Mobile Phones, Digital Inequality and Fertility: Longitudinal Evidence from Malawi*

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Abstract

In this paper we draw upon unique longitudinal data from young women in southern Malawi to argue that the digital revolution is contributing to the fertility decline in high-fertility settings. Fixed-effect panel data models spanning a period of three years show that mobile phone ownership reduces ideal family size and overall parity among phone-owning women compared to their phone-less counterparts. Using cross-sectional data from a follow-up study fielded in 2015, we explore the pathways through which mobile-phone effects on fertility may be operating. Our analyses suggest that role modeling, preference change, and access to information, rather than substitution effects, are driving the decline. Furthermore, Cox proportional hazard models suggest that while mobile phones are not changing the

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1 Introduction

Over the past 20 years, digital technologies have revolutionized people's life and everyday activities. This digital revolution did not come without costs: inequality arose because of the differential opportunity in access the resources needed to access digital technology. As a result, while digital technologies have empowered many women and men, others lagged behind, generating a growing "digital divide" both within and across countries (DiMaggio et al., 2001; Norris, 2001).

In several developing countries, with the advent and increasing diffusion of cheap, ubiquitous and multitasking mobile phones, that have quickly substituted any other communication technology, the digital revolution has completely skipped the landline stage of development to straightly enter a wireless age. This "mobile phone revolution" has been so disruptive that today, according to a recent Afrobarometer report, while less than one in three people in Africa have a proper drainage system, 93% of Africans have access to a cell phone service (Mitullah et al., 2016).

The potentials of this mobile phone revolution in low-income societies are several. Apart from connecting individuals to individuals, mobile phones are crucial instruments in the spread of information and services, especially in rural and remote areas. Farmers use their mobile phones to get information regarding the prices of crops and livestocks; rural households can receive remittances from relatives living in urban areas or pay school fees through mobile money services; medical centers and NGOs can send text messages to their patients to remind them to take their medicines (Aker and Mbiti, 2010). The fact that mobile phones are two-way media makes the social implications of their technology qualitatively different from the ones of older one-way mass media, like radio or television (DiMaggio et al., 2001).

While this revolution was taking place, social scientists have started to measure its impact, by showing that mobile phone ownership positively affects market performance (Jensen, 2007; Aker, 2010; Aker and Fafchamps, 2014), household income (Blauw and Franses, 2016; Hübler and Hartje, 2016), education (Aker et al., 2012), and political participation (Manacorda and Tesei, 2017). Furthermore, health interventions based on mobile phones improve the delivery of health services, including antiretroviral Lester et al. (2010) and malaria therapy (Zurovac et al., 2011). Mobile money transfer services lead to higher opportunities to smooth consumption in the face of shocks (Jack and Suri, 2014; Munyegera and Matsumoto, 2016), to reduced food insecurity (Murendo and Wollni, 2016), and to increased financial resilience and savings (Suri and Jack, 2016).

In this paper, we focus on the effect of mobile phone ownership on fertility in a high-fertility setting. Although a growing literature to date shows that mass media could significantly affect fertility decisions in developing countries,[1], a study of the effect of the most recent and now widespread digital technology, mobile phones, is still lacking.

We here hypothesize that mobile phones can influence fertility through four main mechanisms. First, *information provision.* Mobile phones can amplify the traditional social learning path that influences contraceptive use and fertility change in high-fertility contexts. Prior to the digital revolution, these exchanges would have been restricted to either in-person social networks or mass media (Bongaarts and Watkins, 1996). Second, *role modeling.* Social influence, previously restricted to in-person networks and traditional mass-media is amplified by having access to social media and social networking. Third, *preference change.* Mobile phones can be associated to increased financial inclusion, and reduce the preferences for larger families as an insurance against unexpected shocks. Fourth, *substitution effect.* The combination of technology and mobility integrated in cell-phones allow people to rely on broad social networks by making also more easy to keep in touch with relatively distant people with a resulting effect in terms of substitution between real-life and virtual relationships.

Our empirical analyses exploit the richness of the Tsogolo la Thanzi (TLT) longitudinal study conducted in Balaka, Malawi. As a preview of our findings, our fixed-effect panel data model shows that mobile phone ownership reduces fertility, with this effect being mainly driven by highly educated women. Complementary cross-sectional analyses of the same study suggest that the main mechanisms by which mobile phone ownership affects fertility are role modeling, preference change, and access to information, rather than substitution effects. Furthermore, Cox proportional hazard models suggest that while mobile phones are not changing the first steps of family formation for women, they have consequences for fertility trajectories on a longer time-horizon.

The remainder of this paper is organized as follows: Section 2 describes the conceptual background and the context of our study; Section 3 presents data and methods; Section 4 presents the results; Section 5 concludes.

2 Conceptual background and context

2.1 Conceptual background

In a broad analysis of fertility transitions focused on Africa's uniqueness, Bongaarts (Bongaarts, 2017) characterizes Africa's fertility transition as later (in terms of timing), earlier (in terms of level of development at the onset of the transition), slower (in terms of the pace of fertility decline), higher (in terms of the fertility levels at a given level of development). The slow pace of this transition is of particular concern to population scholars. We argue

[1]For a recent review see Della Vigna and La Ferrara (2015).

that digital technology, and mobile phones in particular, might contribute to an acceleration in Africa's unique and slow fertility transition.

More specifically, we hypothesize that mobile phones can influence fertility through four main mechanisms. First, mobile phones can reduce information search costs (Aker, 2010), thus helping individuals to take more informed decisions, including on contraception, and amplifying the traditional social learning paths that influence fertility change (Montgomery and Casterline, 1996; Bongaarts and Watkins, 1996), and that were restricted to personal social networks and mass media before the digital revolution. For instance, in a study on Kenya, Kohler and colleagues have shown that social learning through in-person social networks is an important mechanism in fertility choices in areas with lower exposure to markets (Kohler et al., 2001). In general, this mechanism could be particularly important in poor areas, where information is scarce and individuals hold diffuse priors (La Ferrara, 2016). We refer to this mechanism as *information provision*.

Second, the use of social networking sites (e.g., Facebook), and the access to "the life of others" through the Internet might impact on the desirability and social acceptability (La Ferrara et al., 2012) of certain behaviors (e.g., having several children or using contraceptives), amplifying the traditional social influence paths to fertility change that were restricted to personal social networks or mass media (Montgomery and Casterline, 1996; Bongaarts and Watkins, 1996). We refer to this mechanism as *role modeling*.

Third, mobile phones can be associated with increased financial inclusion, through the use of mobile money services (Suri and Jack, 2016). In several developing countries, in the absence of efficient credit markets, children constitute a buffer against shocks (Dillon, 2013), and an important source of income either direct (through involvement in formal wage employment) or indirect (through involvement in domestic activities, particularly hazardous chores). By improving financial inclusion, mobile phones reduces the demand for children as a way to self-insure households, especially the most vulnerable, against unexpected shocks therefore reducing fertility. We refer to this demand-based mechanism as *preference change*.

Fourth, mobile phones affect individuals' relational life (e.g. Miller-Ott et al., 2012; McDaniel and Coyne, 2016; Rotondi et al., 2016). By connecting individuals to "on-line others" (Turkle, 2012) and, by diverting attention away from face-to-face social interactions (Katz and Aakhus, 2002), they generate a substitution between real and virtual-life social relations. While this effect can be expected to facilitate dating even with relatively distant others, it can be expected to reduce fertility when it implies fewer real-life encounters and more virtual ones. We refer to this mechanism as *substitution effect*.

The mechanisms we illustrated depend upon the opportunities to have access to mobile phones. The notion of a "digital divide", however, was coined to emphasize that access to digital technologies is socially stratified (DiMaggio et al., 2001; Norris, 2001). In addition to inequalities in access to digital technology, social inequalities may determine a differential not only in accessing mobile phones, but also in the capabilities needed to exploit their potentials. While we refer to inequalities in access to digital technology as a *digital divide*, we refer to inequalities in the capability to use digital technology as a *second-level digital divide*, following Hargittai (2002). Mobile phones constitute an exceptionally flexible, cheap, simple and multitasking technology with a strong potential: given the low price and high portability and connectivity, they are potentially able to close the digital divide, acting as an equalizer of opportunities. Given that Malawi is one of the most expensive countries in Sub-Saharan Africa to use mobile phones (ITU, 2014), given the restricted area of research characterized by homogeneous access to infrastructures, and given the study design aimed at restricting the age group to an homogeneous group of women, we expect to detect a digital divide across wealth and educational status. However, we expect to detect a second-level digital divide, only in terms of education and not in terms of wealth. In fact, even simple basic feature phones, affordable with a few tens of dollars, are capable of calling, texting and browsing the web. These basic features are enough to allow people to use their devices to save money, access information, stay connected with relatively far others for a relatively low cost. However, connectivity alone does not suffice. In order to fully exploit the potentials of the technology, people must have the capabilities to use it and this latter aspect crucially relates to their level of education .

2.2 Context

To explore the relationship between technology and fertility, we rely on data from the Tsogolo la Thanzi (TLT) panel study set in Balaka, southern Malawi, between 2009 and 2015; our population of interest is young women who are just beginning their reproductive careers. At least three features of the study context are worth noting in more detail here: 1) the socio-economic backdrop, 2) the fertility patterns characterizing the region, the country, and this period of the life-course, and 3) (at the macro-level) the proliferation of mobile phones – not just in Malawi but across sub-Saharan Africa – over the course of the study period.

First, with respect to the socio-economic situation, Malawi is one of the world's poorest countries and, within it, Southern Malawi features especially low levels of educational attainment and higher levels of poverty when compared to the Central and Northern regions. In other words, the small corner of the world in which our study is set is marked by disadvantages even within the national context (National Statistical Office Malawi, a,b).

Second, although fertility in Malawi has been declining in recent decades (falling from almost 7 children per woman in the early 1990s), fertility remains high (TFR stood at 4.4 children per woman in 2014) and childbearing still begins early – at around age 19 (slightly earlier in the southern region) (National Statistical Office Malawi, b). The age-specific fertility rate for 15-19 year-old Malawian women in 2010 was about 150 births per thousand; the ASFR peaks for women ages 20-24 (at slightly over 250) and then declines. The TLT study observed young women during the period of the life course that is most salient for understanding fertility concerns, and did so in a very high-fertility setting.

Third, Malawi and Balaka in particular are subject to the same technological forces that have been sweeping the entire sub-continent in the past six or seven years. According to the International Telecommunication Union's 2009 Report on Africa, mobile cellular penetration rose dramatically across the region from less than two percent in 2000 to an estimated 33 percent in 2008 (ITU, 2010) and has constantly grown after 2010 (ITU, 2014). Not surprisingly given the country's economic profile, cell phone penetration in Malawi lags behind the region as a whole; in 2008, it stood about 8 percent and, at this same point in time, Internet use was estimated at 2.2 per 100 inhabitants and an estimated 4 percent of households had a computer.

3 Data and Methods

In order to provide a deep and detailed understanding of the changes that characterize young adulthood in a low-resource, high-fertility, and high-HIV setting, the TLT study collected eight waves of data at closely-spaced intervals (every four-months) for a period of three years. The initial sample, drawn in 2009, was comprised of 1500 female and 600 male respondents between the ages of 15-25 residing in census enumeration areas within seven kilometers of the district capital. The response rate at baseline was 95.6 percent; again at every subsequent wave, the TLT study collected detailed information at both the individual and household levels, providing a detailed and dynamic view of personal and household goods, household composition, and fertility-related behaviors and outcomes. Respondents were interviewed up to 8 times between the baseline survey and December 2011. Three years later, between June and September of 2015, TLT fielded a follow-up survey that included a specific module about media and ICTs. By this time, the youngest members of the cohort had turned 21 and the oldest 31.

We study both fertility preferences and outcomes. We anchor our analyses to understand whether and to what extent *parity* in this population, measured as children ever born, is influenced by mobile phone ownership; we also test for differences in preferences, operationalized as *ideal family size* (IFS), which is frequently used to proxy demand for children in developing settings and ranges from 1 to 12 in our sample (mean). We also take into account proximate determinants of fertility, including marital status (currently married vs. not), *coital frequency* (measured in the past month) using woman's self reports, and current use of a *modern contraceptive method* (condoms almost every time or more, pill, injectables, norplant, IUD, or sterilization).

Table 1: Summary statistics: (2009-2011)

Variable	Mean	Std. Dev.	Min.	Max.	N
Parity	1.06	1.1	0	6	10589
Desired # children	3.31	1.05	0	12	10590
SELF OWN: Mobile phone	0.28	0.45	0	1	10592
HH Wealth Index	0	1.63	-1.31	3.22	10566
Age (months)	247.78	40.23	180	328	10596
HH has television	0.16	0.36	0	1	10593
Low educ.	0.22	0.41	0	1	10596
Coital frequency, 4 weeks	3.7	5.46	0	30	10596
Married/Cohabiting	0.5	0.5	0	1	10593
Contraception, last 3 partners	0.27	0.44	0	1	10596

Consistently with Behrman's et al. analysis of contraceptive choices in a high fertility setting (Behrman et al., 2002), and given the time dimension of the data set (8 waves), our identification strategy relies on a panel data fixed effects model as the one depicted in (1):

$$y_{it} = \beta_1(x_{1it-2}) + \beta_2 x_{2i} + \alpha_i + \eta_{it} \tag{1}$$

where y_i is parity for individual i, x_{1i} is a dummy variable tacking value 1 if the respondent owns a mobile phone, 0 otherwise. x_{2i} is our set of control variables (a measure of wealth of the household[2], age, wether the household owns a television so as to control for potential confounding effects driven by other technologies used to access information (La Ferrara, 2016), and whether the respondent is ranked in the lowest quartile of the educational distribution in the sample), η_{it} is the idiosyncratic error component, i.i.d. $(0, \sigma^2_\eta)$, uncorrelated with $(x_{1it}, x_{2i}, \alpha_i)$, and α_i is i.i.d. $(0, \sigma^2_\alpha)$, potentially correlated with x_{1it} and x_{2i}. Assuming that the omitted variables are time-invariant (with time-invariant effects), a fixed effect panel estimator adjusts for omitted variable bias and is the most conservative test we can use. We also estimate a random effect model, using an estimator that is more efficient and allows us to estimate the parameters of time-invariant regressors but behaves inconsistently with respect to the unobservable effects that could be

[2]Measured on a linear index comprising household structural assets (e.g., flooring and roofing material, water supply, and sanitation) with the Weights being calculated for each asset using principal-components analysis.

correlated with the included controls.[3] Given the timing of fertility, mobile phone ownership is lagged by two waves (x_{1it-2}), 8 months.

Given space constraints and the overall consistency of the results from these different adjustments (fixed vs. random effects and balanced vs. unbalanced panel), we focus our discussion on estimates generated by *fixed effects* models generated by the *unbalanced panel* (respondents who contributed at least two waves to the study are included, N=10,557 person-waves from 1498 individuals). In ancillary analyses, not presented here, all key relationships were confirmed by models relying on other combinations of specifications.

Finally, we conduct an exploratory analysis of the pathways through which mobile phone ownership can impact fertility, by exploiting (1) a survival analysis on the panel data and (2) TLT cross-sectional data collected in 2015 for which summary statistics are reported in Table 2. Note that the results of this exercise are intended to shed further light on the mechanisms underlying the relationship between mobile phone ownership and fertility but should be taken with caution given the concerns about omitted variable bias described above.

Table 2: Summary statistics (2015)

Variable	Mean	Std. Dev.	Min.	Max.	N
Parity	1.95	1.31	0	6	1454
Desired # children	3.56	1.02	1	10	1452
SELF OWN: Mobile phone	0.47	0.5	0	1	1453
Uses mob. phone: Mobile money	0.19	0.4	0	1	1453
Uses mob. phone: Internet	0.14	0.35	0	1	1453
Uses mob. phone: Call	0.47	0.5	0	1	1455
Uses mob. phone: SMS	0.44	0.5	0	1	1455
Uses mob. phone: Videos	0.26	0.44	0	1	1455
HH Wealth Index	0	1.46	-1.31	2.49	1450
Age (month)	305.93	43.52	180	492	1442
HH has television	0.22	0.42	0	1	1453
Low educ.	0.21	0.41	0	1	1455
Married/living together	0.72	0.45	0	1	1453

4 Results

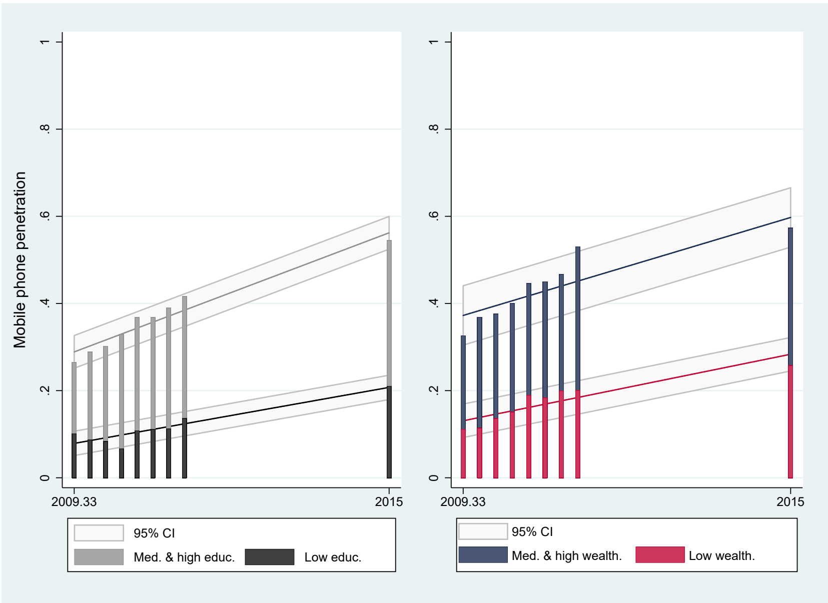
The analyses that follow proceed in five parts. 1) We describe the digital divide in Balaka. 2) We present the gross differences in children ever born

[3] Given the comparison of the estimates for the fixed and random effects models, we perform Hausman tests of the null hypothesis that the individual-specific component of the error term (α_i) is uncorrelated with the regressors.

between phone-owning and non-owning women to establish the magnitude of this divide with respect to fertility. Part 3 is the centerpiece of our analyses; in it, we estimate the effect of mobile-phone ownership on fertility preferences and outcomes using fixed-effects panel models. We then use 4) Cox proportional hazard models and a 5) a cross-sectional analyses of a follow-up survey conducted in 2015 to identify the mechanisms by which mobile phones are influencing young women's fertility in this part of the world.

4.1 A First Glimpse at Balaka's Digital Divide

Figure 1: Trends in Mobile Phone Ownership in Balaka (2009-2015)



Before examining the relationship between mobile phone ownership and fertility dynamics, we first establish the magnitude of the digital revolution in this part of the world by describing the expansion of mobile phones among young women in Balaka between 2009 and 2015. As evidenced by Figure 1, phone ownership was relatively rare when TLT began in late 2009 (about 20 percent), but just as described by the ITU report (ITU, 2014), phones proliferated throughout Balaka over the course of the study period to such an extent that by the end of the intensive longitudinal portion of the study (2011), 35 percent of the women declared to own a mobile phone; by the time of the follow-up survey in 2015, nearly half of the women in the study (47 percent) owned mobile phones. This is a dramatic transformation. As expected, mobile phone ownership was, at the beginning – and continues to be, patterned by education level (left panel of Figure 2) and by household wealth (right panel of Figure 2). But the pace of penetration, as measured by the slope, is comparable for each of these groups. In other words, the digital divide is evident in the educational-wealth gradient (see also Table 3 reporting t-test of the difference in means for each sub-group), but the divide itself is not growing during the period under examination (t-test of the slopes, non-significant).

Table 3: Digital divide: Mobile phone ownership by wealth and education

	(1)		(2)		(3)	
	Low education		Med. & high educ.		Difference	
	mean	sd	mean	sd	b	t
By education	0.16	0.37	0.41	0.49	0.24***	(29.34)
	Low income		Med. & high income.		Difference	
	mean	sd	mean	sd	b	t
By wealth	0.16	0.37	0.41	0.49	0.25***	(30.11)

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

4.2 Mobile phone ownership and fertility: A Bivariate View (TLT, 2009-2011)

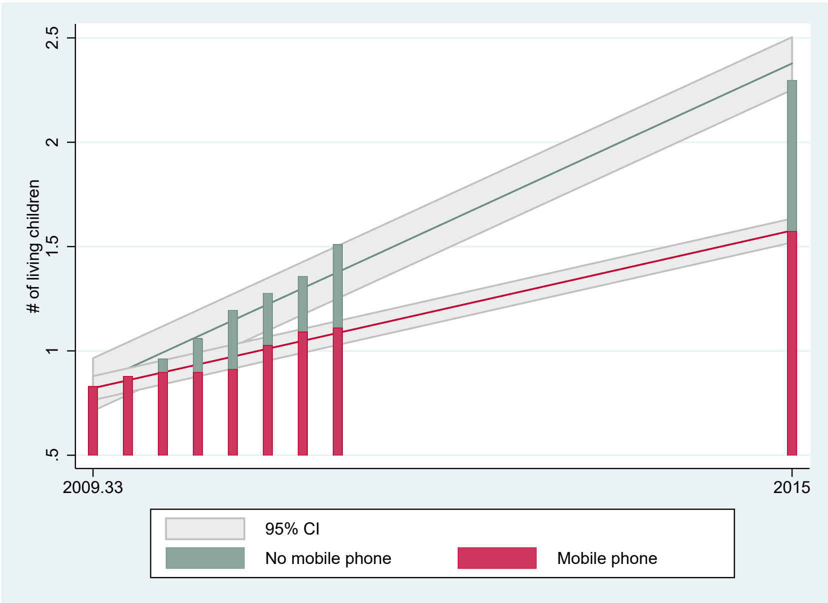
Figure 2 provides a simple bivariate assessment of the patterning of fertility (children ever born) over time, by mobile phone ownership. Overall, the growth in average number of living children per woman is significantly steeper (blue columns in Figure 2) among women without mobile phones than it is among those who own them (red columns in Figure 2). The difference is large – almost staggering. While no differences are evident at the very beginning of the study in 2009, differences in family size emerges clearly in 2010 and grows; by the time of the follow-up survey in 2015, the difference is nearly one full child (1.55 vs. 2.40, p<.001). However, it is not clear whether this path is driven by selection on observable traits (like education, socio-economic status, age), selection on unobservables (like genetic differences, motivation, forward looking behavior), or whether it may be driven by a true causal effect. In the analyses that follow, we use a variety of estimation tools to further unpack and explain this difference.

4.3 Specifying the Phone-Fertility Relationship

4.3.1 Estimates from Panel Data (TLT, 2009-2011)

Tables 4 and 5 contain the main results of our empirical analyses. Column 1 of Table 4 and 5 present estimation results for equation (1) using as dependent variables ideal family size (IFS) and the number of living children,

Figure 2: Children Ever Born by Mobile Phone Ownership Over Time (2009-2015)



respectively. All models control for the individual-level characteristics shown in Table 1. Columns 2-3 of Table 4 and 3-5 of Table 5 present estimates that adjust for proximate determinants of fertility while column 4 (6) of Table 4 (5) adjusts for all controls and covariates jointly. Column 2 of Table 5 estimates equation (1) for children ever born, adjusting for preferences. While in Table 4 all the controls are measured contemporaneously with the dependent variable, in Table 5 use of the mobile phone, preferences, coital frequency, marital status, and contraception are lagged two waves (8 months; approximately the length of a full-term pregnancy). By including potential pathways in the model we aim to gauge the extent to which the estimated effect of mobile phone ownership on fertility can be explained by differences in measurable attitudes, statuses, and behaviors.

Across models, the behaviors of the control variables for all specifications in Table 4 and across the six different specifications in Table 5 are in line with expectations generated by several decades of literature on fertility across contexts: age, currently married, and coital frequency are all positively related to fertility. Women with low levels of educational attainment have higher fertility, and women who are contracepting two-waves prior to the measured outcome have fewer children.

The estimated coefficient for mobile phone ownership on IFS is negative, stable, and statistically significant at the 10-percent level across the four models (Table 4), suggesting that the estimated effect of mobile phone ownership on fertility cannot be explained by coital frequency nor by differences in marital status. Accordingly, table 5 shows that none of the proximate

Table 4: Effects of mobile phone on preferences: Fixed effect model

	Main	Proximate determinants of fertility		All
	(1)	(2)	(3)	(4)
Dep. var.: Desired # of children				
SELF OWN: Mobile phone	-0.0330*	-0.0326*	-0.0328*	-0.0326*
	(0.0197)	(0.0197)	(0.0197)	(0.0197)
HH Wealth Index	-0.0069	-0.0070	-0.0070	-0.0071
	(0.0100)	(0.0099)	(0.0099)	(0.0099)
Age (months)	0.0053***	0.0051***	0.0050***	0.0049***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
HH has television	-0.0679*	-0.0679*	-0.0670*	-0.0672*
	(0.0350)	(0.0350)	(0.0349)	(0.0349)
Low educ.	-0.0389	-0.0368	-0.0351	-0.0343
	(0.1009)	(0.1009)	(0.1008)	(0.1009)
Coital frequency, 4 weeks		0.0025*		0.0017
		(0.0014)		(0.0015)
Married/Cohabiting			0.0569*	0.0474
			(0.0329)	(0.0344)
N.	10557	10557	10555	10555

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. Fixed-effect model. * p<0.10, ** p<0.05, *** p<0.01

determinants included in the analysis (preferences, coital frequency, marital status, and contraception) explain the effect of mobile phone ownership on fertility preferences. In line with a previous literature about technology and ideational change (Faria and Potter, 1999; La Ferrara et al., 2012; Thornton, 2001), women living in households that possess a television report a smaller ideal family size but do not exhibit distinctive fertility outcomes in terms of children ever born. Beyond the statistical significance observed in Table 4, the estimated effect of mobile phone ownership on fertility itself (see Table 5) provides evidence that mobile phone owners have fewer children than non-owners.

4.3.2 Robustness Checks

Phones, Wealth, and Income

Due to data limitations, the results presented in Table 4 are based on specifications that do not include a direct measure of income among the explanatory variables but rather measure socio-econimic status using a linear index comprised of household structural assets. To the extent that this index may not adequately capture access to money, and since mobile phone ownership is related to income, the results presented above may be misleading if they are simply indicating that individuals with higher income have fewer children. In order to shed light on this alternative interpretation, Table 6 presents estimation results for a specification that also includes the interaction between

Table 5: Effects of mobile phone on parity: Fixed effect model

	Main	Preferences	Proximate determinants of fertility			All
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Parity						
SELF OWN: Mobile phone (t-2)	-0.0401***	-0.0405***	-0.0397***	-0.0401***	-0.0436***	-0.0446***
	(0.0145)	(0.0146)	(0.0145)	(0.0139)	(0.0143)	(0.0136)
HH Wealth Index	-0.0037	-0.0044	-0.0036	-0.0031	-0.0031	-0.0030
	(0.0060)	(0.0060)	(0.0060)	(0.0058)	(0.0059)	(0.0057)
Age (months)	0.0194***	0.0195***	0.0193***	0.0181***	0.0198***	0.0186***
	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0009)	(0.0008)
HH has television	-0.0141	-0.0143	-0.0141	-0.0143	-0.0216	-0.0226
	(0.0175)	(0.0175)	(0.0175)	(0.0170)	(0.0172)	(0.0165)
Low educ.	0.2251***	0.2257***	0.2315***	0.2094***	0.1775***	0.1496***
	(0.0101)	(0.0101)	(0.0113)	(0.0096)	(0.0096)	(0.0096)
Desired # of children (t-2)		-0.0101				-0.0078
		(0.0067)				(0.0065)
Coital frequency (t-2)			0.0017			-0.0019*
			(0.0012)			(0.0011)
Married (t-2)				0.2620***		0.2879***
				(0.0252)		(0.0246)
Contraception (t-2)					-0.1296***	-0.1399***
					(0.0125)	(0.0124)
N.	7614	7609	7614	7611	7614	7606

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. Fixed-effect model. * p<0.10, ** p<0.05, *** p<0.01

mobile phone ownership and wealth. The coefficient for mobile phone ownership is not significantly smaller for wealthy individuals. Furthermore, the coefficient for mobile phone ownership is still negative and statistically significant. These findings indicate that mobile phone use is not simply acting as a proxy for income.

Random vs. Fixed Effects

Assuming that the omitted variables are time-invariant (with time-invariant effects), a fixed effect panel estimator may provide a means for controlling for omitted variable bias. However, fixed-effects models are inefficient; they also focus on within-person change rather than on differences between groups of individuals and are, therefore, extremely conservative tests. We consider here, as an alternative, results from a parallel set of random effect models, wherein the estimator is more efficient, can estimate the parameters of time-invariant regressors, but can behave inconsistently in the presence of unobservable effects correlated with the included controls. The results, reported in Table 7, indicate significant and negative associations between mobile phone ownership and fertility-related outcomes that are slightly larger than the estimates obtained from the fixed-effects models. However, the Hausman tests suggest that the preferred model is the fixed effects one and that failing to account for unobserved heterogeneity would mis-estimate the impact of mobile phone ownership on fertility.

Table 6: Effects of mobile phone on parity: Fixed effect model, interaction with wealth

	Main	Preferences	Proximate determinants of fertility			All
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Parity						
SELF OWN: Mobile phone (t-2)	-0.0390**	-0.0394**	-0.0385**	-0.0406***	-0.0417***	-0.0444***
	(0.0154)	(0.0154)	(0.0154)	(0.0147)	(0.0152)	(0.0144)
HH Wealth Index	-0.0026	-0.0032	-0.0025	-0.0035	-0.0012	-0.0028
	(0.0063)	(0.0063)	(0.0063)	(0.0061)	(0.0062)	(0.0060)
SELF OWN: Mobile phone (t-2)=1 × HH Wealth Index	-0.0036	-0.0036	-0.0037	0.0012	-0.0059	-0.0007
	(0.0071)	(0.0071)	(0.0071)	(0.0069)	(0.0070)	(0.0067)
Age (months)	0.0194***	0.0195***	0.0193***	0.0181***	0.0198***	0.0186***
	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0009)	(0.0008)
HH has television	-0.0140	-0.0142	-0.0140	-0.0143	-0.0215	-0.0226
	(0.0175)	(0.0175)	(0.0175)	(0.0170)	(0.0173)	(0.0165)
Low educ.	0.2263***	0.2269***	0.2328***	0.2090***	0.1794***	0.1499***
	(0.0105)	(0.0105)	(0.0116)	(0.0100)	(0.0100)	(0.0099)
Desired # of children (t-2)		-0.0101				-0.0078
		(0.0067)				(0.0065)
Coital frequency (t-2)			0.0017			-0.0019*
			(0.0012)			(0.0011)
Married (t-2)				0.2622***		0.2878***
				(0.0252)		(0.0246)
Contraception (t-2)					-0.1299***	-0.1399***
					(0.0125)	(0.0124)
N.	7614.0000	7609.0000	7614.0000	7611.0000	7614.0000	7606.0000

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. Fixed-effect model. * p<0.10, ** p<0.05, *** p<0.01

Table 7: Effects of mobile phone on fertility: Random effects model

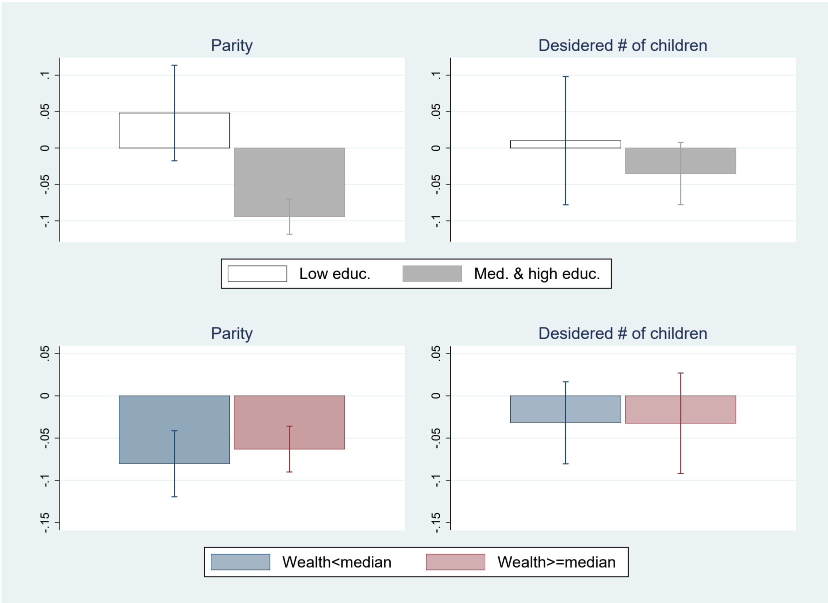
	(1)	(2)
	Parity	Desired # children
SELF OWN: Mobile phone (t-2)	-0.0619***	
	(0.0142)	
SELF OWN: Mobile phone		-0.0581***
		(0.0189)
N.	7614	10557
Hausmann test χ^2	154.40	3084.24
Hausmann test $Prob > \chi^2$	0.0000	0.0000

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

4.3.3 Second-level digital divide

Analyses and discussion to be added before PAA 2018

Figure 3: Second-level digital divide by education and income



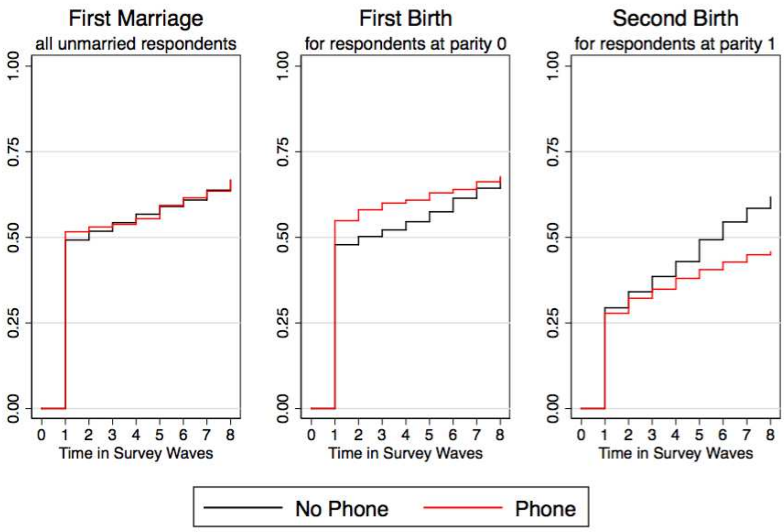
4.4 Phones and Family Formation (Survival analysis, TLT 2009-2011)

The fact that fertility, measured as children ever born, varies by mobile phone ownership among young adult women in Balaka is readily apparent from Figure 2. The process by which this difference is manifest, however, remains unclear. While the fixed-effects estimation approach ensures that the observed association is not driven by omitted variables, the exact point of divergence between the two groups cannot be identified. To shed additional light on the divergence in the fertility trajectory of phone-owning vs. non-owning women, we estimated Cox proportional hazard models to examine trends in 1) first marriage, 2) first birth, and 3) second birth. The underlying models, plotted in Figure 4, adjust for the same set of co-variates that were included in the fixed-effects models and allow us to estimate relationship of mobile-phone ownership on the hazard of each event for the population at risk: never-married women, women at parity zero, and women at parity one, respectively.[4] While we find no differences in time to first-marriage or

[4]Because very few women had three or more children during the study period, estimates for higher-order births are somewhat unstable and are not presented here but are available upon request.

first-birth for mobile-phone-owning women, panel three shows evidence of divergence at parity two. Net of age, education, and a host of other relevant covariates, women with cell phones are significantly less likely to experience a second birth during the study period (coef.=-0.147; hazard ratio=0.863), which we interpret as evidence of longer first birth intervals (aka postponement) for this group. In other words, while mobile phones are not changing the first steps of family formation for women in Balaka, they seem to have consequences for fertility trajectories on a longer time-horizon.

Figure 4: Hazard rates by phone ownership



4.5 Examining Mechanisms: From Ownership to Use (TLT, 2015)

So far, we have focused exclusively on mobile phone ownership and its effect in terms of fertility and preferences. The fixed effect models show that the effect of mobile phones is robust to omitted variable bias, while the Cox proportional hazard models show the effect of mobile phones on fertility is most salient after a first birth. We interpret these results as evidence of a change in preferences towards smaller families and the manifestation of this preference in child-spacing.

One of the key features of mobile phones is that they subsume a variety of technological tools. Even the most simple feature-phones allow users to make a phone call, send and receive text messages, take photos, transfer money, listen to music, watch videos, and search the Internet – with all these activities being performed on the move. Here we exploit cross-sectional data from the TLT 2015 follow-up survey in which the same women were asked, three years after their last 2011 interview, more detailed questions about mobile phone use. We intend for these analyses to shed further light on the mechanisms by which mobile phone *use* (as opposed to *ownership*) affects fertility preferences and parity.

As depicted in Table 2, while more than 40 percent of the women in the sample (in 2015) were using their mobile phones to send messages and make calls, only 14 percent were accessing the Internet and one in five women were making mobile money transactions using their ICT. In order to identify which aspects of phone use are correlated with fertility preferences and with actual fertility we estimate a simple OLS model, adjusting for the same set of controls used throughout this entire paper. The results, presented in Table 8, indicate that in a cross-sectional view, not all forms of phone use have the same relationship to the fertility-related outcomes of interest.

Table 8: Effects of mobile phone on fertility: Mechanisms

	(1)	(2)	(3)	(4)
	Desired # children		Parity	
SELF OWN: Mobile phone	-0.171***		-0.313***	
	(0.056)		(0.059)	
Uses mob. phone: Mobile money		-0.096		-0.139*
		(0.077)		(0.078)
Uses mob. phone: Internet		-0.223***		-0.206**
		(0.081)		(0.080)
Uses mob. phone: Call		-0.124		0.378
		(0.125)		(0.295)
Uses mob. phone: SMS		-0.253*		-0.245
		(0.147)		(0.164)
Uses mob. phone: Videos		0.009		-0.057
		(0.073)		(0.073)
N.	1435	685	1437	685

Note: Covariates as described in Table 2. Heteroskedasticity-robust standard errors reported in brackets. OLS. * p<0.10, ** p<0.05, *** p<0.01

The first line of Table 8 shows again, and not surprisingly, that mobile phone ownership has a strong and negative association with women's fertility preferences and parity – even in the cross-section. Examining differences in preferences and parity *within* the sub-set of mobile-phone owners, columns 2 and 4 shed additional light on the possible mechanisms by which the digital divide is manifest in the domain of fertility, with a specific focus on type of use. Only Internet access (a proxy for access to information) is negatively and significantly related to both preferences and actual parity. Net of a host of relevant covariates, Women who use phones to access the Internet state a smaller IFS than women who own phones but do not use the phone for this purpose; they also have fewer children. Among the phone-owning population, use of a mobile phone to send and receive SMS messages is negatively related to ideal family size but the same relationship is an insignificant predictor of fertility. Indeed, it appears that use of a mobile phone that is receptive rather than proactive simply making calls (or listening to music and watching videos), has no significant relationship to either dimension of fertility. This brings into view the extent to which phone-use that is geared towards gather information may have distinct implications for the fertility transition than use that is either directed at conversations with family members and friends or geared towards entertainment.

5 Discussion and conclusions

To be added before PAA 2018

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