Money or power? Financial infrastructure and optimal policy

Susanna Berkouwer[a] Pierre Biscaye[b] Eric Hsu[c] Oliver Kim[c]
Kenneth Lee[d] Edward Miguel[e] Catherine Wolfram[f]

This version: July 9, 2021

Abstract

In response to the Covid-19 crisis, 186 countries implemented direct cash transfers to households, and 181 introduced in-kind programs that lowered the cost of utilities such as electricity, water, transport, and mobile money. Do cash or in-kind transfers generate greater welfare improvements? And, does a country's financial infrastructure affect optimal aid disbursement? Through a parallel set of surveys in two urban regions in Africa—with comparable education, cell phone ownership, and electricity connectivity—we show that optimal government aid disbursement hinges on financial infrastructure. In line with economic theory favoring direct cash transfers, in a randomized experiment in Kenya 95% of urban recipients prefer mobile money over electricity transfers of a similar monetary value. But Kenya is an outlier with high mobile money adoption: this increases its value and reduces transaction costs of buying electricity credit. By contrast, in Ghana—where mobile money is less widespread and the transaction costs for buying electricity are higher—half of recipients prefer electricity transfers, and many are willing to forego significant value to receive electricity instead of mobile money. These results have several important policy implications. First, the optimal government policy in response to an economic crisis is not uniform: cash and in-kind transfers have different advantages that make each suitable for specific contexts. Second, the adoption of modern financial technologies will likely increase the efficiency of government cash transfer programs, even as in-kind transfers continue to be preferred in settings where mobile money uptake is slow. Finally, giving recipients a choice harnesses valuable local information that a policy maker may not have access to.
JEL: D04, I38, O12, O13, H23, L94, Q48

[a]The Wharton School, University of Pennsylvania; [b]Department of Agricultural and Resource Economics, University of California, Berkeley. [c]Department of Economics, University of California, Berkeley; [d]Energy Policy Institute, University of Chicago; [e]Department of Economics, University of California, Berkeley and NBER; [f]U.S. Department of the Treasury, on leave from Haas School of Business, University of California, Berkeley and NBER. The views expressed in this article do not necessarily represent the views of the U.S. or the U.S. Department of the Treasury. We thank PEDL, the IGC, and the DFID EEG initiative for generous financial support. We thank Joaquin Fuenzalida Bello, Geetika Pandya, and Nachiket Shah for excellent research assistance. We thank Dennis Egger and seminar participants at the World Bank and the UK Foreign, Commonwealth & Development Office for helpful comments. We thank Kwame Abrokwah, Jane Adungo, Carolyne Nekesa, and Joseph Otieno for superbly implementing field activities. Oliver Kim acknowledges support from the National Science Foundation Graduate Research Fellowship under Grant No. 1752814. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors(s) and do not necessarily reflect the views of the National Science Foundation. A Pre-Analysis Plan for the Kenya portion of this study is pre-registered with the AEA RCT Registry (ID: 5941). This study has IRB approval in Kenya (MUERC/27/13) and the U.S. (Berkeley CPHS 2016-11-9365; CPHS 2017-12-10599). To prevent any increased risk of Covid-19 transmission, all surveys conducted by this research team between April 1 and December 31, 2020 were conducted over the phone.

1 Introduction

Many countries expanded their social programs in response to the Covid-19 pandemic: 186 introduced or expanded cash transfer programs and 181 introduced programs lowering or postponing payments for utilities such as electricity, water, transport, and mobile money transactions (Gentilini et al. 2021). Cash transfers are theoretically utility-maximizing, and evidence shows they dampened the economic impacts of the pandemic and subsequent lockdowns (Egger et al. 2021; Banerjee et al. 2020). But in-kind transfers may be preferable if they circumvent savings constraints or lower transaction costs, especially when transfers are inframarginal (Southworth 1945; Bruce and Waldman 1991; Currie and Gahvari 2008; Gadenne et al.; Hirvonen and Hoddinott 2021; Cunha 2014). What programs most effectively address the economic consequences of a nationwide emergency such as a public health crisis? How does a country's financial infrastructure affect the distribution of government aid?

We elicit preferences of 4,100 adults in Ghana and Kenya to compare demand for and impacts of transfers in the form of mobile money and pre-paid electricity credit. Although urban Ghana and Kenya are have similar levels of education, cell phone ownership, and electricity connectivity, responses vary significantly.[1] In urban Kenya, in line with basic economic theory, 95% of respondents prefer cash, and many are willing to forego significant value to receive mobile money rather than an electricity transfer. Responses in Accra, the capital of Ghana, are strikingly different: 49% prefer pre-paid electricity over a mobile money transfer of the same value, and many are willing to forego significant value to receive electricity rather than mobile money.

We attribute these differences to heterogeneity in mobile money infrastructure and its integration with economic activity. Cash gives recipients the flexibility to spend money on goods and services with the highest marginal utility, but this benefit disappears if cash is disbursed via mobile money in contexts where mobile money is not widely accepted. In Kenya, where 75% of adults use mobile money and 97% of households have at least one mobile money account, mobile money adoption and usage is almost twice as high as in Ghana. The integration of the payment system of Kenya Power—Kenya's nationwide electric utility—with Kenya's mobile money infrastructure also significantly lowered the transaction costs of buying electricity. The time and effort required to buy electricity in Ghana increases demand for electricity transfers that allow recipients to circumvent these costs. While urban respondents in Ghana report five times greater electricity spending than urban Kenyan respondents, this is unlikely to be driving the differences: the gap exists even among respondents with similar electricity consumption, and there is no correlation between electricity spending and preference for electricity. Finally, many respondents in Ghana received government electricity and water transfers, but this does not correlate strongly with preferences, and few respondents in Ghana or Kenya report having received any other form of Covid-19 aid from government or NGOs.

These differences demonstrate how financial infrastructure affects the disbursement of govern-

[1] The World Bank estimates that 94% and 91% of urban residents in Ghana and Kenya have access to electricity; 98% and 99% progress to secondary school; and they have 134 and 104 mobile cellular subscriptions per 100 people. The populations of Accra and Nairobi are 3.3 million and 4.7 million, respectively.

ment aid. The rapid expansion of mobile money in some contexts will make government cash transfers cheaper, faster, and more secure. Ghana is currently experiencing rapid adoption of mobile money technologies—36% from 2017 to 2018, for example—so even the results in this study may not hold not far in the future. But mobile money uptake may be slow in some settings, including those where intended recipients are too poor or lack the technological know-how to own a cellphone. In these contexts, in-kind transfers may remain preferred for some time. Importantly, optimal policy is a function of local financial infrastructure and access, which can vary across contexts and may not always be known to the social planner. Building on concerns about external validity of experiments raised by Allcott (2015), Bold et al. (2013), and Vivalt (2020), this paper demonstrates that empirical findings cannot necessarily be extrapolated beyond the study context, and care must be taken when doing so for the purposes of policy recommendations. Furthermore, involving recipients in policy decisions when choosing the form of aid promotes inclusivity and dignity, and can harness local private knowledge frequently unavailable to a remote policy maker (Alatas et al. 2012; Shapiro 2019; Thomas et al. 2020).

To study the impacts of electricity transfers, we implement a randomized experiment in Kenya among a subset of respondents. The results suggest that biased attention or mental accounting may affect preferences and impacts of cash and electricity transfers. Some were randomly assigned to treatment groups in which they state their preferences between cash and electricity transfers and then receive the selected option. This makes the decisions incentivized and also identifies the causal impacts of the transfers. In theory, electricity and cash transfers should generate identical increases in electricity consumption by fully rational agents in an efficient market. However, we find that pre-paid electricity transfers generate significant increases in electricity consumption while cash transfers do not. We find no impacts of electricity transfers on a wide range of socioeconomic outcomes, consistent with other work which finds limited social and economic impacts of rural electrification (Lee et al. 2020; Burlig and Preonas 2016), though transfer sizes are small.

In Ghana, preference elicitation coincided with a government Covid-19 relief program to provide all connected households with a monthly electricity transfer. Berkouwer et al. (2021) find that many households in Accra experienced delays in transfer receipt, and over 30% of eligible households never received any transfer. Variation in the timing of transfer receipt within households allows us to estimate the impacts of electricity transfer receipt. Households receiving transfers significantly reduce their electricity spending, though by less than the transfer amount, and also reduce the number of trips taken to add to their pre-paid credit. As in Kenya, we find no correlation between electricity transfers and socioeconomic outcomes.

The rest of this paper proceeds as follows. Section 2 provides background on Covid in Ghana and in Kenya. Section 3 presents the sample and surveys, and discusses the experimental component. Section 4 presents the results and Section 5 discusses the potential mechanisms and policy implications of these results. Section 6 concludes.

2 Background

Kenya and Ghana both confirmed their first Covid-19 positive patient on March 12, 2020. Three days later, Kenya's President Uhuru Kenyatta and Ghana's President Nana Addo Dankwa Akufo-Addo both announced a broad set of physical distancing measures which eventually included bans on social gatherings in crowded places, closures of schools, universities, and congregations in places of worship, and significant travel restrictions both domestically and internationally. The economic impacts of the Covid-19 public health crisis and its accompanying policies were substantial. Egger et al. (2021) find that "*50 to 80% of sample populations in [Ghana and Kenya] report income losses during the COVID-19 period*," and that average firm profits and revenues in Kenya fell by 51 and 44% respectively.

Numerous governments introduced or expanded cash transfer programs to help alleviate Covid-19 related economic downturns. In March 2020 the Government of Kenya expanded its existing social safety net, *Inua Jamii*, which provides cash transfers to society's most vulnerable populations—including the elderly, orphaned children, survivors of sexual and gender-based violence, people with disabilities, and pregnant and lactating mothers—and launched urban public works employment schemes (Gentilini et al. 2021). In May 2020 Ghana provided an additional round of cash transfers to existing recipients of the Livelihood Empowerment Against Poverty (LEAP) Program, which targets around 5% of Ghana's poorest households (Dadzie and Raju 2020). In many African countries mobile money is an important tool for providing cash transfers, particularly for populations excluded from formal financial institutions.

At the same time, many countries introduced in-kind transfer programs. These can be attractive to governments lacking infrastructure to distribute cash broadly, beyond vulnerable populations already receiving government aid. In May 2020, the government of Ghana launched an electricity relief program, citing the importance of reliable electricity during economic downturns. All households with an electricity connection were eligible to receive a monthly transfer, with transfer amounts pinned to consumption in March 2020 before the program was announced (ECG 2020). Customers who consumed less than Ghana's 'lifeline' amount of 50 kWh in March were eligible to receive 50 kWh in electricity credit—worth USD 3.50—each month, while all other customers would receive 50% of their March consumption, which averaged USD 15 in our sample. In theory, all electricity customers were eligible for transfers from May to July 2020, and eligibility for lifeline customers—around 10% of our sample—continued until March 2021. In practice, not all households received transfers and there was significant variation in the timing and consistency of monthly transfer receipt (Berkouwer et al. 2021). Among respondents in our sample in Ghana, more than two-thirds had received at least one electricity transfer in the first three months of the program, and almost half had received a Covid-19 water subsidy transfer (the other main government pandemic relief program).

Other than the programs described above, aid was limited. In both Kenya and Ghana, fewer than 10% of respondents reported receiving any cash, food, or other aid from the government or an NGO in the past 1-2 weeks.

3 Study Design

Over a study period of seven months, between May and November 2020, 3,211 respondents in Kenya and 911 in Ghana were surveyed by phone between one and three times each All respondents in Ghana were eligible for electricity transfers through the government's Covid-19 relief program and completed a stated preference survey on electricity versus cash transfers. In Kenya, a subset of 2,053 respondents—those with pre-paid electricity meters—were enrolled in a randomized field experiment. Each respondent was randomly assigned to one of four groups: a control group, a group that received pre-paid electricity tokens, and two groups that were given a choice between cash or electricity transfers at different rates. 1,041 respondents in Kenya also answered stated preference questions on electricity versus cash transfers.

3.1 Sample

The primary sample is located in urban areas of Kenya and Ghana and consists of 983 and 911 households respectively that are connected to the grid and use pre-paid meters to pay for electricity in advance.[2] Customers with a pre-paid meter may only consume electricity that they pay for in advance by purchasing electricity credit, or *tokens*. In Ghana, most pre-paid customers must purchase credit from a local utility office or shop. In Kenya most pre-paid customers can purchase credit remotely using mobile money.

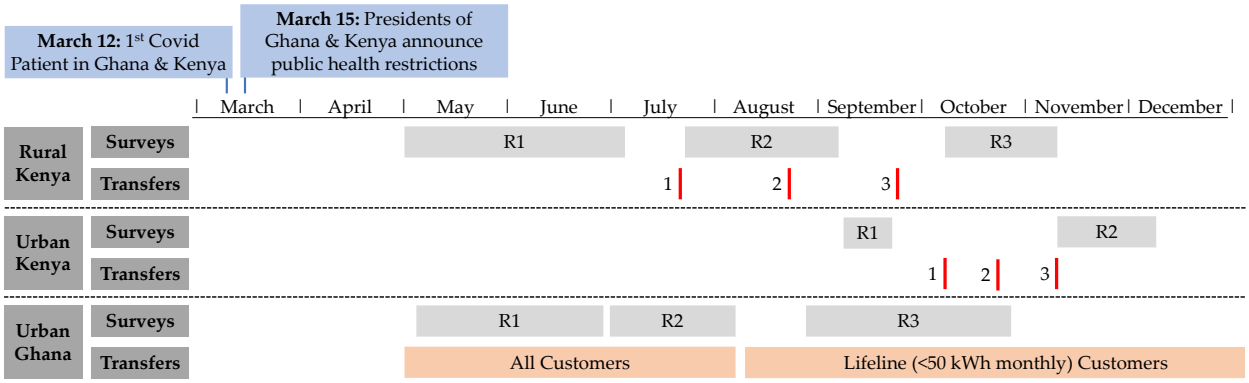
Table A1 and Table A2 present summary statistics for the Ghana and Kenya samples respectively and compare these with the broader population. The samples are broadly similar to electricity customers in Accra and urban Kenya based on observable characteristics like housing quality and appliance ownership. The urban samples skew slightly younger than census data, likely because mobile phones were used to recruit respondents and conduct surveys. Rates of appliance ownership are higher in our sample than in the representative samples, likely because an electricity connection was required to participate in our study.

In Kenya, we also surveyed 2,228 respondents located in rural areas of Western Kenya, Nyanza, and Rift Valley who previously participated in Lee et al. (2020) or Wolfram et al. (2021). 1,070 rural respondents had pre-paid meters and were included in the experimental sample. 355 had post-paid meters (receiving monthly bills) and 803 did not have any electricity connection: these respondents were excluded from the experimental sample, but still completed the socioeconomic surveys to allow us to investigate descriptive heterogeneity.[3]

[2]Respondents in Ghana were enrolled in 2018 and 2019 and are distributed across western Accra (Klugman et al. 2019). Respondents in urban Kenya were recruited through Ajua, a mobile survey firm, and are located in Nairobi (39%), Eldoret (11%), Mombasa (9%), and elsewhere.

[3]Due to budget constraints, a random subset of unconnected households was surveyed in the first survey round, and the remainder were surveyed in the second survey round.

Figure 1: Timeline



Timeline displaying the various study components implemented in 2020. R1, R2, R3 refer to survey rounds 1, 2, and 3. Vertical red lines represent experimental cash or electricity transfers in Kenya. Orange boxes represent phases of government electricity transfers in Ghana.

3.2 Study components and timeline

Figure 1 displays the timeline of study activities. All respondents completed between one and three phone surveys between May and November 2020.

All respondents in Ghana were eligible for government electricity transfers for at least 3 months in 2020. On average, respondents were eligible to receive USD 10 per month, equivalent to 95 kWh using local electricity tariffs, or 17 days of average pre-pandemic electricity spending for this sample.

Kenya did not have a similar government electricity transfer program. Instead, we implemented a randomized transfer program. Study participants received—per month, for three months—either USD 5 in electricity, USD 3.50 or USD 5 in mobile money, or no transfers. Among the urban sample, USD 5 represents 50 days of average electricity spending. Section 3.4 discusses the treatments in more detail.

3.3 WTP elicitation

The elicitation for the experimental sample in Kenya was incentive compatible—respondents received their selected transfer—while respondents in Ghana were informed choices were hypothetical.

In each survey round, respondents in Ghana were presented with an iterated sequence of hypothetical dichotomous choices to elicit their Willingness To Pay (WTP) for a GHS 50 (USD 8.60) electricity transfer. This amount roughly equals monthly government pandemic relief transfer expected in our sample, and represents 15 days of average electricity spending. In each question the respondent chooses between a GHS 50 electricity transfer or a cash transfer of a certain amount, which varies depending on the prior response. WTP is the highest cash transfer amount the respondent rejects in favor of the electricity transfer. Berkouwer et al. (2021) provides more information on the elicitation methodology.

In Kenya, one-third of respondents were randomly assigned to a treatment group that allowed them to choose between either mobile money transfers or electricity tokens (we discuss random

assignment more in Section 3.4). One-sixth of participants were given a choice between three monthly transfers of KSH 500 (around USD 5) each of either mobile money or electricity tokens; a separate one-sixth of participants were given a choice between three monthly transfers of either KSH 500 in mobile money or KSH 350 in electricity tokens.

In addition, rural respondents and urban respondents in a smaller pilot survey were given a non-incentivized decision, which we use to confirm that results hold when comparing the non-incentivized decisions in Ghana and Kenya. The structure of the non-incentivized decisions mirrors the structure in Ghana, with a reference electricity transfer of USD 5.

3.4 Randomized experiment

In Kenya, all 983 urban respondents and 1,070 of the rural respondents—those with pre-paid meters—participated in a randomized field experiment.[4] Each respondent was randomly assigned to one of four groups: a control group, a group that receives electricity tokens (redeemable for pre-paid credit), and two groups that are given a choice between cash or electricity transfers at different rates and are then given their chosen option.[5] Figure A1 displays the sample size for each treatment. Participants in the treatment groups received three transfers—either cash or electricity—in between the baseline and endline surveys.

[C] Control group (33.3%) Participants are surveyed but did not receive any transfers.

[T1] Token transfer (33.3%): Participants received three transfers of pre-paid electricity tokens valued at USD 5 each.

[T2A] Token vs high cash choice (16.7%): Participants were given a choice between USD 5 worth of electricity tokens or USD 5 in cash, transferred via mobile money. Whichever option they chose, they received each USD 5 transfer three times within a two month period.

[T2B] Token vs low cash choice (16.7%): Participants were given a choice between USD 5 worth of electricity tokens or USD 3.50 in cash, transferred via mobile money. Whichever option they chose, they received each transfer three times within a two month period.

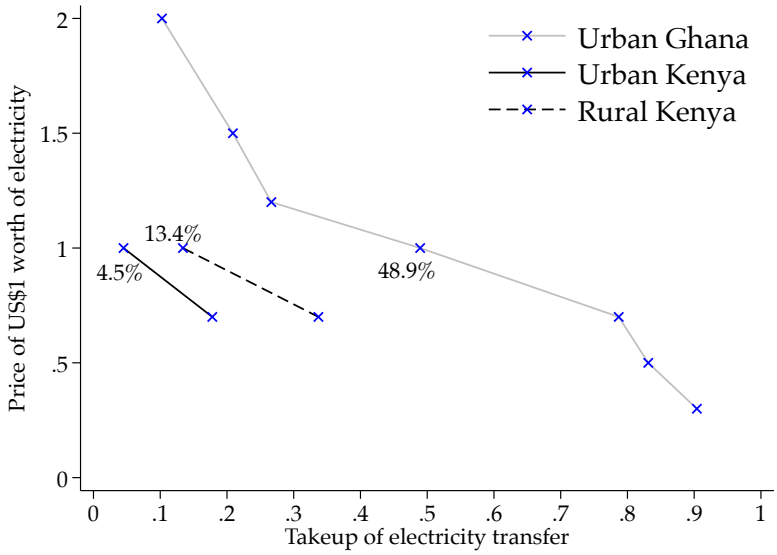
For 70% of respondents, the USD 5 transfer bought around 32 kWh in pre-paid electricity.[6] All experimental transfers were transmitted remotely. Cash was transferred using Safaricom's M-Pesa

[4] Electricity transfers in Kenya within this study's timeframe were logistically feasible only among households with a pre-paid electricity connection. Households with post-paid meters have higher average income and education.

[5] Random assignment is implemented separately for the urban and rural samples. To avoid spillover contamination, treatments for the rural sample are randomly assigned at the village level, stratified by the number of respondents in each village and the study each village was originally a part of. Given the low likelihood of urban spillovers, randomization for the urban sample is done at the individual level.

[6] Kenya Power's tariff changes slightly month-to-month. In addition, those connected through the government's Last Mile Connectivity Project (LMCP)—including most respondents from Wolfram et al. (2021) and those not connected through Lee et al. (2020)—were paying monthly installments for their connections. In these cases, part of each top-up is applied to debt repayment before being used to buy kWh of electricity. 15% received around 22kWh, 7% received around 16kWh, and the rest received between 10 and 30 kWh per transfer. Respondents connected through Lee et al. (2020) did not have debt outstanding and generally received around 32 kWh. 32 kWh per month is Kenya's 'lifeline' amount and is roughly equivalent to operating 4 light bulbs, a television, a cell phone charger, and an iron for month under average usage patterns.

Figure 2: Demand for Electricity Transfers by Context



Demand for USD 1 of electricity expressed in USD of mobile money. The numbers shown indicate the share of respondents who prefer USD 1 of electricity to USD 1 in mobile money in an equal trade-off, by context. The choice is incentivized in Kenya, as respondents receive the transfer they choose, while in Ghana the choice is presented as hypothetical.

mobile banking service to a mobile money account corresponding to a phone number provided by the respondent. Electricity transfer tokens were first purchased at a local Kenya Power office,[7] and the token ID was then sent to respondents via SMS, who could then enter it into their meter to activate the credit.

4 Results

In Kenya, households overwhelmingly prefer mobile money, and are willing to forego on average 40% of value to receive mobile money instead of an electricity transfer. By contrast, in Ghana, respondents are on average willing to forego 4% of value to receive an electricity transfer instead of mobile money. Electricity transfers modestly increase electricity usage in Kenya and decrease electricity spending and transactions in Ghana, but have limited impacts on broader socioeconomic outcomes.

4.1 Preferences for electricity and mobile money

Figure 2 displays take-up of electricity expressed as the implicit choice price indicating the value of the mobile money transfer offer relative to the electricity credit transfer offer. In Kenya, when the implicit price of USD 1 of electricity is USD 1 of mobile money, 5% of urban participants take up the electricity transfer (choosing USD 5 in electricity over USD 5 in mobile money). Even

[7] To prevent fraud, each token is tied to a respondent's Kenya Power account number.

when USD 1 of electricity has an implicit price of only USD 0.70 in mobile money, only 18% select electricity. This preference for cash is only slightly lower among urban respondents: 13% and 34% choose electricity, respectively.[8]

In Ghana, on the other hand, almost half of respondents choose electricity at an implicit price of USD 1. Even with an implicit price of USD 1.20, 26% still choose electricity credit.[9]

Table 1 explores correlates of preference for electricity over an equal amount of mobile money by context. In Ghana respondents with many appliance types, and who experienced fewer outage hours in the past month, were more likely to choose electricity. WTP for electricity is also higher for households who—conditional on total electricity spending—top up less frequently: they may face higher transaction costs of purchasing electricity credit, for example living further from a vendor. We discuss transaction costs more in Section 5.

In Kenya, households with a refrigerator are more likely to prefer electricity over cash,[10]

4.2 Impact of transfers

We next analyze how cash and electricity transfers affect economic outcomes. Electricity transfers nudge recipients towards electricity consumption, despite relatively low transaction costs in using mobile money to purchase electricity tokens. Other than this, the treatment has no significant effects on a wide range of socio-economic outcomes.

The following equation estimates the effects of each randomly assigned treatment for the Kenya experimental sample:

$$y_{si} = \beta_0 + \beta_1 T^1_{si} + \beta_2 T^{2A}_{si} + \beta_3 T^{2B}_{si} + X_{si}\Gamma + \varepsilon_{si} \tag{1}$$

where y_{si} is the outcome of interest for respondent i at site s, $T^1_{si} = 1$ if the respondent is assigned to the direct token transfer arm (T1), $T^{2A}_{si} = 1$ for the USD 5 tokens / USD 5 cash arm (T2A), $T^{2B}_{si} = 1$ for the USD 5 tokens / USD 3.50 cash arm (T2B), and X_{si} is a vector of controls, pre-specified in Berkouwer et al. 2020.ε_{si} are clustered by village for the rural sample but allowed to vary by individual for the urban sample.

In Ghana we leverage quasi-random variation in respondent receipt of the ongoing government electricity relief program to estimate these effects. Berkouwer et al. (2021) describes the variation in whether and when households received government electricity relief in more detail. We analyze impacts of government transfer receipt using the following household fixed effects specification:

$$y_{it} = \beta_0 + \beta_1 T^{30}_{it} + \beta_2 T^{pre-30}_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{2}$$

where y_{it} is the outcome of interest for respondent i at time t, $T^{30}_{it} = 1$ if the respondent received

[8] While more respondents choose electricity over cash in non-incentivized elicitation in both rural and urban Kenya, we still observe a strong preference for mobile money (Figure A2).

[9] Responses in Ghana are similar across survey rounds and among respondents that had and had not received government electricity relief (Figure A3).

[10] Just 2% of rural households in this sample have a refrigerator.

Table 1: Correlates of choosing electricity credit over a cash transfer of equal value

	(1) Ghana	(2) Rural Kenya	(3) Urban Kenya
Count of appliance types held	0.013***	0.047	-0.006
	(0.005)	(0.042)	(0.014)
Has a TV	0.065	0.021	-0.083
	(0.061)	(0.102)	(0.051)
Has a refrigerator	0.002	1.183**	0.164***
	(0.035)	(0.468)	(0.055)
Has a generator	0.069		
	(0.065)		
Total spending in last 7 days excl. food and energy (USD 10s)	-0.000		
	(0.000)		
Total spending in last 7 days excl. food (USD 10s)		-0.011**	0.001
		(0.004)	(0.001)
Food spending in last 7 days (USD 10s)	-0.003	0.002	-0.003
	(0.006)	(0.006)	(0.002)
Non-electricity energy spending in last 7 days (USD 10s)	-0.019		
	(0.018)		
Electricity spending in last 7 days		0.045	-0.011
		(0.046)	(0.024)
Last 30 days electricity spending (USD 100s)	-0.034		
	(0.109)		
Meter balance (kWh)		-0.001	-0.000
		(0.001)	(0.001)
Shares meter with other users	-0.033		
	(0.031)		
Weeks between prepaid meter topups	0.012*		
	(0.007)		
Outage hours in past 30 days (100s)	-0.069*		
	(0.036)		
Received any gov't electricity relief	0.048*		
	(0.029)		
Received cash from gov't, politician, or NGO in past 7 days	0.156		
	(0.119)		
Received goods from gov't, politician, or NGO in past 7 days	-0.004		
	(0.094)		
Received any gov't or NGO assistance in past 14 days		-0.018	0.143
		(0.131)	(0.106)
Respondent age	0.004***	-0.000	0.003
	(0.001)	(0.002)	(0.004)
Respondent is female	-0.039	-0.039	
	(0.030)	(0.071)	
Number of adults (=18)	-0.000	-0.033	0.002
	(0.008)	(0.023)	(0.018)
Number of children (18)	0.004	-0.024	0.003
	(0.009)	(0.015)	(0.018)
Observations	1893	115	126
Dep. Var. Mean	0.506		
SEs clustered at household level.			

This table presents estimates of the correlations between respondent characteristics and preference for electricity relative to cash, elicited through a series of choices between an electricity credit transfer and a mobile money transfer of a varying amount. The dependent variable is a dummy for preferring an electricity credit transfer to a mobile money transfer of equal value. "Respondent is female" indicator is omitted for the urban Kenya sample due to missing values. Estimates in column (1) include week and district fixed effects, and SEs are clustered by household. Column (1) includes all households in the Ghana sample. Columns (2) and (3) include households in Kenya in the experimental treatment arm T2A that were offered an incentivized choice between USD 5 worth of electricity tokens or USD 5 in cash.

government relief in the last 30 days, $T_{it}^{pre-30} = 1$ if the respondent previously received government relief but not in the last 30 days, μ_i is a household fixed effect, and τ_t is a week of year fixed effect. Standard errors are clustered at the household level. The coefficient on $T_{it}^{30} = 1$ can be interpreted as the effect of receiving relief relative to never receiving any government electricity transfers. Transfer receipt in this sample is plausibly quasi-random: we do not find any evidence

Table 2: Impact of transfers on energy and other consumption, Kenya

Panel A: Urban Sample

	N	Control Mean (SD)	Token Treatment (SE)	500 Ksh vs Tokens (SE)	350 Ksh vs Tokens (SE)
Electricity usage since baseline (kWh)	651	40.88	42.73***	3.21	9.89*
		(40.06)	(4.32)	(4.10)	(5.20)
Electricity usage since baseline (approx value in USD)	651	3.74	3.91***	0.29	0.91*
		(3.67)	(0.40)	(0.38)	(0.48)
Prepaid electricity expenditure in the past 2 weeks in USD	897	1.39	-0.58***	0.26	0.17
		(1.92)	(0.14)	(0.18)	(0.18)
Meter balance (kWh)	690	10.03	15.48***	-1.43	3.96**
		(13.86)	(1.69)	(1.20)	(1.84)
Energy spending in the past 7 days in USD (excl. electricity)	894	0.72	0.17	0.10	0.12
		(1.66)	(0.14)	(0.17)	(0.16)
Energy spending in the past 7 days in USD (excl. electricity and charcoal)	891	0.17	-0.03	0.05	-0.01
		(0.54)	(0.04)	(0.06)	(0.04)
Non-energy spending in the past 7 days in USD	887	32.89	-1.09	-3.00	-0.69
		(25.66)	(2.01)	(2.38)	(2.39)
Dissaving (pc) in the past 14 days in USD	908	7.17	2.09	3.51	-0.06
		(38.69)	(2.73)	(5.73)	(2.60)
Total consumption in the past 7 days in USD	887	34.32	-0.94	-2.51	-0.30
		(26.35)	(2.08)	(2.46)	(2.44)

Panel B: Rural Sample

	N	Control Mean (SD)	Token Treatment (SE)	500 Ksh vs Tokens (SE)	350 Ksh vs Tokens (SE)
Electricity usage since baseline (kWh)	1219	47.34	30.21***	20.57***	6.20
		(46.27)	(3.70)	(5.97)	(4.76)
Electricity usage since baseline (approx value in USD)	1219	4.34	2.77***	1.88***	0.57
		(4.24)	(0.34)	(0.55)	(0.44)
Prepaid electricity expenditure in the past 2 weeks in USD	1692	1.05	-0.40***	0.07	-0.27**
		(1.49)	(0.10)	(0.14)	(0.11)
Meter balance (kWh)	1322	11.64	13.32***	1.93	7.74***
		(20.88)	(1.61)	(2.00)	(2.19)
Energy spending in the past 7 days in USD (excl. electricity)	1703	0.66	0.35***	-0.17	0.17
		(1.64)	(0.12)	(0.12)	(0.17)
Energy spending in the past 7 days in USD (excl. electricity and charcoal)	1700	0.48	0.06	0.01	0.04
		(1.27)	(0.08)	(0.11)	(0.10)
Non-energy spending in the past 7 days in USD	1733	24.43	3.62**	0.89	-0.29
		(23.04)	(1.64)	(1.84)	(1.99)
Dissaving (pc) in the past 14 days in USD	1735	1.86	-1.88	-3.43*	-2.37
		(24.14)	(1.32)	(1.95)	(1.52)
Total consumption in the past 7 days in USD	1733	25.54	3.85**	0.68	-0.25
		(23.82)	(1.72)	(1.90)	(2.09)

Estimates of Equation 1 for energy and consumption outcomes in Kenya. From left to right, the columns show the number of observations, the control mean, and the treatment effects of T1, T2A, and T2B (all relative to control). Regressions include baseline controls for sex, education, banking status, and housing quality (from Lee et al. (2020) or Wolfram et al. (2021)); and the Covid-19 survey baseline value for each outcome. FDR q-values for all coefficients are statistically insignificant at $\alpha = 0.10$, except for electricity usage for T1 (FDR q-value = 0.00). Electricity usage since baseline (kWh) is the sum of (1) the difference between baseline and endline meter balance, (2) household top-ups since baseline, (3) kWh received through treatment (if any).

that baseline socioeconomic characteristics predict receipt, and by including household fixed effects we rule out inter-household selection bias. However, since the timing of transfer receipt is not randomly assigned, these results should be interpreted as suggestive.

Panel A of Table 2 estimates equation 1 for the urban sample.[11] Panel B estimates equation 1

[11] As a newly collected sample recruited over SMS, the urban data lack the same detailed set of outcomes as for the REPP and LMCP samples, so the regressions instead include indicator variables for each of the eight Living Standard Measure (LSM) scores as controls.

Table 3: Government relief and energy and other consumption, Ghana

	N	Control Mean (SD)	Relief in last 30 days (SE)	Relief before last 30 days (SE)
Electricity usage since previous survey (kWh)	246	168.64	-24.46	-104.91**
		(137.38)	(50.45)	(53.48)
Electricity usage since previous survey (USD)	246	18.43	-2.67	-11.46**
		(15.01)	(5.51)	(5.84)
Electricity spending in past month (USD)	2312	15.20	-1.49*	-1.32
		(13.49)	(0.83)	(0.98)
Current balance on prepaid meter (USD)	759	5.05	0.23	0.01
		(7.01)	(0.88)	(1.15)
Pre-paid topups in last 30 days	2000	1.90	-0.19*	-0.10
		(1.40)	(0.11)	(0.13)
Average topup amount in last 30 days (USD)	2004	10.21	-0.13	-0.41
		(9.56)	(0.57)	(0.71)
Total consumption in the past 7 days (USD)	2349	113.27	0.18	-0.63
		(110.53)	(6.92)	(8.41)
Energy spending (excl. electricity) in the past 7 days (USD)	2325	4.39	0.09	0.13
		(6.37)	(0.52)	(0.58)
Food spending in the past 7 days (USD)	2329	32.63	0.44	1.82
		(25.97)	(1.69)	(1.84)
Worried about having enough food in past 7 days (=1)	2350	0.22	-0.04	-0.04
		(0.41)	(0.03)	(0.03)
Number of days in past 7 that adults skipped meals	2348	0.86	-0.13	0.02
		(1.88)	(0.12)	(0.13)

Estimates of Equation 2 for energy and consumption outcomes in Ghana. From left to right, the columns show the number of observations, the control mean, and the effects of receiving government electricity relief in the last 30 days and of previously receiving relief but not in the last 30 days (relative to never receiving relief). Timing of transfer receipt is not randomly assigned, so these estimates should be interpreted as suggestive correlations. Regressions include household and week fixed effects, and we cluster SEs at the household level. FDR q-values for all coefficients are statistically insignificant at the $\alpha = 0.10$ level.

for the rural sample, pooling survey rounds 2 and 3 to increase statistical power. Table 3 estimates equation 2 for Ghana.

In Kenya, electricity transfers increased electricity usage by 30 kWh (worth USD 3) for the rural sample and 43 kWh for the urban sample. They also led to higher electricity meter balances at endline for both groups, and to decreases in recent electricity spending. These effects are large: relative to the control group, treated households increased electricity usage by 66% in the rural sample and 105% in the urban sample.

On the other hand, the T2A treatment arm had no effect on electricity usage among urban respondents—95.5% of whom chose mobile money. Given that electricity is storable and transaction costs for using mobile money to purchase electricity tokens are low, there is no reason *ex ante* for the electricity transfers in T1 to generate larger increases in electricity usage. Instead, mental accounting, or increased attention to electricity usage due to the treatment, might account for increased electricity consumption among T1.

In Ghana, electricity expenditure falls by USD 1.50 in the last 30 days for respondents that received electricity relief in that time period. This reduction is less than the median amount received in the last 30 days among recipients (7 USD), suggesting recipients are increasing electricity consumption relative to non-recipients. Pre-paid meter balance at the time of the survey increases, but unlike in Kenya this is not significant—households appear to be largely consuming rather than storing their transfers. This indicates that monthly relief transfers were generally inframarginal to

optimal monthly household electricity consumption. We do not measure electricity usage since baseline, but for a subset of households we can calculate approximate electricity usage between survey rounds. Unlike in Kenya, we do not find that transfer receipt is associated with increased electricity usage for this subset of households, despite the above evidence suggesting electricity transfers increase usage overall. Instead, households receiving electricity relief top up their electricity credit significantly less frequently, but do not decrease their expenditures when they do top up. Electricity transfers allow households to avoid transaction costs associated with topping up electricity.

Other than electricity use, there are minimal effects of electricity transfers on other outcomes such as non-energy spending and food security in both Kenya and Ghana. Table A3 reports results for additional socio-economic outcomes in Kenya.

5 Discussion

We document a striking difference in preferences for cash versus in-kind transfers across similar contexts in Kenya and Ghana. We argue that the effectiveness of cash transfer programs hinges on the financial infrastructure used to disburse government aid, and its integration with payment platforms.

In 2007, the Kenyan firm M-PESA launched one of the first mobile money products in the world. Today, 97% of Kenyan households have at least one M-PESA account, and 68% live within 1 km of an M-PESA agent (Suri et al. 2021). But while 75% of adults in Kenya use mobile money at least somewhat regularly, it is not as widespread everywhere. In Ghana, only 39% of adults use mobile money (World Bank 2019). The usage gap is even starker: in the past 90 days only 32% of Ghanaian mobile money accounts had transacted, whereas in Kenya more than 85% of mobile money account owners had used their accounts (Bank of Ghana 2019, Central Bank of Kenya 2019).

These differences in financial infrastructure have important implications for the effectiveness of government aid disbursement. In Kenya, the high penetration of mobile money infrastructure increases its value by broadening the set of goods and services it can buy. In contexts where mobile money infrastructure is less advanced, recipients are limited in what they can do with these transfers, reducing their value. This may also be the case when the use of mobile money incurs high transaction fees: 10% of respondents in Ghana state that they "worry about mobile money charges/costs."

Mobile money also affects the utility's payment infrastructure. The 2013 launch of Lipa-na-MPESA (*'Pay-with-MPESA'*) facilitated the use of mobile money for commercial transactions in Kenya. Customers of Kenya Power can buy electricity credit easily using mobile money. But 93% of customers in our Ghana sample must travel to an ECG office or official electricity vendor to purchase credit—only 7% have a 'smart' pre-paid meter that allows mobile top-up. Among adults who pay utility bills, 82% in Kenya had used mobile money to do so while only 23% in Ghana had (World Bank 2018). Respondents who choose electricity credit avoid the time and cost of travelling to an electricity vendor to purchase credit and any fees or costs associated with using mobile money.

These patterns are reflected in our survey data. In Ghana, 21% of respondents who preferred electricity state that it "takes too much time/effort to top up," while in Kenya only 10% of respondents report the same. Lipa-na-MESA penetration is also lower in rural Kenya, lowering the value of mobile money to rural respondents and increasing transaction costs to buy electricity, which can help explain the gap between urban and rural preferences.

But the financial landscape is rapidly changing. The evolution of mobile money infrastructure will likely spur cash transfers as a fast and cost-effective tool to disburse government aid. While mobile money usage is currently still lower in Ghana than in Kenya, Ghanaians are rapidly adopting mobile money. Between December 2017 and December 2018 the number of of registered mobile money accounts increased by 36%—from 24 million to 33 million—and the number of mobile money agents more than doubled—from 195,000 to almost 400,000 (Bank of Ghana 2019). Thus, if (indeed, when) Ghana reaches the high levels of mobile money adoption that currently characterize Kenya's financial landscape, the optimal channels through which to disburse government aid will likely change too.

At the same time, mobile money penetration may remain persistently low in some communities—including those with low financial literacy, and the ultra-poor, for whom mobile banking fees can be prohibitive. There, in-kind transfers may continue to be preferred.

Several other differences between Kenya and Ghana are unlikely to be driving the difference in preferences. Table A1 and Table A2 for example show that monthly electricity spending is five times as high in Ghana as in Kenya, at USD 15 and USD 3.20 per month in urban Ghana and Kenya, respectively. To rule out that electricity spending drives differences in take-up of electricity, Figure A4 shows the correlation between monthly electricity expenditures and preference for electricity, separately for each country. Preferences are relatively constant along this dimension, and, crucially, the difference between Kenya and Ghana holds even when comparing respondents with relatively similar electricity expenditures.

Respondents in Kenya might also prefer cash if they lack trust that Kenya Power could implement mobile money transfers in practice. This is less likely to be a concern for respondents in Ghana given the ongoing government electricity transfer program, particularly for respondents who had actually received transfers themselves. However, it does not appear that this is an important channel. In Ghana, respondents who received at least one government electricity transfer are slightly more likely to opt for electricity, but this difference is less than 5% and only marginally significant at the 10% significance level. Just 6% of respondents in Ghana who preferred electricity to mobile money indicated a lack of trust that the government would provide the money as a reason for preferring electricity.

Some concerns were shared by respondents across the two contexts. Households may have present-biased consumption preferences or face social or intra-household pressures but recognize that they would benefit in the future from allocating more resources to electricity credit. 36% of respondents in Ghana that choose electricity over cash, and 73% of those in Kenya, state that they worry they "will spend the money on something else." For such households having a transfer go

directly to their electricity meter would help them optimize spending. Pre-paid electricity generally does not expire and can thus be a useful savings device.

At the same time, households are also more likely to face exacerbated short-term liquidity constraints during an economic crisis. This may increase preferences for mobile money over electricity credit. Some households—particularly in Kenya where the electricity transfers are larger relative to typical consumption—would take several months to consume the full transfer amount. Since electricity credit cannot generally be converted back to cash, fungible cash may provide these households with much needed short-term liquidity. Households that prefer electricity to cash appear to be those who do not face major liquidity constraints: 62% of respondents in Ghana and 46% of those in Kenya who prefer electricity state that they "would use the money for electricity anyway." For these households, electricity is the marginal expenditure, so they do not benefit from the flexibility of choosing the mobile money transfer which they could spend on other forms of consumption.

The electricity transfer has a significant impact on electricity usage but no other outcomes, and the cash transfers have no impact on any of the measured outcomes. Given the existing literature finding large positive effects of cash transfers (Haushofer and Shapiro 2016; Handa et al. 2018), the limited detectable impacts may be the result of limited statistical power, especially considering the modest transfer size. We therefore interpret these results cautiously.

6 Conclusion

During an economic crisis, should policy makers distribute cash transfers or in-kind transfers such as electricity subsidies? And how does a country's financial infrastructure affect the relative efficiency of these types of government aid?

We complement preference elicitation surveys in Kenya and Ghana with a randomized field experiment in Kenya where respondents are offered either electricity tokens or the choice between tokens and a varying amount of cash. These two contexts—urban settings in Sub-Saharan Africa with high rates of electricity connectivity—are comparable along most observable characteristics, yet we find strikingly different results. In urban Kenya, 95% of respondents prefer cash, with most choosing cash even when offered prepaid electricity tokens worth 40% more in monetary value. In urban Ghana, on the other hand, the median respondent prefers electricity, and many respondents are willing to forego significant value to receive electricity rather than mobile money.

These differences likely stem from advances in mobile money infrastructure in Kenya, and its integration with utility payment platforms. Mobile money is almost ubiquitous in Kenya and is well-integrated with Kenya Power's payment system, increasing the value of mobile money and reducing the transaction costs of buying electricity. By contrast, in Ghana mobile money is less common, limiting its value, and direct electricity transfers allow recipients to avoid the transaction costs associated with buying prepaid electricity credit.

These results demonstrate that financial infrastructure affects the efficiency of government aid disbursement, and may thus affect a social planner's optimal policy choice. In contexts with rapid

mobile money adoption, cash transfers will likely become a cheaper and more effective channel through which to disburse government aid. But in contexts with limited mobile money adoption but with a more developed utility infrastructure, in-kind transfers may continue to be preferred. The results thus emphasize the importance of understanding local contexts and extrapolating from study results only after carefully considering any differences that may affect policy recommendations (Allcott 2015; Bold et al. 2013; Vivalt 2020).

For governments, mobile money infrastructure provides a channel to transfer funds cheaply and quickly. It may also alleviate financial pressures that electricity subsidies impose on utilities. In theory the mode of transfer should not affect the fiscal source of funding, but in practice, the cost of electricity transfers is often borne by utilities, whereas cash transfer programs are often paid for by other government agencies. This is an important concern. Electric utilities in 37 out of 39 Sub-Saharan African countries are currently operating at a cost that exceeds the revenue recovered through existing tariffs (Kojima and Trimble 2016). In contexts where utilities are majority government-owned, they may receive a mandate of providing subsidized electricity without financial compensation for the additional cost this would incur. This added social responsibility may increase financial strain on a utility's ability to provide reliable electricity. Fiscal and financial responsibilities will vary by context and may also affect optimal policy.

References

Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A. Olken, and Julia Tobias. 2012. "Targeting the Poor: Evidence from a Field Experiment in Indonesia". *American Economic Review* 102, no. 4 (): 1206–40.

Allcott, Hunt. 2015. "Site Selection Bias in Program Evaluation". *The Quarterly Journal of Economics* 130, no. 3 (): 1117–1165.

Banerjee, Abhijit, Michael Faye, Alan Krueger, Paul Niehaus, and Tavneet Suri. 2020. *Effects of a Universal Basic Income during the pandemic*. Tech. rep. UC San Diego.

Bank of Ghana. 2019. *Payment System Statistics*. https://www.bog.gov.gh/wp-content/uploads/2019/10/Payment-Systems-Statistics-First-Half-2019-Table.pdf.

Berkouwer, Susanna, Pierre Biscaye, Steven Puller, and Catherine Wolfram. 2021. "Electricity transfers in practice: Evidence from COVID-19 relief in Ghana". Working paper.

Berkouwer, Susanna, Kenneth Lee, Oliver Kim, Eric Hsu, Catherine Wolfram, and Edward Miguel. 2020. "Resilience to economic shocks through continued electricity access in Kenya". ID: AEARCTR-0005941, *AEA RCT Registry*.

Bold, Tessa, Mwangi Kimenyi, Germano Mwabu, Alice Ng'ang'a, and Justin Sandefur. 2013. *Scaling-up What Works: Experimental Evidence on External Validity in Kenyan Education*. CSAE Working Paper Series 2013-04. Centre for the Study of African Economies, University of Oxford.

Bruce, Neil, and Michael Waldman. 1991. "Transfers in Kind: Why They Can be Efficient and Nonpaternalistic". *American Economic Review* 81 (5).

Burlig, Fiona, and Louis Preonas. 2016. "Out of the Darkness and Into the Light? Development Effects of Rural Electrification in India". *Energy Institute at Haas Working Paper*, no. 268.

Central Bank of Kenya. 2019. *2019 FinAcess Household Survey*. https://www.centralbank.go.ke/uploads/financial_inclusion/2050404730_FinAccess%202019%20Household%20Survey-%20Jun.%2014%20Version.pdf.

Cunha, Jesse M. 2014. "Testing Paternalism: Cash versus In-Kind Transfers". *American Economic Journal: Applied Economics* 6, no. 2 (): 195–230.

Currie, Janet, and Firouz Gahvari. 2008. "Transfers in Cash and In-Kind: Theory Meets the Data". *Journal of Economic Literature* 46, no. 2 (): 333–83.

Dadzie, Christabel Ewuradjoa, and Dhushyanth Raju. 2020. *Economic relief through social safety nets during the COVID-19 crisis: the case of Ghana*. https://blogs.worldbank.org/nasikiliza/economic-relief-through-social-safety-nets-during-covid-19-crisis-case-ghana.

Demirguc-Kunt, Asli, Leora Klapper, Dorothe Singer, Saniya Ansar, and Jake Hess. 2018. *The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution*. The World Bank Group.

ECG. 2020. *Coronavirus: 'Free' electricity will start May 1 – ECG Boss*. http://www.ecggh.com/index.php/pages/news-events/coronavirus-free-electricity-will-start-may-1-ecg-boss.

Egger, Dennis, et al. 2021. "Falling living standards during the COVID-19 crisis: Quantitative evidence from nine developing countries". *Science Advances* 7 (6).

Gadenne, Lucie, Samuel Norris, Monica Singhal, and Sandip Sukhtankar. *In-Kind Transfers as Insurance*. Tech. rep. NBER Working Paper #28507. National Bureau of Economic Research.

Gentilini, Ugo, Mohamed Almenfi, Pamela Dale, A. V. Lopez, I. Mujica, R. Quintana, and U. Zafar. 2021. "Social Protection and Jobs Responses to COVID-19: A Real-Time Review of Country Measures".

Handa, Sudhanshu, Silvio Daidone, Amber Peterman, Benjamin Davis, Audrey Pereira, Tia Palermo, and Jennifer Yablonski. 2018. "Myth-busting? Confronting six common perceptions about unconditional cash transfers as a poverty reduction strategy in Africa". *The World Bank Research Observer* 33 (2): 259–298.

Haushofer, Johannes, and Jeremy Shapiro. 2016. "The short-term impact of unconditional cash transfers to the poor: experimental evidence from Kenya". *The Quarterly Journal of Economics* 131 (4): 1973–2042.

Hirvonen, Kalle, and John Hoddinott. 2021. "Beneficiary Views on Cash and In-Kind Payments: Evidence from Ethiopia's Productive Safety Net Programme". *The World Bank Economic Review* 35(2):398–413.

Klapper, Leora, Saniya Ansar, Jake Hess, and Dorothe Singer. 2019. "Mobile money and digital financial inclusion". *World Bank Group: Sub-Saharan Africa Series.*

Klugman, Noah, Joshua Adkins, Susanna Berkouwer, Kwame Abrokwah, Ivan Bobashev, Pat Pannuto, Matthew Podolsky, Aldo Suseno, Revati Thatte, Catherine Wolfram, et al. 2019. "Hardware, apps, and surveys at scale: insights from measuring grid reliability in Accra, Ghana". In *Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies*, 134–144.

Kojima, Masami, and Chris Trimble. 2016. "Making Power Affordable for Africa and Viable for Its Utilities". *World Bank Group, Africa Renewable Energy and Access Program, Energy Sector Management Assistance Program.*

Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2020. "Experimental Evidence on the Economics of Rural Electrification". *Journal of Political Economy* 128 (4).

Shapiro, Jeremy. 2019. "The impact of recipient choice on aid effectiveness". *World Development* 116:137–149.

Southworth, H. M. 1945. "The Economics of Public Measures to Subsidize Food Consumption". *Journal of Farm Economics* 27 (1): 38–66.

Suri, Tavneet, Jenny Aker, Catia Batista, Michael Callen, Tarek Ghani, William Jack, Leora Klapper, Emma Riley, Simone Schaner, and Sandip Sukhtankar. 2021. "Mobile Money". *VoxDevLit* 2 (1).

Thomas, Catherine C., Nicholas G. Otis, Justin R. Abraham, Hazel Rose Markus, and Gregory M. Walton. 2020. "Toward a science of delivering aid with dignity: Experimental evidence and local forecasts from Kenya". *Proceedings of the National Academy of Sciences* 117 (27): 15546–15553.

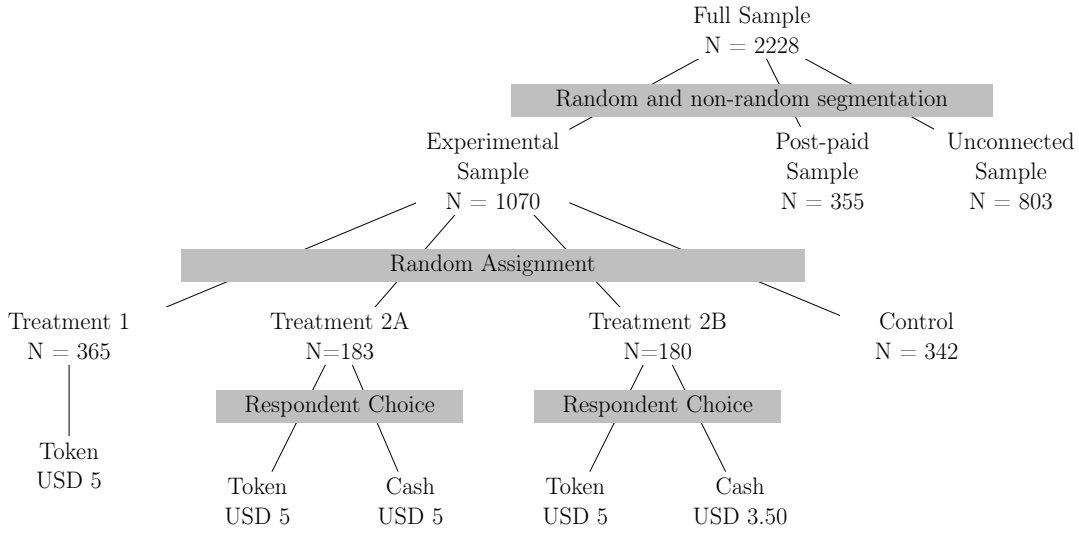
Vivalt, Eva. 2020. "How Much Can We Generalize From Impact Evaluations?" *Journal of the European Economic Association* 18, no. 6 (): 3045–3089.

Wolfram, Catherine, Edward Miguel, Eric Hsu, and Susanna Berkouwer. 2021. "Promoting accountability in public projects: Donors, audits, and rural electrification". EDI Working paper.

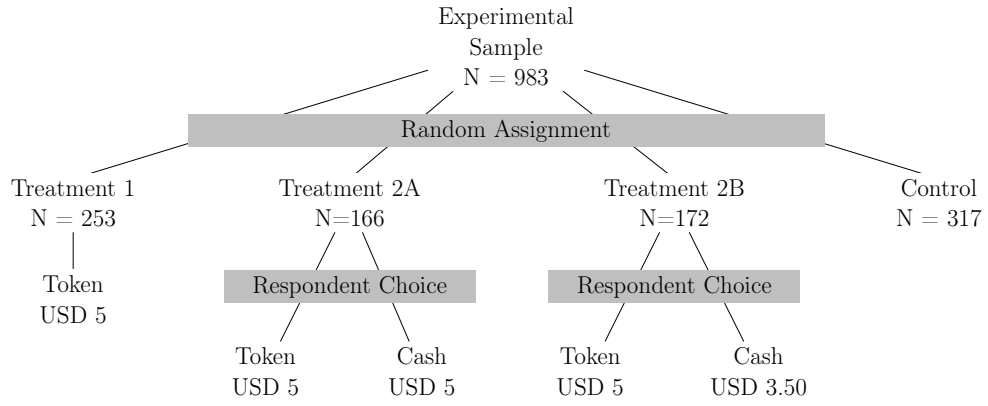
Appendix A: Additional Figures

Figure A1: Experimental design

Panel A: Rural Sample

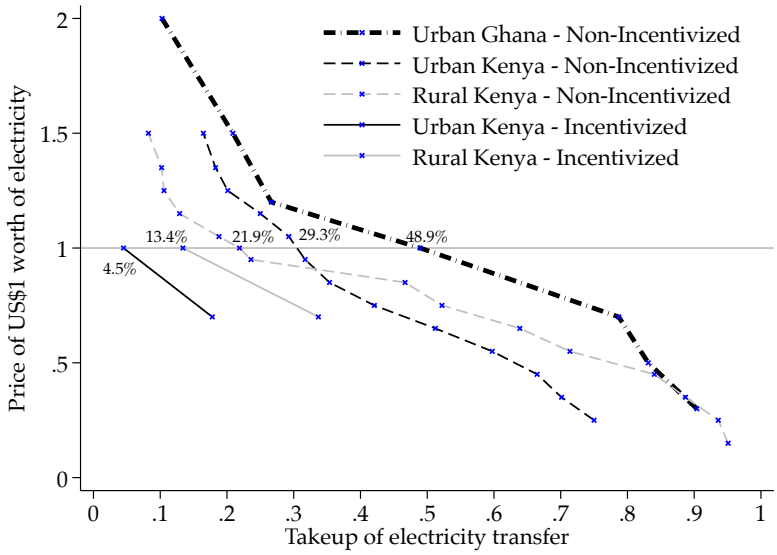


Panel B: Urban Sample



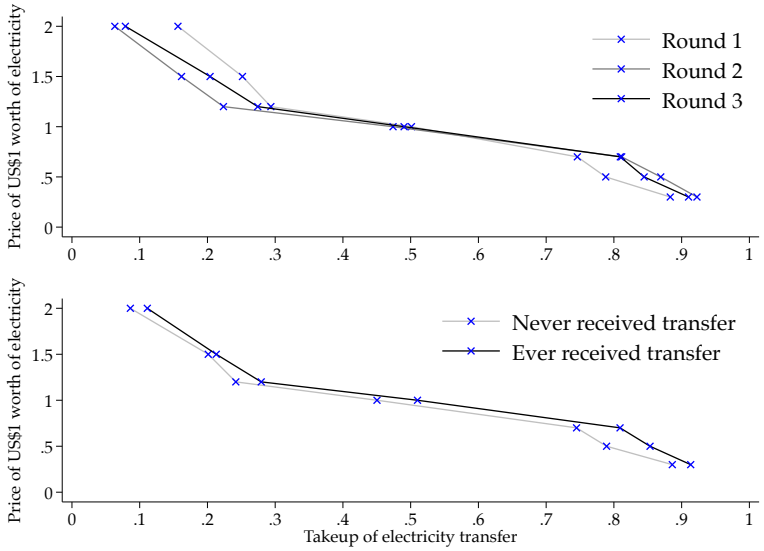
Panel A displays the non-experimental sample as well as treatment assignment within the experimental sample for rural households. Panel B displays treatment assignment among urban households. Attrition causes modest discrepancies between groups and subgroups.

Figure A2: Demand for Electricity Transfers by Context (including non-incentivized elicitation)



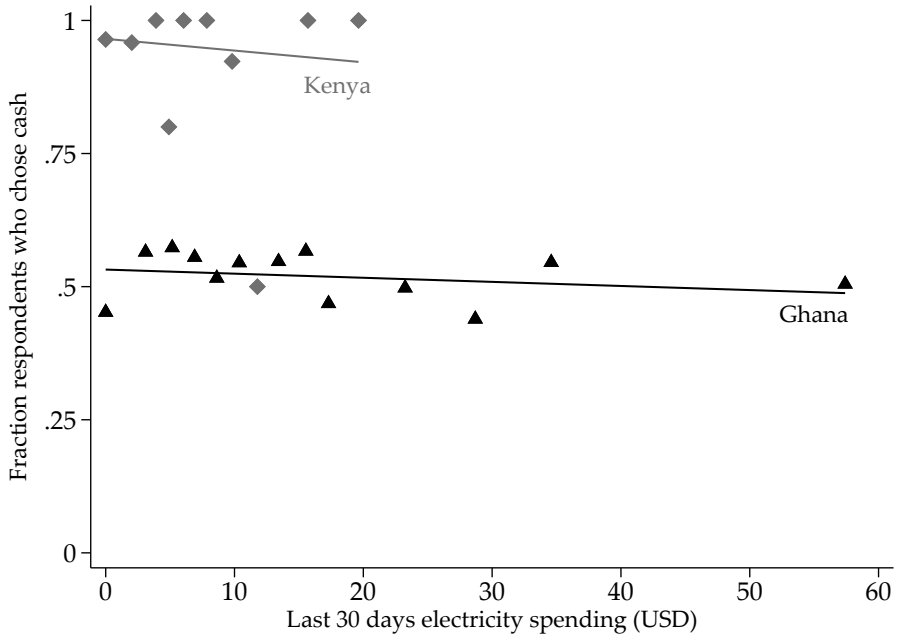
Demand for USD 1 of electricity expressed in USD of mobile money. The horizontal line represents the point where USD 1 of electricity costs USD 1 in mobile money. The numbers shown indicate the share of respondents who prefer electricity to cash in an equal trade-off, by context. Solid lines indicate incentivized elicitation, where transfers that respondents receive depend on their responses. Dashed lines indicate non-incentivized elicitation, where respondents indicate preferences over hypothetical tradeoffs between electricity and cash transfers. Data for the Ghana non-incentivized willingness-to-pay is based on the Ghana sample, as described in section 3. Data for the Kenya incentivized willingness-to-pay as well as the rural Kenya non-incentivized willingness-to-pay is based on the experimental Kenya sample. Due to data limitations, data for the urban Kenya non-incentivized willingness-to-pay is based on a sub-sample of 164 urban respondents.

Figure A3: Demand for Electricity Transfers by Round and Transfer Receipt in Ghana



Demand for USD 1 of electricity expressed in USD of mobile money, from a series of hypothetical choices between receiving a 50 GHS electricity transfer or receiving a specific mobile money transfer amount.

Figure A4: Correlation between electricity take-up and electricity expenditures by country



Preference for cash when given the choice between USD 5 of cash or USD 5 of pre-paid electricity. At all levels of monthly electricity spending, demand for cash is almost twice as high in Kenya as in Ghana.

Appendix B: Additional Tables

Table A1: Summary statistics, Ghana sample

	N	Mean	SD	Min	25^{th}	50^{th}	75^{th}	Max	Accra Pop Mean
Household characteristics									
Number of adults (>=18)	911	2.96	1.82	1.0	2.0	2.0	4.0	11.0	2.11[a]
Number of children (<18)	911	1.37	1.69	0.0	0.0	1.0	2.0	15.0	1.34[a]
Respondent age*	911	29.48	9.21	18.0	22.0	27.0	34.0	65.0	45.39[a]
Respondent is male*	911	0.70	0.46	0.0	0.0	1.0	1.0	1.0	0.67[a]
Primary roof material is metal sheets	88	0.65	0.48	0.0	0.0	1.0	1.0	1.0	0.48[b]
Primary wall material is concrete	88	0.97	0.18	0.0	1.0	1.0	1.0	1.0	0.91[b]
Has a generator	911	0.04	0.21	0.0	0.0	0.0	0.0	1.0	0.02[a]
Has a television	911	0.94	0.24	0.0	1.0	1.0	1.0	1.0	0.85[b]
Has a refrigerator/freezer	911	0.79	0.41	0.0	1.0	1.0	1.0	1.0	0.62[b]
Number of household phones	499	1.78	2.49	1.0	1.0	1.0	2.0	23.0	3.02[a]
Total spending per capita in past 7 days (USD)	2417	34.48	49.20	0	14.06	21.93	35.81	730.1	27.72[a]
Food spending per capita in past 7 days (USD)	2403	8.94	8.70	0.0	4.0	6.9	11.5	121.1	10.87[a]
Electricity connection and use									
Shares meter with other users	854	0.30	0.46	0.0	0.0	0.0	1.0	1.0	.
Current balance on prepaid meter (USD)	1045	5.75	8.08	0.0	1.0	3.3	6.9	51.9	.
Count of prepaid meter topups in last 30 days	2186	1.83	1.32	0.0	1.0	2.0	2.0	9.0	.
Average topup amount in last 30 days (USD)	2188	10.48	15.50	0.0	4.5	8.6	10.4	519.0	.
Electricity spending in past month (USD)	2392	14.63	12.79	0.0	6.9	10.4	17.3	69.2	15.34[a]
Lifeline customer according to March spending	826	0.08	0.28	0.0	0.0	0.0	0.0	1.0	.
Government relief									
Ever received electricity relief	824	0.75	0.43	0.0	0.0	1.0	1.0	1.0	.
Received electricity relief in last 30 days	2405	0.39	0.49	0.0	0.0	0.0	1.0	1.0	.
Electr. transfer received in last 30 days (USD)	2218	3.45	7.69	0.0	0.0	0.0	5.2	173.2	.
Electr. relief received in total (USD)	638	15.09	20.01	0.0	0.0	10.4	23.9	259.5	.
Received cash from govt/NGO in last 7 days	2417	0.01	0.09	0.0	0.0	0.0	0.0	1.0	.
Received food from govt/NGO in last 7 days	2417	0.01	0.12	0.0	0.0	0.0	0.0	1.0	.
Ever received water subsidy	824	0.43	0.50	0.0	0.0	0.0	1.0	1.0	.

The Ghana sample is drawn entirely from urban households in three Accra West electricity districts in the Greater Accra Region. For time-invariant characteristics, we report means for the first time a household is surveyed. For time-varying characteristics, we report summary statistics across survey rounds. Data on housing materials and phones are drawn from prior surveys administered to this sample. Summary statistics for the Ghana Statistical Service's 2017 Ghana Living Standards Survey (GLSS)[a] and the 2015 Labor Force Survey (LFS)[b] and are for urban households in the Greater Accra Region. Both of these surveys are designed to be representative at the region level and by urban/rural location. Survey weights are applied to generate representative estimates. *The respondent for the Ghana sample may be an adult other than the head of household. For the LFS and GLSS, we present data on the head of household for comparison.

Table A2: Summary statistics, Kenya sample

Panel A: Rural Sample

	N	Mean	SD	Min	25^{th}	50^{th}	75^{th}	Max	Kenya Pop Mean (Rural)
Number of adults in the household	1014	3.10	1.49	1.00	2.00	3.00	4.00	11.00	.
Number of children	1014	2.93	2.10	0.00	1.00	3.00	4.00	15.00	.
Respondent age	913	46.63	17.62	18.00	33.00	45.00	60.00	102.00	38.60
Respondent is male	1024	0.39	0.49	0.00	0.00	0.00	1.00	1.00	0.50
Completed Secondary School	997	0.16	0.37	0.00	0.00	0.00	0.00	1.00	0.21
High quality roof material	1023	0.95	0.21	0.00	1.00	1.00	1.00	1.00	0.87
High quality wall material	1023	0.29	0.45	0.00	0.00	0.00	1.00	1.00	0.26
High quality floor material	1023	0.41	0.49	0.00	0.00	0.00	1.00	1.00	0.37
Has TV	890	0.57	0.50	0.00	0.00	1.00	1.00	1.00	0.27
Has Refrigerator	890	0.02	0.15	0.00	0.00	0.00	0.00	1.00	0.02
Consumption in past 7 days	1034	23.32	15.38	1.05	16.47	22.83	22.83	156.68	.
Food spending in past 7 days	1038	15.92	10.81	0.00	11.36	15.60	15.60	128.24	.
Electricity spending in past 2 weeks	1009	0.82	1.60	0.00	0.00	0.00	0.92	18.32	.
Meter balance (kWh)	864	11.86	42.03	0.00	2.00	5.00	12.00	1077.00	.
Received govt/NGO assistance in past 14 days	1013	0.09	0.28	0.00	0.00	0.00	0.00	1.00	0.07

Panel B: Urban Sample

	N	Mean	SD	Min	25^{th}	50^{th}	75^{th}	Max	Kenya Pop Mean (Urban)
Number of adults in the household	995	2.32	1.33	1.00	1.00	2.00	3.00	10.00	.
Number of children	993	1.10	1.47	0.00	0.00	1.00	2.00	8.00	.
Respondent age	992	28.16	59.82	18.00	23.00	25.00	28.00	1901.00	34.00
Has TV	995	0.73	0.44	0.00	0.00	1.00	1.00	1.00	0.63
Has Refrigerator	995	0.14	0.35	0.00	0.00	0.00	0.00	1.00	0.19
Consumption in past 7 days	977	43.34	45.66	0.50	18.00	31.60	52.67	543.65	.
Food spending in past 7 days	981	17.47	23.87	0.00	6.41	11.91	20.15	448.84	.
Electricity spending in past 2 weeks	983	1.63	2.65	0.00	0.00	0.92	1.83	45.80	.
Meter balance (kWh)	807	9.29	21.78	0.00	2.15	4.50	10.00	300.00	.
Received govt/NGO assistance in past 14 days	985	0.02	0.13	0.00	0.00	0.00	0.00	1.00	0.07

This table presents summary statistics for the Kenya rural (panel A) and urban (panel B) samples from the baseline survey. The Kenyan rural sample is from Western Kenya, Nyanza, and Rift Valley. The Kenyan urban sample is from Nairobi, Mombasa, Kisumu, Eldoret, Nakuru, and other major cities. Rural and urban population means are taken from the 2019 Kenyan Census.

Table A3: Socioeconomic Outcomes

Panel A: Rural Sample

	N	Control Mean (SD)	Token Treatment (SE)	500 Ksh vs Tokens (SE)	350 Ksh vs Tokens (SE)
Total household income (pc) in the past 14 days in USD	1860	3.11	0.22	-1.47**	-0.63
		(8.87)	(0.65)	(0.64)	(0.74)
Total labor supply in hours	1372	44.72	1.16	3.58	0.62
		(40.46)	(2.83)	(4.08)	(3.57)
Total earnings from enterprises in the past 14 days in USD	1821	9.42	0.31	-2.17	2.72
		(36.15)	(1.97)	(2.06)	(2.98)
Food security index (SD)	1821	0.06	-0.02	0.04	-0.01
		(1.09)	(0.08)	(0.10)	(0.09)
Child education index (SD)	1354	0.01	-0.08	-0.06	-0.03
		(1.10)	(0.08)	(0.10)	(0.09)
COVID knowledge index (SD)	1777	-0.01	0.11*	0.05	0.06
		(1.03)	(0.06)	(0.07)	(0.07)
Number of COVID-19 symptoms in the past 14 days (out of 11)	1821	0.49	-0.03	-0.05	0.01
		(1.01)	(0.06)	(0.07)	(0.06)
Number of in-person interactions in the last 14 days	1817	17.74	2.18	0.86	3.47*
		(24.53)	(1.37)	(1.50)	(1.82)
CES-D-10 index	1868	8.97	0.12	-0.21	-0.60
		(5.23)	(0.30)	(0.36)	(0.44)

Panel B: Urban Sample

	N	Control Mean (SD)	Token Treatment (SE)	500 Ksh vs Tokens (SE)	350 Ksh vs Tokens (SE)
Total household income (pc) in the past 14 days in USD	914	19.54	-5.08*	-2.22	-2.49
		(41.10)	(2.97)	(4.13)	(3.47)
Total labor supply in hours	848	25.48	-1.71	-0.42	1.18
		(32.87)	(2.63)	(3.34)	(2.99)
Total earnings from enterprises in the past 14 days in USD	908	13.52	-2.12	-2.52	-10.29***
		(48.53)	(3.79)	(5.12)	(3.92)
Food security index (SD)	902	0.06	-0.19**	0.02	-0.11
		(0.92)	(0.09)	(0.09)	(0.09)
Child education index (SD)	225	0.01	0.10	0.10	0.88***
		(1.05)	(0.16)	(0.18)	(0.25)
COVID knowledge index (SD)	878	-0.01	0.01	0.08	-0.07
		(1.02)	(0.08)	(0.10)	(0.10)
Number of COVID-19 symptoms in the past 14 days (out of 11)	900	0.20	-0.01	-0.03	0.06
		(0.62)	(0.05)	(0.06)	(0.07)
Number of in-person interactions in the last 14 days	888	33.45	-4.68	-4.33	-1.12
		(48.82)	(4.03)	(4.72)	(4.73)
CES-D-10 index	900	8.12	0.60	0.57	0.66
		(5.23)	(0.44)	(0.51)	(0.54)

This table presents estimates of Equation 1 for major socioeconomic outcomes. From left to right, the columns show the number of observations, the control mean, and the treatment effects of T1, T2A , and T2B (all relative to control). Regressions include baseline controls for sex, education, banking status, and housing quality; all collected during enrollment in Lee et al. (2020) or Wolfram et al. (2021)), as well as the Covid-19 survey baseline round value for each outcome. FDR q-values for all coefficients are statistically insignificant at the $\alpha = 0.10$ level.

Table A4: Correlates of choosing electricity credit over a cash transfer of equal value (Rural Kenya; non-incentivized WTP

	(1) Rural Kenya (non-incentivized WTP)
Respondent age	-0.001
	(0.001)
Respondent is female	0.011
	(0.033)
Number of adults in the household	0.020*
	(0.012)
Number of children	-0.007
	(0.008)
Electricity spending in past 2 weeks	-0.008
	(0.020)
Non-food expenditure in the past 7 days in USD	0.001
	(0.002)
Food spending in past 7 days	-0.001
	(0.002)
Meter balance (kWh)	-0.000
	(0.000)
Has TV	0.024
	(0.043)
Has Refrigerator	-0.057
	(0.113)
Number of electric appliances owned	0.061***
	(0.017)
Received any gov't or NGO assistance in past 14 days	-0.028
	(0.057)
Constant	0.110
	(0.075)
Observations	757

This table presents estimates of the correlations between respondent characteristics and preference for electricity relative to cash, elicited through a series of choices between an electricity credit transfer and a mobile money transfer of a varying amount. The dependent variable is a dummy for preferring an electricity credit transfer to a mobile money transfer of equal value. The sample include rural households in Kenya in the experimental sample.