Online appendix to Charging ahead: Prepaid metering, electricity use and utility revenue

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A.1 Appendix tables and figures



4244 3009

Figure A.1: Prepaid electricity receipts - Lifeline customer



Figure A.2: Electricity tariffs

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.

sed	Units u	New reading	Previous reading	Motor dotaile
1,998.16		rent account: Total due	Cur	
147.5			T on amounts marked with * above mounts marked with # above	Add 14% VAI 0% VAT on al
39.8	20.50		1434 KI 🐨 N 14,0400	2·1 (C)
_	08 QE	@ R 7.2000 @ R 8.2500	28/06/2014 : (1) 0.4140 kl free (2) 0.3110 kl 306 kl @ R 13.5600 31/07/2014 : (1) 3.3140 kl free (2) 2.4850 kl 445-4 tl @ R 14 6400	From 2 (3) 0.1 From ((3) 1 0
			al charroe	* At
		2014 - 27 Days) (Actual reading)	ERAGE (Period 28/06/2014 to 24/07/2	SEWE
95.9			ì	
0.0	0.00		e charge (1 X 140L RECYL X 1 Removals) e charge (1 X 240lBIN X 1 Removals)	* Refuse * Refuse
		.) 31 Days	SE (Period 02/07/2014 to 01/08/2014	REFU
55.3	55.32	@ R 8.7500	01/07/2014 : (1) 4.7340 kl free (2) 3.5510 kl 1928 kl @ R 12.5400	From (3) 1.4
		@ R 7.6000	28/06/2014 : (1) 0.5920 kl free (2) 0.4440 kl 862 kl @ R 11 6100	From 2 (3) 0.1
		Daily average 0.407 kl	r no: // / Consumption 11.000 kl /	* Meter
		- 27 Days) (Actual reading)	ER (Period 28/06/2014 to 24/07/2014	WATI
862.79	652.10 671.40	(2) 157.8080 kWh @ R 1.3476 1.6387)	mption charge: domestic 31/07/2014 : (1) 118.3560 kWh @ R 1.3476. 7.2610 kWh @ R 1.3476 (4) 8.6089 kWh @ F al of estimated consumption (537.123 kWh	* Consu From ((3) 19: Revers
~	882.05	@ R 1.2500 R 1.5200	2.6030 kWh @ R 1.2500 (2) 230.1370 kWh (7.6710 kWh @ R 1.2500 (4) 12.5551 kWh @	(1) 177
		h / Daily average 20.085 kWh	r no: // Consumption 1185.000 kW	A Meter
		2014 - 59 Days) (Actual reading)	TRICITY (Period 27/05/2014 to 24/07/	
72.96.7	98.26	65 x 31	02/07/2014 : R 185000.00 @ 0.0062540 ÷ 3	From (
	7.97.	5 x 31	utory repate creat. 32/07/2014 : R 15000.00 @ 0.0062540 ÷ 36	From (
~	902.97	365 x 31	i value 22/07/2014 : R 1700000.00 @ 0.0062540 ÷	# Tota From (
		1/08/2014) 31 Days	ERTY RATES (Period 02/07/2014 to 0	PROP



Figure A.3: Sample consolidated bill



Figure A.4: Randomization groups

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



Figure A.5: City of Cape Town average marginal costs

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



Figure A.6: Pre-project kWh residuals

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



Figure A.7: 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 project.



Figure A.8: Average and marginal prices on prepaid metering

Notes: Average and marginal prices at the monthly (left) and transaction (right) level for all customer-months (left) or customer-purchases (right) following the switch to prepaid metering.



Figure A.9: Monthly usage data, on Domestic (left) and Lifeline (right) tariffs Notes: Histograms show customer-month observations of the imputed average daily kWh variable aggregated over the days in the month in 10 kWh bins, with tariff schedules overlaid.



Figure A.10: Alternative cost environments and net revenues

Notes: Monthly net revenue under postpaid (solid line) and prepaid (dashed line) metering for alternative cost environments. The vertical dotted line represents the point on the x-axis that corresponds to Cape Town. The left figure varies the annual interest rate. The middle figure varies the marginal supply cost (and therefore the margin per kWh). The right figure varies the impact on losses (technical and non-technical) from prepaid metering, holding losses under postpaid metering fixed.

	Group	Phase 1	Phase 2	Switch	Ever
	order	order	order	date	switched
	(1)	(2)	(3)	(4)	(5)
Daily kWh	0.006	-0.106	-0.018	-0.000	0.153
	(0.037)	(0.073)	(0.038)	(0.004)	(0.312)
Amount owed per month	0.011	-0.511	-0.101	-0.003	0.600
	(0.157)	(0.306)	(0.160)	(0.019)	(1.366)
Months late	0.006	0.028	0.011	-0.001	0.208
	(0.018)	(0.027)	(0.017)	(0.002)	(0.177)
Share paid late	0.003^{***}	0.001	0.003^{**}	0.000^{**}	0.012
	(0.001)	(0.002)	(0.001)	(0.000)	(0.016)
Outstanding debts	0.008^{***}	0.002	0.007^{***}	0.000	-0.180***
	(0.002)	(0.003)	(0.002)	(0.000)	(0.022)
Ever disconnected	0.002	-0.000	0.002	0.000	-0.050***
	(0.001)	(0.003)	(0.001)	(0.000)	(0.016)
Lifeline tariff	0.003	0.016***	0.006***	0.000	-0.050**
	(0.002)	(0.003)	(0.002)	(0.000)	(0.020)
Log property value	-0.002	-0.011	-0.004	-0.000	-0.079
	(0.005)	(0.007)	(0.005)	(0.001)	(0.055)

Table A.1: Balance

Notes: Correlations between project implementation variables and pre-project, time invariant customer characteristics, at the customer level. The administrative variables are the 27 randomization groups (column 1), two splines in the 27 randomization groups (columns 2-3, corresponding to a single regression), the actual switch date (column 5) and whether the customer was ever switched to a prepaid meter (column 6). Column 5 is conditional on switching to a prepaid meter (N=3213).

Table A.2: First stage

	Prepaid
	(1)
Phase 1 order x December 2014	-0.037***
	(0.007)
Phase 2 order x December 2014	-0.020***
	(0.003)
Phase 1 order x January 2015	-0.035***
	(0.012)
Phase 2 order x January 2015	-0.033***
	(0.005)
Phase 1 order x February 2015	0.003
	(0.006)
Phase 2 order x February 2015	-0.031***
	(0.003)
Phase 1 order x March 2015	-0.000
	(0.005)
Phase 2 order x March 2015	-0.028***
	(0.003)
Phase 1 order x April 2015	0.008
	(0.007)
Phase 2 order x April 2015	-0.016***
	(0.004)
F-stat	2576.322
R^2	0.671
N	21,759
N customers	$4,\!175$

Notes: First stage results for Tables 2 and 4. Regression includes household and month-year fixed effects, and clusters standard errors at the randomization group level. Phase 1 order runs from 1 to 13, while Phase 2 order runs from 14 to 27. November 2014 is the omitted month for both phases.

	$\operatorname{Base}(1)$	Group IV (2)	$\begin{array}{c} 1.Group_g \text{ IV} \\ (3) \end{array}$	Long panel (4)	DD Postpaid (5)	DD Prepaid (6)
spaid	-1.908^{***} (0.098)	I	Pane	el A: OLS -2.137*** (0.114)	-1.933^{**} (0.081)	-1.852^{***} (0.063)
paid	-1.923^{***} (0.176)	-2.133^{***} (0.267)	Pan -1.930*** (0.142)	lel B: IV -1.715*** (0.256)	-1.852^{***} (0.094)	-1.779^{***} (0.066)
customers onth-year FE	21,759 $4,175$ x	21,759 $4,175$ x	21,759 $4,175$ x	206,470 4,185 x	28,841 5,363 x	223,484 38,060 x

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

panel (from January 2012 to June 2016) and sets the instruments equal to zero outside of the phase-in window. Column 5 adds a comparison group of postpaid customers, not in the project (i.e. never switched), sampled based on property value. Column 6 Notes: Robustness to alternative specifications. The base result (column 1) corresponds to columns 3 and 4 of Panel A in Table 2. Column 2 uses a linear group order variable (i.e., omits the break between phases) interacted with time dummies as instruments. Column 3 uses indicators for each randomization group interacted with time dummies as instruments. Column 4 uses the full adds a comparison group of prepaid customers in the project areas.

	Avg da	ily kWh	Log avg d	aily kWh
	OLS	IV	OLS	ĪV
	(1)	(2)	(3)	(4)
	Panel	A: Phase 1	(Mitchell's I	Plain)
Prepaid	-1.745***	-1.656***	-0.124***	-0.108**
	(0.164)	(0.321)	(0.020)	(0.046)
Wild-bootstrap p	0.000	0.000	[0.000]	[0.100]
R^2	0.000	0.000	0.007	0.007
Ν	$11,\!295$	$11,\!295$	11,269	11,269
N customers	$2,\!240$	$2,\!240$	2,239	2,239
		Panel B:	Phase 2	
Prepaid	-2.077***	-2.222***	-0.132***	-0.122**
	(0.193)	(0.479)	(0.020)	(0.055)
Wild-bootstrap p	0.000	0.000	0.000	[0.100]
R^2	0.022	0.024	0.059	0.058
Ν	10,464	10,464	10,394	10,394
N customers	1,935	1,935	1,929	1,929

Table A.4: Robustness check: By study phase

Notes: Impacts on average daily kWh for the Mitchells Plain sample only (Panel A) and other suburbs (Panel B). Otherwise, specifications follow Table 2.

	$\operatorname{Base}(1)$	Switchers only (2)	No debt recovery (3)	Trimmed (4)	Smoothed (5)	Balanced (6)
Prepaid	-1.908^{**} (0.098)	-1.889^{***} (0.108)	Panel A: OL' -1.922*** (0.104)	S -1.883*** (0.094)	-1.974*** (0.095)	-1.891^{***} (0.098)
Prepaid	-1.923*** (0.176)	-1.968^{***} (0.153)	Panel B: IV -1.928*** (0.182)	-1.898*** (0.160)	-1.973^{***} (0.171)	-1.923^{***} (0.176)
N N customers Month-year FE	21,759 4,175 x	16,256 3,238 x	21,326 $4,165$ x	21,420 4,150 x	21,664 4,168 x	21,768 4,175 x

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

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

	Base	Tariff error	Consolidated bills	Placebo test
	(1)	(2)	(3)	(4)
		Pa	anel A: OLS	
Prepaid	-1.908***	-2.044^{***}	-1.537***	-0.004
	(0.098)	(0.110)	(0.126)	(0.100)
		F	Panel B: IV	
Prepaid	-1.923***	-2.128***	-1.448***	-0.053
	(0.176)	(0.183)	(0.244)	(0.155)
Ν	21,759	$17,\!141$	$7,\!441$	20,792
N customers	$4,\!175$	$3,\!252$	$1,\!426$	4,014
Month-year FE	Х	х	Х	х

Table A.6: Robustness checks (average daily kWh)

Notes: Robustness to project implementation issues. The base result (column 1) corresponds to columns 3 and 4 of Panel A in Table 2. Column 2 drops customers with tariff mistakes. Column 3 limits the sample to customers receiving a separate electricity bill prior to the project. Column 4 implements a placebo check that moves the instrument and switch date to one year earlier.

			OL	OLS		
	N oust	Maan	Total effects	Difference	Total effects	Difference
	n cust	mean	(1)	(2)	(3)	(4)
Domestic	2.857	17.34	-0.133***	0.055^{**}	-0.146^{***}	0.086^{*}
Domestic	2,001	11.01	(0.013)	(0.025)	(0.015)	(0.048)
Lifeline	1.294	9.74	-0.078***	[0.000]	-0.060	[0.100]
	-,-0 -	0111	(0.020)		(0.044)	
			0 1 40***	0.044**	0 150***	0.071**
Above median kWh	2,111	19.86	$-0.142^{+0.1}$	0.044^{**}	-0.159^{+++}	0.071^{**}
			(0.010)	(0.018)	(0.015)	(0.033)
Below median kWh	2,040	9.93	-0.098	[0.100]	-0.089^{+++}	[0.000]
			(0.017)		(0.050)	
			-0 106***	-0 043**	-0 100***	-0.068**
High prop value	1,464	17.29	(0.014)	(0.016)	(0.024)	(0.030)
			-0.149***	[0.100]	-0.169***	[0.000]
Low prop value	$2,\!687$	13.71	(0.011)	[0.200]	(0.018)	[0.000]
					()	
	0.000	12.07	-0.116***	-0.032*	-0.128***	-0.023
Usually on time	2,083	13.97	(0.012)	(0.016)	(0.018)	(0.031)
Hanally late	2 069	15.07	-0.148***	[0.000]	-0.151***	[0.300]
Usually late	2,008	10.97	(0.014)		(0.025)	
No debts	3 090	15.02	-0.126***	-0.025	-0.140***	-0.001
	0,000	10.02	(0.010)	(0.018)	(0.018)	(0.050)
Outstanding debts	1.061	14.80	-0.151***	[0.100]	-0.141***	[1.000]
	1,001	1 1.00	(0.019)		(0.044)	
			0 196***	0.017	0 1 4 6 * * *	0.091
Never disconnected	3,324	14.88	$-0.130^{-0.0}$	0.01($-0.140^{-0.17}$	(0.051)
			(0.009)	(0.032)	(0.017)	(0.031)
Ever disconnected	827	15.32	$-0.118^{-0.01}$	[0.300]	-0.114	[0.500]
			(0.051)		(0.047)	

Table A.7: Heterogeneous treatment effects (log average daily kWh)

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

	Lifeline	Low kWh	Low prop value	Usually late	Unpaid bills	Disconnected	PP transactions
Lifeline	H			þ.	ĸ		
Low kWh	0.611^{***}	1					
Low prop value	0.221^{***}	0.220^{***}	1				
Usually late	-0.118^{***}	-0.144^{***}	0.0228	1			
Unpaid bills	-0.00941	0.0190	0.0849^{***}	0.313^{***}	1		
Disconnected	-0.0778***	-0.0458^{**}	-0.0441^{**}	0.349^{***}	0.298^{***}	1	
PP transactions	-0.211^{***}	-0.232***	0.114^{***}	0.278^{***}	0.158^{***}	0.228^{***}	1

Table A.8: Correlation between heterogeneity variables

by the pre-project period unless otherwise noted. Lifeline equals one for customers primarily on Lifeline tariff. Low kWh equals 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 Notes: Pairwise correlations of variables used in the heterogeneity analysis, at the customer level. All characteristics are defined one if the average daily kWh measure is below the median. Low prop value equals one for customers with a 2012 ZAR property customers that were ever disconnected on postpaid. PP transactions is the customer average number of prepaid purchases per month for all months that the customer was on a prepaid meter.

	Average returns	Relative returns
	Postpaid	Pre / Post
Domestic	25	1.21
		(0.03)
Lifeline	4	2.03
		(0.51)
Above median kWh	29	1.17
		(0.03)
Below median kWh	7	1.62
		(0.20)
High prop value	26	1 18
ingii prop value	20	(0.04)
Low prop value	14	1 25
Low prop value	11	(0.07)
Usually on time	19	1.01
		(0.03)
Usually late	17	1.47
		(0.07)
No debts	22	0.94
		(0.02)
Outstanding debts	7	4.81
o accounting accou		(0.71)
Never disconnected	20	1.14
		(0.03)
Ever disconnected	13	1.81
		(0.24)

Table A.9: Heterogeneity in returns to prepaid metering

Notes: Returns to prepaid metering relative to postpaid metering, by customer characteristic. See Figure 5 for further detail.

B.1 Additional details on the bunching analysis

This appendix describes in greater detail the bunching analysis discussed in Section IV. It then lays out a simple decomposition of the change in consumption resulting from the metering switch into the share that might be explained by the change in marginal price sensitivity and the share associated with other channels.

B.1.1 Bunching analysis

The bunching analysis includes Lifeline tariff customers only; they face a considerably larger price increase at their main tariff step (almost 250 percent increase in the marginal price) than do Domestic tariff customers (20 percent increase in the marginal price), and correspondingly show some visual evidence of bunching, while Domestic tariff customers do not. Only customers switched through the metering replacement project are included in the sample used to estimate elasticities.

We use data from the 2013 billing year (July 2013 to June 2014), when all customers were on postpaid metering, and data from the 2015 billing year (July 2015 to June 2016), when all customers were on prepaid metering. For each billing year, we construct 10 kWh bins of monthly consumption, and count the number of customer-month observations that fall in each bin. Collapsing the data to the bin level, we construct the counterfactual distribution of consumption by regressing the customer count per bin on a polynomial in the bin order, omitting the bunching window around the tariff step. Our baseline specification uses a 7th order polynomial and a widow of 40 kWh to the right of the tariff step based on the visual evidence and the proposed mechanism for price feedback discussed in the main text. We conduct robustness checks on both of these modeling decisions.

The excess mass in the bunching window in the observed distribution has to be drawn from elsewhere in the counterfactual distribution, i.e., the integral of the counterfactual and observed distributions should be equal. Since we lack a clear theory to determine from where in the counterfactual distribution the excess mass is drawn, we satisfy the integration constraint by iteratively increasing the counterfactual distribution by a uniform amount for each bin until the constraint is satisfied. An alternative approach that increases the counterfactual distribution proportional to the share of the observations that fall in each 10 kWh bin results in similar estimates, but a less close visual match to the histograms than the uniform approach.

The excess mass, ΔB , in the bunching window is calculated as the difference between the mass under the observed and the counterfactual distributions. The additional mass at the tariff step is informative of customers' sensitivity to the change in price at that tariff step. We convert the corresponding response as an elasticity, $\varepsilon = \frac{\%\Delta B}{\%\Delta p}$. Standard errors are constructed by block bootstrapping the elasticity (and excess mass) calculations; in this case, the sampling error is associated with the estimation of the counterfactual distribution. As discussed in the main text, a change in price sensitivity across metering types may arise from a difference in marginal price elasticity or from a change in optimization frictions.

We repeat this procedure using five different bunching window widths and three different polynomial orders. Results are summarized in Table B.1, which includes the test statistic for equal means in the postpaid and prepaid samples, for both the excess mass measure and the elasticity estimate. Results are largely robust to these different parameter choices, though the estimated marginal price elasticity on prepaid metering shrinks as the bunching window increases.

B.1.2 How much of the change in q can be explained by the change in price sensitivity?

We are interested in how a difference across metering types in sensitivity to marginal prices, measured at a single point on the tariff schedule, relates to an overall change in demand as estimated by the prepaid metering experiment. We implement a highly simplified calibration exercise to provide a quantitative benchmark.² Assume a point elasticity of demand $\varepsilon = \frac{p}{q} \times \frac{\partial q}{\partial p}$. We are interested in the relationship between a change in ε and a change in q, holding p constant.

 $^{^{2}}$ We abstract from heterogeneity in demand by ignoring any component of demand not driven by sensitivity to marginal prices. Assuming that these other aspects of demand do not vary with metering type, we take the difference in sensitivity to marginal prices as our starting point.

$$\varepsilon_1 - \varepsilon_0 = \left(\frac{p_1}{q_1} \times \frac{\partial q_1}{\partial p_1}\right) - \left(\frac{p_0}{q_0} \times \frac{\partial q_0}{\partial p_0}\right)$$

With $p = p_1 = p_0$, this becomes

$$\varepsilon_1 - \varepsilon_0 = \frac{p}{\partial p} \left(\frac{\partial q_1}{q_1} - \frac{\partial q_0}{q_0} \right) = \frac{p}{\partial p} \times \ln(\frac{q_1}{q_0}).$$
 (B.1)

To calibrate the share of the change in quantity that can be explained by the change in ε , we take our empirical point estimates and plug them into (B.1), adding the scalar α to the righthand side, to account for the share of the total change potentially explained by the change in elasticities (lefthand side).

$$-0.121 - 0.001 = \alpha \left(\frac{p}{\partial p} \times \ln(\frac{13}{15}) \right)$$
$$-0.122 = \alpha \left(-0.14 \times \frac{p}{\partial p} \right)$$

The lefthand side is the observed change in price elasticity, while the righthand side is the observed change in quantity multiplied by $\frac{p}{\partial p}$. Taking the price change associated with the tariff step as $\frac{p}{\partial p} = \frac{0.18}{0.104} = 1.7$, we get $\alpha = 0.51$, implying that the change in elasticity associated with greater price salience may account for up to 51 percent of the overall decline in consumption that we observe.

Note that this exercise uses marginal price elasticities estimated off of a discrete price jump at 350 kWh (and the associated price jump) to explain differences in average consumption (i.e. not local to 350 kWh). Furthermore, the marginal price elasticities are calculated for the subset of Lifeline tariff customers only. Using these marginal price elasticities to interpret changes in average consumption effectively assumes that the marginal price elasticities can be generalized to other points along the tariff schedule. A more sophisticated model would consider cumulative demand, whether customers anticipate their final marginal price when making consumption decisions early in the month, and other factors. Whether this calibration reflects an over- or under-estimate of the true fraction of the overall demand response explained by a change in sensitivity to marginal prices depends on the joint distribution of (differential) marginal price elasticities and demand.

		Ex	cess mass		I	Elasticity	
Window	Polynomial	Postpaid	Prepaid	T-stat	Postpaid	Prepaid	T-stat
		(1)	(2)	(3)	(4)	(5)	(6)
20	5	0.065	0.263	2.201	-0.049	-0.150	-1.810
		(0.043)	(0.079)		(0.033)	(0.045)	
20	7	0.024	0.249	2.315	-0.018	-0.142	-2.000
		(0.039)	(0.084)		(0.030)	(0.048)	
20	9	0.009	0.233	2.346	-0.006	-0.133	-2.081
		(0.040)	(0.084)		(0.030)	(0.048)	
30	5	0.042	0.256	2.502	-0.031	-0.145	-2.194
		(0.035)	(0.063)		(0.027)	(0.036)	
30	7	0.002	0.256	2.682	-0.002	-0.146	-2.389
		(0.033)	(0.067)		(0.025)	(0.038)	
30	9	-0.015	0.244	2.806	0.011	-0.139	-2.530
		(0.033)	(0.068)		(0.025)	(0.039)	
40	5	0.037	0.203	2.702	-0.028	-0.115	-2.431
		(0.030)	(0.074)		(0.022)	(0.042)	
40	7	-0.002	0.212	2.704	0.001	-0.120	-2.449
		(0.027)	(0.074)		(0.021)	(0.042)	
40	9	-0.021	0.200	2.716	0.016	-0.114	-2.487
		(0.029)	(0.073)		(0.022)	(0.041)	
50	5	0.040	0.177	2.615	-0.030	-0.100	-2.388
		(0.026)	(0.076)		(0.019)	(0.043)	
50	7	0.004	0.190	2.591	-0.003	-0.108	-2.374
		(0.025)	(0.075)		(0.019)	(0.043)	
50	9	-0.014	0.182	2.588	0.010	-0.104	-2.382
		(0.027)	(0.072)		(0.021)	(0.041)	
60	5	0.029	0.140	2.493	-0.022	-0.080	-2.292
		(0.025)	(0.078)		(0.019)	(0.044)	
60	7	-0.005	0.161	2.462	0.004	-0.092	-2.272
		(0.024)	(0.077)		(0.018)	(0.044)	
60	9	-0.025	0.153	2.439	0.019	-0.087	-2.263
		(0.028)	(0.079)		(0.021)	(0.045)	

Table B.1: Bunching mass and elasticity estimates

Notes: Robustness checks on the bunching window and polynomial order used to calculate bunching mass (columns 1 and 2) and marginal price elasticities (columns 4 and 5). The t-statistics are associated with a test of equal means based on the bootstrapped standard errors associated with the mass and elasticity estimates.

C.1 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.

C.1.1 Data sources and dataset construction

The City of Cape Town maintains billing records for any property served Billing records or taxed by the municipality. As discussed in the main text, most customers 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).² 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).

²Estimates 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.

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.

Customers purchase electricity frequently: the median frequency is every 3.3 days. Out of over 50,000 customer-month observations on prepaid metering in the full panel, 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 customers 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, meters in the randomization file for which we do not have any observations during the phase-in window (November 2014 and April 2015) were dropped from the sample.

C.1.2 Variables

• Average daily kWh: We construct an average daily kWh variable at the customermonth 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.

- Revenue due: 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.
- Time to pay: We construct a variable that describes the months 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.³ 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 supply 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

 $^{^{3}}$ 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.

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 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.