Pay as You Go: Pre-paid Metering and Electricity Expenditures in South Africa

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Much of the coming growth in energy demand is expected to come from the developing world (Wolfram, Shelef and Gertler 2012). Existing evidence on the effects of electrification suggests that this is good news for development (Dinkelman 2011; Lipscomb, Mobarak and Barham 2013). However, it also introduces new challenges for both households and electric utilities since newly electrified households are likely to be poorer and more liquidity constrained. Thus, they may struggle to pay lumpy utility bills, resorting to non-payment when they do not have enough cash on hand or when service quality is poor (Szabó and Ujhelyi 2014; McRae 2015). Utilities must provide larger amounts of energy at higher marginal costs and balance concerns over non-payment with the political and logistical cost of disconnecting households.

We study a technological solution to the non-payment problem among low-income households: pre-paid electricity meters. Pre-paid meters constitute a large share of residential electricity connections in South Africa and are undergoing a rapid expansion in the developing world. We use detailed customer transaction data from Cape Town, South Africa to

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characterize electricity expenditures under pre-paid metering. By studying how expenditure patterns vary with property values, we provide suggestive evidence that expenditures by poorer households are driven by liquidity constraints and a difficulty smoothing income. This indicates that the monthly billing model is inconsistent with a revealed preference for small infrequent purchases among the poor, a preference also documented in other settings (e.g. Attanasio and Frayne 2006).

1 Residential electricity in Sub-Saharan Africa

Over the past two decades, the share of households in Sub-Saharan Africa with access to electricity has crept up slowly, from 16 percent in 1990 to just over 30 percent in 2011. In contrast, during that same time period, South Africa went from a connection rate comparable to elsewhere in Sub-Saharan Africa to over 80 percent access (NERSA 2002; IEA 2013).

South Africa's rapid electrification program relied on a technological solution to ensuring timely electricity payments: pre-paid meters (Bekker et al. 2008). This payment innovation mirrors the predominant billing system for cellular technologies in developing countries, which have expanded rapidly among the very poor. Like a pre-paid mobile phone, users load credit onto the meter using a meter-specific encrypted code purchased from a physical vendor or online or mobile retailer. The credit is then drawn down until the balance reaches zero and the power shuts off until more credit is loaded.[1]

Pre-paid electricity meters appear poised to spread rapidly in the developing world. At present, there are more pre-paid meters in South Africa than in the rest of Sub-Saharan Africa combined, though a recent industry report forecasts the number of pre-paid meters in Sub-Saharan Africa to grow by 200 percent in the coming decade (Northeast Group 2014).

[1]Electricity theft, which requires physical tampering with the meter or wiring, becomes the only feasible form of non-payment.

2 Case study: Cape Town, South Africa

We examine the relationship between property value – which is likely to correlate with socioeconomic status – and electricity purchasing patterns for residential pre-paid electricity customers in Cape Town, South Africa between 2004 and 2014. Electricity is billed on an increasing block tariff, which resets on the first of each month. Customers move up the tariff schedule based on cumulative purchases during the month.

2.1 Data

We assemble a customer-level panel dataset using administrative records from the City of Cape Town's municipal electric utility.[2] Approximately 665,000 residential customers were served by the utility in 2014, 78 percent of whom were on pre-paid metering. Our unit of observation is a pre-paid electricity transaction; we observe the size (in South African Rand (ZAR) and kWh), date and time of each purchase. We do not observe electricity consumption outcomes. We combine the transaction data with property value records from 2012.[3]

2.2 Descriptive statistics

We analyze a 10 percent sample of the pre-paid residential customers for whom we have valid property values: 31,570 customers and 15,667,457 observations. Table 1 shows sample statistics. All monetary units are in 2012 South African Rand (ZAR; 1 USD2012 = 8.54 ZAR2012). The median customer is observed in the dataset for 74 months and purchases an average of 481.5 kWh of electricity per month in 5.8 separate transactions. For comparison, the Energy Information Administration reports that the average U.S. household consumed 903 kWh of electricity per month in 2012.

Purchasing patterns vary considerably over time. As shown in Figure 1, monthly expen-

[2]The data and dataset construction are described in greater detail in an online appendix, together with additional summary statistics and robustness checks.

[3]This represents the most recent available property value for most dwellings in the City of Cape Town's administrative records.

ditures have increased since 2004, while purchase quantities in kWh have remained relatively constant. This pattern is explained by annual tariff increases, particularly since 2007/8.

2.3 Heterogeneity by property value

We expect liquidity constraints to present a greater barrier to income smoothing among poorer households. To isolate the relationship between property values and purchasing patterns, we estimate

$$y_{it} = \sum_{q=2}^{4} \delta_q prop_q + \gamma_m + \eta_y + \epsilon_{it} \quad (1)$$

where y_{it} is an outcome for customer i at time t. Each δ_q captures the effect of a property value quartile relative to the first quartile. We include month (γ) and year (η) fixed effects to control for seasonality and annual trends. We weight each customer by the number of times it appears in the panel and cluster standard errors at the customer level.

Table 2 presents the relationship between property values and purchasing patterns. The number of transactions per month is decreasing across property value quartiles, with an average of around 10 transactions per month in the bottom quartile and around 3 in the top quartile (column 1). The average monthly expenditure in both ZAR and kWh is increasing across property value quartiles (columns 2 and 3). Column (4) shows that the average transaction goes from around 24 ZAR2012 (just under 3 USD) in the lowest property value quartile to around 153 ZAR in the highest quartile. Finally, column 5 presents the estimated point elasticities of monthly kWh purchases with respect to property value, calculated at the median property value within each quartile.[4] The elasticity is increasing across quartiles, and is in line with estimates of the income elasticity of electricity demand from other developing country settings (Khanna and Rao 2009).[5]

[4]We include a squared term for property values in the estimating equation to allow for a non-linear relationship between kWh purchases and property value. Because property value is time invariant in our data, results should be interpreted as long run elasticities.

[5]Income elasticities of electricity demand are expected to be higher in developing than in developed countries (Wolfram, Shelef and Gertler 2012). Residential long run income elasticities in the developing country studies reported in Khanna and Rao (2009) range from 0.2 to 1.8.

These descriptive patterns indicate that households in the bottom quartile purchase over three times as often (every three days) and in increments that are less than a fifth as large as those in the top quartile. Small, frequent transactions are consistent with liquidity constraints and difficulty smoothing income.

We turn next to a more direct examination of income smoothing. Liquidity constrained households may be more likely to spend money when income arrives, which occurs on Fridays for many wage laborers. We analyze the share of a customer's transactions that occur on each day of the week, and we modify equation 1 to interact quartiles with day of the week indicators. We show the estimated marginal effects in the top panel of Figure 2. An increase in purchase shares on Fridays is evident in the lower half of the property value distribution and, in particular, in the bottom quartile. Moving up the property value distribution, the pattern of Friday purchases disappears almost completely.[6] The F-statistic for the test that purchase shares are equal across days in the second half of the week (Wednesday-Saturday) is 488.05 for quartile 1 and 4.39 for quartile 4.

More frequent purchases on Fridays may be due both to liquidity constraints and to the fact that poorer households are more likely to receive weekly wages. We repeat the analysis using purchase shares by day of the month in the bottom panel of Figure 2. Purchase shares are more evenly distributed in the top property value quartile. We see little evidence of purchase increases on salary paydays (15th, 25th or 30th) in the top quartile, though the middle two quartiles display significant increases in purchase shares on the 15th and 25th of the month. The bottom quartiles display relatively large spikes in purchase shares on the first of the month, when the tariff resets and the same amount of money purchases more kWh of electricity.[7]

The observed distribution of purchases over time vary considerably between richer and poorer households. Customers with low property values purchase more often immediately following a common payday, and are more sensitive to the tariff structure in their allocation

[6] We speculate that the higher purchase shares on Mondays in the top property value quartile may be attributed to the start of the work week.

[7] Note that because the tariff increases over the course of the month are based on cumulative expenditures by the customer, total spending is unaffected by when during the month a purchase takes place. Thus, delaying expenditures until the first of the month is consistent with difficulty smoothing income.

of purchases across the month.

3 Conclusion

In addition to addressing non-payment of utility bills, pre-paid electricity meters introduce new flexibility in how and when poor, liquidity constrained households purchase electricity. To the extent that difficulty smoothing income underlies the failure to pay monthly bills, this added flexibility allows customers to smooth expenditures to income and potentially improves customer welfare. We observe that poor households in Cape Town take advantage of the added flexibility by purchasing electricity often and in small amounts. A relatively sparse literature has documented similar patterns of small, frequent purchases of a variety of consumption goods by poor households in developing countries (Attanasio and Frayne 2006).

The question remains as to why poor households find monthly payments difficult. The sensitivity to payday and to the tariff schedule shown in our analyses is consistent both with expenditures driven by liquidity constraints (e.g. Johnson, Parker and Souleles 2006) and with more behavioral explanations, such as time inconsistency (e.g. Shapiro 2005).[8] Better understanding of the reasons poor households fail to pay their electricity bills, and the potential set of tools – including but not limited to pre-paid metering – to increase payment rates, is crucial for expanding energy access to the poor in the developing world.

[8] The patterns we observe could also be driven by differences in transaction costs between richer and poorer households. Electricity can be purchased from a variety of vendors convenient for rich households, including grocery stores, gas stations and via mobile phone or internet.

References

Attanasio, O, and Christine Frayne. 2006. "Do the poor pay more?" *Working Paper.*

Bekker, Bernard, Anton Eberhard, Trevor Gaunt, and Andrew Marquard. 2008. "South Africa's rapid electrification programme: Policy, institutional, planning, financing and technical innovations." *Energy Policy*, 36(8): 3125–3137.

Dinkelman, T. 2011. "The effects of rural electrification on employment: New evidence from South Africa." *American Economic Review*, 101(7): 3078–3108.

IEA. 2013. "World Energy Outlook Electricity Access Database." International Energy Agency.

Johnson, David S., Jonathan A. Parker, and Nicholas S. Souleles. 2006. "Household Expenditure and the Income Tax Rebates of 2001." *American Economic Review*, 96(5): 1589–1610.

Khanna, Madhu, and Narasimha D Rao. 2009. "Supply and demand of electricity in the developing world." *Annual Review of Resource Economics*, 1(1): 567–596.

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

McRae, Shaun. 2015. "Infrastructure Quality and the Subsidy Trap." *American Economic Review*, 105(1): 35–66.

NERSA. 2002. "Electricity supply statistics for South Africa 2002." National Electricity Regulator of South Africa.

Northeast Group. 2014. "Sub-Saharan Africa Electricity Metering: Market Forecast (2014 to 2024)." Northeast Group, LLC.

Shapiro, Jesse M. 2005. "Is there a daily discount rate? Evidence from the food stamp nutrition cycle." *Journal of Public Economics*, 89(2): 303–325.

Szabó, Andrea, and Gergely Ujhelyi. 2014. "Can Information Reduce Nonpayment for Public Utilities? Experimental Evidence from South Africa." Mimeo.

Wolfram, Catherine, Orie Shelef, and Paul Gertler. 2012. "How Will Energy Demand Develop in the Developing World?" *Journal of Economic Perspectives*, 26: 119–138.

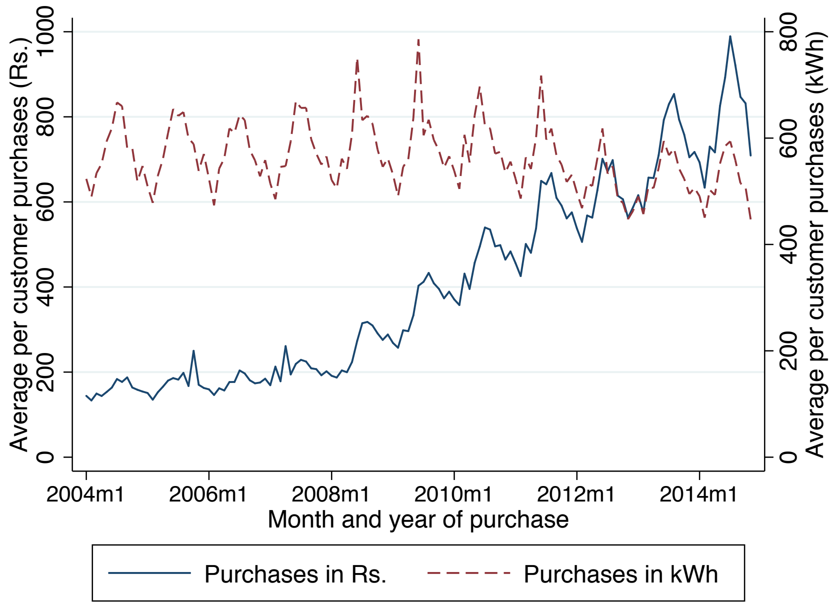

Figure 1: Monthly purchases

Notes: Average per-customer monthly purchases in ZAR and kWh.

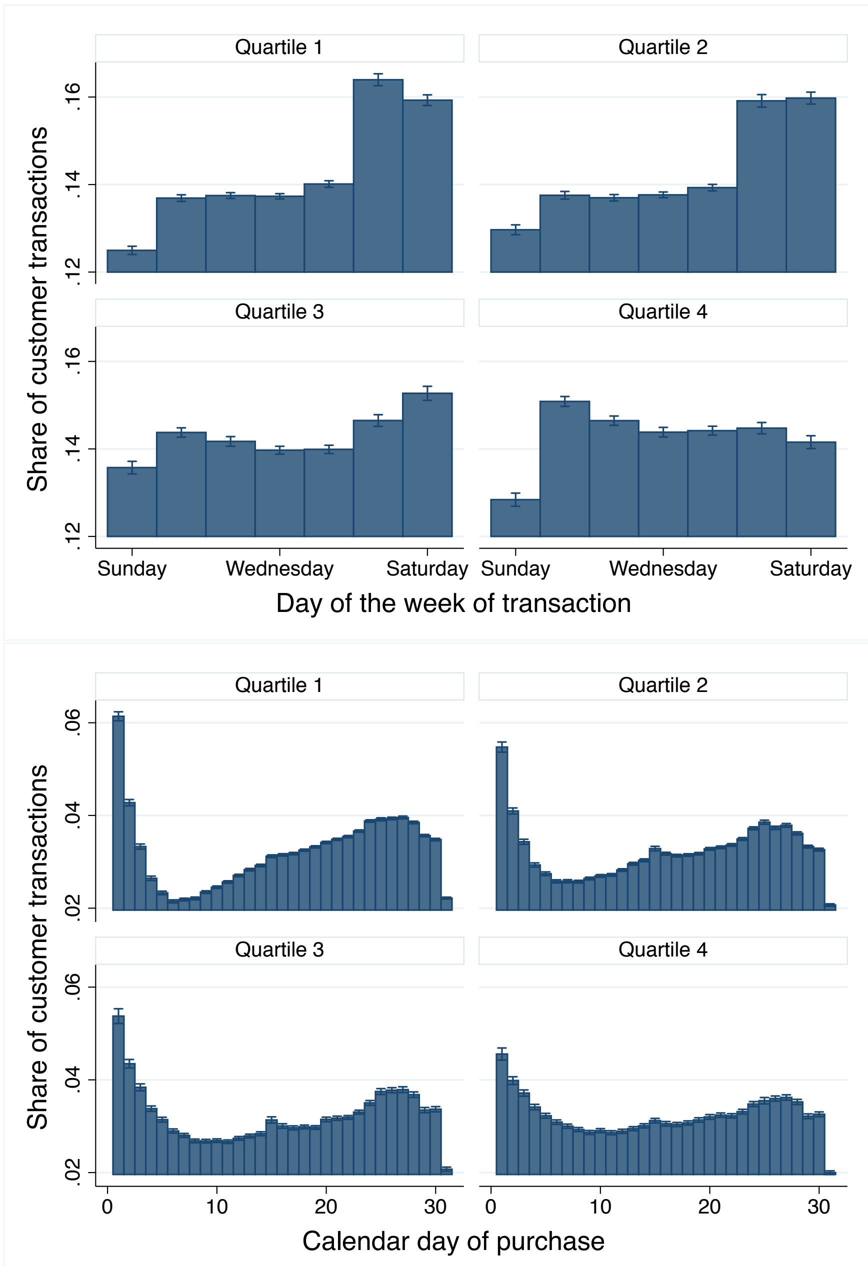

Figure 2: Heterogeneity by property value quartile.
Notes: Estimated marginal effects for the share of customer purchases on each day of the week (top) and day of the month (bottom).

Table 1: Summary statistics

	Mean	**Median**	**Std. Dev.**	**Min.**	**Max.**
Months active	71.666	74	44.465	1	131
Average transactions per month	8.453	5.844	8.267	1.000	195.831
Average ZAR per month	638.282	474.541	650.285	0	21000.000
Average kWh per month	587.925	481.517	474.296	5.300	18000.000
ZAR per transaction	65.862	29.334	112.978	0	3954.325
kWh per transaction	78.367	39.769	118.430	5.300	2943.430
Property value ('000 ZAR)	910	570	1200	3.827	9700

Summary statistics at the customer (N=31,570) and transaction (N=15,667,457) level.

Table 2: Expenditure patterns.

	Transactions per month	kWh per month	ZAR per month	ZAR per transaction	Property value elasticity
Quartile 1					0.221***
					(0.005)
Quartile 2	-1.336***	122.665***	104.684***	8.827***	0.356***
	(0.133)	(3.697)	(3.473)	(0.497)	(0.006)
Quartile 3	-5.427***	246.139***	225.693***	46.541***	0.478***
	(0.112)	(4.586)	(4.281)	(1.650)	(0.006)
Quartile 4	-7.064***	521.983***	465.666***	128.658***	0.530***
	(0.104)	(7.870)	(6.749)	(8.319)	(0.005)
Observations	2,262,647	2,262,647	2,262,647	15,667,457	2,262,647
Quartile 1 mean	10.208	340.258	249.384	24.431	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All regressions include month and year fixed effects and cluster standard errors at the customer level (N=31,570). Columns (1), (2), (3) and (5) are estimated on a monthly panel; column (4) is estimated on a transaction-level panel. Column 5 reports the point elasticity of kWh per month with respect to property value, calculated at the median property value in each quartile. See the online appendix for further detail.