

# Leaping or creeping up the energy ladder? Electricity diffusion in a rural African setting

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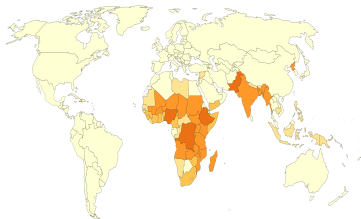
<sup>4</sup>UCT and DataFirst

This work was supported by the IGC.

# Modern energy access and use is limited in LICs

## Number of people without access to electricity, 2019

The definition used in international statistics adopts a very low cutoff for what it means to 'have access to electricity'. It is defined as having an electricity source that can provide very basic lighting, and charge a phone or power a radio for 4 hours per day.



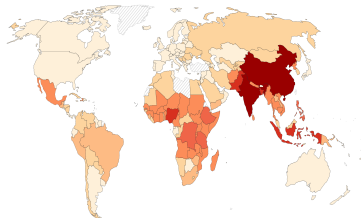
No data 0 1 million 5 million 10 million 50 million 100 million 500 million 1 billion

Source: Calculated by Our World in Data based on the World Bank

OurWorldInData.org/energy • CC BY

## Number of people without access to clean fuels for cooking, 2016

Clean cooking fuels and technologies represent non-solid fuels such as natural gas, ethanol or electric technologies.



No data 0 1 million 5 million 10 million 50 million 100 million 500 million 1 billion

Source: Calculated by Our World in Data based on the World Bank

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- ▶  $\approx 1$  billion lack access to electricity
- ▶ Even more need cleaner fuels

# Push for universal access is speeding up

- ▶ **Goals:** SDG7 “Access to affordable and clean energy” by 2030
- ▶ **Initiatives:** PowerAfrica (USAID), SEForAll (UN), Lighting Africa (World Bank), Renewable Energy Performance Platform (UK), China’s BRI
- ▶ **Finance:** \$ 8.5bn Just Energy Transition finance for South Africa, more for Vietnam, Indonesia and others
- ▶ Grid, some mini-grid, some off-grid, focus on clean energy finance

# How fast can modern energy plausibly change rural areas?

## Mixed messages from the literature

- ▶ No/small changes in SR (2-5 years)
  - ▶ e.g. *Burlig and Preonas 2022; Lee, Miguel, Wolfram 2020; Dinkelman 2011*
- ▶ Transformative effects in LR (20-100 years)
  - ▶ e.g. *Fried and Lagakos 2021; Lipscomb, Barham and Mobarak 2017; Kline and Moretti 2014; Rud 2012*

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- ▶ Transformative effects in LR (20-100 years)
  - ▶ e.g. *Fried and Lagakos 2021; Lipscomb, Barham and Mobarak 2017; Kline and Moretti 2014; Rud 2012*
- ▶ Missing link? **Transition dynamics**

# Do rural households leap up or creep up the energy ladder?

## This paper:

1. Estimate # of years before rural households in South Africa meaningfully respond to community-level electrification
  - ▶ Parameter of interest: **Median time-to-adoption.**
  - ▶ How many years until half of the village has adopted productive electrical appliances?
2. Test whether income (level, composition) hastens adoption and transition to electricity use

Empirical approach: Duration analysis (survival models) using 15 years of longitudinal data capturing household-level appliance adoption.

# Contributions

1. **Technology adoption** in developing countries: focus on ag. tech, health tech., info/financial tech. Now home tech.
  - ▶ e.g. *Mobarak and Saldahna (2022)*
2. **Adoption in the Environmental literature:**
  - ▶ Clean(er) cookstoves/clean(er) fuel: credit constraints vs behavioural biases  
e.g. *Berkouwer and Dean (2022)*
  - ▶ Energy ladder: role of income  
e.g. *Gertler, Shelef, Wolfram, Fuchs (2016)*,  
*Hanna and Oliva (2015)*
3. **Unique Data and Setting for SSA:** the only longitudinal data covering this length of time, spanning mass electrification event

# Outline

- ▶ Rural electrification in South Africa
- ▶ Study Site and Main Data: Agincourt Health and Demographic Surveillance Site (HDSS)
- ▶ Empirical approach and parameter of interest
- ▶ Additional Data
- ▶ Summary statistics
- ▶ Results
  - ▶ Time-to-adoption
  - ▶ MFX of income, by sources of income
  - ▶ Probing why income composition may matter



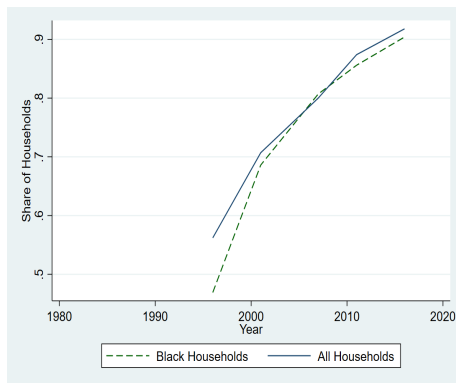
Caveat: This is not a paper about loadshedding

# South Africa's National Electrification Program (NEP)

- ▶ 1990s + 2000s: Heavily subsidized electricity connections rolled out at village-level, “best-case” for growing energy access in SSA  
*Dinkelman (2011), Gaunt (2003)*
- ▶ Eskom connections were free, low capacity (20Amps), pre-paid meters
- ▶ Until recently, costs of electricity were relatively low

Monthly cost of appliances over time

Per kWh cost of electricity over time

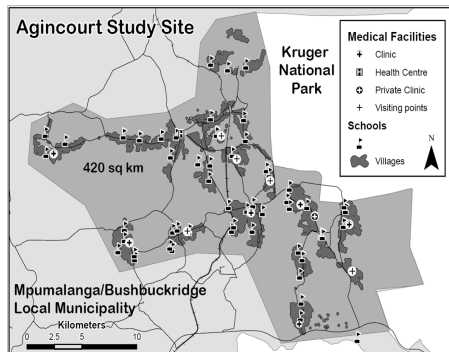


**Share of HHs with electricity**

Source: SA Census data

# Study Setting: Agincourt

- ▶ BBM: border of MP and Limpopo, Kruger Park
- ▶ Agincourt: villages in former homeland Gazankulu
- ▶ Densely populated, rural, poor: median monthly HH exp. in 2001 was \$155
- ▶ 1/3rd self-identify as Mozambican refugees from pre-1992
- ▶ Temporary labour migration to cities is very common
- ▶ Village-level electrification through NEP starts early 1990s



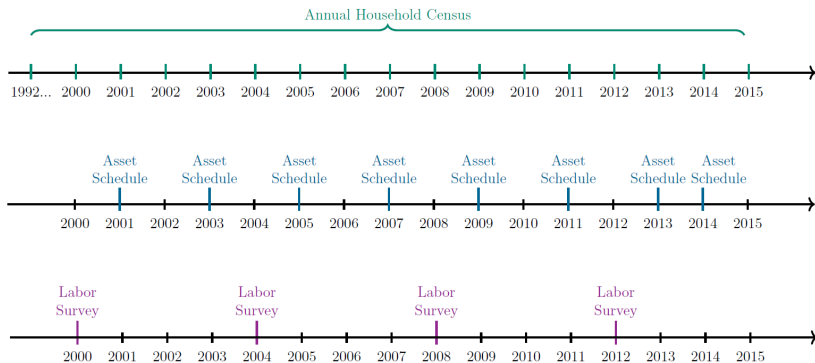
# Key Dataset: The HDSS

## **Agincourt Health and Socio-Demographic Surveillance System (HDSS)** run by Wits/SAMRC.

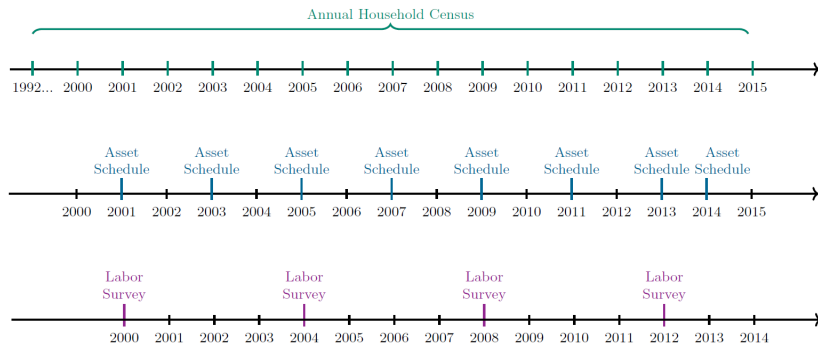
A DSS provides **Census-level coverage** of all households in specified geographic area: births, deaths, in- and out-migrations.

- ▶ 1992: 60K individuals, 8.8K HHs, 21 villages
- ▶ 2023: 230K individuals, 30K HHs, 36 villages
- ▶ People, HHs, move in and out of area - no survey attrition, natural churn is low, 2-5% per year Churn
- ▶ **Asset modules** biannually 2001-2013, then annually; track households to 2014
- ▶ **Labor modules** every four years from 2000-2014
- ▶ Follow original 1992 villages until 2014, years that span grid rollout of Eskom-subsidized connections

# Data structure



# Data structure



# Building a HH panel dataset

The HDSS is organized as a series of events. Converting to (unbalanced) panel data structure of HHs is not straightforward.\*

Consequential for our analysis:

- ▶ "flatten" the dataset on 30 November each year
- ▶ treat 2001 as baseline
- ▶ omit villages entering later
- ▶ match HH asset schedules to HH in 2001, 2003 etc
- ▶ generate HH worker data to match with households in years 2001, 2005, 2009, 2013
- ▶ match community-level information to villages
- ▶ match HHs over time: HHID and demographics

\*Martin Wittenberg, Mark Collinson, Taryn Dinkelman, Cho Kabudula, Takwanisa Machemedze, Wayne Twine, Kathleen Kahn and Stephen Tollman. 2020. "The Agincourt HDSS Energy Panel Dataset User Guide, Version 1"

# Thought experiment

Electricity arrives (exogenously) in your village and everyone gets a free connection.

How many years until *you* start adopting electrical appliances (e.g. stove)?

How many years until half of the village has adopted?



# Empirical approach: Duration analysis (1)

## Definitions:

- ▶  $t_0$  = year electricity arrives
- ▶ random variable  $t = T_{adopt} - t_0$  The number of years w/o stove
- ▶ always adopters:  $T_{adopt} = 0$ , left-censored
- ▶ never adopters:  $T_{adopt} = t_{max}$ , right-censored

**Problem:** Censoring leads to bias in OLS

# Empirical approach: Duration analysis (1)

For any time  $t$ , among the set of households still without a stove, what is the probability of remaining (surviving) in the non-stove state?

- **Kaplan-Meier Survivor Functions** (non-parametric):

$$S(t) = Pr(T_{adopt} \geq t)$$

$$\hat{S}(t) = \prod_{k|t_j < t} (1 - \hat{h}_k) \quad (1)$$

where

$$\hat{h}_k = \frac{\#HHadoptingat k}{\#HHatriskatk} \quad (2)$$

# Empirical approach: Duration analysis (1)

- ▶ **Median Survival Time:**  $t^* = S^{-1}(0.5)$   
number of periods until **half** of the sample has adopted a stove, or when the KM survivor function evaluates to 0.5

## Empirical approach: Duration analysis (2)

**Adding observables:** What is the probability of adopting a stove in the next period, conditional on not having adopted up to time  $t$ ?

- **Cox Proportional Hazards model** (semi-parametric):

$$Pr(stove_t | no\_stove_{t-1}) = h(t; X_i) = h_0(t) * e^{X_i \beta}$$

$h_0$  = baseline hazard

**Median time-to-adoption conditional on X's:**

$$t^*(\bar{X}_i) = S^{-1}(0.5; \bar{X}_i)$$

Key observables: measures of income. But HDSS does not measure income.

## Additional Data: Imputed earnings, income

**Key question:** the role of income in adoption; the cost of speeding up use of electricity.

Measure total *baseline* HH earnings when HH first enters the dataset:

**Total HH income = remittances + social grants + labor market earnings**

- ▶ Dummy variables for any income source
- ▶ Continuous variables, imputed

# Remittances

- ▶ **Temporary Migrants:** annual records in HDSS
- ▶ **Remittances:** actual remittances (ideal). For now: impute average monthly remittance values (ZAR) for male and female temporary migrants, aggregate to HH

Mean monthly remittances (ZAR)			
Temp. migrant	2001	2008	2013
Male	471	662	1,115
Female	310	501	837

Source: Collinson and Biyase 2021

# Social Grants

**Social grants:** Eligibility based on age at baseline, aggregated to HH level

- ▶  $Eligible_{ij}^g$  dummies for individual  $j$  in HH  $i$  eligible for social grant type  $g = [\text{child support; pension}]$  with value  $G$
- ▶ Impute Household  $i$ 's total potential income from social grants:

$$ExpSocialGrants_i = \sum_g \sum_{j=1}^J G^g * 1[Eligible_{ij}^g]$$

# Labor market earnings

- ▶ **Job type**, HDSS: 2001 industry, occupation, public/pvt sector
- ▶ **Earnings**, PALMS: earnings by industry and occupation



# Labor market earnings

- ▶ **Job type**, HDSS: 2001 industry, occupation, public/pvt sector
- ▶ **Earnings**, PALMS: earnings by industry and occupation
  - ▶ Restrict to rural MP; compute 2001 average earnings by industry/occupation
  - ▶ Match to HDSS workers using 2001 industry/occupation group
  - ▶ Aggregate to HH-level
  - ▶ Impute mean earnings for missing data, include missing indicators
- ▶ **Note**: separate public and private sector workers

# Distribution of private and public sector earnings in 2001

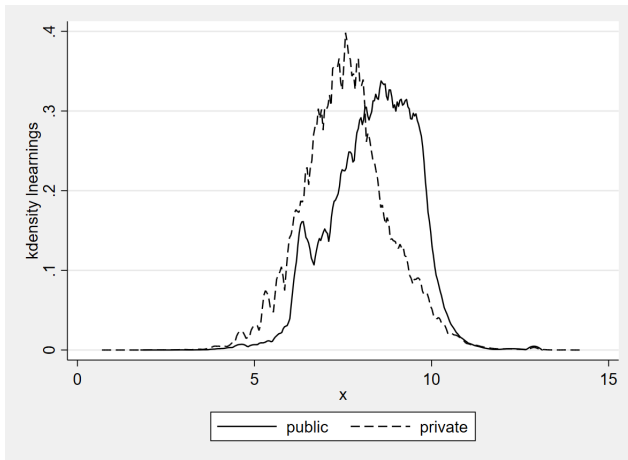


Figure: PALMS data

Public sector work: higher mean, lower variance

## Final data piece: Village connection date

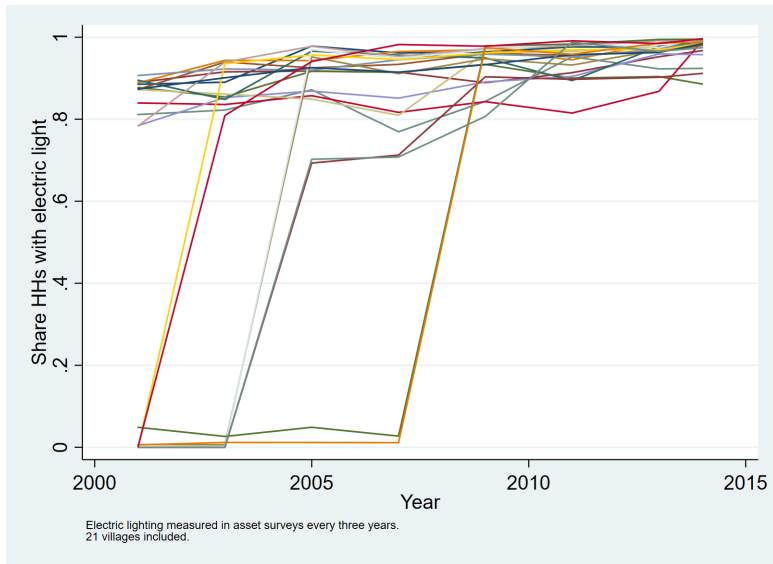
Key outcome:  $t = T_{adopt} - t_0$ , num. years without a stove (fridge, TV, electric cooking).

Ideal definition:  $t_0$  is when electricity arrived in the village.

Challenge: measuring  $t_0$  in the absence of administrative data?

Two ways to measure...

## (1) Date when village lighting is above 85%



Share of HHs using electric light, one line per village

## (2) Crowd-sourced data

Data on village-level electrification:

- ▶ Focus group discussions (FGD) with communities (Aug 2022):  
Thanks to excellent field work by **Sizzy Ngobeni** and **Sydwell Mathebula**
- ▶ Crowd-sourced recollections of when electricity arrived in the village
- ▶ Reported by local chiefs, leaders
- ▶ Matched to survey data on village names

## Two measures of time-to-adoption

1.  $t^1 = T_{adopt} - \min(t : t_{lightshare} \geq 85\%)$

Downside: exclude left-censored HHs.

Upside: four “late electrified” villages have accurate  $t_0$ .

2.  $t^2 = T_{adopt} - t_{FGD}$  where  $t_{FGD}$  is electrification year reported by community leaders, in FGD villages.

Most villages have  $t_{FGD} < \min(t : t_{lightshare} \geq 85\%)$

Upside: bring back left-censored HHs under assms; bounds.

Downside: can't estimate impact of baseline covariates.

# Sample of villages

- ▶ Exclude villages new to the DSS in the late 2000s (e.g. RDP villages)
- ▶ Include original 21 villages
  - ▶ 17 villages already electrified by 2000: Early Connected
  - ▶ 4 villages get electrified after 2000: Late Connected
  - ▶ Results for complete sample and subset of Late Connected

# Baseline characteristics: HH energy sources and Appliances

	Mean	SD	N
<i>Lighting Source</i>			
<b>Electricity</b>	0.77	0.42	9836
Candles	0.15	0.36	9836
Paraffin	0.07	0.26	9836
Battery	0.00	0.03	9836
Solar	0.00	0.02	9836
<i>Cooking Fuel</i>			
<b>Electricity</b>	0.16	0.37	9836
Wood	0.74	0.44	9836
Paraffin	0.07	0.26	9836
Gas	0.02	0.15	9836
Other	0.00	0.07	9836
<i>Electrical Appliances</i>			
<b>Stove</b>	0.44	0.50	9835
Fridge	0.43	0.50	9835
TV	0.55	0.50	9836
Video	0.06	0.25	9829
Radio	0.42	0.49	9834
Cellphone	0.37	0.48	9835



## Baseline characteristics: HH characteristics

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	Mean	SD	N
Num. Modern Attributes	3.76	1.23	9836
Female HH [0/1]	0.36	0.48	9836
Refugee HH [0/1]	0.25	0.43	9836
HH size	4.88	3.31	9836
Any Temporary Migrant	0.56	0.50	9836
Any Govt. Job	0.14	0.34	9836
Any Private Job	0.67	0.47	9836
No Job(s)	0.21	0.41	9836
Any Social Grant Eligible	0.75	0.44	9836

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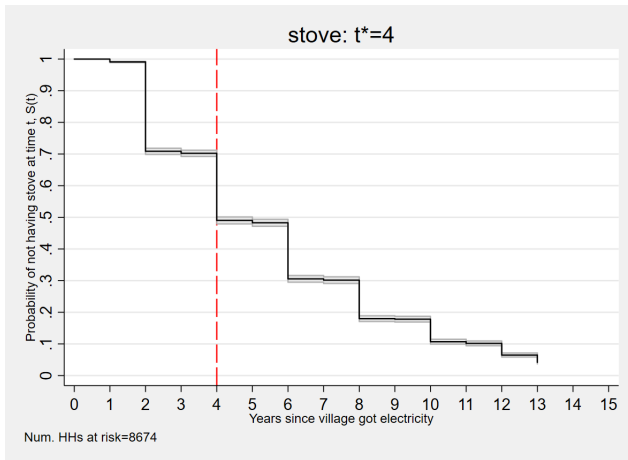
## Baseline characteristics: HH characteristics

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	Mean	SD	N
<b>HH cons. per month (ZAR)</b>	1291.36	763.34	9836
Pot. CSG+Pensions	316.06	357.36	9836
Imputed remittances	133.12	277.11	9836
Earnings, Public Sector Worker(s) (ZAR)	367.03	1154.50	9836
Earnings, Private Sector Worker(s) (ZAR)	877.09	881.40	9836
<b>Earnings, All Worker(s) (ZAR)</b>	1244.11	1368.58	9836
Total Income	1693.30	1471.92	9836
Missing Total Earnings	0.06	0.23	9836

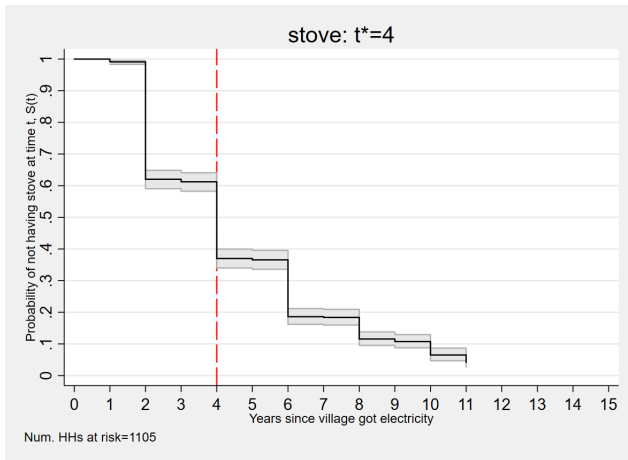
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## Results(1a): Time-to-adoption of stoves ( $t^1$ ), all villages



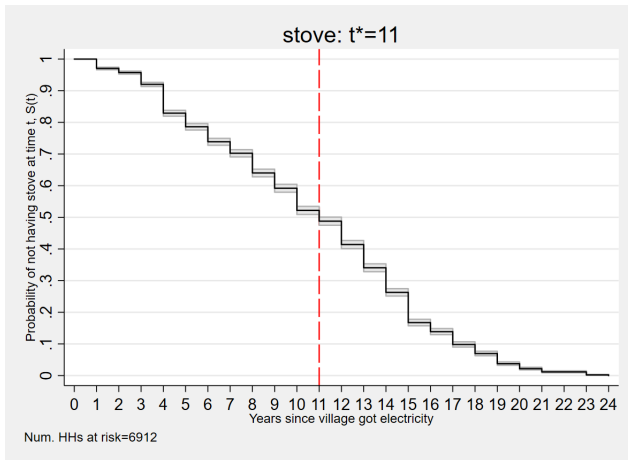
*Notes:* Kaplan-Meier estimates. Red line marks median time to adoption. Grey areas are pointwise C.I.

## Results(1b): Time-to-adoption of stoves ( $t^1$ ), only new elec. villages



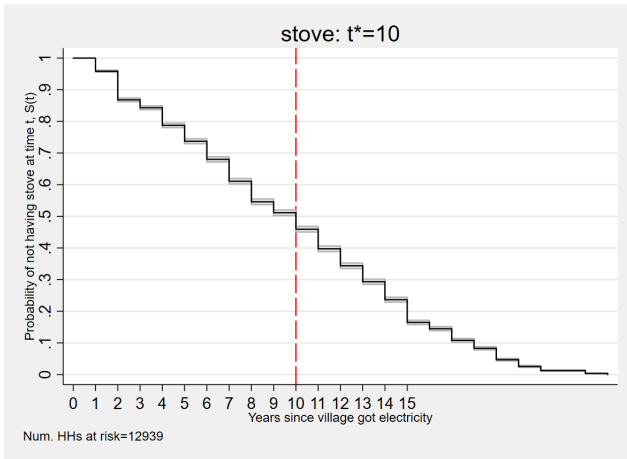
*Notes:* Kaplan-Meier estimates. Red line marks median time to adoption. Grey areas are pointwise confidence intervals.

## Results(1c): Time-to-adoption of stoves ( $t^2$ ), all villages, sample w.o. stoves at entry



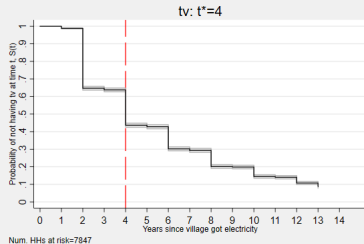
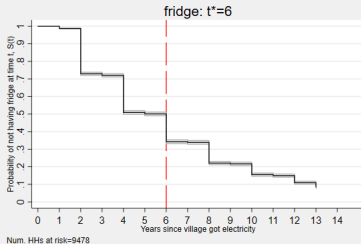
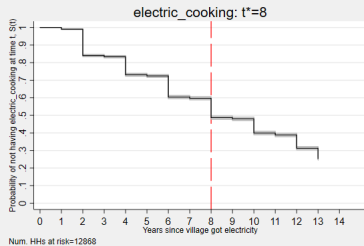
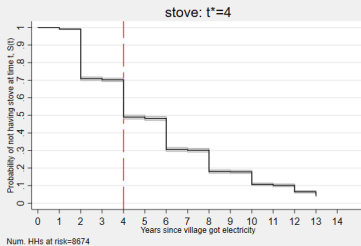
Notes: Kaplan-Meier estimates. Red line marks median time to adoption. Grey areas are pointwise confidence intervals.

## Results(1d): Time-to-adoption of stoves ( $t^2$ ), all villages, imputed for left-censored outcomes



*Notes:* Kaplan-Meier estimates. Red line marks median time to adoption. Grey areas are pointwise confidence intervals.

# Time-to-adoption ( $t^1$ ): other appliances, all villages



Notes: Sample includes all villages , and all HHs in these villages first observed without the appliance.

**Notes:** Red line marks median time to adoption. Grey areas are pointwise confidence intervals.

# Main result (1): Adoption is slow for all appliances

1. Households are creeping, not leaping, up the energy ladder: even with free connections and subsidised/free electricity
2. Long median adoption lags (and hence potential impacts): 4-11 years US benchmark
3. Inexact connection date underestimates adoption lags: all vs late villages;  $t^1$  vs  $t^2$
4. Grid access  $\neq$  adoption, adoption  $\neq$  use: stove adoption vs primary electric cooking



## Results (2): Time-to-adopt: Cox model for Stove

	(1) All Villages	(2) New Villages
HH size	-0.008** (0.003)	0.002 (0.007)
Female Head [0/1]	-0.047*** (0.017)	-0.009 (0.030)
N. Modern Attributes	0.174*** (0.012)	0.158*** (0.026)
Refugee Head [0/1]	-0.238*** (0.050)	-0.183** (0.086)
Any Grant(s)	0.485*** (0.141)	0.654*** (0.219)
Temp. Migrant(s)	0.080*** (0.028)	0.053 (0.065)
Any Govt. Job(s)	0.157*** (0.050)	0.167** (0.065)
Any Private Job(s)	-0.111*** (0.037)	-0.020 (0.113)
Observations	8674	1105
Test P Value Govt = Public	0	0

All controls measured in 2001. New villages are not connected to the grid in 2001. Village indicators for 21 villages included. Standard errors are robust and clustered at the village level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

## Results (2): Time-to-adopt: Cox model for Stove

	(1) All Villages	(2) All Villages	(3) New Villages	(4) New Villages
HH size	-0.006* (0.003)	-0.005* (0.003)	0.001 (0.008)	0.003 (0.006)
Female Head [0/1]	-0.032** (0.016)	-0.038** (0.019)	0.016 (0.038)	0.013 (0.036)
N. Modern Attributes	0.173*** (0.012)	0.175*** (0.012)	0.163*** (0.026)	0.165*** (0.025)
Refugee Head [0/1]	-0.227*** (0.048)	-0.236*** (0.047)	-0.191** (0.085)	-0.189** (0.081)
Public Sector Earnings	0.108*** (0.016)		0.019** (0.009)	
Private Sector Earnings	-0.018 (0.018)		0.016 (0.030)	
Monthly Potential Grants	-0.069* (0.040)		0.020 (0.117)	
Total Remittances	0.020 (0.040)		-0.034 (0.156)	
Total Income		-0.015 (0.015)		0.005 (0.011)
Share of Public Earnings		0.316*** (0.076)		0.098 (0.077)
Observations	8674	8674	1105	1105
Test P Value Govt = Public	0		.9	

All controls measured in 2001. New villages are not connected to the grid in 2001. Village indicators for 21 villages included. Standard errors are robust and clustered at the village level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

# How much does median $t^*$ change conditional on earnings?

- ▶ Evaluate survival functions for 0 and mean government earnings; compute  $\Delta t^*$
- ▶ Mean government earnings ( $\simeq$  average social grants, ZAR360/month or USD300/year) shrink median  $t^*$  of fridges by 2 years, median  $t^*$  of electric cooking in new villages by 1 year. No effect on  $t^*$  for stoves, TVs.
- ▶ Significant impacts of public sector earnings at HH-level; BUT too few govt jobs overall to significantly shift  $t^*$

## Main Results (2): Income hastens adoption (sometimes)

1. Earnings/access to local labor market income (sometimes) speeds up adoption
2. Even in best-case scenario – grid connections paid for, highly-subsidized subsidized electricity – may only see meaningful impacts of rural electrification over 5-10 year horizon.
3. Implications for research design: data over the longer run is essential
4. **Source** of earnings matters: public sector jobs in HH speed up adoption relative to private sector jobs. Why?

# Why do public sector earnings matter for adoption?

- ▶ Income levels? Households w/ public sector earnings earn more, can overcome credit constraints and self-finance? (Gertler et al 2016). Large documented public sector wage premia e.g. Finan, Olken, and Pande (2017), 40%+ in SA, Kerr and Wittenberg (2017).
- ▶ Income certainty? Earnings from public sector jobs more certain on two dimensions: longer-lasting job (long tenure e.g. Farber 2010), and more rigid wage schedules
- ▶ Preferences?

# Public vs private sector jobs: Tenure and job security in BBM

$$JobFeature_{it} = \alpha_0 + \alpha_1 * PublicSector_{it} + X_{it}\lambda + W_t\gamma + \epsilon_{it}$$

**Table: Job tenure and job security, PALMS data for BBM 1993-2019**

	(1) Tenure	(2) Tenure	(3) Written Contract	(4) Written Contract
Public sector empl.	6.759*** (0.305)	4.858*** (0.303)	0.321*** (0.019)	0.235*** (0.021)
Observations	2737	2737	2714	2714

Data are from the Post-Apartheid Labour Market Series (PALMS) data (version 3.3) Year indicators are included as controls in all regressions. Every second regression specification includes age, age2, female, years of education, and race group dummies. Robust standard errors. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

# Why would income certainty matter for adoption?

Stores widely provide credit in this area:

26% of households in the Agincourt Integrated Household Survey 2002 reported buying appliances on “hire purchase” (store credit)

# Do public sector workers use more credit?

$$AnyCredit_i = \alpha_0 + \alpha_1 * PublicSector_i + X_i\lambda + \epsilon_i$$

**Table: Differences between public sector and private sector jobs (OLS): IES data 2000/2001**

	(1) Any Credit	(2) Any Credit
public	0.084*** (0.010)	0.063*** (0.011)
private	0.046*** (0.008)	0.003 (0.018)
Observations	26265	25186

Data are from the Income and Expenditure Survey (IES) data (2000/2001). Controls in the second specification include: number of people in the household, race of household head, province dummies, and total monthly expenditure. Robust standard errors. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$



# Evidence against unobserved heterogeneity (preferences)?

- ▶ Conditional on same level of HH income, HHs with *both* private and public sector earnings should adopt faster if a larger *share* of income is from public sector work
- ▶ Restricting to HHs with private *and* public sector earnings reduces role of preferences in driving adoption decisions; controlling for income level deals with higher earnings from public sector work

# Is adoption faster in households with larger share of earnings from public sector?

**Table: Time to adoption in HHs with both public and private sector earnings (Cox Model estimates)**

	(1) Stove	(2) Electric Cooking	(3) Fridge	(4) TV
Total Income	0.0178 (0.30)	0.0566 (1.80)	0.00165 (0.03)	-0.0230 (0.34)
Share public earnings	0.845** (2.13)	0.929** (3.35)	1.709*** (4.08)	1.300** (2.71)
Observations	464	762	499	424

All other controls and village fixed effects included. \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), \*\*\* ( $p < 0.001$ )

# Conclusions

Increases in HH energy demand likely to be slow in SSA. Electricity access  $\neq$  appliance adoption  $\neq$  modern energy use.

- ▶ Conditional on grid access, long adoption lags in rural settings
- ▶ Median time-to-adoption for appliances: 4-11 years US Benchmark
- ▶ (some) Income speeds up adoption (somewhat)
- ▶ HH-level: Reliable earnings may matter, not just level

# Conclusions

Increases in HH energy demand likely to be slow in SSA. Electricity access  $\neq$  appliance adoption  $\neq$  modern energy use.

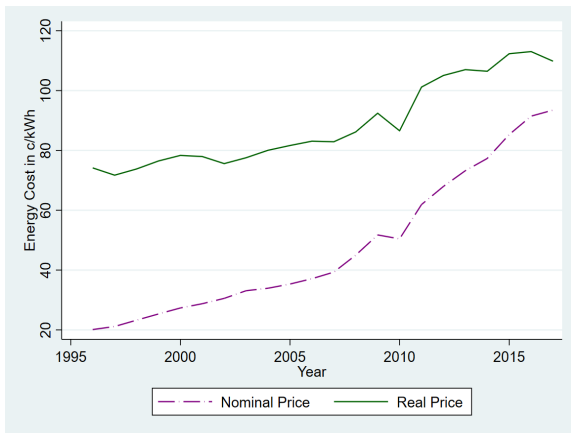
- ▶ Conditional on grid access, long adoption lags in rural settings
- ▶ Median time-to-adoption for appliances: 4-11 years US Benchmark
- ▶ (some) Income speeds up adoption (somewhat)
- ▶ HH-level: Reliable earnings may matter, not just level
- ▶ Cost of complementary appliances an important *additional* barrier to adoption of modern energy, even with energy subsidies
- ▶ Challenging limitations for research designs trying to capture impacts on welfare; for utilities forecasting consumption. Understanding credit environment is key.

Thank you! Comments and suggestions welcome at  
tdinkelm@nd.edu



# Electricity costs have risen over time

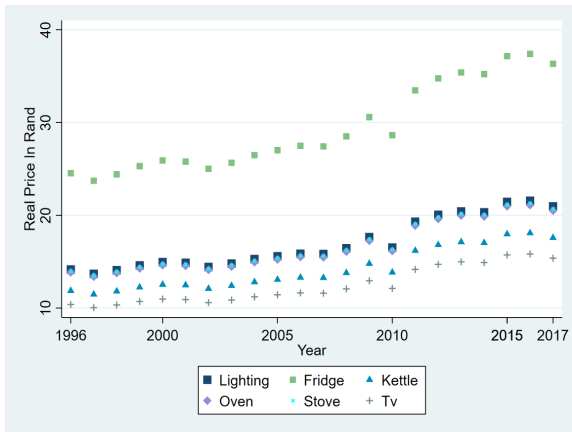
**Figure:** Per kilowatt hour cost of electricity over time



Unit cost series constructed from Eskom tariff booklets for the Homelight 20Amp tariff. [Back](#)

# Appliance running costs: Fridges are costly

Figure: Ave. monthly cost of running appliances



Average monthly cost of using appliances (real ZAR), Cost series constructed by combining our data series on tariffs with energy consumption estimates for low-income households reported in Hughes (2021). [Back](#)



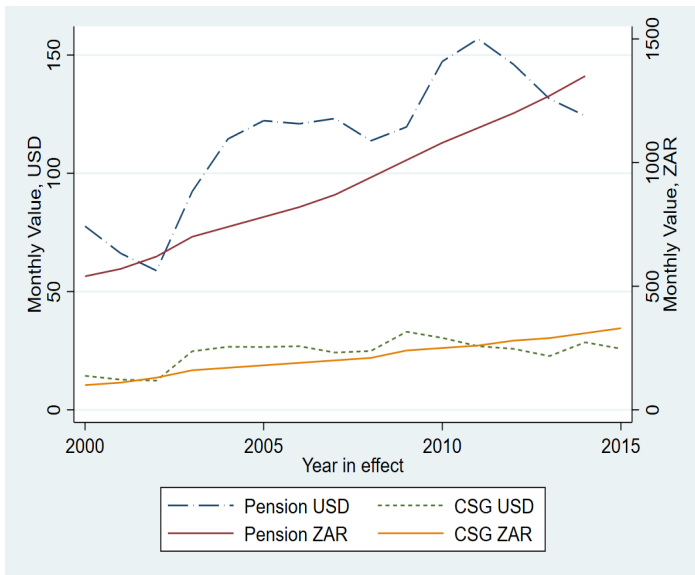
## Household attrition/churn in asset survey is low

Year	Num. unique HHs with asset data	Num. unique HHs entering sample in this year	Num. unique HHs dissolving next year*	Exit rate from asset survey by year
2001	11,052	454	531	0.05
2003	11,576	369	438	0.04
2005	11,485	255	372	0.03
2007	12,007	279	284	0.02
2009	12,872	362	408	0.03
2011	11,937	360	258	0.02
2013	11,636	355	222	0.02
2014	12,499	372	12,499	0.00
Total		2,806	15,012	

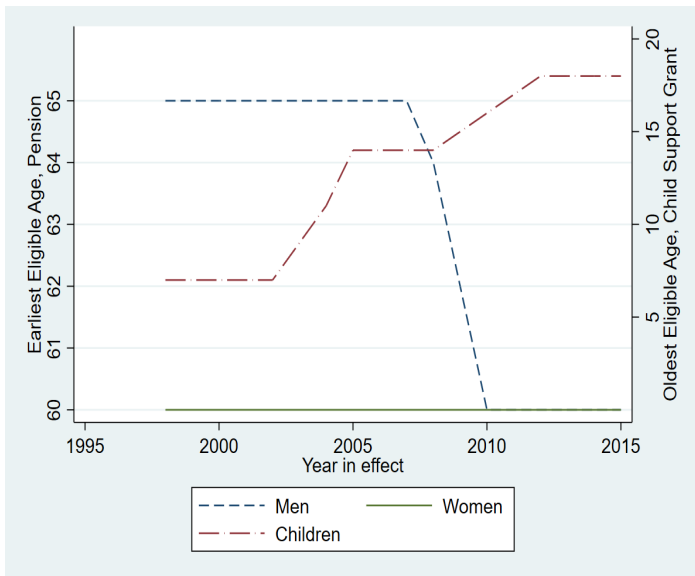
\* indicates households seen for the last time in year t. Total number of distinct households across 2001-2014: 24,466.

Back

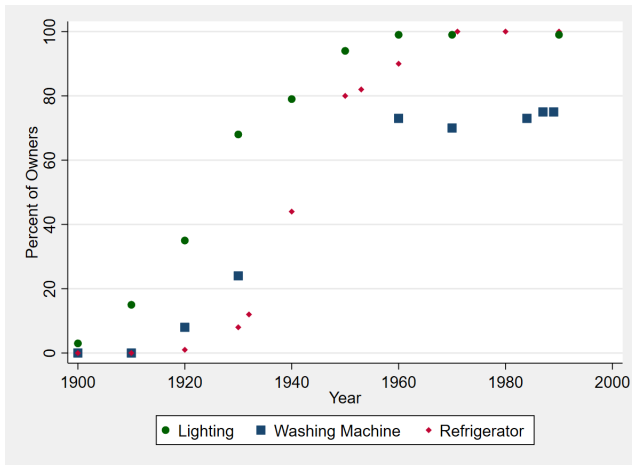
# Social grants value over time



# Social grants value over time



# Benchmark: Appliance adoption in the USA



**Figure:** Adoption of appliances: Data are from Lebergott (1976, 1993) and US Census data.