Mobile-Phone Ownership Increases Poor Women's Household Consumption: A Field Experiment in Tanzania[1]

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Abstract
The poverty-reducing effects of mobile phones are widely touted but rest on uncertain observational evidence. In a large (*n* = 1,352) randomized control trial among poor women in Tanzania, we assigned no-cost basic handsets, smartphones, and a cash placebo compared to control. After one year, phones increased usage of digital financial services, financial inclusion, and household consumption. Mobile phone churn, however, was high among study participants. At endline nearly one third in the phone groups no longer owned a phone. Phone loss significantly attenuated consumption effects. Participants retaining phones experienced consumption increases estimated at 16-24 percent compared to control, indicating that mobile phones may provide cost-effective poverty reduction.

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Few other global trends have outpaced the rate at which people living in poverty are acquiring mobile phones and using them to improve their economic welfare. From Indian fishermen making calls while still at sea to locate the most competitive fish markets (Jensen 2007) to grain farmers in Niger leveraging mobile phones to gather information on prices and inventory (Aker 2010) to Kenyans using their phones as a digital wallet to protect themselves from economic shocks and to increase savings (Jack and Suri 2014), the potential economic gains from mobile phone ownership are enormous – especially for those who traditionally face steep barriers to long-distance communication, acquiring market information, and gaining access to financial institutions. The most comprehensive study to date on the impact of mobile technology on poverty reduction found that the take-off of mobile money in Kenya (as measured by density of mobile money agents) reduced extreme poverty for female-headed households by 22% (Suri and Jack 2016).

To estimate the effects of mobile technology on poverty reduction, most prior studies have employed instrumental variables based on the staged geographic rollout of cell or mobile-money service over time (Suri and Jack 2016, Jack and Suri 2014). Alternatively, others have analyzed before-and-after effects using panels or waves of successive surveys (Mbiti and Weil 2016, Muto and Yamano 2009).

However, such observational evidence faces well-known challenges regarding unobserved confounding variables (Gerber and Green 2012). Notably, mobile network operators deliberately choose new locations for market expansion based on the accessibility, wealth, and dynamism of local economies, among many other factors potentially correlated with outcomes. Similarly, the timing of acquiring a phone may reflect the greater welfare of the buyer generally, the broadly improving prospects in the community, or other endogenous variables. This may introduce bias and overstate the welfare effects of mobile phone technology. Employing control variables in statistical analysis may not fully neutralize these confounds. Additionally, ecological fallacies weaken the inferences that can be drawn from as-if-random cluster-design studies of the rollout of mobile phone service or mobile money. Namely, it is impossible to isolate the individual impact of mobile-phone ownership vis-à-vis the positive economic externalities that arise from certain areas becoming early adopters of this new technology and spurring the concomitant clustering of mobile money agents (who also have other commercial ventures). Individual-level experimental approaches are designed to overcome these inferential challenges.

To estimate the causal effects of mobile phones on the welfare of women from low-income households, we undertook a large (n = 1,348) randomized control trial (RCT) in Tanzania in 2016-17 in which we randomly assigned the bequest of basic handsets, smartphones, and a cash placebo and compared outcomes to a control condition in which subjects were placed on a waitlist for the phones to be received one year later. To our knowledge this is the first pure RCT testing the effectiveness of mobile phones on poverty reduction.[8]

We focused on women because in Tanzania, like in many other developing countries, mobile phone ownership for women is significantly lower than among men (GSMA 2015). This digital inequality risks compounding existing structural inequalities. Non-phone owners are deprived the agency and voice that comes from low-cost access to

[8] This builds on the pioneering work of Jennifer Aker and colleagues (Aker, Boumnijel, McClelland, and Tierney 2016) who conducted some of the first RCTs on mobile tech and mobile money.

information and communication enabled by mobile phone technology (Klugman et al. 2014). Moreover, non-phone owners are significantly less likely to reap the economic benefits that come from mobile money (Mirzoyants 2013).

Following best research practices, we registered our experimental design and pre-analysis plan detailing anticipated statistical analyses prior to the collection of outcome data.[9] The study and results reported here follow this plan with any departures specified. To recruit subjects, we partnered with two organizations that have a national presence in Tanzania: the microfinance organization, BRAC, and the Tanzanian government's anti-poverty Social Action Fund, TASAF. Both organizations work primarily with women from low-income households, though BRAC members typically own their own small businesses and are significantly better off than TASAF members, who must pass a poverty means test to receive TASAF services. With facilitation from BRAC and TASAF, we reached out to a pool of potential participants and screened for mobile phone ownership through a brief, inconspicuous survey on ownership of various household and personal assets, including a mobile phone.

We worked in 11 districts across in five different regions of Tanzania dispersed throughout the country – Arusha, Mwanza, Iringa, Tanga, and Ruvuma – that provided both broad geographic diversity and a balanced mix of rural, peri-urban and urban residents. (See Figure S1 for map of field sites.) We organized participants into blocks based on rural vs. urban location, organizational affiliation (BRAC or TASAF), and income level (above and below median). We block randomized the 1,348 non-phone owners according to pre-

[9] We registered the pre-analysis plan with the Evidence in Governance and Politics (EGAP) research network, ID 20170308AA.

determined treatment proportions in a fully crossed factorial design assigning basic handsets, smartphones, cash (40,000 Tanzanian Shillings, or US $18, the equivalent value of a basic phone), group vs. individual mobile phone training, mobile credit vouchers, and solar chargers.[10] After the baseline survey, participants were invited to enroll in a two-year program, the Mobile Phone and Livelihoods of Women Project, through which, it was explained, enrollees would receive a SIM card and be eligible to receive mobile technology, training or small cash grants (see Table S1 for consent form). Women assigned to control were told that they would be placed on a waitlist to receive their items in year two of the program. See Table S2 in the Supplementary Materials (SM) for the distribution of experimental conditions across experiments, locations, and blocks. Table SX reports balance across key covariates taken from the baseline survey.

After random assignment, participants were invited to attend a distribution meeting where they received a SIM card (from one of the three major Tanzania mobile network operators with strong coverage in their area) and the mobile technology items they were assigned.[11] Cutting across the mobile phone experiment was a training intervention. Training walked participants through how to install a SIM card, charge the phone, turn on the phone, use the radio and flashlight, make a phone call, send SMS, use mobile money, and, for smartphone recipients, how to access the internet and download an app. Some received this training individually, some as a group and others received no training at all.

[10] A second experiment, for 648 women who already owned phones, similarly randomized smartphones, cash (reflecting the cost of the smartphone), mobile credit, and solar chargers. We report results from this second experiment elsewhere.
[11] The MNOs provided the SIM cards free of charge and sent their agents to the distribution meetings to register and activate participants' SIM cards. The MNOs also agreed to share data so that we could employ information on actual mobile usage to validate key survey outcomes for subjects who consented to our examination of anonymized usage data.

Outcome measures assessing many items including phone ownership, mobile-money use, and household consumption were drawn from answers to in-person surveys conducted at baseline (July-August 2016), midline (February-March 2017), and endline (October-November 2017).[12] See Figure S2 for project timeline. Training and surveys were conducted by Tanzanian female enumerators in Swahili. Pre-registered key outcomes of interest here include phone use, mobile-money use, and economic well-being, with results for other registered outcomes reported in the SM. To obtain a behavioral measure of mobile money use, at the end of the midline and endline surveys we offered participants with a grant that varied by amount depending on whether they chose to receive it as cash at 4,000 Tazanian shillings (TZX) or via mobile money at 8,000 TZX.[13] The amounts were roughly equivalent to 1 or 2 US dollars, respectively. (For results of endline small grant exercise, see Tables S4A-S4B). Attrition at endline was low. We managed to re-survey 94% of participants. As shown in Figure S3, attrition was higher for the cash group but displayed no significant difference between the phone groups and control.[14]

As pre-registered, statistical analysis was performed to estimate differences in means using randomization inference, a non-parametric technique in which the test statistic is drawn from random permutations of the actual assignments to experimental conditions rather than based on assumptions of normal distribution (Gerber and Green 2012). Robustness was checked using regression analysis with covariates for

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[12] The main text concentrates on endline results.

[13] At midline we randomly assigned participants to receive one of three offers: 1.) 4,000 Tanzanian Shillings (US $1.80) for the grant in cash or 4,000 TSh as mobile money; 2.) 6,000 TSh in cash or 4,000 TSh as mobile money; 3.) 4,000 TSh in cash or 6,000 TSh as mobile money. As at midline, even condition 3 only incentivized 7% of participants to choose mobile money, we substantially increased the mobile money premium at endline to 100% over cash (8000 Tanzanian Shillings, or $3.60, for mobile money versus 4000 Tanzanian Shillings, or $1.80, in cash).

[14] Midline attrition was much higher than at endline. We were only able to reach 84% of participants. We were significantly more likely to survey those in the phone groups than in control. Given this non-random midline attrition, at this stage we primarily report endline results.

demographics, socioeconomic status, and blocking strata, with standard errors clustered at the district level. At endline one year after distribution of the phones, women assigned to the basic and smartphone conditions were, as expected, significantly more likely to own phones, use mobile money, use phones for income-generating activities, and score higher on an index of financial inclusion. See Tables S5A-S8B. All of these results suggest that cellphones alter people's economic outlook and offer the potential for welfare gains.

Nevertheless, substantial turnover occurred in cellphone ownership between distribution and endline. This likely reflects important dynamics in cellphone ownership among poor people in developing countries. But it also indicates significant non-compliance with the study's experimental conditions. Fully 31 percent of women in the basic phone group and 26 percent in the smartphone condition did not own any phone at endline, reporting their project phone either lost, broken, stolen, or sold. See Figure S4.

Moreover, many other women in the smartphone group had only basic phones at endline, having traded or sold their project smartphone. At endline, only 53 percent of women in the smartphone condition claimed to still own their project phone and, when asked by the enumerator to produce it, only 34 percent could do so. See Figures S5A-S5B. Additionally, in the cash group in which women were given money equivalent to the cost of a basic phone, 55 percent possessed phones at endline, indicating that many used their cash gift to buy a phone. Given the many other pressing needs on which subjects in the study may have spent the cash, this high rate of phone purchasing in the cash group suggests the premium that poor women place on phone ownership. Reinforcing this point, in the control group 27 percent had actually acquired a phone on their own by endline.

Despite these extensive levels of non-compliance across all experimental conditions, intent-to-treat effects of assignment to the phone conditions were substantively meaningful and significant statistically for the primary pre-registered outcome assessing economic welfare, which focuses on household consumption. This measure represents the monthly sum of amounts from 15 independent survey items inquiring after common expenses made recently, such as food, fuel, transportation, water, and electricity.[15] Given that these items are discrete and cover a wide range of common expenses, their sum should be relatively insensitive to social-desirability bias. We based the survey consumption battery on prior research (Suri and Jack 2016).

Assignment to the two phone conditions significantly increased monthly household consumption. See Tables S9A-S9B. Subjects in the phone conditions reported monthly consumption increases compared to control of 9 to 16 percent, representing effect sizes in standard-deviation units of .14 to .17, depending on the method employed for normalizing the skewed consumption data.[16] Assignment to the smartphone condition had effects that were larger and more robust to alternative specifications than the basic-phone treatment. Consistent with the local average treatment effects below, these results are driven by participants who hold on to their smartphones compared to those who do not retain them and possibly sell them.

[15] Other household consumption components included household items, mobile technology expenses, alcohol and tobacco, entertainment, household maintenance, clothing, ceremonies and funerals, healthcare, education, and property taxes. Note that the results reported here are broadly robust to the exclusion of mobile expenses from the measure of consumption. Mobile expenses are retained because they represent meaningful consumption for households in addition to other categories.

[16] Methods included a logarithmic transformation and Winsorization of the data by bounding observations with extremely high values at the 90th, 95th, and 99th percentiles. Results are generally similar across these methods, with stronger effect sizes tending toward the higher Winsorization percentiles but more precision in estimation at the lower percentiles.

It is worth reiterating that these results report the intent-to-treat (ITT) effects based on assignment to experimental conditions independent of compliance rates. As an alternative to ITT and an addition to the pre-specified analysis, in light of high non-compliance we can estimate the treatment effects on the treated, also known as the complier-average causal effect (Gerber and Green 2012). This is done by employing a two-stage model in which assignment to treatment is used as an instrument satisfying the exclusion restriction to simultaneously estimate both the compliance rate and the outcome measure. In essence, this estimates the treatment effect on consumption of being assigned to receive a phone but only for the subjects, called compliers, that actually retained a phone at endline.

The treatment effects on the treated are larger substantively and more precisely estimated. Compliers in the phone treatment groups reported improvements in household consumption of 16-24 percent with effect sizes of .24 to .27. See Table S10. In substantive terms, this represents an increase in monthly household consumption of $12 to $20, which likely feels significant to the poor women in our study whose households were consuming $2.59 per day on average. Given that basic phones cost $18 and smartphones $65, the results here suggest that the interventions produce a very high yield on investment and may well provide a cost-effective means of poverty reduction. It appears that the main mechanisms through which the phones improve economic welfare involve mobile-money use and employment of the phones in small businesses.

In sum, mobile phones appear to boost household consumption among the very poor. However, these effects emerge only in the face of substantial turnover in mobile phone ownership. Observers may be tempted to assume that an essential threshold will be reached when all poor people possess a mobile phone. The results here suggest that mobile phone ownership is quite tenuous and that the very poor living at the margins simply cannot easily or readily replace a lost, broken, or stolen phone. So, any phone-based consumption-generating activities must necessarily wait for a windfall or for savings to accumulate – and our data suggest that such a moment may take many months or even years. While mobile phones may indeed provide part of the answer in the struggle against global poverty, deeper consideration must be given to the challenges faced by poor people when they confront the loss of valued assets.

References

Aker, Jenny C. 2010. "Information from markets near and far: Mobile phones and agricultural markets in Niger." *American Economic Journal: Applied Economics* 2, no. 3: 46-59.

Aker, Jenny C., Rachid Boumnijel, Amanda McClelland, and Niall Tierney. 2016. "Payment Mechanisms and Antipoverty Programs: Evidence from a Mobile Money Cash Transfer Experiment in Niger." *Economic Development and Cultural Change* 65 (1):1-37. doi: 10.1086/687578.

Jensen, Robert. 2007. "The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector." *The Quarterly Journal of Economics* 122, no. 3: 879-924.

Suri, Tavneet, and William Jack. 2016. "The long-run poverty and gender impacts of mobile money." *Science* 354, no. 6317: 1288-1292.

Jack, William, and Tavneet Suri. 2014. "Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution." *American Economic Review* 104, no. 1: 183-223.

Mbiti, Isaac and David N. Weil. 2016. “Mobile Banking: The Impact of M-Pesa in Kenya.” In Sebastian Edwards, Simon Johnson, and David Weil, eds. *African Successes, Volume III*. Chicago: University of Chicago Press.

Muto, Megumi, and Takashi Yamano. 2009. "The impact of mobile phone coverage expansion on market participation: Panel data evidence from Uganda." *World Development* 37, no. 12: 1887-1896.

Gerber, Alan S., and Donald P. Green. 2012. *Field experiments: Design, analysis, and interpretation*. New York: W.W. Norton.

GSMA. 2015. "Bridging the Gender Gap: Mobile Access and Usage in Low- and Middle-Income Countries." London: GSMA.

Klugman, Jeni, Lucia Hanmer, Sarah Twigg, Tazeen Hasan, and Jennifer McCleary-Sills. 2014. *Voice and Agency: Empowering Women and Girls for Shared Prosperity.* Washington, D.C.: World Bank.

Mirzoyants, Anastasia. 2013. "Mobile Money in Tanzania: Use, Barriers and Opportunities." *The Financial Inclusion Tracker Surveys Project.* Washington, D.C., London, and Nairobi: InterMedia.

Blumenstock, Joshua, Gabriel Cadamuro, and Robert On. 2015. "Predicting poverty and wealth from mobile phone metadata." *Science* 350, no. 6264: 1073-1076.

Supplementary Materials

Mobile-Phone Ownership Increases Poor Women's Income and Consumption: A Field Experiment in Tanzania

Figure S1: Field Sites in Tanzania

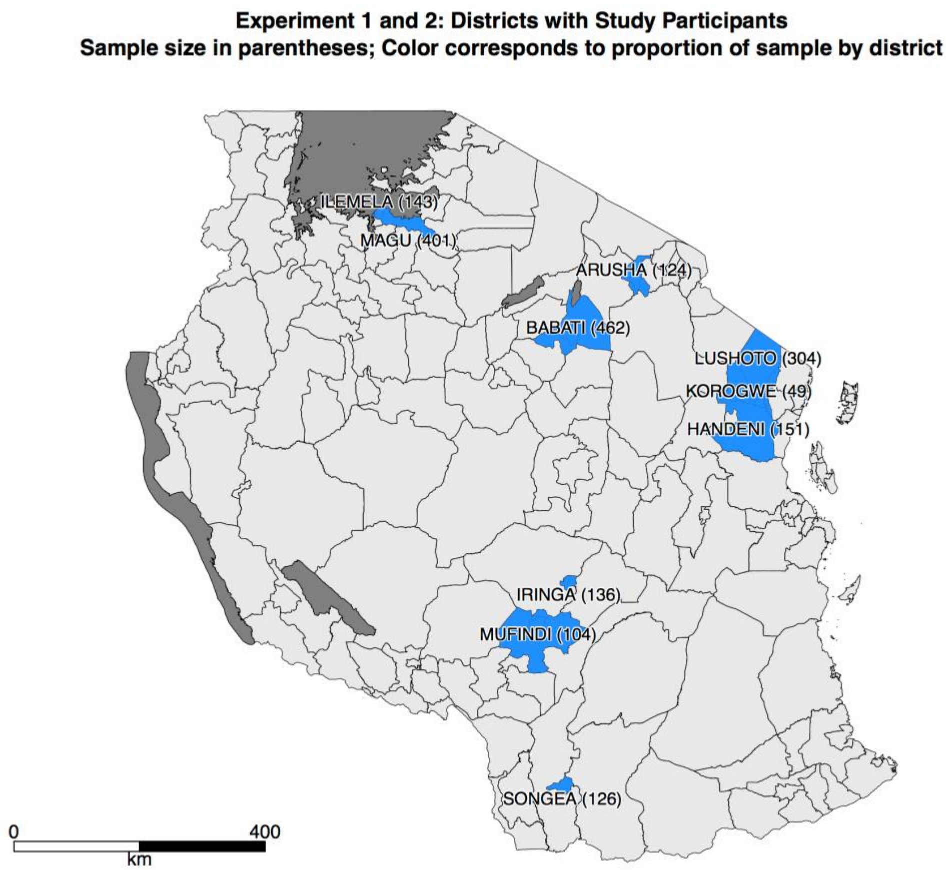

Table S1: Project Consent Form

Mobile Phone and Livelihoods of Women Project
PARTICIPATION AND CONSENT FORM

You have been selected to participate in the Mobile Phone and Livelihoods of Women Project. This program is funded by the Bill and Melinda Gates Foundation and is being implemented through a partnership between BRAC, TASAF, Tigo, Vodacom, and Airtel. This program is focused on improving women's access to mobile technology (mobile phone use) and digital financial services (for example, mobile money use).

Today we are seeking consent from you to be part of this program. As part of this program, we are increasing access to mobile technology, including mobile phones. Because we are unable to provide each of you with mobile technology at the same time, we will have two rounds of our program during the coming year. In the first round of the program we can provide some women with mobile technology. Those who are not chosen to receive mobile technology in the first round will receive mobile technology in the second round of the program, starting in next year. To be fair to everyone, we will decide which women are part of round one and which women are part of round two through a lottery system.

This program involves a research evaluation with our partners at REPOA, the College of William and Mary in Virginia, USA and Brigham Young University in Utah, USA. They will gather information related to the program, which will be used for academic purposes. The information will also be totally anonymous. Participation in this program and the related evaluation are completely voluntary. If at any time, you wish to discontinue your participation in the program and/or evaluation, you are welcome to do so.

If you have any questions with this program and evaluation for any reasons, you can contact Dr. Flora Myamba of REPOA at (22) 2700083 or the Tanzanian Commission for Science and Technology (COSTECH), Director of Social Science, (22) 2927546.

Consent for the Mobile Phone and Livelihoods of Women Project and evaluation:

"I agree to participate in the survey. I understand that my participation is voluntary."

☐ NDIYO / YES
☐ HAPANA / NO

NAME: ____________________________________

BRAC / TASAF GROUP AND MEMBER ID: ______________________________________

Please return this completed form.

Table S2: Assignment Proportions to Conditions

Proportion of Subjects Assigned to Different Treatment Conditions

	Total Subjects Per Condition	Individual Training (of total subjects)	Group Training (of total subjects)	Vouchers (of total subjects)	Solar Charger (of total subjects)
A. Basic Phone	385	97/385	231/385	100/385	100/385
B. Smartphone	385	97/385	231/385	100/385	100/385
C. $20 Cash Transfer	175	44/175	88/175	50/175	50/175
D. Control Group	405	67/405	68/405	50/405	50/405

Figure S2: Project Timeline

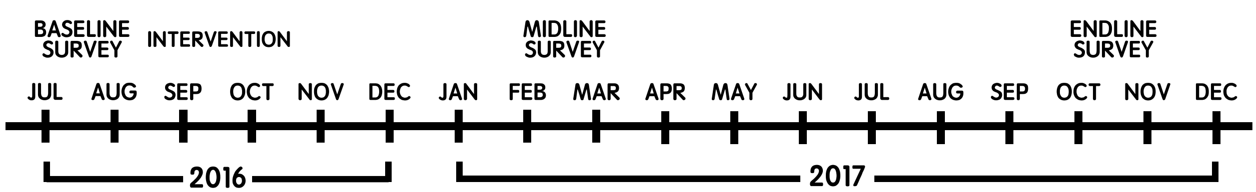

Table S3: Randomization Balance

	Control		Cash		Basic		Smart	
Variable	**N**	**Mean/SE**	**N**	**Mean/SE**	**N**	**Mean/SE**	**N**	**Mean/SE**
Rural v. Urban	411	1.187	177	1.181	384	1.185	380	1.179
		[0.019]		[0.029]		[0.020]		[0.020]
TASAF v. BRAC	411	1.550	177	1.559	384	1.552	380	1.547
		[0.025]		[0.037]		[0.025]		[0.026]
Personal income (range)	411	0.504	1ß77	0.525	384	0.513	380	0.508
		[0.025]		[0.038]		[0.026]		[0.026]
Age	411	45.063	177	44.062	384	44.469	380	45.232
		[0.749]		[1.031]		[0.795]		[0.824]
Head of Household	411	0.353	177	0.311	384	0.359	380	0.355
		[0.024]		[0.035]		[0.025]		[0.025]
Spouse in Household	410	0.646	176	0.653	384	0.615	380	0.600
		[0.024]		[0.036]		[0.025]		[0.025]
Illiterate	411	0.401	177	0.412	384	0.398	380	0.442
		[0.024]		[0.037]		[0.025]		[0.026]
Farmer	411	0.380	177	0.362	383	0.379	379	0.377
		[0.024]		[0.036]		[0.025]		[0.025]
Owned Phone in Past	410	0.549	177	0.571	383	0.548	379	0.530
		[0.025]		[0.037]		[0.025]		[0.026]

Table S3 reports the randomization balance across key variables in the experiment among subjects who were non-phone owners. There are no statistically significant differences between any of the study groups on these variables.

Table S4A: Difference-in-Means Results for Small-Grant Exercise

	Control Mean	Control N	Treat Mean	Treat N	Difference	(p-value)
Phone	0.49	386	0.59	723	0.10	0.001
Basic	0.49	386	0.63	359	0.14	0.000
Smart	0.49	386	0.54	364	0.05	0.091
Cash	0.49	386	0.61	157	0.12	0.009

Table S4A reports difference-in-means results for the two phone conditions pooled, each phone condition separately, and the cash condition all compared to control. *P*-values computed using randomization inference with 1,000 draws. Subjects in phone conditions opted for cash at significantly greater rates, though in the smartphone condition the difference is inconsistent with the null hypothesis only at the 0.1 level.

Table S4B: Logistic Regression Results for Small-Grant Exercise

	Model 1 b/se	Model 2 b/se
Phone	0.441*** (0.16)	
Basic Phone		0.623*** (0.18)
Smart Phone		0.266* (0.16)
Cash	0.559** (0.22)	0.559** (0.22)
Age	0.023 (0.03)	0.022 (0.03)
Age Squared	-0.000 (0.00)	-0.000 (0.00)
Education	0.165* (0.09)	0.162* (0.09)
Spouse in Household (HH)	0.032 (0.18)	0.030 (0.18)
No HH Phone at Baseline	-0.326** (0.15)	-0.329** (0.15)
Owned Phone in Past	0.416** (0.17)	0.414** (0.17)
Urban Block	0.646* (0.35)	0.644* (0.35)
TASAF Block	-0.392 (0.24)	-0.399 (0.24)
Income Block	-0.018 (0.22)	-0.017 (0.23)
Constant	-0.774 (1.05)	-0.735 (1.06)
N	1259	1259

Table S4B reports logistic regression results for the two phone conditions pooled (Model 1) and each phone condition separately (Model 2), with control as comparison group. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

Figure S3: Attrition Checks at Endline

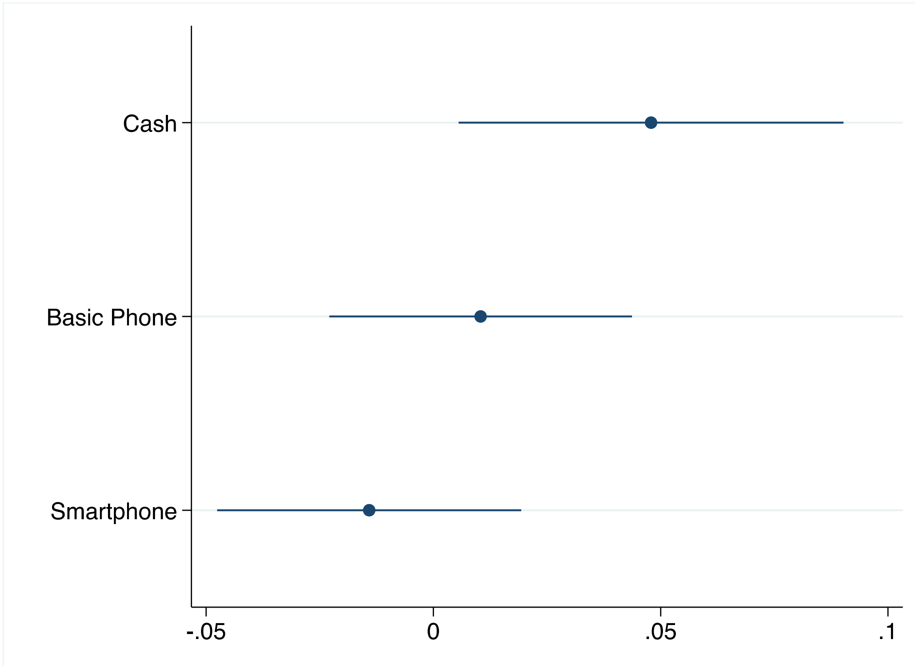

Figure S3 displays a coefficient plot of attrition from the study (not being interviewed in final survey) at endline across treatment conditions relative to control. The regression includes district-level fixed effects but no covariates. At endline the cash group had significantly higher levels of attrition than control.

Table S5A: Difference-in-Means Results for Phone Ownership at Endline

	Control Mean	Control *N*	Treat Mean	Treat *N*	Difference	(p-value)
Phone	0.27	386	0.72	724	-0.45	0.000
Basic	0.27	386	0.69	359	-0.42	0.000
Smart	0.27	386	0.74	365	-0.47	0.000
Cash	0.27	386	0.55	157	-0.28	0.000

Table S5A reports difference-in-means results on the outcome of phone ownership at endline for the two phone conditions pooled, each phone condition separately, and the cash condition all compared to control. *P*-values computed using randomization inference with 1,000 draws.

Table S5A: Logistic Regression Results for Phone Ownership at Endline

	Model 1	Model 2
	b/se	b/se
Phone	2.029***	
	(0.27)	
Basic Phone		1.901***
		(0.28)
Smart Phone		2.165***
		(0.28)
Cash	1.284***	1.285***
	(0.30)	(0.30)
Age	0.083***	0.084***
	(0.02)	(0.02)
Age Squared	-0.001***	-0.001***
	(0.00)	(0.00)
Education	0.230**	0.233**
	(0.11)	(0.11)
Spouse in Household (HH)	-0.164**	-0.163**
	(0.08)	(0.08)
No HH Phone at Baseline	-0.304**	-0.305**
	(0.14)	(0.15)
Owned Phone in Past	0.420***	0.423***
	(0.11)	(0.11)
Urban Block	0.485*	0.491**
	(0.25)	(0.25)
TASAF Block	0.072	0.079
	(0.19)	(0.19)
Income Block	0.045	0.046
	(0.18)	(0.18)
Constant	-4.123***	-4.168***
	(0.43)	(0.43)
N	1260	1260

Table S5B reports logistic regression results for the outcome of phone ownership at endline for the two phone conditions pooled (Model 1) and each phone condition separately (Model 2), with control as comparison group. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

Table S6A: Difference-in-Means for Mobile Money Use at Endline

	Control Mean	Control N	Treat Mean	Treat N	Difference	(p-value)
Phone	1.48	377	1.81	713	-0.33	0.000
Basic	1.48	377	1.92	351	-0.44	0.000
Smart	1.48	377	1.70	362	-0.22	0.025
Cash	1.48	377	1.74	156	-0.26	0.040

Table S6A reports difference-in-means on the outcome of mobile-money use frequency (on a 1-6 ordinal scale from 1 = every day to 6 = never) at endline for the two phone conditions pooled, each phone condition separately, and the cash condition compared to control. *P*-values computed using randomization inference with 1,000 draws.

Table S6B: Ordered Probit Results for Mobile Money Use at Endline

	Model 1 b/se	Model 2 b/se
Phone	0.295***	
	(0.07)	
Basic Phone		0.380***
		(0.06)
Smart Phone		0.212**
		(0.10)
Cash	0.277***	0.278***
	(0.09)	(0.09)
Age	0.010	0.009
	(0.01)	(0.01)
Age Squared	-0.000	-0.000
	(0.00)	(0.00)
Education	0.134**	0.132**
	(0.06)	(0.06)
Spouse in Household (HH)	0.033	0.032
	(0.05)	(0.05)
No HH Phone at Baseline	-0.009	-0.009
	(0.07)	(0.07)
Owned Phone in Past	0.202***	0.200***
	(0.08)	(0.08)
Urban Block	0.283***	0.281***
	(0.11)	(0.11)
TASAF Block	-0.561***	-0.564***
	(0.09)	(0.09)
Income Block	0.086	0.088
	(0.07)	(0.07)
N	1239	1239

Table S6B reports ordered probit regression results for the outcome of mobile-money use frequency (on a 1-6 ordinal scale from 1 = every day to 6 = never) at endline for the two phone conditions pooled (Model 1) and each phone condition separately (Model 2), with control as comparison group. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

Table S7A: Difference-in-Means for Phone Use for Income Generation

	Control Mean	Control N	Treat Mean	Treat N	Difference	(p-value)
Phone	0.32	387	0.41	724	-0.09	0.004
Basic	0.32	387	0.42	359	-0.11	0.000
Smart	0.32	387	0.40	365	-0.08	0.020
Cash	0.32	387	0.38	157	-0.06	0.119

Table S7A reports difference-in-means on the outcome of subjects' reporting that they use the phone for income-generating activities for the two phone conditions pooled, each phone condition separately, and the cash condition compared to control. *P*-values computed using randomization inference with 1,000 draws.

Table S7B: Logit Results for Phone Use for Income Generation

	Model 1	Model 2
	b/se	b/se
Phone	0.481***	
	(0.12)	
Basic Phone		0.537***
		(0.12)
Smart Phone		0.425***
		(0.15)
Cash	0.388	0.388
	(0.24)	(0.24)
Age	0.071***	0.071***
	(0.03)	(0.03)
Age Squared	-0.001***	-0.001***
	(0.00)	(0.00)
Education	0.185**	0.184**
	(0.09)	(0.09)
Spouse in Household (HH)	0.053	0.053
	(0.10)	(0.10)
No HH Phone at Baseline	-0.008	-0.008
	(0.20)	(0.20)
Owned Phone in Past	0.484**	0.483**
	(0.19)	(0.19)
Urban Block	0.260*	0.259*
	(0.15)	(0.15)
TASAF Block	-0.935***	-0.937***
	(0.10)	(0.10)
Income Block	0.325**	0.326**
	(0.15)	(0.15)
Constant	-1.977**	-1.971**
	(0.80)	(0.80)
N	1261	1261

Table S7B reports logistic regression results for the outcome of subjects' reporting that they use the phone for income-generating activities at endline for the two phone conditions pooled (Model 1) and each phone condition separately (Model 2), with control as comparison group. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

Table S8A: Difference-in-Means for Index of Financial Inclusion

	Control Mean	Control N	Treat Mean	Treat N	Difference	(p-value)
Phone	0.69	367	1.02	692	-0.32	0.000
Basic	0.69	367	1.05	338	-0.36	0.000
Smart	0.69	367	0.98	354	-0.29	0.000
Cash	0.69	367	0.81	152	-0.11	0.148

Table S8A reports difference-in-means on the outcome of an index of financial inclusion (which tallies subjects' having their own mobile-money account, obtaining bank loans, securing loans from mobile-network operators, and using mobile money for savings) for the two phone conditions pooled, each phone condition separately, and the cash condition compared to control. *P*-values computed using randomization inference with 1,000 draws.

Table S8B: Ordered Probit Results for Index of Financial Inclusion

	Model 1	Model 2
	b/se	b/se
Phone	0.515***	
	(0.07)	
Basic Phone		0.545***
		(0.08)
Smart Phone		0.486***
		(0.08)
Cash	0.253**	0.253**
	(0.10)	(0.10)
Age	0.015*	0.015*
	(0.01)	(0.01)
Age Squared	-0.000**	-0.000**
	(0.00)	(0.00)
Education	0.243***	0.242***
	(0.05)	(0.05)
Spouse in Household (HH)	-0.039	-0.039
	(0.06)	(0.06)
No HH Phone at Baseline	-0.099***	-0.099***
	(0.03)	(0.03)
Owned Phone in Past	0.134**	0.134**
	(0.06)	(0.06)
Urban Block	0.418*	0.417*
	(0.25)	(0.25)
TASAF Block	-0.330***	-0.331***
	(0.04)	(0.04)
Income Block	-0.040	-0.039
	(0.05)	(0.05)
N	1205	1205

Table S6B reports ordered probit regression results for the outcome of an index of financial inclusion (which tallies subjects' having their own mobile-money account, obtaining bank loans, securing loans from mobile-network operators, and using mobile money for savings) at endline for the two phone conditions pooled (Model 1) and each phone condition separately (Model 2), with control as comparison group. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

Figure S4: Phone Ownership Across Treatment Conditions Over Time

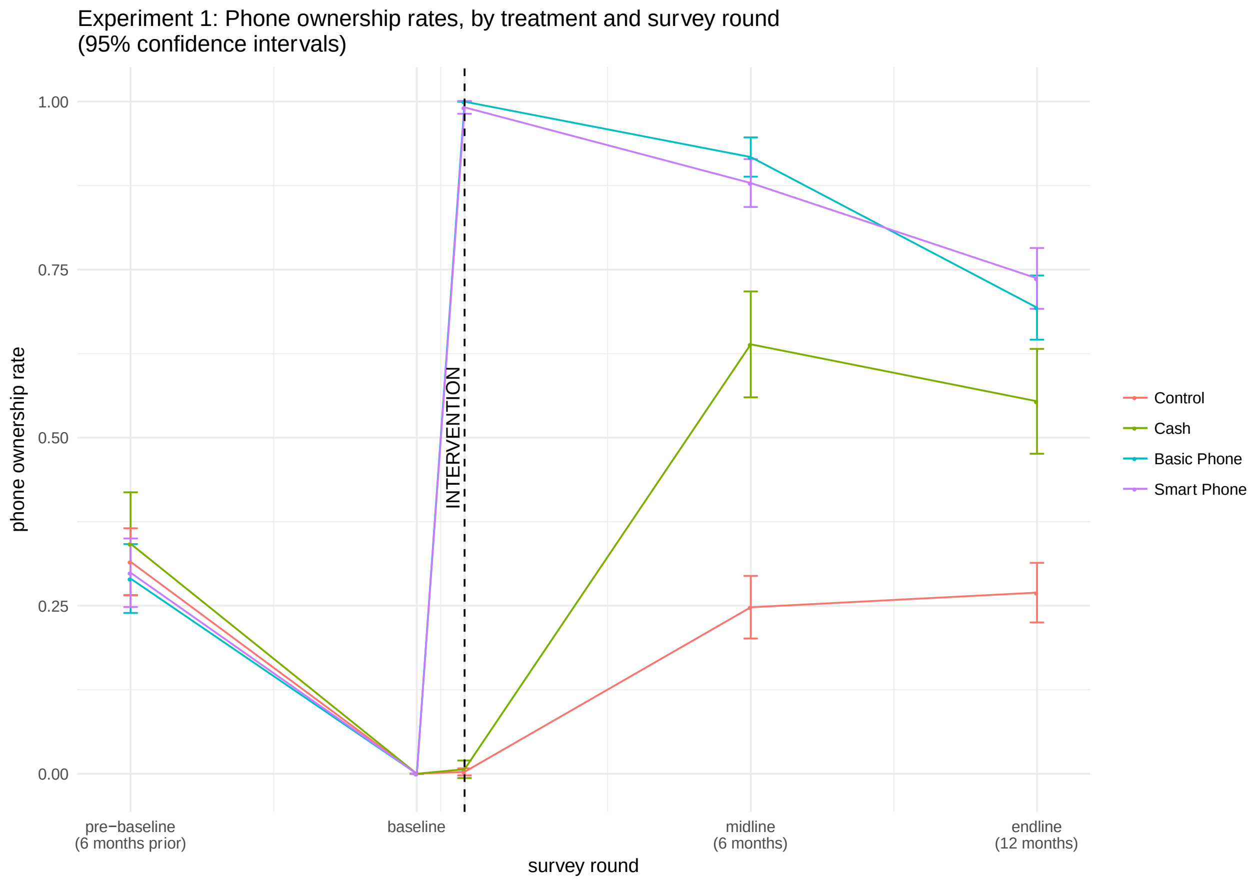

Figure S4 illustrates phone ownership from 6 months before the baseline, at intervention, at midline, and at endline. As is clear, there was high attrition in phone ownership among those in the phone groups. By endline less than 75% of participants still owned a phone.

Figure S5A: Retention of Phones Across Phone Treatment Conditions Over Time for Self-Report of Retaining Project Phone

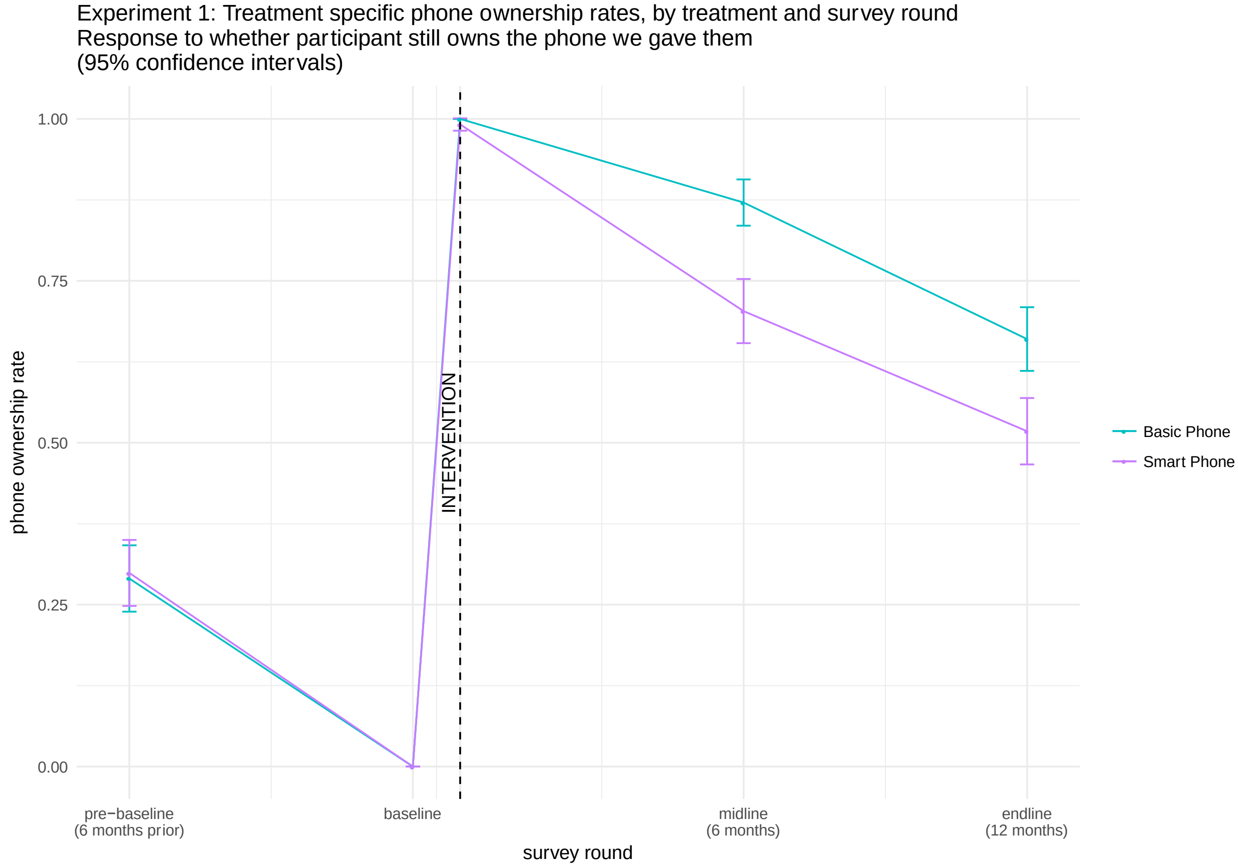

Figure S5 illustrates retention of the specific project phone for those in the basic condition (who received Nokia 105s) and those in the smart group (who received the Huawei Y360). The figure depicts ownership of the project phone when asked at endline if subjects still possess the project phone.

Figure S5B: Retention of Phones Across Phone Treatment Conditions Over Time for Enumerator-Verified Project Phone

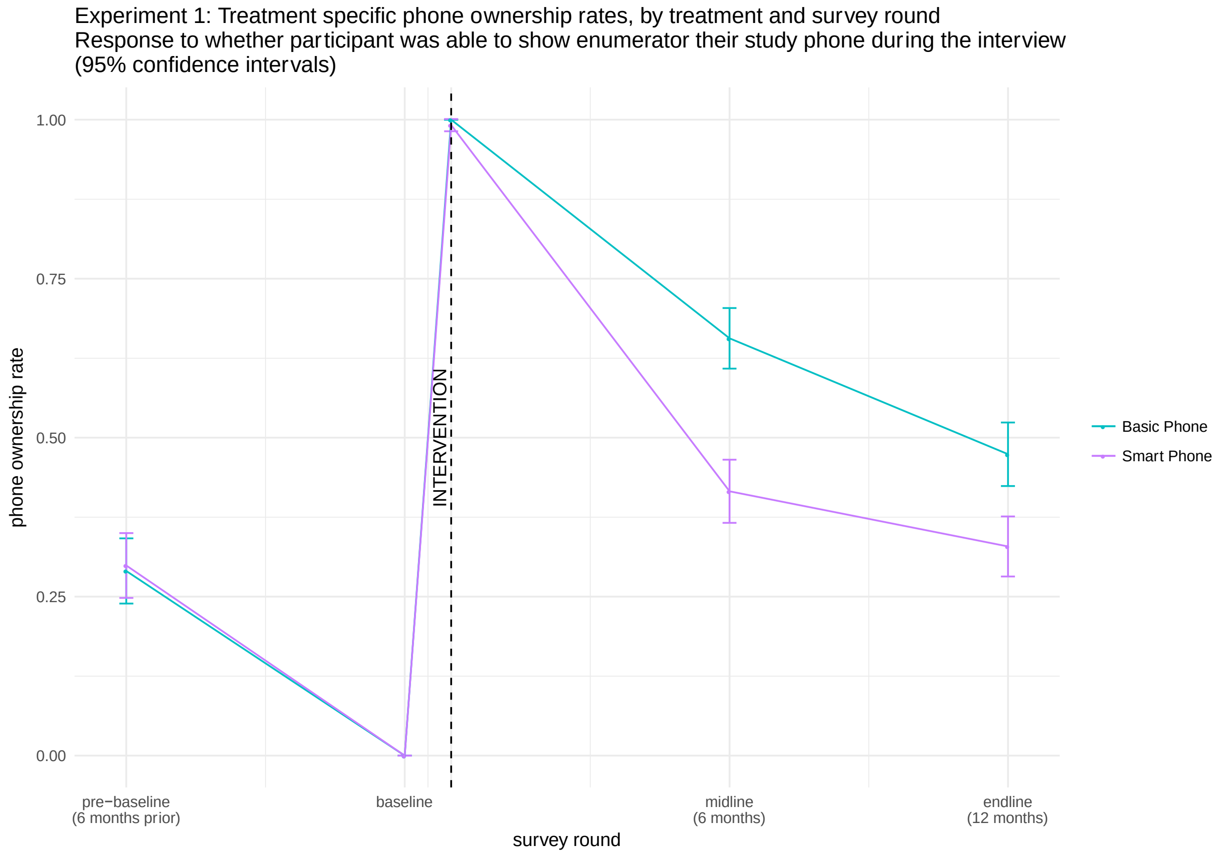

Figure S5B illustrates retention of the specific project phone for those in the basic condition (who received Nokia 105s) and those in the smart group (who received the Huawei Y360). This figure depicts ownership of the project phone based on whether subjects could show the phone to the enumerator.

Table S9A: Difference-in-Means for Household Consumption

	Control Mean	Control N	Treat Mean	Treat N	Difference	(p-value)
Phone	176,897	387	196,453	724	-19,556	0.029
Basic	176,897	387	190,620	359	-13,723	0.192
Smart	176,897	387	202,190	365	-25,293	0.024
Cash	176,897	387	196,503	157	-19,606	0.173

Table S9A reports difference-in-means on the outcome of household consumption Winsorized at the 95^{th} percentile for the two phone conditions pooled, each phone condition separately, and the cash condition compared to control. *P*-values computed using randomization inference with 1,000 draws.

Table S9B: Least Squares Regression Results for Household Consumption

	Model 1	Model 2
	b/se	b/se
Phone	20023.777**	
	(6730.90)	
Basic		13000.055*
		(6922.96)
Smart		26950.244***
		(7751.90)
Cash	15305.750	15308.856
	(12814.83)	(12823.55)
Baseline HH Consumption	0.218***	0.218***
	(0.03)	(0.03)
Age	6024.703***	6047.506***
	(905.02)	(881.96)
Age Squared	-58.361***	-58.601***
	(7.40)	(7.20)
Education	213.422	377.932
	(5125.46)	(5087.92)
Spouse in Household (HH)	13196.195	13290.404
	(9442.21)	(9380.05)
No HH Phone at Baseline	-15745.818***	-15713.936***
	(4905.67)	(4847.29)
Owned Phone in Past	19634.399*	19737.919*
	(9043.17)	(8987.84)
Urban Block	38018.214**	38173.860**
	(14211.40)	(14170.17)
TASAF Block	-53277.600***	-53079.745***
	(10071.42)	(9978.44)
Income Block	6963.595	6912.582
	(7327.95)	(7339.49)
Age	14068.685	12757.022
	(36888.30)	(36521.21)
R-Squared	0.263	0.264
N	1261	1261

Table S9B reports ordinary least squares regression results for the outcome of household consumption at endline for the two phone conditions pooled (Model 1) and each phone condition separately (Model 2), with control as comparison group. Consumption values Winsorized at the 95^{th} percentile. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

Table 10: Two-Stage Least Squares Regression Results for Treatment on Treated of Phone Ownership on Household Consumption

	Model 1 b/se	Model 2 b/se	Model 3 b/se
Phone Treat. → Own Phone	45889.186***		
	(14694.17)		
Basic Treat. → Own Phone		567.931	
		(24879.72)	
Smart Treat. → Own Phone			77999.112***
			(20956.43)
Cash	2759.897	2382.264	3027.449
	(12527.14)	(11951.12)	(13126.53)
Baseline Consumption	0.214***	0.220***	0.210***
	(0.03)	(0.03)	(0.03)
Age	5280.026***	5898.231***	4842.030***
	(902.54)	(824.87)	(1047.93)
Age Squared	-51.751***	-57.308***	-47.814***
	(8.63)	(6.85)	(10.78)
Education	-1864.438	-217.362	-3031.384
	(4882.54)	(5403.03)	(4699.74)
Spouse in Household (HH)	14632.509	11952.058	16531.598*
	(9249.49)	(9117.25)	(9645.19)
No HH Phone at Baseline	-13046.581**	-16307.673***	-10736.111*
	(5441.58)	(5186.89)	(6181.23)
Owned Phone in Past	15834.594*	19375.706**	13325.731
	(9350.49)	(8881.05)	(10007.86)
Urban Block	33101.656**	36902.210***	30408.978**
	(14424.88)	(13462.74)	(15278.37)
TASAF Block	-54349.395***	-53439.696***	-54993.913***
	(9803.09)	(9728.39)	(10102.99)
Income Block	6465.009	7046.092	6053.314
	(5992.33)	(7232.10)	(5354.69)
Constant	31041.432	32760.543	29823.449
	(35458.02)	(36023.77)	(35215.88)
R-Squared	0.248	0.258	0.209
N	1260	1260	1260

Table S10 reports two-stage least squares regression results estimating the treatment effect on the treated using assignment to a phone condition as an instrument to predict phone ownership, which is then used to estimate local-average treatment effects on the outcome of household consumption at endline compared to control. Consumption values are Winsorized at the 95^{th} percentile. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01