete modeling of consumer and utility decisions. For example, utility decisions about enforcing non-payment affect both revenue recovery rates and revenue recovery costs. On the customer side, we take point estimates from our impact evaluation as given and do not model the mechanisms that relate the metering technology to consumption. In addition, we ignore capital and fixed supply costs, including the meter itself. A prepaid meter costs around USD 66, while a postpaid meter costs around USD 30.

$$PV^m = \frac{pq^m}{(1+i)^{t+s^m}} - \frac{cq^m + b^m}{(1+i)^t}. \tag{2}$$

Calculation of the monthly present value requires estimation of three parameters: (1) the revenue paid to the utility (pq^m), (2) the timing of payment (s^m) and (3) the cost of supply and revenue recovery ($cq^m + b^m$). We discuss each in turn.

Revenue The customer consumes quantity q^m in month t. We account for the increasing block tariff structure by calculating the total amount owed (pq^m) for consumption in month t. In our setting, tariffs are the same across metering technologies, though the utility shares a small fixed margin per kWh (0.002 USD) with vendors on the prepaid system, regardless of the price paid by the customer. This revenue measure therefore differs from what we calculate as the amount owed for consumption in Section 4.3 in that it is net of vendor margins and is set to zero in the case of non-payment, which is is defined as debts that are not recovered within three years of the month of billing.[30]

Timing of payment The value of consumption to the electric utility also depends on when the customer pays, s^m, which is expressed in months relative to the consumption month t. On prepaid metering, $s^{pre} \leq 0$ since the customer cannot consume until they have purchased electricity. On postpaid metering, $s^{post} > 0$ since the customer does not receive a bill until sometime after consumption occurs. This measure is the same as what we estimate in Section 4.3, expressed in months instead of days.

Cost of supply and revenue recovery The utility's average marginal cost per kWh varies by time of the day and and month of the year, but we observe only average consumption per month which we use to calculate a monthly kWh supply cost, which is the same as in Section 4.3. We add to this technical and non-technical losses of 11.25 percent, based on estimates provided by the Electricity Department (i.e. the cost of each kWh supplied is 1.1125 times the average marginal cost). Recurring monthly costs b^m include meter reading

[30]Debts older than three years are officially written off by the City. To calculate payment probabilities for unpaid bills at the end of our panel that are younger than three years, we calculate a "hazard rate" or the probability of default given that no payment has occurred by the number of months since billing. Overall, we estimate that around 1.9 percent of the revenue owed on the postpaid system is never recovered, which is consistent with the estimates used by the City of Cape Town, but is much better than revenue recovery rates for most developing country utilities. See Section 3.1 and Appendix A.2 for further discussion of the payment variables.

costs and bill preparation, which are the same for all postpaid customers in the data, and total 1.74 USD per customer per month.[31] We also observe that around 20 percent of the customers in our data are disconnected (and eventually reconnected) in at least one month while on postpaid metering. Conditional on ever being disconnected, the average number of disconnections is two. Disconnections are costly to the City, which charges customers only 30 USD of the 120 USD it takes to disconnect and reconnect a customer. We include the cost of disconnection in the month in which a disconnection is observed. Finally, our calculations ignore fixed costs associated with infrastructure and operation, which are covered out of the rate structure in Cape Town. Thus, results should not be interpreted as a measure of overall utility profits.

Relative returns to the utility The electric utility's object of interest is the value of prepaid metering relative to postpaid metering, i.e. ${}^{PV^{pre}}/_{PV^{post}}$. We can calculate this for the City of Cape Town by plugging our estimates from the meter replacement project together with administrative costs obtained from the City into (2). A summary of the values we use is provided in Table 5. The predicted means of revenue, supply costs and timing of payment are estimated for the sub-sample of compliers (i.e. switched customers) using OLS with separate calendar month and year fixed effects, and controls for the tariff and the months with tariff errors (see Section 3.3.1).[32] The final rows show the average per-customer monthly value of net revenue for the City of Cape Town for an annual interest rate of 8 percent.[33] Bootstrapped standard errors are in parentheses. The results show that the average customer generates around 10 percent higher net revenue on prepaid metering than on monthly postpaid billing. Note that this proportional gain ignores the one-time cost of the meter and so is constant over time, i.e. the relative returns from prepaid metering is 10 percent higher over any time horizon. It takes a little over seven years for the additional net

[31]Monthly billing costs vary across customers. We use a system wide average for residential customers which may be below the cost for customers in our sample, who tend to be located in areas with a relatively low density of postpaid meters that require monthly readings. Using this number also leads to a conservative estimate of the cost savings from switching customers to prepaid meters if entire meter reading routes are eliminated.

[32]For the purpose of analyzing average costs and benefits associated with meter type, we restrict the sample to compliers only and focus on the policy relevant average treatment effects from the OLS specification as opposed to the local average treatment effects produced by the IV. For most outcomes, the OLS and IV specifications produce similar results. In addition, Appendix table A.4 shows similar effects on electricity use for compliers only as for the whole sample.

[33]The City of Cape Town uses a discount rate approved by the National Energy Regulator of South Africa (NERSA) for project evaluation. From 2010 to 2016, the rate was was 8% and a payback period of 25 years, as stipulated by the South African electricity grid code.

revenue to cover the fixed costs of the prepaid meter (USD 66, versus around USD 30 for a new postpaid meter).

We perform back of the envelope calculations to calibrate the share of the gains that come from different sources. The value of receiving revenue sooner results in net revenue from prepaid metering that are around 4.5 percent higher than on postpaid, or nearly half of the overall increase.[34] The utility also avoids an expected loss of 0.84 USD per customer per month associated with billing defaults, which amounts to 1.6 percent of the revenue owed. On prepaid metering, the utility also avoids billing and meter reading costs that result in fixed per customer costs per month. On the prepaid system, these are replaced, in part, by vendor commissions that are proportional to consumption. For monthly consumption less than 880 kWh per month (93 percent of customer-months on postpaid), the costs of prepaid vending commissions are less than the costs of meter reading and bill preparation. Finally, the utility avoids an expected enforcement cost of disconnection of 0.89 USD per customer per month. The relative returns from prepaid metering is considerably below what would be expected if the reduction in consumption were ignored. If consumption did not change, then the difference in administrative costs, together with earlier payments, leads to payoffs that are around 33 percent higher for prepaid metering, i.e. over three times the number we calculate.

5.2 Heterogeneity and generalizability

The costs and benefits of prepaid metering depends both on the consumption and payment behavior of the customer base and also on features of the tariff and cost environment. As a result, the numbers from Cape Town need not generalize to other settings. We extend our average cost benefit calculation to examine how the results vary by customer type and the administrative setting.

First, we revisit the customer characteristics analyzed in Section 4.2. We calculate estimates of the returns from prepaid metering relative to postpaid metering for each sub-group. Note that a relative return of 100 percent implies that prepaid and postpaid meters generate the same returns to the utility. Figure 6 summarizes the results along with bootstrapped 95 percent confidence intervals (see also Appendix table A.8). We include the monthly net revenue from postpaid metering for each customer type on the figure, and observe considerable

[34]This return is based on equation (2) using revenue and costs for prepaid metering, and s^m from each meter type based on estimates in Table 5. If instead we calculate the effect of earlier payments using revenue and costs for postpaid metering, the relative returns are around 5.4 percent.

heterogeneity by characteristic in the baseline returns to the electric utility for serving each type of customer. Prepaid metering improves returns from both tariff types. Low consumers generate considerably higher relative returns than do high consumers. Low property value customers, defined by the 300,000 Rand value cutoff used for other policies by the City of Cape Town, also generate higher relative returns than customers with higher property values. Perhaps unsurprisingly, relative returns improve when delinquent customers are switched to prepaid, i.e. those with late payments, outstanding debts or a history of disconnection on postpaid. Less delinquent customers, including those who usually pay on time and those with no outstanding payments at the end of the panel, actually generate negative returns on prepaid relative to postpaid metering. Notably, the customer characteristics that are associated with the greatest improvements in net revenue under prepaid metering are likely to be considerably more prevalent in other developing country settings, and are the mostly likely types of customers to be rationed on a postpaid billing system.

Next, we look to alternative assumptions about the cost environment. In Cape Town, the discount rate used for project evaluation is relatively low at 8 percent. This places little weight on the value of revenue received earlier under prepaid metering. The top panel of Figure 7 shows that net revenue under each metering type fall as interest rates rise, with a steeper slope for postpaid meters. The bottom panel shows net revenue by multiples of the average marginal cost of supply. Losses on the City of Cape Town's network are around 11.25 percent, including both technical and non-technical losses. Other developing country utilities tend to have higher loss rates (Trimble et al. 2016), and so may face a higher cost of supply. Alternatively, in settings where costs are high relative to tariffs, the estimates showing higher average marginal costs suggest that the relative benefit of prepaid metering will be higher. This is due largely to the fact that reductions in consumption are less costly to the utility as the marginal kWh becomes less profitable.

6 Conclusion

Finding ways to expand energy access while maintaining the financial viability of the electricity sector presents a policy challenge in many developing countries. Across Sub-Saharan African countries, the annual value of uncollected bills averages 0.17 percent of national GDP (Kojima and Trimble 2016). Prepaid metering has been proposed as a technological solution to improve revenue recovery at relatively low cost, yet claims have so far been largely anecdotal. We study the impact of prepaid electricity metering on residential electricity use and utility revenue and costs in Cape Town, South Africa. Using a unique dataset that tracks customers as they are involuntarily switched from postpaid to prepaid metering, we document a 13 percent decrease in electricity use, which persists for the 12 months following the switch. The average effects mask considerable heterogeneity, with larger proportional reductions from poorer customers and those with a history of paying their monthly bills late.

Customer responses, both in terms of overall consumption and in the effect of the metering change on payment patterns, have implications for utility revenue and cost flows. We calculate the costs and benefits to the utility from prepaid metering, relative to postpaid metering. On the one hand, the utility recovers the revenue it is owed sooner and more completely. On the other hand, lower consumption implies lower revenue owed to the utility. Our cost-benefit analysis for Cape Town also accounts for billing costs, prepaid vendor margins, and technical and non-technical losses on the system. We show that the relative returns from prepaid metering will depend on these features of the cost environment, as well as on the customer base. In our sample, smaller and poorer consumers and more delinquent customers yield the highest returns to prepaid metering relative to monthly billing. These characteristics are likely to be shared by customers in other developing country settings, where the decision to connect a customer may depend on expected returns. Therefore prepaid metering may be an important tool for expanding energy access via the grid to poor consumers.

Our data do not allow for a clear accounting of the mechanisms underlying the customer's response to prepaid metering, though we clearly show that customer responses must be taken into consideration when assessing the utility's payoffs from prepaid metering. Ignoring them results in a substantial over-estimate of the benefits of prepaid metering to the utility. A full welfare accounting must, of course, consider the impacts on the customer. In many settings, the choice between prepaid and postpaid metering is likely to affect the extensive margin of access. Consequently, the proper welfare comparison may be electrification with prepaid metering or no electricity access at all.

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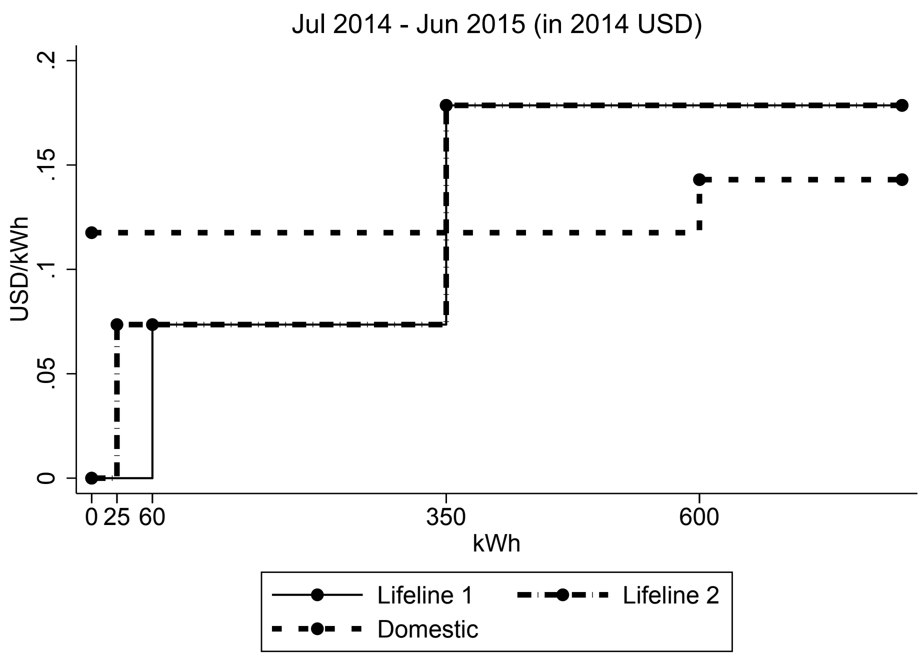


Figure 1: City of Cape Town electricity tariffs 2014-2015

Notes: Tariff schedules for July 2014 to June 2015. Tariff assignments are determined by a 12 month rolling average of past electricity use. See text for additional details.

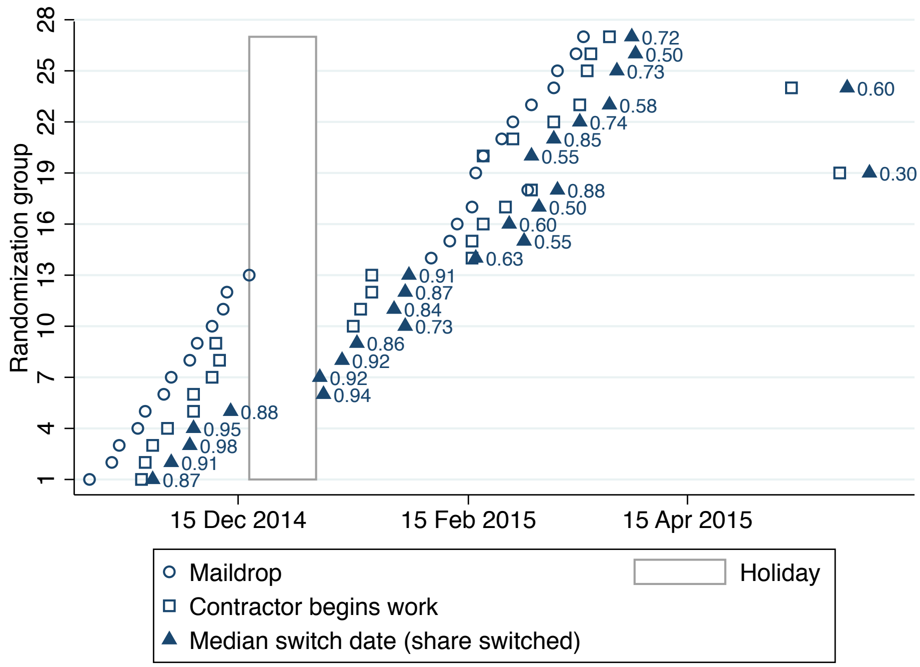


Figure 2: Switching patterns by randomization group

Notes: Project dates by randomization group (groups 1-13 correspond to the Mitchell's Plain sample). The contractor instrument turns on on the first date that more than one contractor team is working in the group. The maildrop instrument turns on on the first date that customers in the group received information about the meter replacement program. The median switch date is conditional on switching and the share of customers that ever switched in the group is printed on the figure.

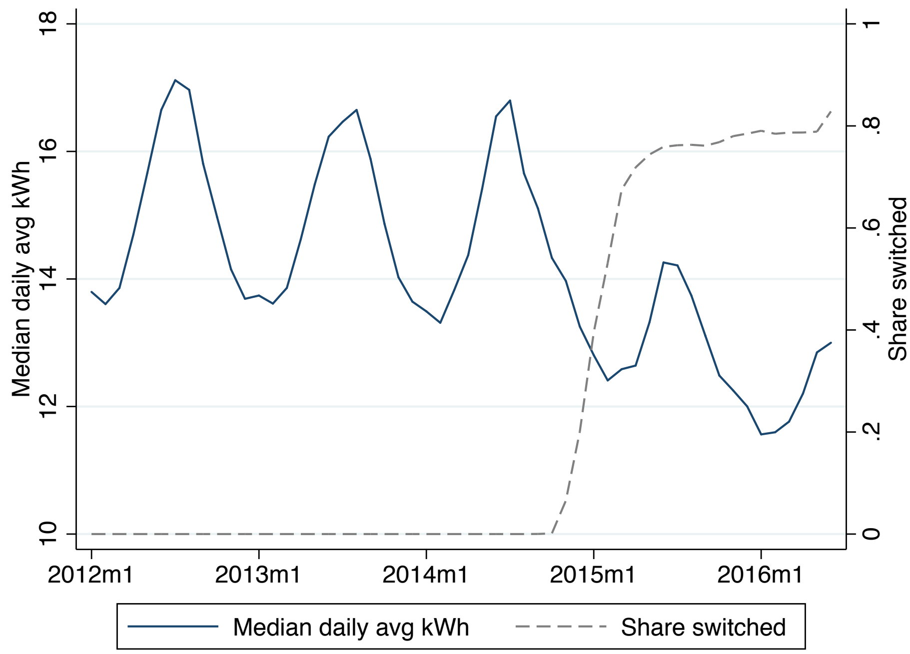


Figure 3: Daily average kWh/month and share switched over time

Notes: Median average kWh in each month and the share of targeted customers switched to prepaid metering. Note that the peak months of June and July correspond to the winter months in Cape Town.

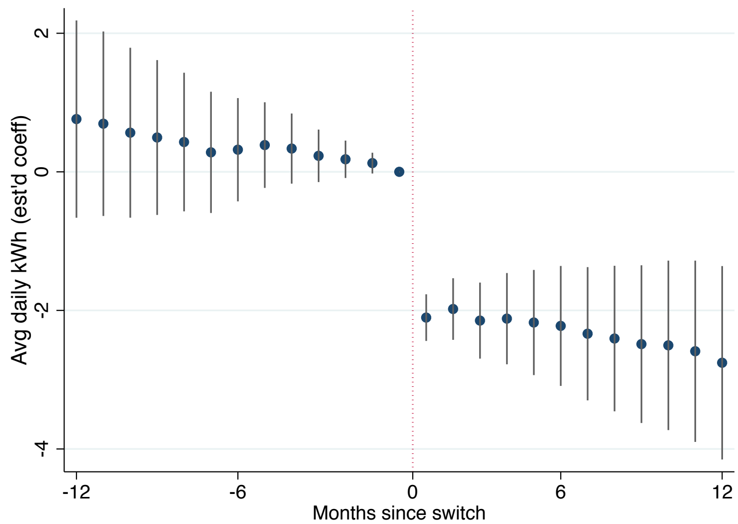


Figure 4: Event study (average daily kWh)

Notes: Event study of the effect of prepaid metering on average daily kWh. The OLS specification sets the month prior to the meter switch as the base month and regresses average daily kWh on months since the switch, conditional on month and year fixed effects.

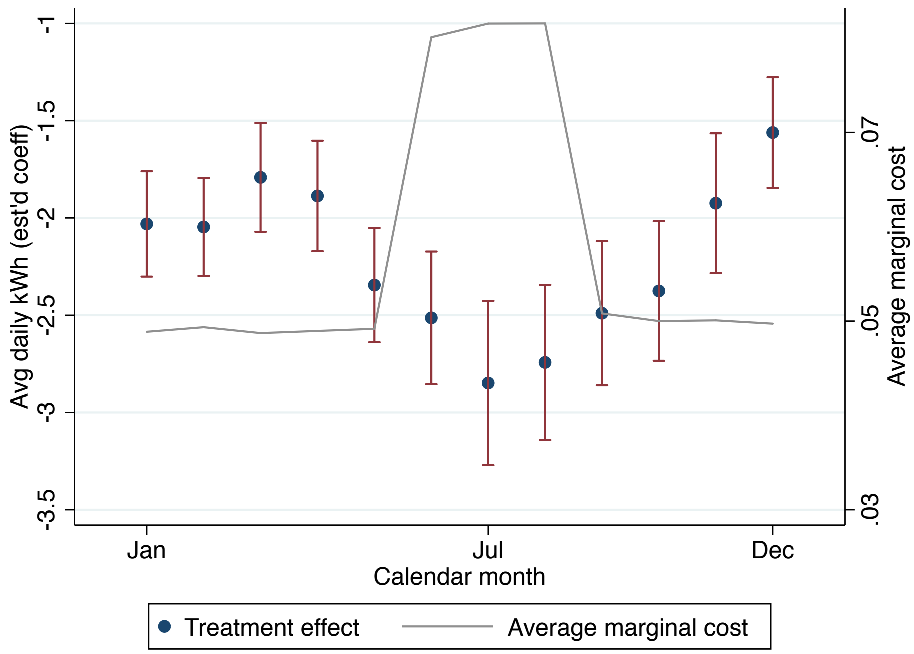


Figure 5: Treatment effects by month

Notes: Month-specific treatment effects, from OLS regression with customer and month-year fixed effects.

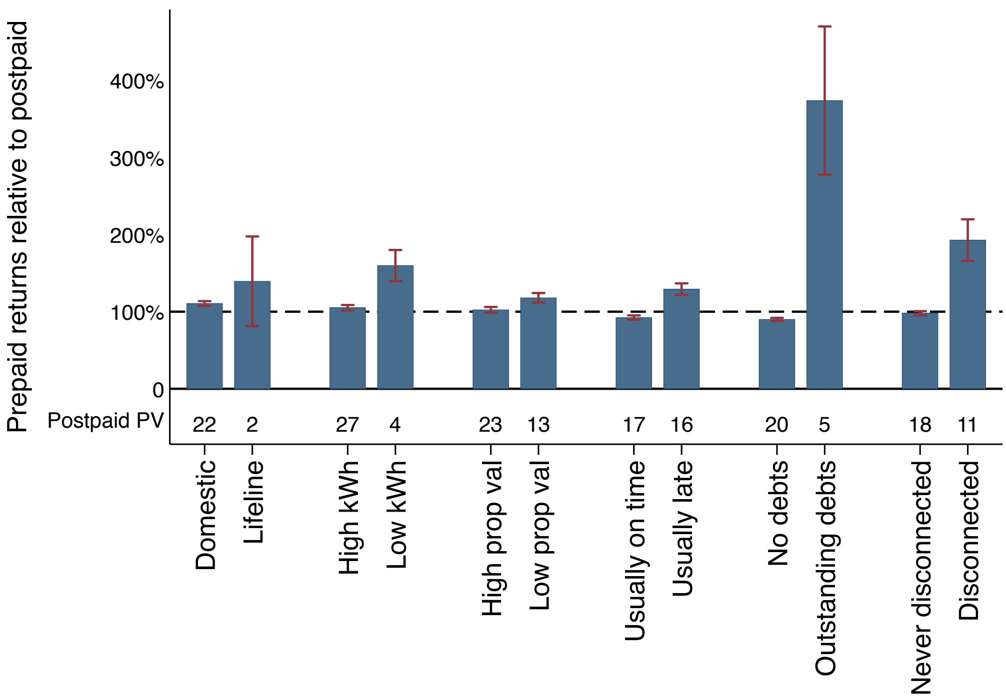


Figure 6: Heterogeneity in relative returns to prepaid metering

Notes: Returns to prepaid metering relative to postpaid metering per customer per month. Separate effects are calculated for each customer characteristic (each pair of bars splits the population), and standard errors are bootstrapped. Heterogeneity variables are as described in Table 3. The present value of the monthly returns to the utility for each customer type on postpaid metering are printed below the bars.

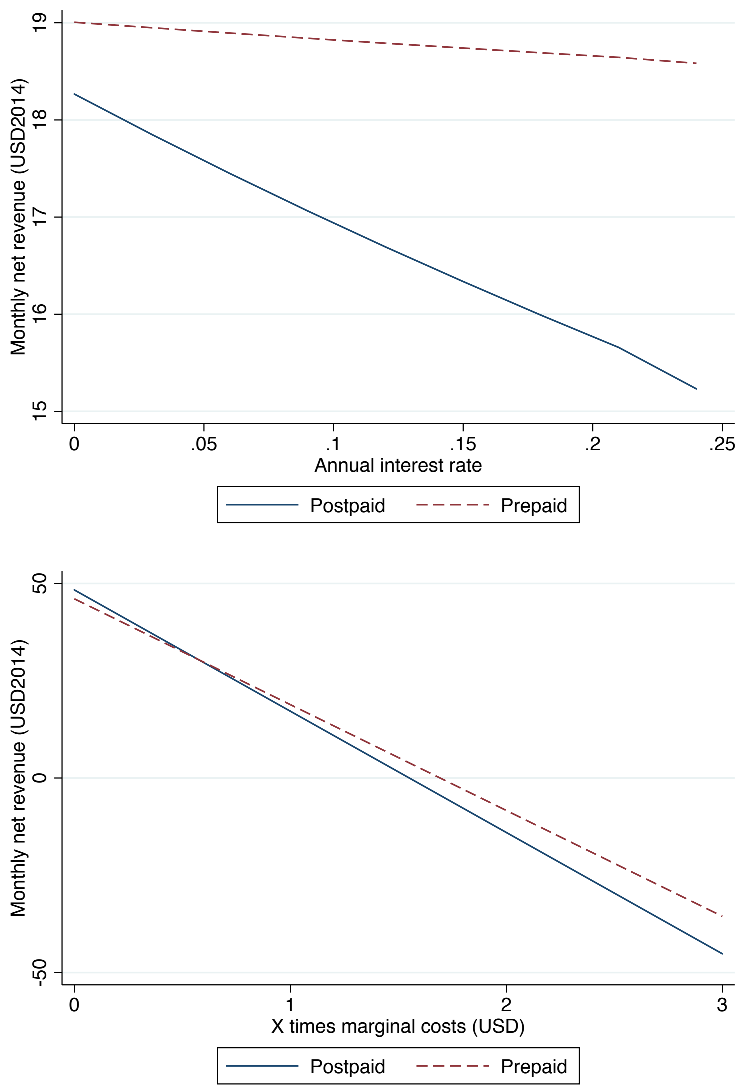


Figure 7: Returns, under alternative cost assumptions

Notes: The present value per month, by meter type. The top figure shows results as interest rates vary and the bottom figure shows results by multiples of the observed average marginal costs of supply.

Table 1: Sample statistics

	Number	Mean	Median	SD	Min	Max
Total obs.	211,190	-	-	-	-	-
Total cust	4,245	-	-	-	-	-
Obs. per cust	-	49.75	54	8.965	1	54
Prepaid obs. per cust	-	15.25	16	7.595	0	22
		Pre-project customer-level statistics				
Daily kWh	-	16.17	15	8.19	0	101
Amount owed per mo.	-	52	49	35	0	404
Days to pay	-	97.24	67	130.82	-969	1,381
Share paid late	-	0.54	0.58	0.33	0	1
Outstanding debts	-	0.26	-	-	0	1
Ever disconnected	-	0.21	-	-	0	1
Lifeline tariff	-	0.31	-	-	0	1
Property value	-	29,847	26,662	14,106	10,704	156,908

Notes: Summary statistics for the sample. Pre-project customer level statistics are calculated for all observations before November 2014 at the customer level. Days to pay is calculated as the number of days between when consumption occurs and payment is received by the utility. Share paid late is the share of months in which the customer paid past the billing due date. Outstanding debts is an indicator for whether the customer had multiple unpaid bills at the end of the panel. Ever disconnected equals one if payment was ever enforced through disconnection. Lifeline is the share of customers that had ever received the Lifeline tariff prior to the program. Property values are assessed values for tax purposes. All monetary units are in 2014 USD.

Table 2: Average daily kWh

	OLS		IV	
	(1)	(2)	(3)	(4)
		Panel A: Avg daily kWh		
Prepaid	-2.117***	-2.152***	-1.966***	-1.912***
	(0.110)	(0.137)	(0.110)	(0.200)
R^2	0.149	0.153	0.149	0.152
N	207,930	207,930	207,929	207,929
N customers	4,245	4,245	4,244	4,244
Fixed effects	month, year	month-year	month, year	month-year
		Panel B: Log avg daily kWh		
Prepaid	-0.133***	-0.139***	-0.120***	-0.150***
	(0.010)	(0.012)	(0.010)	(0.017)
R^2	0.087	0.090	0.087	0.090
N	206,995	206,995	206,994	206,994
N customers	4,245	4,245	4,244	4,244
Fixed effects	month, year	month-year	month, year	month-year

Notes: The table shows the effect of prepaid metering on average daily kWh per customer per month in levels (Panel A) and logs (Panel B). Columns 1 and 2 report OLS coefficients on an indicator for prepaid metering, columns 3 and 4 instrument for the switch date with assignment to prepaid metering. See the main text for further description of the instrument. All specifications exclude the switch month and include customer fixed effects and a time-varying tariff control and cluster standard errors at the customer level. Odd numbered columns include calendar month and year fixed effects; even numbered columns include month-year fixed effects.

Table 3: Heterogeneous treatment effects

	N	Mean	OLS Total effects (1)	OLS Difference (2)	IV Total effects (3)	IV Difference (4)
Domestic	2,907	17.72	-2.152***	1.259***	-1.935***	1.216***
			(0.137)	(0.203)	(0.125)	(0.254)
Lifeline	1,325	9.36	-0.893***		-0.719***	
			(0.150)		(0.221)	
Above median kWh	2,132	20.05	-2.638***	1.633***	-2.591***	1.915***
			(0.170)	(0.208)	(0.154)	(0.208)
Below median kWh	2,100	10.07	-1.005***		-0.675***	
			(0.121)		(0.140)	
High prop value	1,481	17.56	-1.824***	-0.486**	-1.705***	-0.414*
			(0.194)	(0.235)	(0.180)	(0.227)
Low prop value	2,751	13.77	-2.310***		-2.119***	
			(0.132)		(0.138)	
Usually on time	2,105	14.03	-1.752***	-0.783***	-1.749***	-0.518**
			(0.128)	(0.221)	(0.128)	(0.216)
Usually late	2,127	16.15	-2.535***		-2.267***	
			(0.181)		(0.174)	
No debts	3,134	15.13	-2.115***	-0.091	-2.101***	0.404
			(0.111)	(0.287)	(0.114)	(0.312)
Outstanding debts	1,098	15.00	-2.206***		-1.697***	
			(0.264)		(0.290)	
Never disconnected	3,363	14.84	-2.202***	0.190	-2.122***	0.557
			(0.110)	(0.334)	(0.111)	(0.340)
Ever disconnected	869	16.11	-2.012***		-1.565***	
			(0.315)		(0.322)	

Notes: Effects of the prepaid meter on average daily kWh by sub-group. Each coefficient is from a separate regression. Columns 1 and 2 report OLS coefficients and Columns 3 and 4 report IV coefficients. Specifications include separate month and year fixed effects interacted with the heterogeneity variable to allow for differential seasonal time trends by characteristics. All characteristics are defined by the pre-project period as follows: Lifeline equals one for customers primarily on lifeline tariff, Low prop value equals one for customers with a 2012 ZAR property value below 300,000, Usually late equals one for customers who paid above the median share of their monthly bills past the due date, Outstanding debts indicates that the customer had multiple unpaid bills at the end of the panel. Ever disconnected equals one if the customer was ever disconnected on postpaid metering.

Table 4: Revenue-related outcomes

	Amount owed (1)	Avg marg cost (2)	Days to pay (3)
		Panel A: OLS	
Prepaid	-6.850***	-2.880***	-74.790***
	(0.549)	(0.248)	(3.992)
		Panel B: IV	
Prepaid	-6.842***	-2.831***	-84.854***
	(0.793)	(0.362)	(4.932)
N obs	207,930	207,930	200,134
N customers	4,245	4,245	4,233
Month-year FE	x	x	x

Notes: The table shows the effect of prepaid metering on the amount owed for consumption (column 1), the monthly kWh supply cost to the City (column 2), and the days between consumption and payment (column 3).

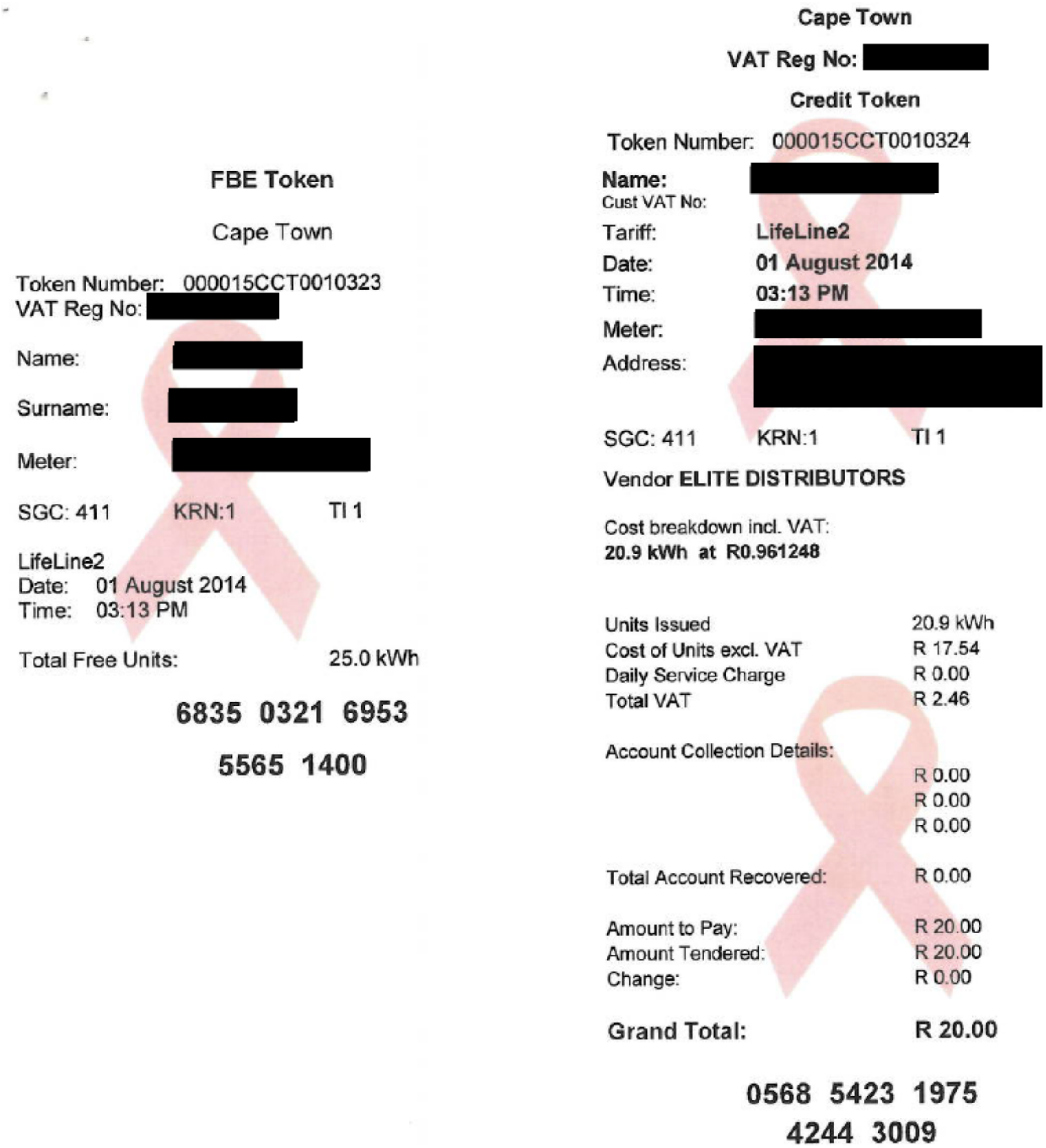
Table 5: Present value of net revenue ($i = 0.08$)

	Postpaid	Prepaid
	Revenue estimate	
Revenue (pq^m)	51.12	45.20
	(0.26)	(0.26)
Includes:		
- Vendor commission	0	0.002/kWh
	Payment timing estimate	
Months since consumption (s^m)	2.71	-0.11
	(0.05)	(0.05)
	Cost estimate	
Cost ($cq^m + b^m$)	33.67	27.01
	(0.13)	(0.13)
Includes:		
- Meter reading	0.91	0
- Billing	0.85	0
- Losses (percent)	11.25	11.25
- Disconnections	90	0
Present value	16.46	18.11
	(0.28)	(0.33)

Notes: Monthly net revenue in USD2014 by metering type for the City of Cape Town. Predicted means and standard errors (delta method) are reported for each estimate, together with a list of the administrative inputs to the calculations. The bottom panel presents the present value of net revenue per month at an annual interest rate of 8 percent, with bootstrapped standard errors.

Appendix to *Charging ahead: Prepaid electricity metering in South Africa*

A.1 Appendix tables and figures



FBE Token

Cape Town

Token Number: 000015CCT0010323
VAT Reg No: [redacted]

Name: [redacted]

Surname: [redacted]

Meter: [redacted]

SGC: 411 KRN:1 TI 1

LifeLine2
Date: 01 August 2014
Time: 03:13 PM

Total Free Units: 25.0 kWh

6835 0321 6953

5565 1400

Cape Town

VAT Reg No: [redacted]

Credit Token

Token Number: 000015CCT0010324

Name: [redacted]
Cust VAT No:

Tariff: **LifeLine2**
Date: **01 August 2014**
Time: **03:13 PM**
Meter: [redacted]
Address: [redacted]

SGC: 411 KRN:1 TI 1

Vendor **ELITE DISTRIBUTORS**

Cost breakdown incl. VAT:
20.9 kWh at R0.961248

Units Issued	20.9 kWh
Cost of Units excl. VAT	R 17.54
Daily Service Charge	R 0.00
Total VAT	R 2.46
Account Collection Details:	
	R 0.00
	R 0.00
	R 0.00
Total Account Recovered:	R 0.00
Amount to Pay:	R 20.00
Amount Tendered:	R 20.00
Change:	R 0.00
Grand Total:	**R 20.00**

0568 5423 1975

4244 3009

Figure A.1: Prepaid electricity receipts - Lifeline customer

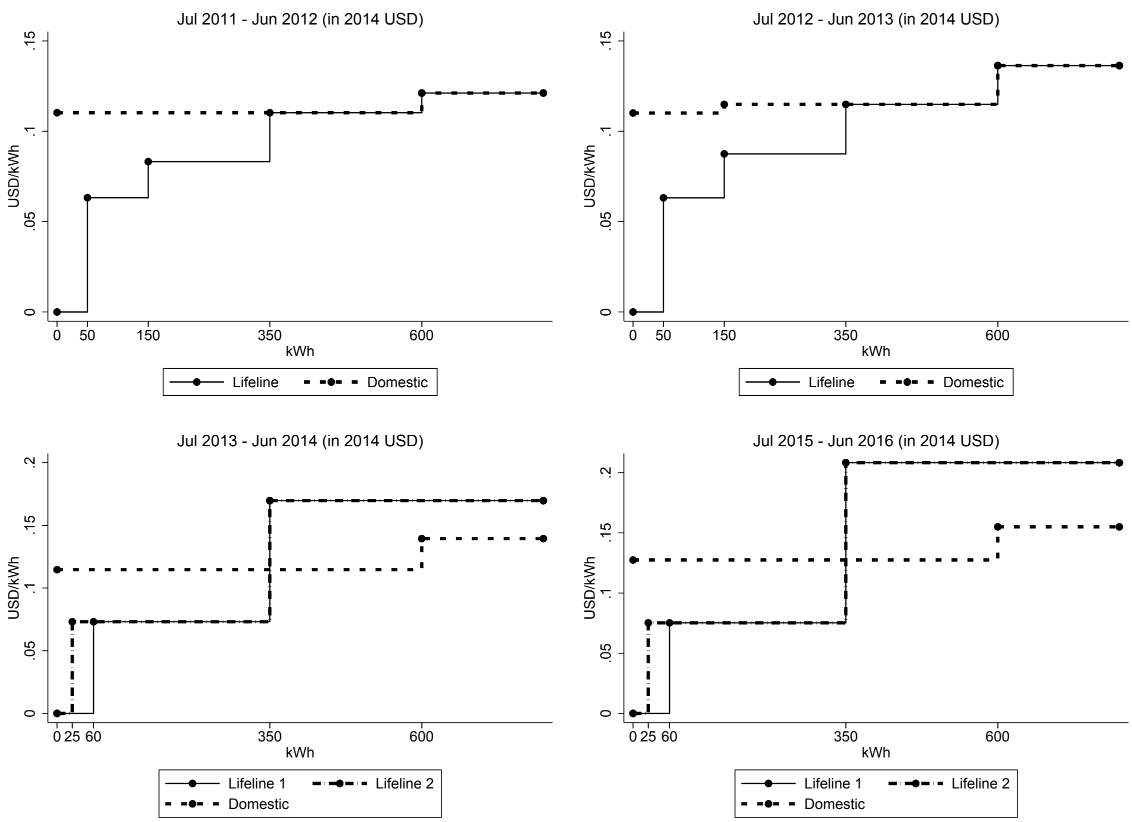


Figure A.2: Electricity tariffs

Page 1 of 4

CITY OF CAPE TOWN
ISIXEKO SASEKAPA
STAD KAAPSTAD

Civic Centre
12 Hertzog Boulevard 8001
PO Box 655 Cape Town 8000
VAT Registration number
4500193497

Tax invoice number	[redacted]
Customer VAT registration number	
Account number	[redacted]
Distribution code	
Business partner number	[redacted]

Copy tax invoice

022110588401082014

[redacted]

Tel: 086 010 3089 - Fax: 086 010 3090
Tel: overseas clients +27 21 401 4701
E-mail: accounts@capetown.gov.za
Correspondence : Director Revenue
PO Box 655 Cape Town 8000
Web address: www.capetown.gov.za

Account summary as at 01/08/2014 — **Due date 26/08/2014**

At [redacted] **/ Erf** [redacted]

Previous account balance		3964.99
Less payments (31/08/2014)	Thank You	3964.99-
(a)		**0.00**
Latest account - see overleaf		1998.16
Arrangement on arrears of	7417.69	
Current instalment	2300.00	2300.00
Current amount due (b)	**Payable by 26/08/2014**	**4298.16**
	Total (a) + (b)	**4298.16**
Total (a) + (b) above	4298.16	
Arrangement on arrears of	5117.69	
Total liability	**9415.85**	

To receive this municipal account via e-mail SMS your account number and e-mail address to 31223. Standard SMS rates apply

000009

Current charges totalling R 4298.16 will be debited from your bank account.
Please comment on the 2016/17 draft budget during April. Details available from April 4 at subcouncil offices and libraries. For more information go to http://www.capetown.gov.za/en/Budget/Pages/Budget-2016-17.aspx.

Please note: isuinv_20160401_234003.muln 000005 / 000009

1. Payment options
(a)Cheques: (i) Made payable to the City of Cape Town. (ii) Limit of R500 000,00. (iii) Post-dated cheques are not acceptable.
(b)Debit orders: Call 0860 103 089 or visit a Customer Service Centre. (c)Internet payments: Visit Easypay.co.za or payCity.co.za.
(d)Electronic payments (EFT): Select the City of Cape Town as a bank-listed beneficiary on your bank's website. Use only your nine-digit municipal account number as reference.(e)Direct deposit at ABSA Bank: Please insert your account no. 221105884 on deposit slip.
(f)Debit/credit card: Only at City vendors reflected below. Bank charges will be levied on your account in respect of single as well as multiple payments in excess of R5 000,00.
2. Interest will be charged on all amounts still outstanding after the due date.
3. You may not withhold payment, even if you have submitted a query to the City concerning this account.
4. Failure to pay could result in your water and/or electricity supply being disconnected/restricted. Immediate reconnection of the supply after payment cannot be guaranteed. A disconnection fee will be charged and your deposit amount might be increased.

Pay points: City of Cape Town cash offices or the vendors below;

ABSA SHOPRITE Checkers WOOLWORTHS W SPAR Post Office Pick n Pay EasyPay Pay online at www.easypay.co.za payCity connected citizens www.paycity.co.za PEP

[redacted]

Account number	[redacted]
Amount due if not paid in cash	4298.16
Amount due if paid in cash	4298.10
Rounded down amount carried forward to next invoice	0.06

>>>>> [redacted]

Page 2 of 4

Account details as at 01/08/2014 **Account number** [redacted]

>>>>> [redacted]

PROPERTY RATES (Period 02/07/2014 to 01/08/2014) 31 Days

At [redacted]

	# Total value		
	From 02/07/2014 : R 1700000.00 @ 0.0062540 ÷ 365 x 31	902.97	
	# Statutory rebate credit		
	From 02/07/2014 : R 15000.00 @ 0.0062540 ÷ 365 x 31	7.97-	
	# Additional rebate credit		
	From 02/07/2014 : R 185000.00 @ 0.0062540 ÷ 365 x 31	98.26-	
			796.74

ELECTRICITY (Period 27/05/2014 to 24/07/2014 - 59 Days) (Actual reading)

At [redacted]
Meter no: [redacted] **/ Consumption 1185.000 kWh / Daily average 20.085 kWh**

*	Consumption charge: domestic		
	(1) 172.6030 kWh @ R 1.2500 (2) 230.1370 kWh @ R 1.2500		
	(3) 287.6710 kWh @ R 1.2500 (4) 12.5551 kWh @ R 1.5200	882.09	
*	Consumption charge: domestic		
	From 01/07/2014 : (1) 118.3560 kWh @ R 1.3476 (2) 157.8080 kWh @ R 1.3476		
	(3) 197.2610 kWh @ R 1.3476 (4) 8.6089 kWh @ R 1.6387	652.10	
	Reversal of estimated consumption (537.123 kWh)	671.40-	
			862.79

WATER (Period 28/06/2014 to 24/07/2014 - 27 Days) (Actual reading)

At [redacted]
Meter no: [redacted] **/ Consumption 11.000 kl / Daily average 0.407 kl**

*	Consumption charge (domestic)		
	From 28/06/2014 : (1) 0.5920 kl free (2) 0.4440 kl @ R 7.6000		
	(3) 0.1862 kl @ R 11.6100		
	From 01/07/2014 : (1) 4.7340 kl free (2) 3.5510 kl @ R 8.7500		
	(3) 1.4928 kl @ R 12.5400	55.32	
			55.32

REFUSE (Period 02/07/2014 to 01/08/2014) 31 Days

At [redacted]

*	Refuse charge (1 X 140L RECYL X 1 Removals)	0.00	
*	Refuse charge (1 X 240lBIN X 1 Removals)	95.96	
			95.96

SEWERAGE (Period 28/06/2014 to 24/07/2014 - 27 Days) (Actual reading)

At [redacted]

*	Disposal charge		
	From 28/06/2014 : (1) 0.4140 kl free (2) 0.3110 kl @ R 7.2000		
	(3) 0.1306 kl @ R 13.5600		
	From 01/07/2014 : (1) 3.3140 kl free (2) 2.4850 kl @ R 8.2500		
	(3) 1.0454 kl @ R 14.6400	39.82	
			39.82

Add 14% VAT on amounts marked with * above **147.53**
0% VAT on amounts marked with # above

Current account: Total due **1,998.16**

Meter details		**Previous reading**	**New reading**	**Units used**
ELECTRICITY	[redacted]	**36191.000kWh(Actual)**	**37376.000kWh(Actual)**	**1185.000kWh**
WATER	[redacted]	**242.000kl(Actual)**	**253.000kl(Actual)**	**11.000kl**

Figure A.3: Sample consolidated bill

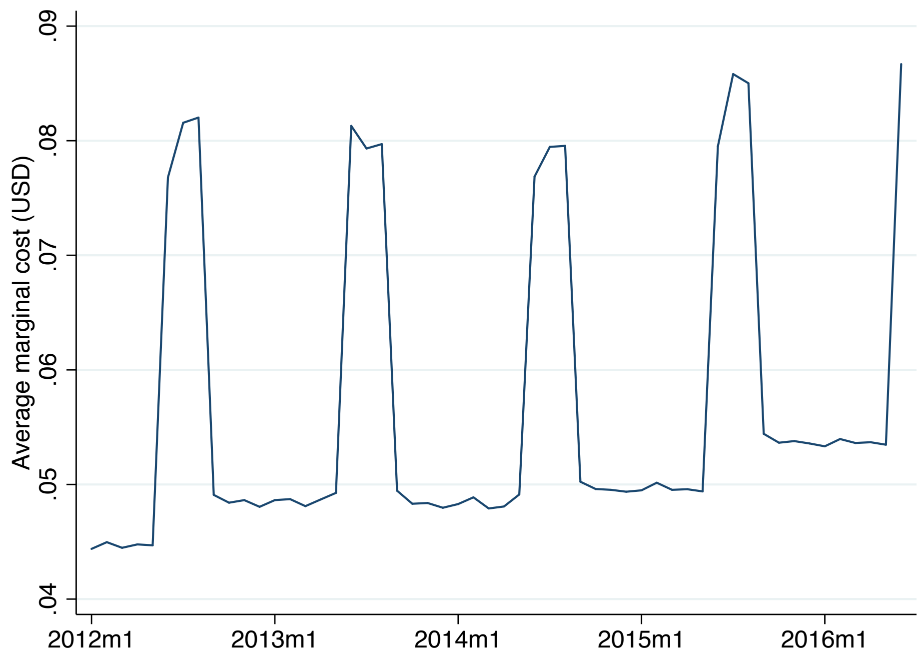


Figure A.4: City of Cape Town average marginal costs

Notes: Average marginal cost of electricity supply per month between 2012 and 2016, in USD2014.

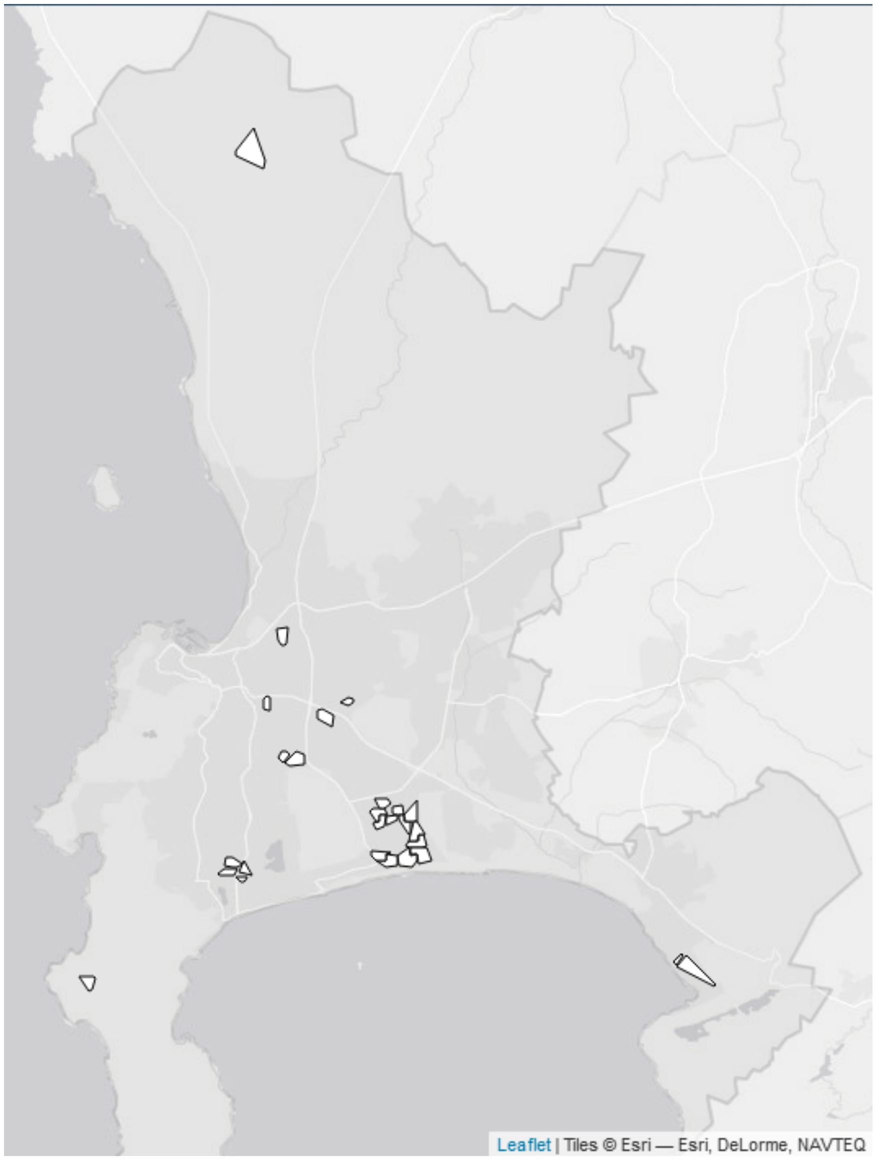


Figure A.5: Randomization groups

Notes: Map of Cape Town. The polygons correspond to the 27 randomization groups. The 13 groups that make up Mitchell's Plain are clustered in the lower center of the map. Each polygon contains between 150 and 200 customers.

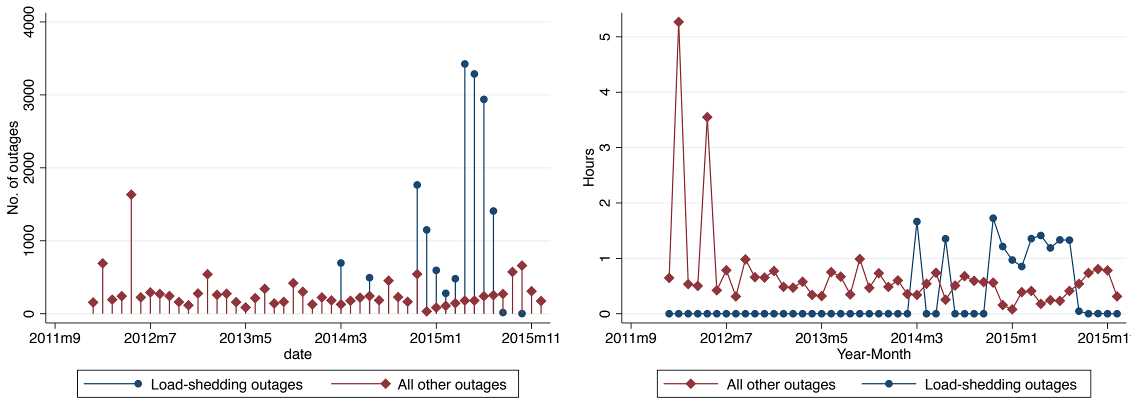


Figure A.6: Load-shedding events in Mitchell's Plain

Notes: Description of loadshedding events and other outages in Mitchells Plain. The left figure shows the total number of separate incidents per month and the right figure shows the total hours per month of each type of outage event.

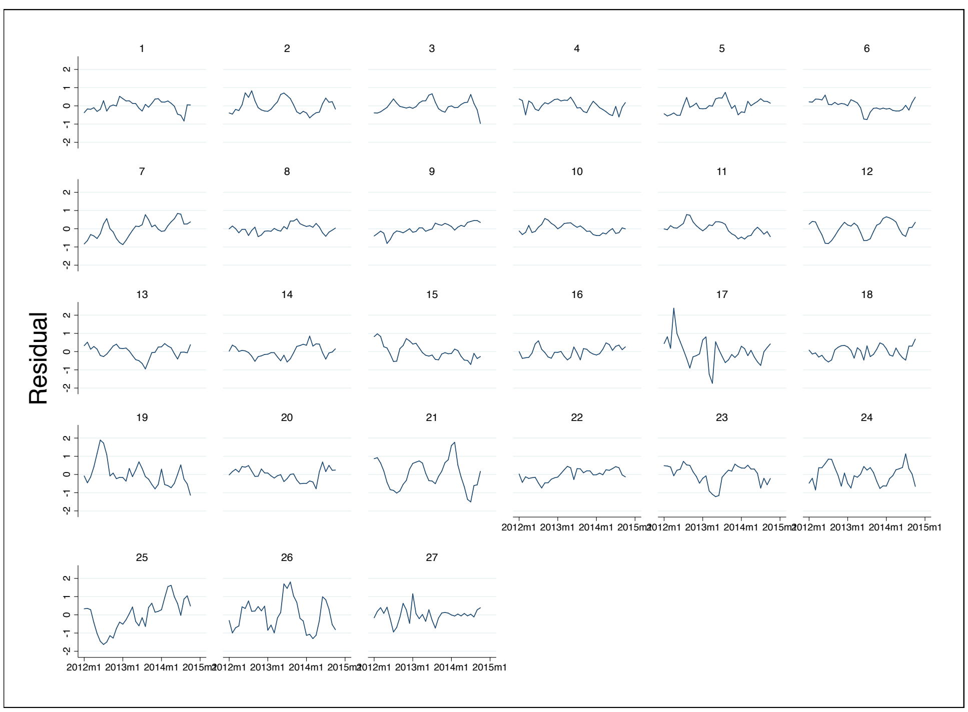


Figure A.7: Pre-program kWh residuals

Notes: Residuals from a regression of pre-program average daily kWh on customer and month-year fixed effects, by randomization group.

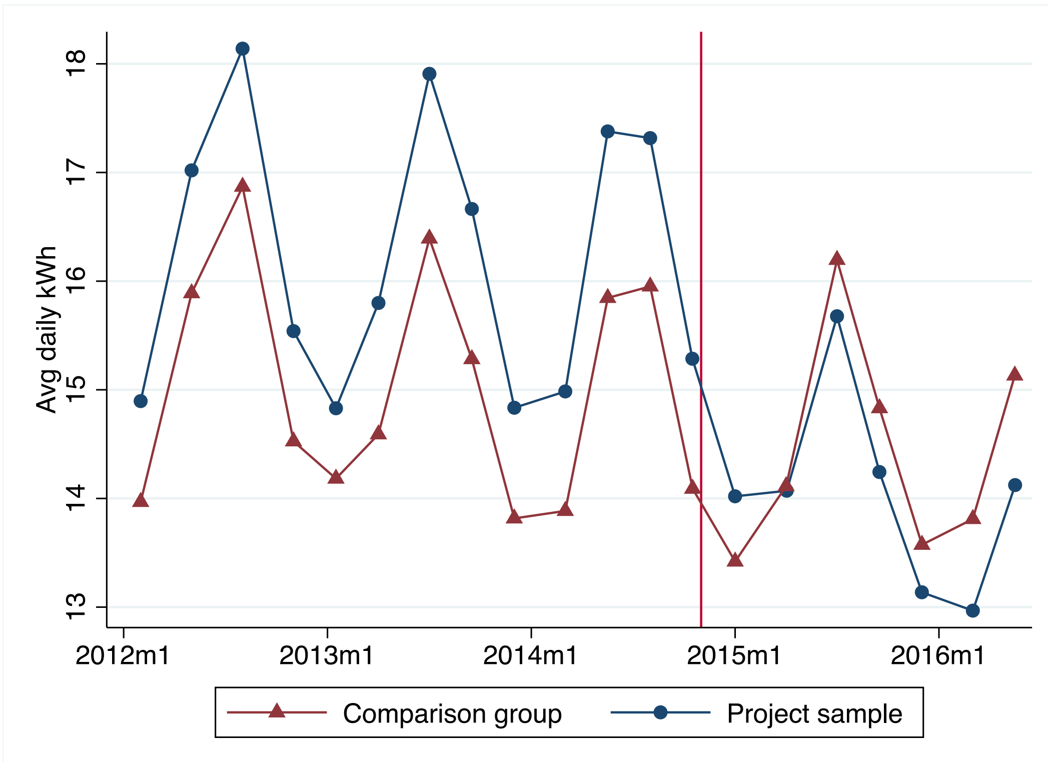


Figure A.8: Average daily kWh, project versus comparison customers

Notes: Monthly mean consumption for project and comparison customers. The comparison group is a sample of postpaid customers, matched on property value. The vertical line in late 2014 represents the start of the meter replacement program.

Table A.1: Balance

	Group	Switch Date Assigned	Switch Date Actual	Switched
Daily kWh	-0.059*	0.002	-0.002	0.500
	(0.032)	(0.005)	(0.003)	(0.314)
Lifeline tariff	0.007***	0.000	0.000	-0.041**
	(0.002)	(0.000)	(0.000)	(0.019)
Property value	-19.356	64.545***	16.454***	-3.8e+03***
	(55.831)	(8.237)	(4.537)	(540.718)

Notes: Correlations between program administrative variables and pre-program customer characteristics, at the customer level. Column 3 is conditional on switching to a prepaid meter (N=3213).

Table A.2: Average daily kWh - Mitchells Plain only

	OLS		IV	
	(1)	(2)	(3)	(4)
		Panel A: Avg daily kWh		
Prepaid	-1.997***	-2.117***	-1.889***	-2.270***
	(0.126)	(0.199)	(0.117)	(0.384)
R^2	0.189	0.194	0.189	0.194
N	112,078	112,078	112,078	112,078
N customers	2,251	2,251	2,251	2,251
Fixed effects	month, year	month-year	month, year	month-year
		Panel B: Log avg daily kWh		
Prepaid	-0.117***	-0.133***	-0.107***	-0.167***
	(0.013)	(0.023)	(0.011)	(0.039)
R^2	0.110	0.114	0.110	0.113
N	111,743	111,743	111,743	111,743
N customers	2,251	2,251	2,251	2,251
Fixed effects	month, year	month-year	month, year	month-year

Notes: Consumption results for the Mitchells Plain sample only. Otherwise, details are as in Table 2.

Table A.3: Robustness checks (average daily kWh)

	Base (1)	Group IV (2)	Mailing IV (3)	DD Postpaid (4)	DD Prepaid (5)
			Panel A: OLS		
Prepaid	-2.152***	–	–	-2.259***	-1.850***
	(0.137)			(0.117)	(0.087)
			Panel B: IV		
Prepaid	-1.912***	-1.762***	-1.814***	-2.331***	-1.722***
	(0.200)	(0.430)	(0.273)	(0.172)	(0.100)
N obs	207,930	207,929	207,929	271,137	2,004,004
N customers	4,245	4,244	4,244	5,451	38,247
Month-year FE	x	x	x	x	x

Notes: Robustness to alternative specifications. The base result (column 1) corresponds to columns 2 and 4 of Panel A in Table 2. Column 2 uses the group order as the instrument (equal to zero prior to the start of the program in November 2014). Column 3 uses the date of the mailing informing customers of the program as the instrument. Column 4 adds a comparison group of postpaid customers, not in the program (i.e. never switched), sampled based on property value. Column 5 adds a comparison group of prepaid customers in the project areas. See text for further details.

Table A.4: Robustness checks (average daily kWh)

	Base (1)	Switchers only (2)	No debt recovery (3)	Trimmed (4)	Smoothed (5)	Balanced (6)	<5 missing (7)
				Panel A: OLS			
Prepaid	-2.152***	-2.254***	-2.171***	-2.169***	-2.305***	-2.098***	-2.053***
	(0.137)	(0.165)	(0.140)	(0.113)	(0.132)	(0.139)	(0.149)
				Panel B: IV			
Prepaid	-1.912***	-2.170***	-1.928***	-2.167***	-1.994***	-1.720***	-2.055***
	(0.200)	(0.182)	(0.206)	(0.175)	(0.196)	(0.209)	(0.212)
N obs	207,930	160,083	204,828	203,738	207,037	209,059	170,678
N customers	4,245	3,252	4,244	4,234	4,245	4,245	3,213
Month-year FE	x	x	x	x	x	x	x

Notes: Robustness to sample and variable construction. The base result (column 1) corresponds to columns 2 and 4 of Panel A in Table 2. Column 2 only includes customers who switched meter types. Column 3 drops observations in which the prepaid meter is used to recover debts. Column 4 trims the top 1 percent of the outcome variable. Column 5 allows for a longer window over which bills or prepaid transactions are averaged. Column 6 balances the panel for all customers, replacing missing outcomes with zeros. Column 7 balances the panel by excluding customers with more than four missing months of data.

Table A.5: Robustness checks (average daily kWh)

	Base	Load-shedding	Tariff error	Consolidated bills	Placebo test
	(1)	(2)	(3)	(4)	(5)
			Panel A: OLS		
Prepaid	-2.152***	-2.172***	-2.467***	-1.234***	-0.148
	(0.137)	(0.138)	(0.147)	(0.235)	(0.121)
			Panel B: IV		
Prepaid	-1.912***	-1.907***	-1.651***	-1.295***	0.188
	(0.200)	(0.201)	(0.222)	(0.304)	(0.193)
N obs	207,929	185,767	162,706	73,498	153,758
N customers	4,244	4,243	3,315	1,450	4,213
Month-year FE	x	x	x	x	x

Notes: Robustness to program implementation issues. The base result (column 1) corresponds to columns 2 and 4 of Panel A in Table 2. Column 2 controls for the average daily hours of regular and load-shedding outages in the month and is restricted to the Mitchell's Plain sample of customers. Column 3 drops customers with tariff mistakes. Column 4 limits the sample to customers receiving a separate electricity bill prior to the program (note that the mean average daily kWh is 15.9 for this subsample versus 16.5 for the full sample). Column 5 implements a placebo check that moves the assigned switch date and actual switch date ahead by one year.

Table A.6: Heterogeneous treatment effects (log average daily kWh)

	N	Mean	OLS Total effects (1)	OLS Difference (2)	IV Total effects (3)	IV Difference (4)
Domestic	2,894	17.72	-0.132*** (0.011)	0.056** (0.025)	-0.124*** (0.010)	0.094*** (0.031)
Lifeline	1,318	9.36	-0.075*** (0.023)		-0.031 (0.029)	
Above median kWh	2,128	20.05	-0.167*** (0.010)	0.094*** (0.021)	-0.165*** (0.009)	0.124*** (0.022)
Below median kWh	2,084	10.07	-0.073*** (0.018)		-0.041** (0.019)	
High prop value	1,475	17.56	-0.111*** (0.015)	-0.037* (0.020)	-0.099*** (0.015)	-0.035* (0.020)
Low prop value	2,737	13.77	-0.148*** (0.014)		-0.134*** (0.012)	
Usually on time	2,095	14.03	-0.101*** (0.014)	-0.066*** (0.020)	-0.099*** (0.012)	-0.046** (0.019)
Usually late	2,117	16.15	-0.167*** (0.014)		-0.145*** (0.015)	
No debts	3,124	15.13	-0.127*** (0.012)	-0.025 (0.023)	-0.123*** (0.010)	0.003 (0.026)
Outstanding debts	1,088	15.00	-0.151*** (0.020)		-0.120*** (0.024)	
Never disconnected	3,349	14.84	-0.138*** (0.011)	0.016 (0.028)	-0.126*** (0.009)	0.021 (0.032)
Ever disconnected	863	16.11	-0.121*** (0.026)		-0.105*** (0.031)	

Notes: Effects of the prepaid meter on log average daily kWh by sub-group. Details are the same as for Table 3, but outcomes are in logs.

Table A.7: Correlation between heterogeneity variables

	Lifeline	Low kWh	Low prop value	Usually late	Unpaid bills	Disconnected
Lifeline	1					
Low kWh	0.610***	1				
Low prop value	0.220***	0.222***	1			
Usually late	-0.116***	-0.142***	0.0229	1		
Unpaid bills	-0.00559	0.0213	0.0881***	0.311***	1	
Disconnected	-0.0715***	-0.0384*	-0.0395*	0.350***	0.301***	1

Notes: Pairwise correlations of variables used in the heterogeneity analysis, at the customer level. All characteristics are defined by the pre-project period as follows: Lifeline equals one for customers primarily on lifeline tariff, Low kWh equals one if the average daily kWh measure is below the median, Low prop value equals one for customers with a 2012 ZAR property value below 300,000, Outstanding debts equals one for customers with multiple unpaid bills at the end of the panel, Usually late equals one for customers who paid above the median share of their monthly bills past the due date. Disconnected equals one for customers that were ever disconnected on postpaid.

Table A.8: Heterogeneity in returns to prepaid metering

	Average returns Postpaid	Relative returns Pre / Post
Domestic	22	1.11
		(0.01)
Lifeline	2	1.39
		(0.30)
Above median kWh	27	1.05
		(0.02)
Below median kWh	4	1.60
		(0.10)
High prop value	23	1.02
		(0.02)
Low prop value	13	1.18
		(0.03)
Usually on time	17	0.92
		(0.01)
Usually late	16	1.29
		(0.04)
No debts	20	0.90
		(0.01)
Outstanding debts	5	3.74
		(0.49)
Never disconnected	18	0.98
		(0.01)
Outstanding debts	11	1.93
		(0.14)

Notes: Returns to prepaid metering relative to postpaid metering, by customer characteristic. See Figure 6 for further detail.

A.2 Data and variables

This appendix details the data sources and how they are combined, and a detailed description of the variables used in the analysis.

A.2.1 Data sources and dataset construction

Billing records The City of Cape Town maintains billing records for any property served or taxed by the municipality. As discussed in the main text, most households receive a consolidated bill for all taxes and services every 25-35 days, with billing dates that vary across customers. We create a billing panel that sequences bills by meter reading date. The resulting panel contains both overlapping billing periods and gaps between billing periods. Overlapping billing periods are most commonly due to estimated meter readings (10.3 percent of bills in the raw data).[35] Once an actual reading is collected, the estimated readings are reversed and the customer is billed for the difference between the estimated and actual readings during the estimated months. Actual readings are used to replace estimated readings in the data, by assigning the actual consumption estimated billing periods assuming equal consumption on each estimated day. Gaps between bills are less common (2.1 percent of bills in the raw data). Gaps and bills with zero recorded consumption are dealt with similarly in the cleaning process. We allow for two alternative assumptions: (1) average over gaps of up to 30 days (including gaps associated with zero consumption bills), working backward from the date of the next non-missing (non-zero) bill, or (2) average over gaps of up to 365 days using the same process. (1) is our main outcome measure, and (2) is used in a robustness check. All gaps longer than 365 days are dropped (N=102).

Prepaid vending records The prepaid vending system records each transaction and the meter with which it is associated. The meters themselves do not communicate with the grid, and as a result, we do not observe prepaid meter consumption directly. To construct monthly outcome measures comparable to those obtained through the billing records, we assume that electricity is consumed at a constant rate between purchases and that customers maintain a steady minimum balance (which may be zero) over time, i.e. there is no accumulation of prepaid credit on the meter.

[35] Estimates are taken when a customer's meter cannot be read, which usually occurs because it cannot physically be accessed. Consumption is instead estimated based on past consumption patterns observed for that customer. At most, three consecutive estimated readings are permitted by the system before an actual reading is obtained and used to "reverse" the estimated readings.

Customers purchase electricity frequently: the median frequency is every 3.3 days. Out of over 50,000 customer-month observations on prepaid metering, only 270 months are associated with no prepaid purchases, corresponding to 147 unique accounts. Consequently, any more sophisticated latent demand model would only affect the assumed within-month variation in demand, which we cannot observe on either the prepaid or postpaid system. We impose analogous averaging assumptions to what is described above for the billing panel to address gaps between prepaid purchases of over a month. We allow for two alternative assumptions: (1) average over gaps of up to 30 days, working forward from the last observed purchase (i.e. assume entire transaction is consumed within 30 days), or (2) average over gaps of up to 365 days using the same process. Gaps of longer than 365 days are dropped. (1) is our main outcome measure, and (2) is used in robustness checks.

Project data The contractor maintained records of attempted and completed meter installations, which we use to match postpaid and prepaid meters. Contractor records also include the date of meter installation, the meter serial number and the date that households received maildrops informing them of the project.

Sample construction and randomization used lists of targeted accounts provided by the Department of Electricity. We include all accounts that were on the lists in our analysis, with the following exceptions. First, non-domestic customers are dropped. Second, customers with 3-phase electricity meters were dropped. The contractor did not replace this type of meter. Finally, 13 meters in the randomization file that did not receive any bills between January 2012 and November 2014 and were not in the contractor installation logs were dropped from the sample.

A.2.2 Variables

- Average daily kWh: We construct an average daily kWh variable at the customer-month level. As described above, our main variable averages over up to 30 days prior to the most recent meter reading or since the most recent prepaid purchase in the case of months with no data. As a robustness check, we allow for a longer averaging window, of up to one year. We also use the total kWh consumed in the month in our benefit-cost analysis. We construct a binary indicator for above median kWh based on the customer's average consumption prior to November 2014.

- Amount owed: We apply the customer's tariff to the constructed consumption measure, calculating the kWh on each tariff block and the marginal price. This results in an amount owed associated with the calendar month of consumption.

- Days to pay: We construct a variable that describes the number of days between when a customer consumes electricity and when he or she pays for that electricity. For prepaid observations, this is calculated as half of the average number of days between transactions, consistent with the assumption of a constant rate of consumption between transactions. For postpaid observations, we take the amount owed on the first bill in the panel and use that as the starting balance that must be cleared. A bill is cleared when cumulative payments catch up with the cumulative amount owed. For customers that receive a consolidated bill, accounting is similar, though debts must also be cleared before a payment is allocated toward electricity.[36] The days to pay is transformed into a months to pay variable for the benefit cost analysis. We also use this variable to construct late payment measures, which equal one if the bill was paid off after its due date. A customer is categorized as usually late if over 58 percent (the median share) of bills before November 2014 are paid late.

- Average marginal cost: We obtain records of the average marginal cost paid each month by the City of Cape Town to Eskom. This is calculated based on the time of consumption for all residential and commercial customers in the City.

- Non-payment: For bills that are not cleared by the end of the panel, we construct a payment probability variable based on observed payment probabilities associated with debts of different ages in a longer panel for the same sample. This payment probability is set to zero for debts older than 3 years, as per South Africa's Municipal Systems Act (i.e. debts older than 3 years are written off). For payments that we do not observe, we set the revenue measure in our benefit cost analysis equal to the amount owed times the payment probability. We use the customer's average time to pay to replace unobserved days to pay. We construct a measure of outstanding debts that equals one if the customer has multiple unpaid bills at the end of the panel.

- Disconnections: Customers are charged for disconnections and reconnections associated with enforcing payment. We record the cost of a disconnection in the month that it

[36] The City of Cape Town assigns payments against the consolidated bill to debt first, followed by electricity, then other services. We therefore assume that the electricity amount owed is cleared once cumulative payments catch up with the cumulative amount owed from past bills plus the current owed for electricity only.

shows up on the customer's bill. The disconnection costs to the City are factored into the benefit cost analysis. We construct an indicator for whether the customer received any disconnections on their postpaid meter.

- Property value: We use the City of Cape Town's 2012 general valuation of properties, which is the basis for property taxes, along with a geographic identifier to match property values to electricity meters. Our binary measure of low property value uses a threshold of 300,000 ZAR, which is the cutoff for several social programs in the City. We assume low values for flats and for a small number of parcels with missing data.

- Administrative cost records: Other details included in the benefit cost analysis were obtained from the City of Cape Town through personal communication with the Electricity Department. These include the rate of technical and non-technical losses, and the cost of preparing bills and reading meters.