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How mobile phones can improve nutrition among pastoral communities: Panel data evidence from Northern Kenya

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How mobile phones can improve nutrition among pastoral communities:

Panel data evidence from Northern Kenya

Martin C. Parlasca*[,a], Oliver Mußhoff[a], and Matin Qaim[a]

Abstract

The digital revolution and the ongoing dissemination of mobile phones carry several prospects for smallholder farmers in Sub-Saharan Africa. Food insecurity remains a major issue among African smallholders. Mobile phones could potentially facilitate access to food markets and thus improve food security and nutrition, but research on such types of effects remains scarce. In this study we analyze whether mobile phones improve dietary quality of pastoralists in Northern Kenya. We use six rounds of household panel data covering the period between 2009 and 2015. During this period, mobile phone ownership in the sample increased from less than 30% to more than 70%. Regression models with household fixed effects allow robust estimation while reducing potential issues of unobserved heterogeneity. The estimates show that mobile phone adoption has increased dietary diversity. The effect size increases with the frequency of mobile phone use. We also examine the underlying mechanisms. Mobile phones improve dietary diversity mainly through better access to purchased foods. These results encourage the promotion of mobile phone technologies as a valuable tool for nutritional improvements, especially in rural settings with poor access to food markets.

Keywords: mobile phones, dietary diversity, nutrition, pastoralism, Africa, Northern Kenya

JEL: I15, O12, O33

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1. Introduction

Mobile phones are a promising tool to improve livelihoods of smallholder farmers in developing countries (Aker & Ksoll, 2016; Nakasone et al., 2014; Aker & Mbiti, 2010). Following rapid diffusion in Sub-Saharan Africa over the last two decades, research has shown that mobile phones can positively influence a wide array of economic dimensions including market participation (Zanello, 2012), agricultural productivity (Lio & Liu, 2006) and livestock herding (Butt, 2015). Much less is known about the effects of mobile phones on concrete welfare dimensions.

Adequate nutrition is one of these welfare dimensions that deserves particular attention. It is a Sustainable Development Goals (SDGs) cornerstone and regarded as "infrastructure for economic development" (Development Initiatives, 2017). Nutrition can enhance equality and inclusion as well as improve food security, peace, and stability (Development Initiatives, 2017). Despite the importance of mobile phones as a widely used information and communications technology (ICT) in Africa, and malnutrition as a major issue in that region (Akombi et al., 2017), empirical evidence that links these two aspects is scarce. Up until now, most studies that have addressed potential nutrition effects of mobile phone use remain qualitative or even anecdotal; others suffer from limited data for robust impact evaluation. The first indications for a potentially positive relationship between mobile phones and nutrition are presented by Beuermann et al. (2012), who find that regional mobile phone coverage can be associated with increases in food expenditure in rural Peru. More recently, Sekabira and Qaim (2017) suggested that mobile phones are associated with improved diets in coffee-producing farm households in Uganda using two rounds of a panel survey. Comprehensive analysis of the effects of mobile phones on diets and nutrition over a longer timespan does not exist. This study aims at addressing this research gap.

Building on a comprehensive panel data set from Northern Kenya covering the years 2009 to 2015 with six survey rounds, the objective of this paper is to expand previous approaches and gain further insights into the links between mobile phone use and nutrition. The study area is located in Kenya's arid and semi-arid landscapes (ASAL) and is one of the country's most marginalized regions (Commission on Revenue Allocation, 2012). Food insecurity and malnutrition still constitute relevant threats (Bauer & Mburu, 2017; Upton et al., 2016; Grace et al., 2014).

The pastoral setting in which the relationship between mobile phones and nutrition is analyzed presents another important novelty addressed in this paper. The potential of ICTs to increase food security is context-dependent (Nakasone & Torero, 2016), and pastoral communities exhibit several characteristics that are different from non-pastoral populations. Pastoralists are oftentimes not fully sedentary. They are generally less integrated in socioeconomic services and live further away from food markets (Opiyo et al., 2014). To survive under harsh climatic conditions many pastoralist communities have adopted complex livelihood strategies and developed strong social bonds (Davies & Bennett, 2007). Malnutrition is often widespread in pastoral communities (Bauer & Mburu, 2017). The potential implications of mobile phones in a pastoral setting are therefore particularly interesting. We are not aware of previous studies that have analyzed links between mobile phones and nutrition in a pastoral environment.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops concrete research hypotheses. Section 3 explains the data used for this study and the measurement of key variables. Section 4 describes the econometric approach to test the hypotheses. Results are presented and discussed in section 5, while section 6 concludes.

2. Background and research hypotheses

Malnutrition is a global threat. According to the recent Global Nutrition Report, about 2 billion people lack important micronutrients such as iron or vitamin A (Development Initiatives, 2017). Alongside individual health problems that can be triggered by malnutrition, the widespread nature of this problem can cause high economic and humanitarian costs for entire regions and countries. Dietary quality and diversity, which look beyond pure calorie consumption and account for nutritional aspects, are key factors to measure and improve nutrition in a comprehensive manner (Sibhatu & Qaim, 2018).

Why is limited dietary diversity problematic especially in Kenya's arid and semi-arid lands (ASAL)? Small-scale farmers in developing countries usually draw a substantial share of their food consumption from self-produced foods. A higher diversity in self-produced foods is therefore generally associated with higher dietary diversity (Koppmair et al., 2017; Snapp & Fisher, 2015; Jones et al., 2014). Most communities in Kenya's ASAL depend on pastoralism for food and income generation. Due to the dry climate and other ecological conditions, growing food is rather the exception than the norm (Mburu et al., 2017). Self-produced foods are therefore usually not very diverse. A high dependency on markets to complement the diet is the consequence.

Recent research suggests that market access and market participation are sometimes more important than production diversity for farm household nutrition (Sibhatu & Qaim, 2018; Hirvonen & Hoddinott, 2017; Koppmair et al., 2017). However, market access and market participation are limited in Kenya's drylands. Opiyo et al. (2014) found that 40% of the households they interviewed in Northwestern Kenya live more than 10 km away from the next market. In Samburu County, a region also located in Kenya's ASAL, the average distance to the next local market is 10 km, whereas the average distance to the next urban market is close to 40 km (Ng'ang'a et al., 2016). Hirvonen and Hoddinott (2017) suggested that a 3 km market distance under typical infrastructure conditions in Eastern Africa may be a threshold for using markets on a daily basis.

The difficulties in growing food and the limited access to markets for food purchases constitute serious constraints for dietary diversity among pastoral communities in Northern Kenya. Droughts present another, more seasonal threat to diets and nutrition. Lacking diversified livelihood options to fall back on during extreme weather events, pastoralists are particularly vulnerable to climate-induced risks (Mburu et al., 2017; Vigan et al., 2017; Upton et al., 2016). Reduction of food consumption is a problematic but widely practiced coping strategy among pastoralists during droughts (Opiyo et al., 2015; Silvestri et al., 2012). Adverse effects on both food quantity and diversity are the consequence.

How can mobile phones potentially mitigate these constraints and thus help improve household diets and nutrition? We identify three possible mechanisms. First, mobile phones can improve household income (Sekabira & Qaim, 2017; Blauw & Franses, 2015; Muto & Yamano, 2009). Income effects can result from better access to information, better access to production inputs and technologies, better access to output markets, and better prices (Roba et al., 2018; Debsu et al., 2016; Zanello, 2012; Aker & Mbiti, 2010). Without mobile phones, personal travel is the principal way to gather information. Such personal travel is associated with high transport costs and opportunity costs of time, especially when roads are bad and distances between places long, as is the case in Northern Kenya. Marsabit County in Northern Kenya has a population density of four people per square-kilometer and – according to official statistics for 2012 – none of the roads were paved (Commission on Revenue Allocation, 2013). Higher incomes will likely result in higher food expenditures and improvements in household diets.

Second, mobile phones can present a valuable tool to smoothen income during shocks. The mobile money system M-PESA, which offers a fast and easy way to send and receive money through mobile phones, is very widely used in Kenya. Jack and Suri (2014) show that family members send remittances to each other using this mobile money system helping them to share risks better and making them less likely to decrease consumption during shocks.

Third, mobile phones can increase nutrition through reduced transaction costs for everyday life activities (Sife et al., 2010), especially in the pastoral context. As mentioned, better access to information and markets may improve income, but also beyond the income mechanism, lower transaction costs may positively affect access to food quantity and variety. For instance, mobile phones can improve knowledge about the times and places of food aid distribution, which is not uncommon especially during drought periods. Mobile phones and mobile money can also facilitate coordination and collective action among pastoralist households, contributing to more regular food purchases. Better coordination allows more frequent market transactions without increasing transport costs for the individual. More frequent transactions may have particularly positive effects for the consumption of fresh and perishable foods, which are important for micronutrient supply.

At the same time, ownership and use of mobile phones is not costless. In our study, households spend on average KES3,226 (approximately US32) on buying a mobile phone, which is equivalent to 150% of the mean monthly per capita income. Consequently mobile phones are often shared among households. About one-third of the Kenyans interviewed in the FinAccess survey in 2009 mentioned sharing mobile phones with friends and relatives (Aker & Mbiti, 2010). A considerable degree of phone sharing was recently also observed in pastoral contexts of East Africa (Debsu et al., 2016; Butt, 2015). Looking at mobile phone ownership alone may therefore not fully capture the effects of mobile phone use (Tadesse & Bahiigwa, 2015; Zanello, 2012). In our analysis, we therefore differentiate between the effects of mobile phone ownership and use.

Given the mechanisms discussed, we expect that mobile phones contribute to improved dietary diversity and nutrition among pastoralists in Kenya. This is analyzed by testing the following concrete hypotheses:

H1: Ownership of mobile phones has a positive effect on household nutrition.

H2: Using mobile phones has a positive effect on household nutrition.

Easier access to food that is not self-produced is one of the key arguments why we expect mobile phones to increase dietary diversity. To shed light on this particular mechanism, we also test the following hypotheses:

H3: Ownership of mobile phones improves access to food sources beyond self-production.

H4: Using a mobile phone improves access to food sources beyond self-production.

3. Data and measurement of key variables

3.1. Data and sampling

This study uses panel data collected in Marsabit, Kenya by the project: *Index based livestock insurance (IBLI) for northern Kenya's arid and semi-arid lands: the Marsabit Pilot* at ILRI. The data cover the years 2009, 2010, 2011, 2012, 2013, and 2015. In the first step of sampling, 16 out of 47 sub-locations in Marsabit County were chosen. These sub-locations were purposively selected to capture variability in various dimensions such as livestock production systems, agro-ecological conditions, market access, and ethnic composition. Within each sub-location, all households were categorized in three groups based on livestock holding size. Respondents were equally drawn from these three groups. In case sampled respondents moved away for a longer time period and could not be interviewed again, replacements were drawn from the same sub-location and livestock size class. A few observations were dropped due to missing data of key variables. The final sample used in this study consists of 5,506 observations. The year 2009 has 916 observations; the years 2010, 2011, 2012, 2013, and 2015 have 912, 920, 922, 919, and 917 observations respectively. 752 household are part of all six survey rounds. A more detailed description of the sampling strategy can be found in Ikegami and Sheahan (2017).

3.2. Measurements of key variables

We use the Household Dietary Diversity Score (HDDS) to measure dietary diversity at the household level. The HDDS counts the number of food groups consumed by the household over a specific period of time, usually 24 hours (Swindale & Bilinsky, 2006), but longer recall periods have also become common in the recent literature (Koppmair et al., 2017; Upton et al., 2016; Arimond et al., 2010). The HDDS is a common tool to assess food security and dietary diversity. Recent research showed that the HDDS is also significantly correlated with household micronutrient consumption as well as individual-level measures of dietary diversity in Kenya and other geographical contexts (Sibhatu & Qaim, 2018; Koppmair et al., 2017). The data used in this study is based on a seven-day food consumption recall at the household level. The 12 food groups usually included in the HDDS are: *cereals; white roots and tubers; legumes, nuts and seeds; vegetables; fruits; meat; eggs; fish and seafood; milk and milk products; sweets and sugars; oils and fats;* and *spices, condiments, and beverages* (Swindale & Bilinsky, 2006). The number of food types in the survey's last round conducted in 2015 is smaller than in the previous rounds, since some foods that were previously disaggregated were combined. To keep consistency over all time periods we slightly alter the items included in two of the usual 12 food groups for the HDDS and do so consistently for all survey rounds. Instead of having one group for meat, poultry and offal, and one group for fish and seafood, we have one group for goat and sheep meat and one group for fish, seafood, offal and all other meat. Goat and sheep meat are the most-commonly consumed meat in the study area, while fish, offal, camel, donkey, or bush meat are eaten less frequently. The correlation of the HDDS using the original 12 food groups as defined by Swindale & Bilinksy (2006) and our modified version of the HDDS for the first five survey rounds is 0.995. This close correlation suggests that our modification is very unlikely to reduce the validity of the indicator.

As an additional nutrition indicator we use a variation of the HDDS that does not include the three calorie-rich but micronutrient-poor food groups *sweets and sugars; oils and fats;* and *spices, condiments, and beverages,* as used for example by Sibhatu et al. (2015) and Arimond et al. (2010). This alternative indicator may be a better proxy of micronutrient consumption, but in the pastoral context of Northern Kenya calorie deficiency is also a widespread problem. Hence, both indicators are of interest here. In the following analysis, we refer to the two indicators as HDDS12 and HDDS9 to clarify the number of food groups included in each case.

The survey data used for the calculation of the HDDS were always collected in October or November, which is when the rainy season typically starts in Marsabit (Upton et al., 2016). Collecting the data always during the same season ensures comparability of the HDDSs over the survey rounds. However, one should be cautious not to over-interpret the HDDS as an indicator of food security during all periods of the year, because possible seasonal differences in food consumption are not captured.

We are also interested in the main sources of food for sample households. We differentiate between self-production and other sources, including purchases, food aid, and gifts. This distinction is based on our expectation that income effects are not the only mechanism through which mobile phones can influence household dietary diversity. As discussed above, mobile phones facilitate communication and coordination and could thus improve access to food aid and food markets also without any income effects. For the HDDS calculations, we categorize a food group as self-produced when the household consumes at least one food item belonging to this group from own production. A food group is categorized as non-self-produced only when all the items belonging to a food group were obtained from other sources.

We consider two different outcome variables concerning the food source. First, we measure the relevance of non-self-produced foods by taking the sum of all non-self-produced food groups that the household consumed in the last seven days. This sum ranges from zero, if the household obtained all of the foods consumed from self-production, to 12, if the household consumed all 12 food groups but obtained all foods from sources other than self-production. The sum of self-produced food groups is consequently always smaller or equal to the household's HDDS12. Second, we measure the relevance of self-produced foods as the sum of all self-produced food groups that the household consumed during the last seven days. This second variable can also range from zero to 12.

The main treatment variables in this study are mobile phone ownership and use. The survey contained questions about the number of mobile phones owned by each household and the frequency of mobile phone use. The frequency was captured as "*never", "once a year", "once a month", "once a week",* or *"every day"*. Table 1 shows that ownership of a mobile phone is not a necessary condition for use. The proportion of people that used a mobile phone without owning one increased over time. Almost half of the respondents without a phone in 2015 mentioned using one at least once a month. This degree of phone sharing exceeds results reported in previous studies carried out in similar settings (Debsu et al., 2016; Butt, 2015; Aker & Mbiti, 2010). Approximately 11% of the respondents in our sample who stated that they own a mobile phone actually never used it during the 12 months prior to the survey. Potential reasons for owning but not using mobile phones are poor network coverage, weak electricity infrastructure, or insufficient mobile phone credit (Butt, 2015). In order not to dilute estimates by households that own but never used a phone, we do not treat these households as owners in the impact analysis. However, the findings do not change much when including these households as mobile phone owner (see Online Appendix Table 1).

To allow for differences in ownership and utilization frequencies and to increase the robustness of our estimations, we construct the following five mobile phone (MP) variables:

- MP ownership variable 1: Dummy if household owns a MP and used it at least once during the 12 months prior to the survey.
- MP ownership variable 2: MP ownership variable 1 multiplied by the number of mobile phones owned by the household divided by the household size (number of members).
- MP utilization variable 3: Dummy if the household used a mobile phone at least once a month.
- MP utilization variable 4: Dummy if the household used a mobile phone at least once a week.
- MP utilization variable 5: Dummy if the household used a mobile phone every day.

Table 1: Share of households that use MPs among households that do not own a MP

	Pooled (N=3,012)	2009 (N=654)	2010 (N=618)	2011 (N=553)	2012 (N=477)	2013 (N=443)	2015 (N=257)
Usage at least once a month	27	20	20	25	27	36	48
Usage at least once a week	17	9	11	16	18	23	42
Usage every day	9	2	3	8	12	13	27

Source: Own elaboration based on panel data from Northern Kenya with 5,506 observations and 1,062 groups. MP = Mobile phone.

We select suitable explanatory variables based on past research to control for several important variations in household characteristics. Mobile phones could be more useful if the number of people from one's network that also own and use mobile phones is higher. To test for this possibility, we include the dissemination of mobile phones in each of the 16 sub-locations by calculating the proportion of sample households owning a mobile phone relative to the total number of households included from that sub-location. Moreover we include radio possession to control for an additional type of technology that can be used to access information.

Hirvonen and Hoddinott (2017) find that the household's cooking source can also influence its dietary diversity. We therefore control for the household's main cooking appliance by constructing a dummy variable that is zero if the household uses a traditional fire and one of the household uses any form of advanced cooking appliance such as a *jiko* (local wood and charcoal stove) or some form of cooker.

We also include the gender, age, and education of the household head as well as the household size. Income is measured as all income received by the household in the last four months including livestock sales, crop sales, cash transfers from family, friends and other people, salaried employment, casual labor and petty trading. To account for inflation, income is consistently measured in Kenyan Shilling (KES) with 2015 as the base year (KES1 ≈ USD1/102).

The size of the land cultivated by the household measured in hectares is included as well. As mentioned in section 2, farming is rarely done in Northern Kenya. This is reflected in the data, where 81% of the observations have no land under cultivation and less than 7% farm more than one hectare. We also control for herd size measured in Tropical Livestock Units (TLU)[1]. In the area of this study, Camels form the largest proportion of the herds in terms of TLU, followed by cattle and goats (Mburu et al., 2017).

[1] One tropical livestock unit refers to either 1 head of cattle, or 0.7 of a camel, or 10 goats, or 10 sheep (Mburu et al. 2017).

Table 2: Socioeconomic characteristics by mobile phone ownership

	2009		2010		2011		2012		2013		2015	
	non-owners (N=654)	owners (N=262)	non-owners (N=618)	owners (N=294)	non-owners (N=559)	owners (N=361)	non-owners (N=483)	owners (N=439)	non-owners (N=449)	owners (N=470)	non-owners (N=271)	owners (N=646)
HDDS12	5.850	7.603***	6.322	7.898***	6.301	7.312***	6.590	7.544***	6.786	7.730***	6.775	7.545***
HDDS9	3.561	5.271***	3.906	5.503***	4.059	5.075***	4.322	5.244***	4.519	5.464***	4.480	5.238***
Self-produced food groups	0.301	0.233**	0.579	0.609	0.537	0.396***	0.801	0.711	0.844	0.963*	0.620	0.761**
Food groups from other sources	5.549	7.370***	5.743	7.289***	5.763	6.955***	5.789	6.834***	5.942	6.766***	6.155	6.783***
MP dissemination at sub-location level	0.209	0.482***	0.235	0.503***	0.304	0.528***	0.395	0.564***	0.418	0.599***	0.628	0.735***
Income [KES1,000,000]	0.013	0.054***	0.020	0.078***	0.014	0.045***	0.020	0.053***	0.026	0.043***	0.020	0.040***
Herdsize [10 TLU]	16.147	16.353	16.090	16.914	11.714	11.242	11.522	12.284	11.874	13.395	9.387	11.893**
Land farmed [hectares]	0.107	0.728***	0.068	0.524***	0.111	0.509***	0.091	0.329***	0.076	0.286***	0.108	0.401***
Radio ownership	0.090	0.576***	0.102	0.524***	0.102	0.497***	0.101	0.448***	0.111	0.447***	0.114	0.424***
Cooking source	0.009	0.073***	0.011	0.068***	0.007	0.053***	0.008	0.050***	0.009	0.049***	0.004	0.050***
Household size	5.440	6.191***	4.748	5.687***	5.812	6.565***	5.979	6.768***	5.967	6.810***	5.833	7.050***
Education HH	0.456	3.408***	0.388	2.942***	0.292	2.573***	0.327	2.091***	0.283	2.009***	0.295	1.613***
Gender HH (1 = female)	0.438	0.202***	0.466	0.194***	0.463	0.244***	0.449	0.296***	0.434	0.302***	0.501	0.319***
Age HH	47.895	47.583	48.748	49.051	48.533	48.820	50.267	48.957	51.062	50.023	54.849	51.196**

Notes: Mean values are shown. Differences in means between owners and non-owners are tested for statistical significance. HDDS = Household Dietary Diversity Score. HH= household head. MP = Mobile Phone. TLU = Tropical Livestock Unit. *** p<0.01, ** p<0.05, * p<0.1.

Herd size and agricultural land can be associated with higher household nutrition for two reasons. On the one hand these are proxies for the households' wealth, and on the other hand they present assets that can directly supply the household with food.

4. Econometric strategy

We use panel data regression models to analyze the effect of mobile phones on nutrition. We run separate regressions for both dietary diversity scores and for each of the five mobile phone variables mentioned above. Since the analysis is based on observational data, self-selection of individuals into mobile phone ownership or utilization is possible. Hence, the estimated effects of mobile phones could suffer from selection bias. To eliminate selection bias resulting from unobserved time-invariant heterogeneity, we use panel data models with household fixed effects (FE) (Verbeek, 2004). The choice of fixed effects over random effects model is supported by Hausman specification tests (Hausman, 1978). A necessary condition for efficient FE estimates is the existence of sufficient data variability within groups over time. Figures 1 and 2 show that both mobile phone ownership and use show substantial variation over the timespan considered. The following equation models the relationship between mobile phones and household dietary diversity:

$$HDDS_{it} = \beta_0 + \beta_1 MP_{it} + \beta_2' X_{it} + \beta_3' T_t + \omega_i + \varepsilon_{it}, \qquad (1)$$

where $HDDS_{it}$ is the Household Dietary Diversity Score (with either 12 or nine food groups) of household *i* at time *t*. MP_{it} is a variable measuring mobile phone ownership or use of household *i*. X_{it} is a vector of time-variant household characteristics. Some of these characteristics, such as gender of the household head, are time-invariant for most households. We still include these characteristics when there are some households where change occurred over time. Higher income is one of the mechanisms through which mobile phones can positively influence nutrition. To better understand this and other mechanisms, we run each regression with and without controlling for income. T_t is a vector of time dummies for the years 2009, 2010, 2011, 2012, and 2013, capturing all structural changes such as economic growth, overall expansion of network coverage, or droughts. ω_i is the household fixed effect. ε_{it} is a normally distributed error term that is robust and clustered at the sub-location level to account for possible heteroskedasticity and serial correlation of errors within sub-locations.

The dependent variables $HDDS12_{it}$ and $HDDS9_{it}$ are censored with a lower limit of zero and an upper limit of 12 or nine respectively. Using a tobit estimator could thus be more appropriate than a linear specification. However, maximum likelihood estimations of non-linear models with group and/or time fixed effects suffer from the incidental parameter problem (Neyman & Scott, 1948; Greene, 2004) and are thus biased and inconsistent. Potential corrections always lead to a trade-off between bias arising either through incidental parameters or through misspecification of unobserved heterogeneity (Bester & Hansen, 2016). In the data at hand there are only very few observations around the upper and lower limits. That is, very few households consume zero food groups and also very few consume all 12 (or nine) food groups. It therefore seems more reasonable to employ a linear model that captures time-invariant heterogeneity consistently rather than using a biased maximum likelihood estimator. We are mostly interested in β_1, since a positive and statistically significant coefficient would imply a positive effect of mobile phone ownership and use on household dietary diversity (hypotheses 1 and 2).

To test hypotheses 3 and 4, we analyze whether mobile phones influence the primary household food sources. As explained above, we decompose HDDS12 into two components, namely the number of consumed food groups from self-production and the number of food groups from other sources, including purchases, food aid, and gifts. To explain these two variables Y_{it} we employ the following linear fixed effect model similar to equation 1:

$$Y_{it} = \beta_0 + \beta_1 MP_{it} + \beta_2' X_{it} + \beta_3' T_t + \omega_i + \varepsilon_{it}. \qquad (2)$$

5. Results

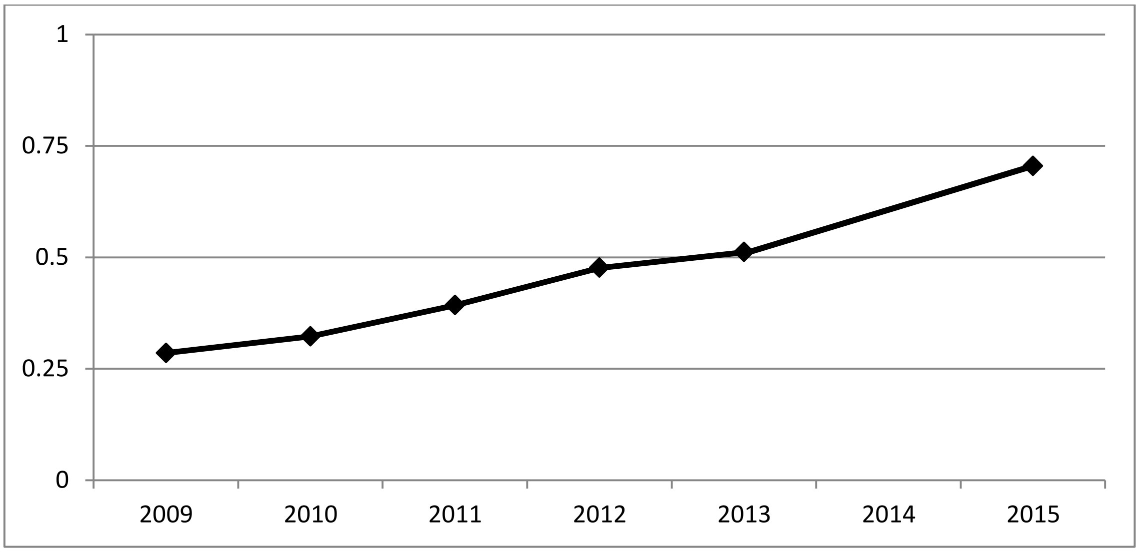
5.1. Descriptive statistics

Mobile phones have spread quickly during the time period considered in this study. Figure 1 shows the development of households owning at least one mobile phone. In the survey's first round in 2009, less than 30% of the households owned a mobile phone, which is well below the national average in Kenya for the same year (Aker & Mbiti, 2010). The proportion of mobile phone owners progressively increased to over 70% in 2015.

Utilization of mobile phones follows a very similar structure. Figure 2 shows that about 55% of the respondents never used a phone in 2009, and only 22% used a mobile phone on a daily basis. In 2015, 65% stated to use a mobile phone daily, while the proportion of households never using a mobile phone dropped to 18%.

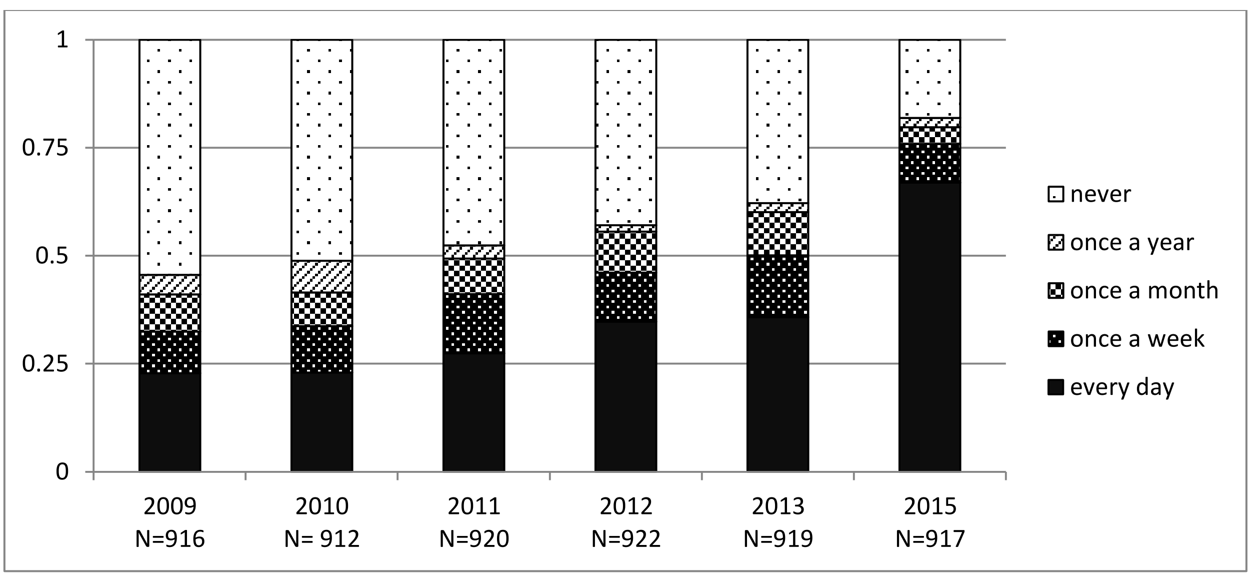
Figure 3 shows the development of average household dietary diversity. The cumulative density function has shifted to the right over time, which implies a general improvement of dietary diversity. Compared to other household dietary diversity scores using seven-day recall data (Sibhatu & Qaim, 2018), the average HDDS in the study region is quite low. This points at high food insecurity and low nutritional quality in the pastoral communities.

Figure 1: Proportion of households owning at least one mobile phone in Marsabit, Kenya



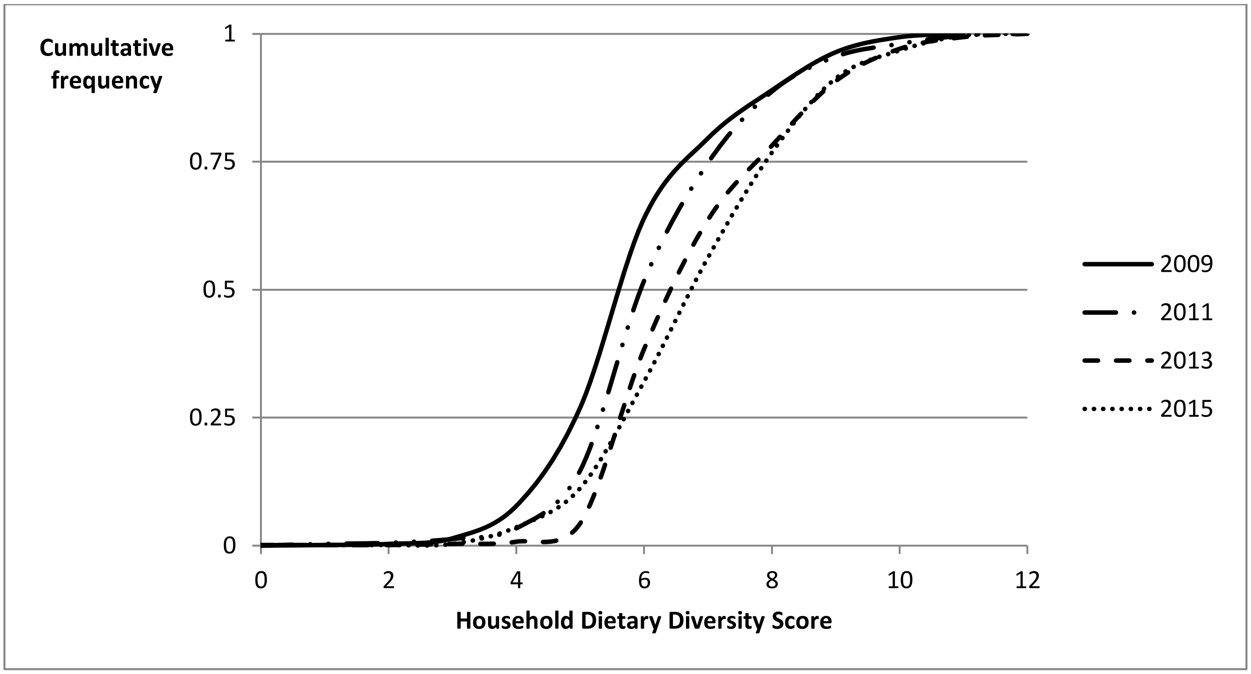
Source: Own presentation based on panel data from Marsabit, Kenya with 5,506 observations and 1,062 groups

Figure 2: Development of mobile phone utilization in Marsabit, Kenya



Source: Own presentation based on panel data from Marsabit, Kenya with 5,506 observations and 1,062 groups.

Figure 3: Cumulative distribution of the Household Dietary Diversity Score in Marsabit, Kenya



Notes: Number of observations for the year 2009 (2011, 2013, 2015) is 916 (920, 919, 917).

Source: Own presentation based on panel data from Northern Kenya with 5,506 observations and 1,062 groups.

Table 2 shows mean socioeconomic characteristics for all six survey rounds. Differences between households owning and not owning mobile phones are tested for statistical significance. Households that own mobile phones have higher dietary diversity scores and live in sub-locations where other households are more likely to own a mobile phone as well. Mobile phone owners also have higher incomes and are more likely to own other assets such as radios, advanced cooking appliances, and agricultural land. For most of the variables, the differences between households owning and not owning mobile phones are largest in 2009 and get smaller over the years with more households owning mobile phones. In the appendix we show the same variables differentiated by daily mobile phone utilization (see Appendix Table 2).

5.2. Regression results

Table 3 shows the estimation results for the models in equation (1) with mobile phone ownership as treatment variable. Columns (1) and (3) show the effect of mobile phone ownership on HDDS with 12 food groups and income included as a control variable. The coefficient estimates are positive and statistically significant for the mobile phone ownership dummy (column 1) and also for the average number of phones per household member (column 3). Columns (5) and (7) show the estimates of the same panel models when the alternative household dietary diversity score with nine food groups is used. In this specification, the number of mobile phones per household member has a statistically significant effect. The coefficient for the mobile phone ownership dummy is positive but insignificant.

Concerning the control variables, income has a positive and significant effect on HDDS, as expected. However, neither the possession of a radio nor the household's cooking source have significant effects in our sample. There is relatively little variation of these variables within households in the observed time period, which causes low efficiency of their corresponding fixed effects coefficient estimates. This could explain the large standard errors, but not the negative sign of the estimate for radio ownership. The size of both the herd and the land under cultivation exhibit positive and statistically significant influences on household nutrition. As mentioned, this could be because they are indicators for household wealth or because they can directly provide the household with food. The household's size also has a significantly positive effect on dietary diversity. This is in contrast to some earlier studies that found a negative relationship between household size and dietary diversity (Sibhatu & Qaim, 2018; Koppmair et al., 2017). All variables dealing with the household heads' characteristics are insignificant.

Columns (2), (4), (6), and (8) in Table 3 show the estimation results without income included as a control variable. As expected, the mobile phone effects are larger, supporting the hypothesis that income gains are one of the mechanisms through which mobile phones improve dietary diversity. However, the differences in the estimates between the models with and without income included are relatively small. This, together with the fact that the mobile phone coefficients are significant in columns (2), (4), and (8) even after controlling for income, clearly suggests that income gains are not the only and probably not the most important mechanism of the mobile phone effects on dietary diversity.

Several of the year fixed effect coefficients in Table 3 are negative and significant. Especially the coefficients for the years 2009 and 2011 are relatively large in absolute terms. This can be explained through severe droughts that affected large parts of the Horn of Africa during 2009 and 2011 (Upton et al., 2016; Nicholson, 2014). Droughts limit the household's possibilities to self-produce foods and own income, resulting in lower food consumption and lower levels of dietary diversity (Opiyo et al., 2015).

In Table 4 we now look at the effects of mobile phone use on household dietary diversity. Throughout all utilization frequencies, mobile phones have positive and statistically significant effects on the household dietary diversity score with 12 food groups as can be seen in columns (1) to (6). The largest effect sizes

Table 3: Effects of mobile phone ownership on Household Dietary Diversity Scores (Fixed Effects Panel Model)

	HDDS (12 food groups)				Alternative HDDS (9 food groups)			
	MP ownership binary		MP ownership per household member		MP ownership binary		MP ownership per household member	
	(1) with income	(2) without income	(3) with income	(4) without income	(5) with income	(6) without income	(7) with income	(8) without income
MP variable	0.227**	0.234**	0.575**	0.630**	0.159	0.167	0.522**	0.581**
	(0.094)	(0.096)	(0.219)	(0.230)	(0.099)	(0.100)	(0.221)	(0.227)
MP dissemination at sub-location level	0.053	0.086	0.175	0.203	0.132	0.166	0.193	0.223
	(0.509)	(0.515)	(0.538)	(0.546)	(0.480)	(0.488)	(0.512)	(0.522)
Income [KES1,000,000]	2.369***		2.323***		2.548***		2.501***	
	(0.431)		(0.414)		(0.439)		(0.433)	
Herd size [10 TLU]	0.004**	0.005***	0.004**	0.005***	0.005**	0.005***	0.005**	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Land farmed [hectares]	0.011**	0.011**	0.011**	0.011**	0.014***	0.014***	0.014***	0.014***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Radio ownership	-0.205	-0.200	-0.203	-0.200	-0.199	-0.194	-0.204	-0.201
	(0.200)	(0.206)	(0.208)	(0.215)	(0.204)	(0.211)	(0.209)	(0.216)
Cooking source	0.118	0.123	0.103	0.106	-0.043	-0.038	-0.060	-0.057
	(0.203)	(0.177)	(0.198)	(0.174)	(0.191)	(0.168)	(0.185)	(0.163)
Household size	0.082***	0.085***	0.095***	0.098***	0.085***	0.087***	0.095***	0.099***
	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Education HH	-0.046	-0.050	-0.044	-0.047	-0.083	-0.087	-0.080	-0.083
	(0.076)	(0.080)	(0.076)	(0.080)	(0.083)	(0.086)	(0.084)	(0.087)
Gender HH (1 = female)	0.143	0.134	0.141	0.133	0.174	0.163	0.174	0.165
	(0.119)	(0.118)	(0.122)	(0.121)	(0.110)	(0.108)	(0.114)	(0.112)
Age HH	-0.001	-0.001	-0.001	-0.001	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
2009	-0.770**	-0.778**	-0.697**	-0.699**	-0.761**	-0.769**	-0.698**	-0.701**
	(0.262)	(0.270)	(0.278)	(0.283)	(0.271)	(0.278)	(0.287)	(0.291)
2010	-0.289	-0.264	-0.225	-0.196	-0.394	-0.367	-0.339	-0.307
	(0.336)	(0.343)	(0.347)	(0.352)	(0.333)	(0.341)	(0.343)	(0.349)
2011	-0.462*	-0.469*	-0.414*	-0.418*	-0.405*	-0.413*	-0.364	-0.368
	(0.218)	(0.224)	(0.227)	(0.232)	(0.217)	(0.223)	(0.226)	(0.230)
2012	-0.210	-0.196	-0.171	-0.154	-0.187	-0.172	-0.152	-0.134
	(0.170)	(0.174)	(0.171)	(0.173)	(0.170)	(0.175)	(0.172)	(0.174)
2013	0.014	0.021	0.044	0.054	0.052	0.060	0.080	0.091
	(0.188)	(0.191)	(0.192)	(0.194)	(0.195)	(0.198)	(0.198)	(0.201)
Constant	6.567***	6.606***	6.419***	6.445***	4.197***	4.239***	4.068***	4.096***
	(0.505)	(0.524)	(0.521)	(0.535)	(0.513)	(0.530)	(0.535)	(0.547)
Model statistics:								
$\mathbf{R}^2$ (within)	0.108	0.097	0.107	0.098	0.106	0.095	0.107	0.096
$\mathbf{R}^2$ (overall)	0.055	0.020	0.074	0.038	0.017	0.002	0.029	0.008
Hausman test, χ^2	221.06***	212.05***	210.09***	200.21***	225.81***	217.71***	214.59***	205.10***

Notes: Estimates are based on an unbalanced panel data set with 5,506 observations and 1,062 groups. Errors shown in parentheses are robust and clustered at the sub-location level. HDDS = household dietary diversity score. HH = household head. MP = mobile phone. TLU = Tropical Livestock Unit. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effects of mobile phone use on Household Dietary Diversity Scores (Fixed Effects Panel Model)

	HDDS (12 food groups)						Alternative HDDS (9 food groups)					
	Using MP at least once a month		Using MP at least once a week		Using MP every day		Using MP at least once a month		Using MP at least once a week		Using MP every day	
	(1) with income	(2) without income	(3) with income	(4) without income	(5) with income	(6) without income	(7) with income	(8) without income	(9) with income	(10) without income	(11) with income	(12) without income
MP variable	0.157**	0.168**	0.128**	0.140**	0.245***	0.257***	0.085	0.097	0.069	0.082	0.231***	0.244***
	(0.067)	(0.684)	(0.059)	(0.059)	(0.069)	(0.069)	(0.063)	(0.065)	(0.059)	(0.060)	(0.068)	(0.069)
MP dissemination at sub-location level	0.118	0.145	0.149	0.176	0.095	0.125	0.204	0.233	0.222	0.250	0.114	0.146
	(0.524)	(0.530)	(0.528)	(0.534)	(0.525)	(0.531)	(0.498)	(0.507)	(0.502)	(0.511)	(0.496)	(0.504)
Income [KES1,000,000]	2.351***		2.360***		2.340***		2.541***		2.547***		2.515***	
	(0.430)		(0.433)		(0.433)		(0.438)		(0.440)		(0.439)	
Herd size [10 TLU]	0.004**	0.005***	0.004**	0.005***	0.004**	0.005***	0.005**	0.005***	0.005**	0.005***	0.005**	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Land farmed [hectares]	0.013**	0.013**	0.013***	0.013**	0.013***	0.013**	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Radio ownership	-0.177	-0.171	-0.175	-0.169	-0.188	-0.183	-0.178	-0.172	-0.177	-0.171	-0.192	-0.186
	(0.199)	(0.205)	(0.201)	(0.207)	(0.198)	(0.205)	(0.202)	(0.209)	(0.203)	(0.210)	(0.201)	(0.208)
Cooking source	0.131	0.136	0.129	0.134	0.119	0.124	-0.034	-0.028	-0.035	-0.029	-0.046	-0.041
	(0.198)	(0.173)	(0.198)	(0.172)	(0.193)	(0.169)	(0.189)	(0.167)	(0.189)	(0.166)	(0.185)	(0.163)
Household size	0.083***	0.086***	0.083***	0.086***	0.081***	0.084***	0.086***	0.088***	0.086***	0.088***	0.083***	0.086***
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)	(0.019)
Education HH	-0.047	-0.051	-0.048	-0.052	-0.045	-0.049	-0.084	-0.088	-0.085	-0.088	-0.081	-0.085
	(0.078)	(0.082)	(0.078)	(0.082)	(0.078)	(0.083)	(0.084)	(0.087)	(0.084)	(0.087)	(0.085)	(0.089)
Gender HH (1 = female)	0.137	0.128	0.131	0.121	0.128	0.118	0.168	0.158	0.165	0.154	0.162	0.151
	(0.119)	(0.118)	(0.120)	(0.119)	(0.123)	(0.121)	(0.111)	(0.109)	(0.113)	(0.110)	(0.115)	(0.112)
Age HH	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
2009	-0.767**	-0.776**	-0.759**	-0.767**	-0.733**	-0.739**	-0.757**	-0.766**	-0.752**	-0.761**	-0.730**	-0.737**
	(0.264)	(0.271)	(0.267)	(0.274)	(0.270)	(0.276)	(0.273)	(0.280)	(0.275)	(0.282)	(0.277)	(0.284)
2010	-0.285	-0.260	-0.279	-0.254	-0.250	-0.224	-0.389	-0.363	-0.386	-0.359	-0.361	-0.333
	(0.340)	(0.347)	(0.341)	(0.348)	(0.343)	(0.350)	(0.336)	(0.345)	(0.337)	(0.345)	(0.339)	(0.347)
2011	-0.463*	-0.470*	-0.456*	-0.464*	-0.422*	-0.428*	-0.404*	-0.413*	-0.401*	-0.409*	-0.370	-0.376
	(.0219)	(0.224	(0.221)	(0.226)	(0.226)	(0.231)	(0.218)	(0.224)	(0.220)	(0.226)	(0.225)	(0.231)
2012	-0.212	-0.199	-0.205	-0.191	-0.178	-0.163	-0.188	-0.174	-0.184	-0.169	-0.157	-0.141
	(0.173)	(0.177)	(0.173)	(0.177)	(0.178)	(0.182)	(0.173)	(0.177)	(0.173)	(0.177)	(0.178)	(0.183)
2013	0.006	0.012	0.014	0.021	0.046	0.054	0.047	0.054	0.052	0.059	0.083	0.092
	(0.188)	(0.191)	(0.190)	(0.193)	(0.194)	(0.196)	(0.195)	(0.198)	(0.196)	(0.199)	(0.200)	(0.203)
Constant	6.544***	6.582***	6.560***	6.599***	6.539***	6.577***	4.181***	4.222***	4.189***	4.232***	4.177***	4.217***
	(0.508)	(0.527)	(0.505)	(0.524)	(0.508)	(0.527)	(0.518)	(0.535)	(0.514)	(0.531)	(0.516)	(0.532)
Model statistics:												
$\mathbf{R}^2$ (within)	0.107	0.097	0.106	0.096	0.109	0.099	0.105	0.094	0.099	0.094	0.108	0.098
$\mathbf{R}^2$ (overall)	0.052	0.019	0.051	0.018	0.066	0.028	0.015	0.001	0.061	0.001	0.024	0.005
Hausman test, χ^2	243.79***	235.54***	238.99***	229.74***	217.86***	209.56***	254.15***	246.61***	248.75***	240.19***	222.40***	214.67***

Notes: Estimates are based on an unbalanced panel data set with 5,506 observations and 1,062 groups. Errors shown in parentheses are robust and clustered at the sub-location level. HDDS = household dietary diversity score. HH = household head. MP = mobile phone. TLU = Tropical Livestock Unit. *** p<0.01, ** p<0.05, * p<0.1

are shown for daily phone utilization in columns (5) and (6). When not controlling for income, the mobile phone effects are larger, further supporting the finding that there are mechanisms other than income gains.

Columns (7) to (12) of Table 4 suggest that only daily utilization of mobile phones significantly increases the household dietary score with nine food groups. Less frequent utilization still leads to positive, but insignificant estimates for the mobile phone variable. A possible explanation for the difference in significance levels between the HDDS12 and the HDDS9 for low utilization frequencies lies in the food groups not included in the HDDS9. The HDDS9 does not contain the food groups *sweets and sugars, oils and fats,* and *spices, condiments, and beverages.* These food groups contain foods that are generally more durable and perish slower than most of the foods in the other food groups. The HDDS9 therefore mostly consists of foods that perish relatively fast such as meat, milk, vegetables, fruit, or eggs. While rare mobile phone utilization might induce better access to foods that last long, it might not be frequent enough to increase access to more perishable foods.

The positive effect of mobile phones on dietary diversity measured in terms of HDDS12 is robust for all mobile phone ownership and use specifications. These results are robust if we use random effects models instead of fixed effects as well (see Appendix Table 3). The effect of mobile phones on dietary diversity measured in terms of HDDS9 is only statistically significant for frequent mobile phone utilization or if we measure ownership in terms of devices per household member.

The regression results in Tables 3 and 4 suggest that income is not the main mechanism trough which mobile phones improve dietary diversity. Furthermore, the partially different results for the HDDS12 and the HDDS9 imply that the effects of mobile phones may depend on the food group classification. To deepen the analysis we now try to look at the effects of mobile phones on the households' food sources. Table 5 shows the regression results of the two models explained in equation (2). Columns (6) to (10) show that all specifications for the mobile phone ownership and use variables have a significant and positive effect on the number of food groups consumed from sources other than self-production. This confirms that mobile phones facilitate the acquisition of food through markets or food aid distributions.

The only other variables that are statistically significant are income (positive), education (negative), and household size (positive). The year fixed effects are also not statistically significant anymore. This is in line with our previous explanation that the negative effects for the years 2009 and 2011 in Tables 3 and 4

Table 5: Effects of mobile phones on dietary diversity obtained from self-production and other sources (Fixed Effects Panel Model)

	Food groups from self-production					Food groups from other sources				
	MP ownership…		MP utilization…			MP ownership…		MP utilization		
	(1) binary	(2) per person	(3) …at least once a month	(4) …at least once a week	(5) …daily	(6) Binary	(7) per person	(8) …at least once a month	(9) …at least once a week	(10) …daily
MP variable	-0.011 (0.050)	0.053 (0.067)	-0.067* (0.032)	-0.062* (0.035)	0.005 (0.053)	0.238** (0.097)	0.522** (0.220)	0.223*** (0.062)	0.190** (0.065)	0.241*** (0.078)
MP dissemination at sub-location level	-0.802* (0.362)	-0.824* (0.358)	-0.740* (0.347)	-0.745* (0.363)	-0.817** (0.373)	0.855 (0.652)	0.999 (0.676)	0.858 (0.660)	0.895 (0.678)	0.912 (0.674)
Income [KES1,000,000]	0.557* (0.261)	0.549* (0.261)	0.573** (0.260)	0.570** (0.258)	0.554** (0.258)	1.812*** (0.378)	1.774*** (0.364)	1.778*** (0.371)	1.790** (0.376)	1.785*** (0.383)
Herd size [10 TLU]	0.002* (0.001)	0.002* (0.001)	0.002** (0.001)	0.002* (0.001)	0.002* (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
Land farmed [hectares]	-0.001 (0.010)	-0.002 (0.001)	-0.001 (0.009)	-0.002 (0.009)	-0.001 (0.010)	0.012 (0.010)	0.013 (0.010)	0.014 (0.010)	0.014 (0.010)	0.014 (0.009)
Radio ownership	0.016 (0.078)	0.012 (0.079)	0.017 (0.078)	0.016 (0.079)	0.014 (0.078)	-0.221 (0.235)	-0.214 (0.242)	-0.193 (0.231)	-0.191 (0.233)	-0.203 (0.231)
Cooking source	-0.068 (0.130)	-0.071 (0.131)	-0.068 (0.131)	-0.067 (0.130)	-0.069 (0.130)	0.186 (0.259)	0.174 (0.258)	0.199 (0.253)	0.196 (0.251)	0.188 (0.247)
Household size	0.028*** (0.009)	0.029** (0.010)	0.029*** (0.009)	0.029*** (0.009)	0.028*** (0.009)	0.054** (0.024)	0.066*** (0.003)	0.054** (0.024)	0.054** (0.024)	0.053** (0.024)
Education HH	0.075** (0.026)	0.076** (0.026)	0.074*** (0.025)	0.074*** (0.025)	0.075** (0.026)	-0.121* (0.064)	-0.119* (0.065)	-0.121* (0.066)	-0.122* (0.066)	-0.120* (0.067)
Gender HH (1 = female)	0.045 (0.089)	0.047 (0.089)	0.044 (0.088)	0.046 (0.087)	0.046 (0.089)	0.098 (0.179)	0.095 (0.182)	0.093 (0.178)	0.085 (0.179)	0.082 (0.182)
Age HH	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	-0.003 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.003 (0.003)
2009	-0.755*** (0.222)	-0.750*** (0.221)	-0.749*** (0.219)	-0.752*** (0.221)	-0.755*** (0.221)	-0.015 (0.453)	0.054 (0.021)	-0.018 (0.452)	-0.007 (0.457)	0.023 (0.459)
2010	-0.405** (0.179)	-0.401** (0.177)	-0.401** (0.177)	-0.403** (0.178)	-0.405** (0.177)	0.116 (0.476)	0.176 (0.467)	0.116 (0.479)	0.124 (0.480)	0.155 (0.484)
2011	-0.470** (0.214)	-0.466** (0.213)	-0.466** (0.212)	-0.469** (0.213)	-0.469** (0.213)	0.008 (0.398)	0.052 (0.487)	0.004 (0.395)	0.013 (0.399)	0.047 (0.404)
2012	-0.142 (0.129)	-0.138 (0.129)	-0.140 (0.127)	-0.143 (0.128)	-0.141 (0.128)	-0.068 (0.247)	-0.033 (0.407)	-0.072 (0.248)	-0.062 (0.249)	-0.037 (0.037)
2013	0.038 (0.065)	0.041 (0.066)	0.040 (0.064)	0.036 (0.064)	0.039 (0.065)	-0.024 (0.196)	0.003 (0.254)	-0.034 (0.195)	-0.022 (0.197)	0.007 (0.201)
Constant	0.865** (0.299)	0.855** (0.304)	0.866** (0.298)	0.859** (0.036)	0.867** (0.300)	5.701*** (0.664)	5.564*** (0.201)	5.678*** (0.663)	5.701*** (0.662)	5.673*** (0.667)
Model statistics:										
$\mathbf{R}^2$ (within)	0.099	0.099	0.010	0.010	0.099	0.033	0.033	0.035	0.033	0.034
$\mathbf{R}^2$ (overall)	0.038	0.037	0.040	0.039	0.038	0.006	0.012	0.007	0.006	0.009
Hausman test, χ^2	96.37***	99.03***	95.65***	97.29***	98.63***	149.74***	138.56***	174.97***	172.74***	152.76***

Notes: Estimates are based on an unbalanced panel data set with 5,506 observations and 1,062 groups. The dependent variable for columns 1-5 is the amount of food groups that the household consumed coming from sources other than self-production. The dependent variable for the columns 6 – 10 is the amount of food groups that the household consumed coming from self-production. Errors shown in parentheses are robust and clustered at the sub-location level. HDDS = household dietary diversity score. HH = household head. MP = mobile phone. TLU = Tropical Livestock Unit. *** p<0.01, ** p<0.05, * p<0.1.

are mainly driven by droughts, as droughts do not affect market access as much as they affect agricultural self-production through farming or livestock. The size of the herd and the agricultural land are not statistically significant in these models, suggesting that the positive effect on HDDS in previous Tables results from higher self-production rather than general wealth implications.

Columns (1) to (5) of Table 5 show the estimates of the model in equation (2) with the number of food groups from self-production as dependent variable. The mobile phone coefficient estimates are negative and approach statistical significance for daily and weekly utilization. We explain this weak negative relationship with the mechanism that mobile phones do not necessarily reduce self-production in absolute terms but rather increase the likelihood that alternative sources become the primary sources of food with better market access.

The result that mobile phones increase foods coming from sources other than self-production beyond potential structural changes in the region while they do not (or negatively) influence self-production of food gives strong reason to assume that mobile phones increase access to purchasable food and food aid in Northern Kenya. We therefore also confirm hypotheses 3 and 4.

6. Conclusion

Mobile phones are widely seen as an important technology for enhancing economic development. Communication without ICTs is associated with high opportunity costs especially in rural areas of developing countries. Mobile phones thus present a promising instrument to improve social welfare in such areas. This paper focused on nutrition as one essential social welfare dimension. We analyzed whether and how mobile phone technology translated into improved dietary diversity among pastoral communities in Kenya. In particular, we used panel data from households in Northern Kenya covering six rounds from 2009 to 2015 to assess the effects of mobile phones on dietary diversity. We considered both mobile phone ownership and usage in our analysis. Dietary diversity was measured at the household level using two dietary diversity indicators.

The results suggest that mobile phones increase dietary diversity of households living in Kenya’s arid and semi-arid lands and are therefore likely to contribute to improved nutrition in these areas. We argue that easier access to purchased foods, resulting from easier communication and coordination, represents the main mechanism through which mobile phones improve dietary diversity.

When dietary diversity is measured using the household dietary diversity score with 12 food groups included, mobile phone use increases dietary diversity regardless of usage frequency. However, when dietary diversity is measured with a score that excludes three calorie-rich but micronutrient-poor food groups, only frequent mobile phone usage improves dietary diversity. Results also show that mobile phones do not affect consumption from self-produced foods, but lead to increased consumption of foods obtained from the market and other sources. The interpretation that dietary diversity is improved through easier communication and better access to purchased food is supported by the data and consistent with economic theory. We are able to control for a wide range of economic and social factors and self-selection of households based on time-invariant characteristics. This suggests that a causal relationship between mobile phones and household nutrition is plausible.

Nevertheless, there are some limitations to our study, two of which deserve particular attention. First, we were not able to control for possible bias due to unobserved time-variant heterogeneity. Also, we could not analyze in more detail how and by whom mobile phones are actually used within the sample households, because such information is not available in the data set. Hence, causal interpretation should be made with some caution, although the effects described here are plausible and cannot easily be explained by factors other than mobile phone use. Second, the relationships observed in the pastoral setting in Northern Kenya may be typical for pastoral communities with relatively poor market access, but should not be generalized beyond the concrete setting. In settings with more food crop production and better market access the effects of mobile phones on dietary diversity and nutrition may potentially be different.

The lack of information regarding who uses mobile phones within the household calls for further scientific investigation in the future. While past research has started to address questions of intra-household phone usage (Sekabira & Qaim, 2017), more in-depth analysis could certainly be worthwhile from a gender perspective. Further research on how mobile phones can be used to improve nutrition would be interesting as well, especially because mobile phones and smartphones also enable the dissemination of various other technologies and services.

Malnutrition is a relevant challenge in Northern Kenya. From the finding that mobile phones can help to improve nutrition in such areas, we draw several policy implications. First, we recommend policy makers to further enable the use of mobile phones in rural areas by improving network coverage and electricity infrastructure. The households living furthest away from urban areas are the ones with the highest opportunity costs of reaching markets and thus can benefit strongly from mobile phone use. Second, policy makers should continue to develop methods to utilize mobile phones in order to reach and inform households about nutritious foods, balanced diets, and healthy lifestyles more generally. Third, it is crucial that costs for phone calls or text messages remain low and affordable. Many households in Kenya's ASAL are poor (Mburu et al., 2017), so that increases in communication costs could quickly diminish benefits. Policies or interventions that keep such costs low could thus be beneficial to many pastoral households.

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Appendix

Appendix Table 1: Effects of mobile phone ownership (including households that never used a mobile phone) on household dietary diversity (Fixed Effects Panel Model)

	HDDS (12 food groups)				Alternative HDDS (9 food groups)			
	MP ownership binary		MP ownership per household member		MP ownership binary		MP ownership per household member	
	(1) with income	(2) without income	(3) with income	(4) without income	(5) with income	(6) without income	(7) with income	(8) without income
MP variable	0.115* (0.062)	0.118* (0.064)	0.340** (0.153)	0.397** (0.176)	0.041 (0.065)	0.04 (0.067)	0.318** (0.147)	0.378** (0.163)
MP dissemination at sub-location level	0.179 (0.541)	0.086 (0.546)	0.227 (0.551)	0.257 (0.558)	0.257 (0.512)	0.297 (0.519)	0.239 (0.515)	0.270 (0.535)
Income [KES1,000,000]	2.388*** (0.434)		2.323*** (0.423)		2.562*** (0.440)		2.533*** (0.435)	
Herd size [10 TLU]	0.004** (0.001)	0.005*** (0.001)	0.004** (0.001)	0.005*** (0.001)	0.005** (0.002)	0.005*** (0.002)	0.005** (0.002)	0.005*** (0.002)
Land farmed [hectares]	0.012** (0.004)	0.011** (0.004)	0.011** (0.004)	0.012** (0.004)	0.015*** (0.004)	0.015*** (0.004)	0.015*** (0.004)	0.015*** (0.004)
Radio ownership	-0.193 (0.200)	-0.200 (0.207)	-0.195 (0.208)	-0.193 (0.216)	-0.183 (0.205)	-0.177 (0.212)	-0.198 (0.209)	-0.195 (0.217)
Cooking source	0.127 (0.202)	0.123 (0.177)	0.116 (0.199)	0.119 (0.174)	-0.035 (0.190)	-0.029 (0.167)	-0.048 (0.186)	-0.045 (0.163)
Household size	0.084*** (0.020)	0.085*** (0.020)	0.095*** (0.019)	0.096*** (0.019)	0.086*** (0.019)	0.089*** (0.020)	0.093*** (0.018)	0.097*** (0.018)
Education HH	-0.051 (0.078)	-0.050 (0.083)	-0.044 (0.078)	-0.051 (0.082)	-0.086 (0.085)	-0.090 (0.088)	-0.083 (0.085)	-0.087 (0.088)
Gender HH (1 = female)	0.139 (0.121)	0.134 (0.119)	0.141 (0.122)	0.131 (0.121)	0.170 (0.111)	0.158 (0.110)	0.173 (0.113)	0.164 (0.111)
Age HH	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.003)	-0.001 (0.003)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)
2009	-0.753** (0.270)	-0.778** (0.277)	-0.697** (0.277)	-0.714** (0.281)	-0.749** (0.277)	-0.757** (0.284)	-0.712** (0.283)	-0.714** (0.288)
2010	-0.276 (0.343)	-0.264 (0.350)	-0.225 (0.347)	-0.210 (0.351)	-0.384 (0.338)	-0.357 (0.346)	-0.353 (0.341)	-0.320 (0.347)
2011	-0.455* (0.223)	-0.469* (0.229)	-0.414* (0.227)	-0.430* (0.231)	-0.400* (0.221)	-0.408* (0.227)	-0.375 (0.224)	-0.378 (0.228)
2012	-0.209 (0.172)	-0.196 (0.176)	-0.171 (0.171)	-0.170 (0.173)	-0.187 (0.172)	-0.172 (0.177)	-0.166 (0.170)	-0.148 (0.173)
2013	0.009 (0.188)	0.021 (0.191)	0.044 (0.190)	0.037 (0.191)	0.049 (0.194)	0.056 (0.198)	0.066 (0.194)	0.076 (0.197)
Constant	6.542*** (0.514)	6.606*** (0.532)	6.419*** (0.519)	6.477*** (0.532)	4.18*** (0.521)	4.221*** (0.537)	4.097*** (0.529)	4.122*** (0.540)
Model statistics:								
$\mathbf{R}^2$ (within)	0.105	0.095	0.105	0.095	0.105	0.094	0.105	0.095
$\mathbf{R}^2$ (overall)	0.046	0.014	0.059	0.025	0.013	0.001	0.021	0.004
Hausman test, χ^2	219.59***	209.98***	210.83***	200.96***	226.10***	217.28***	215.06***	205.64***

Notes: Estimates are based on an unbalanced panel data set with 5,506 observations and 1,062 groups. Errors shown in parentheses are robust and clustered at the sub-location level. HDDS = household dietary diversity score. HH = household head. MP = mobile phone. TLU = Tropical Livestock Unit. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 2: Socioeconomic characteristics by daily mobile phone utilization

	2009		2010		2011		2012		2013		2015	
	non-user (N=707)	Daily user (N=209)	non-user (N=703)	Daily user (N=209)	non-user (N=668)	Daily user (N=252)	non-user (N=602)	Daily user (N=320)	non-user (N=590)	Daily user (N=329)	non-user (N=304)	Daily user (N=613)
HDDS12	5.963	7.665***	6.440	8.139***	6.391	7.567***	6.642	7.800***	6.803	8.103***	6.763	7.592***
HDDS9	3.666	5.349***	4.034	5.722***	4.147	5.282***	4.357	5.522***	4.547	5.818***	4.441	5.299***
Self-produced food groups	0.296	0.234	0.597	0.560	0.549	0.302***	0.762	0.750	0.829	1.042***	0.632	0.763**
Food groups from other sources	5.667	7.430***	5.843	7.579***	5.841	7.266***	5.880	7.050***	5.974	7.061***	6.131	6.828***
MP dissemination at sub-location level	0.217	0.523***	0.248	0.569***	0.310	0.607***	0.395	0.626***	0.430	0.655***	0.619	0.745***
Income [KES1000 000]	0.016	0.053 ***	0.025	0.083***	0.018	0.047***	0.024	0.059***	0.026	0.050***	0.021	0.041***
Herdsize [10 TLU]	16.141	16.423	16.599	15.538	12.162	9.850**	11.837	11.975	12.404	13.098	10.356	11.547
Land farmed [hectares]	0.129	0.811***	0.127	0.511***	0.144	0.591***	0.117	0.368***	0.0954	0.341***	0.110	0.416**
Radio ownership	0.134	0.550***	0.162	0.493***	0.182	0.456***	0.189	0.413***	0.205	0.422***	0.161	0.418***
Cooking source	0.016	0.067***	0.014	0.081***	0.015	0.052**	0.001	0.063***	0.012	0.061***	0.003	0.052***
Household size	5.482	6.239***	4.888	5.598***	5.906	6.642***	6.125	6.788***	6.166	6.815***	6.016	7.024***
Education HH	0.656	3.478***	0.656	3.081***	0.696	2.488***	0.635	2.169***	0.659	2.073***	0.401	1.631***
Gender HH (1 = female)	0.417	0.215***	0.432	0.196***	0.431	0.234***	0.442	0.253***	0.424	0.264***	0.487	0.316***
Age HH	47.636	48.378	48.990	48.359	48.266	49.651	49.832	49.288	50.780	50.085	55.016	50.917***

Notes: Mean values are shown. Differences in means between users and non-users are tested for statistical significance. HH= household head.
*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 3: Effects of mobile phones on dietary diversity obtained from self-production and other sources (Random Effects Panel Model)

	HDDS12					HDDS9				
	MP ownership		MP utilization…			MP ownership		MP utilization		
	(1) Binary MP ownership binary	(2) per person	(3) …at least once a month	(4) …at least once a week	(5) …daily	(6) binary	(7) per person	(8) …at least once a month	(9) …at least once a week	(10) …daily
MP ownership (binary)	0.252*** (0.071)	0.609*** (0.095)	0.252** (0.077)	0.231*** (0.065)	0.330*** (0.070)	0.213*** (0.073)	0.546*** (0.091)	0.205*** (0.077)	0.196*** (0.064)	0.324*** (0.066)
MP dissemination at sub-location level	1.984*** (0.467)	2.019*** (0.481)	1.989*** (0.473)	1.971*** (0.487)	1.875*** (0.498)	2.034*** (0.441)	2.052*** (0.451)	2.048*** (0.449)	2.024*** (0.460)	1.896*** (0.465)
Income [KES1,000,000]	2.831*** (0.493)	2.724*** (0.468)	2.819*** (0.491)	2.829*** (0.497)	2.792*** (0.503)	2.958*** (0.529)	2.856*** (0.515)	2.953*** (0.529)	2.958*** (0.535)	2.910*** (0.539)
Herd size [10 TLU]	-0.001 (0.003)	-0.001 (0.002)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
Land farmed [hectares]	0.039 (.0296)	0.039 (0.029)	0.040 (0.03)	0.040 (0.030)	0.039 (0.030)	0.044 (0.031)	0.044 (0.030)	0.045 (0.031)	0.045 (0.031)	0.044 (0.031)
Radio ownership	0.395*** (0.119)	0.387*** (0.129)	0.419*** (0.117)	0.426*** (0.120)	0.421*** (0.125)	0.406*** (0.114)	0.396*** (0.122)	0.428*** (0.111)	0.433*** (0.114)	0.424*** (0.119)
Cooking source	0.609*** (0.139)	0.592*** (0.130)	0.624*** (0.138)	0.616*** (0.138)	0.583*** (0.130)	0.606*** (0.121)	0.588*** (0.113)	0.620*** (0.120)	0.612*** (0.120)	0.574*** (0.114)
Household size	0.059*** (0.011)	0.070*** (0.012)	0.059*** (0.012)	0.059*** (0.012)	0.058*** (0.012)	0.056*** (0.012)	0.065*** (0.012)	0.056*** (0.012)	0.056*** (0.012)	0.054*** (0.012)
Education HH	0.071*** (0.016)	0.068*** (0.017)	0.072*** (0.016)	0.072*** (0.016)	0.071*** (0.015)	0.069*** (0.015)	0.066*** (0.016)	0.069*** (0.015)	0.070*** (0.015)	0.068*** (0.014)
Gender HH (1 = female)	0.119* (0.064)	0.122* (0.063)	0.11* (0.064)	0.114* (0.064)	0.120* (0.063)	0.100* (0.058)	0.104* (0.057)	0.092 (0.058)	0.095* (0.058)	0.103* (0.057)
Age HH	-0.003 (.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)
2009	0.090 (0.316)	0.118 (0.317)	0.094 (0.316)	0.089 (0.317)	0.094 (0.318)	0.096 (0.304)	0.121 (0.306)	0.100 (0.304	0.097 (0.306)	0.100 (0.307)
2010	0.497 (0.327)	0.518 (0.329)	0.504 (0.328)	0.498 (0.328)	0.508 (0.255)	0.391 (0.314)	0.409 (0.316)	0.397 (0.315)	0.392 (0.315)	0.401 (0.318)
2011	0.187 (0.251)	0.201 (0.252)	0.189 (0.249)	0.187 (0.251)	0.207 (0.255)	0.238 (0.238)	0.249 (0.238)	0.239 (0.236)	0.238 (0.237)	0.257 (0.241)
2012	0.285* (0.155)	0.300* (0.156)	0.287* (0.156)	0.291* (0.158)	0.306* (0.165)	0.307** (0.149)	0.320** (0.150)	0.308** (0.150)	0.312** (0.152)	0.328** (0.159)
2013	0.437** (0.170)	0.446 (0.171)	0.430** (0.17)	0.437** (0.171)	0.461*** (0.173)	0.475*** (0.170)	0.483*** (0.171)	0.469*** (0.170)	0.475*** (0.171)	0.500*** (0.173)
Constant	5.108*** (0.336)	5.048*** (0.334)	5.062*** (0.331)	5.101*** (0.335)	5.124*** (0.339)	2.832*** (0.322)	2.779*** (0.321)	2.794*** (0.315)	2.826*** (0.320)	2.848*** (0.325)
Model statistics:										
$\mathbf{R}^2$ (within)	0.085	0.086	0.084	0.083	0.088	0.082	0.084	0.081	0.081	0.086
$\mathbf{R}^2$ (overall)	0.351	0.350	0.354	0.352	0.354	0.336	0.336	0.338	0.337	0.340

Notes: Estimates are based on an unbalanced panel data set with 5,506 observations and 1,062 groups. Errors shown in parentheses are robust and clustered at the sub-location level. HDDS = household dietary diversity score. HH = household head. MP = mobile phone. TLU = Tropical Livestock Unit. *** p<0.01, ** p<0.05, * p<0.1.