Received: 2 February 2019 | Revised: 23 September 2019 | Accepted: 28 November 2019

DOI: 10.1111/agec.12566

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

ORIGINAL ARTICLE

Can mobile phones improve nutrition among pastoral communities? Panel data evidence from Northern Kenya

Martin C. Parlasca | **Oliver Mußhoff** | **Matin Qaim**

Department of Agricultural Economics and Rural Development, University of Göttingen, Göttingen, 37073, Germany

Correspondence
Martin C. Parlasca, Department of Agricultural Economics and Rural Development, University of Göttingen, Göttingen, 37073, Germany.
Email: martin.parlasca@uni-goettingen.de

Abstract

The digital revolution and the ongoing dissemination of mobile phones carry several prospects for smallholder farmers in sub-Saharan Africa. Food insecurity and low dietary quality remain major issues 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 among pastoral communities 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 and use are positively and significantly associated with dietary diversity. The effects are particularly large for frequent mobile phone users. We also examine the underlying mechanisms. Mobile phone use improves 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 remote rural settings with poor access to food markets.

KEYWORDS

dietary diversity, Kenya, mobile phones, pastoralism

JEL CLASSIFICATION

I15, O33, Q12, Q18

1 | INTRODUCTION

Mobile phones are a promising tool to improve the livelihoods of smallholder farmers in developing countries (Aker & Ksoll, 2016; Aker & Mbiti, 2010; Nakasone, Torero, & Minten, 2014). Following their 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), or livestock herding (Butt, 2015). Much less is known about the effects of mobile phones on different dimensions of household welfare.

Adequate nutrition is one of the welfare dimensions that deserve particular attention. Nutrition is one of the cornerstones of the Sustainable Development Goals and regarded as “infrastructure for economic development” (Development Initiatives, 2017, p. 12). Nutrition can enhance equality and inclusion and 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, Agho, Merom, Renzaho, & Hall, 2017), empirical evidence that links these two aspects is scarce. Up till now, most studies that have addressed potential nutrition effects of mobile phones remain anecdotal; other studies suffer from limited data for robust impact evaluation. First indications for a potentially positive relationship between mobile phones and nutrition were presented by Beuermann, McKelvey, and Vakis (2012), who found that regional mobile phone coverage can be associated with increased food expenditures 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 comprehensive panel data from Northern Kenya, covering the years 2009 to 2015 with six survey rounds, the objective of this study is to expand previous approaches and gain further insights into the links between mobile phones and nutrition. The study area in Northern Kenya belongs to the country’s arid and semi-arid lands (ASAL) and is a particularly marginalized region. Food insecurity and malnutrition still constitute relevant threats (Bauer & Mburu, 2017; Grace, Brown, & McNally, 2014; Upton, Cissé, & Barrett, 2016).

The pastoral setting in which the relationship between mobile phones and nutrition is analyzed here presents another important novelty addressed in this study. 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 farther away from food markets (Opiyo, Wasonga, & Nyangito, 2014). To survive under harsh climate 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 pastoralist environment.

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

2 | CONCEPTUAL FRAMEWORK

Malnutrition is a global threat. About 2 billion people lack important micronutrients such as iron or vitamin A (Development Initiatives, 2018). 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, 2018a).

Small-scale farmers in developing countries usually draw a substantial share of their food consumption from own production. A higher diversity in self-produced foods can therefore be associated with higher dietary diversity (Jones, Shrinivas, & Bezner-Kerr, 2014; Koppmair, Kassie, & Qaim, 2017; Snapp & Fisher, 2015). However, recent research has shown that the association between farm production diversity and dietary diversity is often relatively small and that markets are more important for many smallholders to access food diversity (Hirvonen & Hoddinott, 2017; Koppmair et al., 2017; Sibhatu & Qaim, 2018a). This is especially true in very dry environments—such as Kenya’s ASAL—where food crop production is limited (Mburu, Otterbach, Sousa-Poza, & Mude, 2017). Local communities in Kenya’s ASAL mainly depend on pastoralism for food and income generation, so access to food markets is particularly important to increase dietary diversity. Unfortunately, market access and market participation are constrained due to long distances and poor road conditions. On average, households in Marsabit County need more than 3 hr to reach a market (Mude, Ouma, & Lentz, 2012). In Samburu County, the average distance to the next urban market is even around 40 km (Ng’ang’a et al., 2016). Hirvonen and Hoddinott (2017) suggested that—under typical infrastructure conditions in East Africa—a 3 km distance may be a threshold for using markets on a daily basis.

The difficulties in growing food and limited access to markets for food purchases constitute serious constraints for increasing dietary diversity in pastoral communities. 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; Upton et al., 2016; Vigan et al., 2017). Reduction of food consumption is a problematic but widely practiced coping strategy among pastoralists during droughts (Opiyo, Wasonga, Nyangito, Schilling, & Munang, 2015; Silvestri, Bryan, Ringler, Herrero, & Okoba, 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 (Blauw & Franses, 2015; Muto & Yamano, 2009; Sekabira & Qaim, 2017). Income effects can result from better access to information, better access to production inputs and technologies, better access to output markets, and better prices (Aker & Mbiti, 2010; Butt, 2015; Debsu, Little, Tiki, Guagliardo, & Kitron, 2016; Zanello, 2012). 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. Stable incomes are crucial for high quality diets, especially for smallholders in rural areas (D'Souza, Mishra, & Hirsch, 2019). 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 (Kikulwe, Fischer, & Qaim, 2014). Jack and Suri (2014) show that family members send remittances to each other using mobile money, thus sharing risks and reducing the need for reduced consumption during shocks.

Third, especially in the pastoral context mobile phones can improve nutrition through reducing transaction costs for everyday life activities. Sife, Kiondo, and Lyimo-Macha (2010) found that mobile phones help increase the efficiency of daily affairs, especially when geographically distant people interact with each other. 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 members of pastoral communities for regular food purchases. Since the next market in the study area is on average more than 3 hr away (Mude et al., 2012), arrangements of reciprocal assistance and reachability through a mobile phone bear significant advantages for rural households. 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.

However, ownership and use of mobile phones is not costless. Consequently, mobile phones are often shared between 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 (Butt, 2015; Debsu et al., 2016). 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 differentiate between the effects of mobile phone ownership and mobile phone use.

Given the mechanisms discussed, we expect that mobile phones contribute to improved dietary diversity and nutrition among pastoral communities in Kenya. This is analyzed by testing the following 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 purchased food is one of the key arguments why we expect mobile phones to increase dietary diversity. This relationship has recently experienced increasing empirical support (Hirvonen & Hoddinott, 2017; Koppmair et al., 2017; Luckett, DeClerck, Fanzo, Mundorf, & Rose, 2015). To shed light on this particular mechanism, we also test the following hypotheses:

H3: Ownership of mobile phones improves access to food purchases.

H4: Using a mobile phone improves access to food purchases.

3 | DATA AND MEASUREMENT OF KEY VARIABLES

3.1 | Data and sampling

This study uses panel data collected in Kenya's Marsabit County by the Index Based Livestock Insurance Project (IBLI). The data cover the years 2009, 2010, 2011, 2012, 2013, and 2015. In the first step of sampling, 16 out of 47 sublocations in Marsabit County were chosen. These sublocations were purposively selected to capture variability in various dimensions such as livestock production systems, agro-ecologies, market accessibility, and ethnic composition. The sublocations belong to five larger divisions. Within each sublocation, all households were categorized in three groups based on livestock holding size. Respondents were equally drawn from these three groups. Enumerators usually waited up to 3 days for households during data collection. In case sampled respondents moved away for a longer time period and could not be interviewed again, replacements were drawn from the same sublocation and herd size class. The average attrition rate is 3.4% per round. The sample used in this study consists of 5,506 observations with 752 households participating in all six survey rounds. A more detailed description of the data—including sampling design, survey implementation, and attrition—is presented by 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 hr (Swindale & Bilinksy, 2006), but longer recall periods have also become common in the recent literature (Arimond et al., 2010; Sibhatu & Qaim, 2018a; Upton et al., 2016). The HDDS is a common tool to assess food security and access to calories. It is not a very precise indicator of dietary quality, as it measures the diversity of the food consumed at the household level and therefore ignores issues of intra-household food distribution. More precise indicators of dietary quality, such as individual dietary diversity scores of particular target groups, would require individual-level dietary data, which we do not have in the data set. Recent studies in Kenya and other geographical contexts showed that household-level food consumption indicators are positively and significantly correlated with individual dietary diversity scores and micronutrient intakes of male and female adults and children (Fongar, Gödecke, Aseta, & Qaim, 2019; Koppmair et al., 2017). In other words, the HDDS can be used as a proxy of dietary quality in the absence of individual-level data, even though the results should be interpreted with some caution.

The data used in this study are based on a 7-day food consumption recall. 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 & Bilinksy, 2006). The number of food items 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 types of 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 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, Krishna, and Qaim (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.

Data for the HDDS were always collected in October or November, which is when the rainy season typically starts in Marsabit (Upton et al., 2016). Data collection never overlapped with Ramadan. This ensures comparability of HDDS over the survey rounds. However, the HDDS should not be over-interpreted 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 purchases. As discussed above, mobile phones facilitate communication and coordination and could thus improve access to food markets. For the HDDS calculations, we categorize a food group as self-produced (purchased) when the household consumed at least one food item belonging to this group from own production (purchase).

We consider two different outcome variables concerning the food source. First, we measure the relevance of self-produced foods by taking the sum over all self-produced food groups that the household consumed in the last 7 days. This sum ranges from zero, if the household did not obtain any of the foods consumed from self-production, to 12, if the household produced and consumed all 12 food groups. Second, we measure the relevance of purchased foods as the sum over all food groups consumed in the last 7 days stemming from purchase. This variable can also range from 0 to 12.

Our main treatment variables are mobile phone ownership and use. The surveys 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*." To allow for differences in ownership and use frequencies and to increase the robustness of our estimations, we construct the following five mobile phone (MP) variables:

- MP ownership variable 1: unity if the household owns a MP and used it at least once during the 12 months prior to the survey, zero otherwise.
- MP ownership variable 2: unity if the household owns two or more mobile phones and used a mobile phone during the 12 months prior to the survey, zero otherwise
- MP utilization variable 1: unity if the household used a mobile phone every day, zero otherwise

- MP utilization variable 2: unity if the household used a mobile phone once a week excluding daily use, zero otherwise.
- MP utilization variable 3: unity if the household used a mobile phone at most once a month, zero otherwise.

We select explanatory variables based on past research to control for several variations in household characteristics. Since a household's cooking source can influence its dietary diversity (Hirvonen & Hoddinott, 2017), we control for the household's main cooking appliance by constructing a dummy variable that is zero if the household uses a traditional fire and unity if 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 4 months including livestock sales, crop sales, cash transfers from family, friends and other people, salaried employment, casual labor, and petty trading. All monetary values are measured using 2015 as the base year. Moreover, we include the nomadic status of the household as well as radio possession to control for an additional type of technology that can be used to access information.

Even though crop farming is rarely done in Northern Kenya, it is not completely absent. The size of the land cultivated by the household measured in hectares is therefore included as well. We also control for herd size measured in Tropical Livestock Units (TLU).[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 household's 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 dietary diversity. We run separate regressions for the two dietary diversity scores explained above and for mobile phone ownership and mobile phone use. Since the analysis is based on observational data, self-selection of individuals into mobile phone ownership and use is probable. Hence, the estimated effects of mobile phones could suffer from selection bias. To remove selection bias resulting from unobserved time-invariant heterogeneity, we use panel data models with household fixed effects (FE). The influence of factors such as physical market proximity is therefore eliminated.

[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, Otterbach, Sousa-Poza, & Mude, 2017).

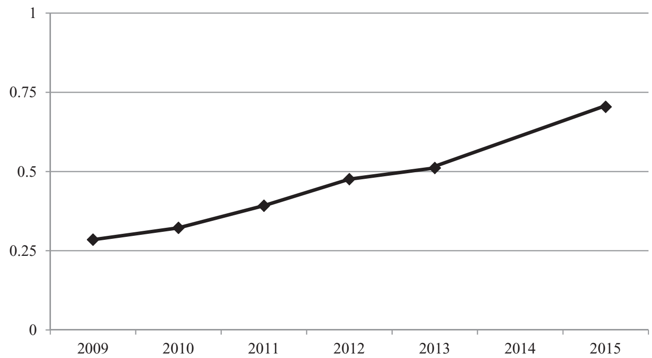

FIGURE 1 Proportion of households owning at least one mobile phone in Marsabit, Kenya
Note: Based on panel data with 5,506 observations and 1,062 groups.

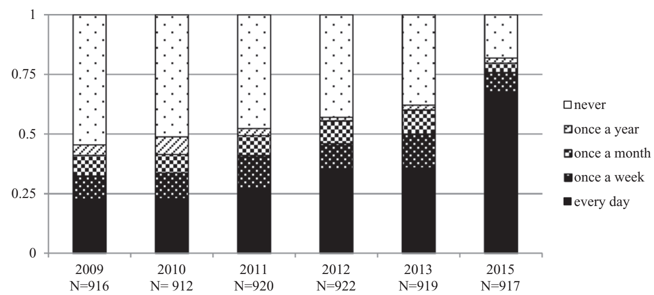

FIGURE 2 Development of mobile phone utilization in Marsabit, Kenya
Note: Based on panel data from with 5,506 observations and 1,062 groups.

A necessary condition for efficient FE estimates is the existence of sufficient data variability within groups over time. Figures 1 and 2 show that mobile phone ownership and use both show substantial variation over the timespan considered.

The following equation models the relationship between mobile phones and dietary diversity:

$$\mathrm{HDDS}_{it} = \beta_0 + \beta_1' MP_{it} + \beta_2' X_{it} + \beta_3' T_t + \omega_i + \varepsilon_{it}, \quad (1)$$

Where HDDS_{it} is the HDDS (with either 12 or 9 food groups) of household i at time t. MP_{it} is a vector of either three or two mobile phone variables that measure mobile phone use or mobile phone ownership 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 but not all households. 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, improvements of general infrastructure, or droughts. We have separate time dummies for each of the five geographical divisions to allow for heterogeneous structural change. ω_i is the household fixed effect. The errors ε_{it} are robust and clustered at the sublocation level to account for possible heteroskedasticity and serial correlation of errors within sublocations.

The dependent variables HDDS12_{it} and HDDS9_{it} are censored with a lower limit of zero and an upper limit of 12 or 9, respectively. Using a tobit estimator could 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 (Greene, 2004; Neyman & Scott, 1948) 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). Our data entail very few observations around the upper and lower limits. That is, very few households consume 0 or all 12 (or 9) 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 positive and statistically significant coefficients would imply a positive effect of mobile phone ownership and use on household dietary diversity (Hypotheses 1 and 2).

The relatively large number of time periods covered by the data allows further analyses of both the persistence of potential benefits as well as controlling if any anticipatory effects occur. Similar to Beuermann et al. (2012), we consider the following model with differential time trends for each individual household:

$$\text{HDDS}_{it} = \beta_0 + \sum_{\tau = -5}^{5} \delta_\tau D_{i\tau} + \beta_2' X_{it} + \beta_3' T_t + \omega_i + \varepsilon_{it}, \quad (2)$$

where τ is the year of first mobile phone access normalized to $\tau = 0$ for the first round of access. $D_{i\tau}$ is a dummy that equals unity for the τth year of mobile phone access. We omit the dummy $D_{i,-1}$ from the analyses, so that δ_{-2} can be interpreted as the mean of the dietary diversity two rounds before first mobile phone access relative to the round before first access. We can interpret δ_0 as the mean of dietary diversity in the round of first access relative to the round before first access (Abraham & Sun, 2019). δ_1 can be interpreted as the mean of dietary diversity in the round after first access, and so forth. If our identification strategy is valid, none of the δ_τ coefficients for $\tau < 0$ should be positive and statistically significant.

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 purchases. To explain these two variables (Y_{it}), we employ the following linear fixed effect model similar to Equation (1):

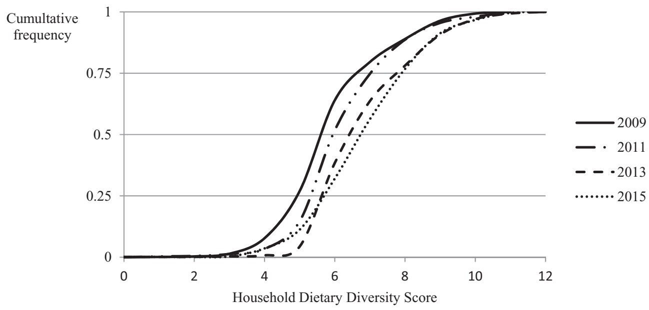

FIGURE 3 Cumulative distribution of the household dietary diversity score in Marsabit, Kenya
Note: Number of observations for the year 2009 (2011, 2013, 2015) is 916 (920, 919, 917).

$$Y_{it} = \beta_0 + \beta_1 MP_{it} + \beta_2' X_{it} + \beta_3' T_t + \omega_i + \varepsilon_{it}. \quad (3)$$

5 | RESULTS AND DISCUSSION

5.1 | Descriptive statistics

Ownership of a mobile phone increased from less than 30% in 2009 to over 70% in 2015 (Figure 1). Actual use of mobile phones follows a similar structure. 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% used a mobile phone daily, while the proportion of households that never used a mobile phone dropped to 18% (Figure 2).

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 in similar settings (Aker & Mbiti, 2010; Butt, 2015; Debsu et al., 2016). 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).

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 HDDSs using 7-day recall data (Fongar et al., 2019; Sibhatu & Qaim, 2018a), the average HDDS in the study region is quite low. This points at high food insecurity and low nutritional quality in the pastoral communities.

AGRICULTURAL ECONOMICS The Journal of the International Association of Agricultural Economists

TABLE 1 Correlations between income, dietary diversity, and mobile phones ($N = 5{,}506$)

	Income	MP use at least once a month	Owning at least one MP	HDDS12
MP use at least once a month	0.206***			
Owning at least one MP	0.235***	0.607***		
HDDS12	0.304***	0.380***	0.396***	
HDDS9	0.296***	0.364***	0.386***	0.947***

Note. HDDS = Household Dietary Diversity Score. MP = mobile phone.
***$p < 0.01$.
Significance levels are Bonferroni-adjusted.

Mean socioeconomic characteristics for all six survey rounds are shown in Table S1 in Supporting Information. We test differences between households owning and not owning mobile phones for statistical significance. Households that own mobile phones have higher dietary diversity scores and are more likely to own other assets such as radios, advanced cooking appliances, and agricultural land. Mobile phone owners also have higher incomes (see Table S1 in Supporting Information).

The relationships between income, mobile phones, and dietary diversity deserve particular attention. Richer households are more likely to use or own mobile phones and are also more likely to have higher dietary quality. A positive association between mobile phones and dietary quality could therefore emerge simply as a by-product of these latent mechanisms. To better understand these relationships, we present correlation coefficients in Table 1. All coefficients are positive and statistically significant, yet with some differences in terms of their magnitude. The correlations between income and mobile phone ownership/use are relatively small. The correlations between income and dietary diversity are slightly larger, and the largest correlation coefficients are observed between the mobile phone variables and dietary diversity. Since the correlation coefficients are based on the pooled sample and do not account for any confounding factors, interpretation should be made with caution. Nevertheless, the relatively weak linear relationship between income and mobile phone use suggests that a positive association between mobile phone use and dietary diversity may not be driven by the income mechanism alone, as predicted in our conceptual framework. This will be further analyzed with the econometric models below.

5.2 | Regression results

In Table 2, we present estimation results for the models in Equation (1). Columns (1)–(4) show results for mobile phone use as the treatment variable. The dependent variable for columns (1) and (2) is the HDDS12 and for columns (3) and (4) the HDDS9. Coefficient estimates for daily mobile phone use are positive and statistically significant for both dietary diversity scores. Less frequent mobile phone use is only statistically significant for HDDS12. A coefficient of 0.3 for daily MP use (column 1) means that those who use mobile phones on a daily basis consume 0.3 food groups more compared to those who do not use mobile phones. This average effect size is larger than that of many agricultural interventions, such as increasing the diversity of farm production among African smallholders (Sibhatu & Qaim, 2018b).

Using the estimates in columns (2) and (4) of Table 2, we can also approximate the proportion of the improvements in average dietary diversity that can be attributed to increased mobile phone use. Multiplying the mobile phone regression coefficients of column (2) with the average increase in mobile phone use and dividing this number by the average increase in HDDS12 reveals that considering the time span analyzed here, mobile phones contributed to roughly 12% of the improvement in HDDS12. Similarly, the mobile phone regression coefficients of column (4) imply that increases in mobile phone use contributed to 10% of improvements in HDDS9.

Columns (5) and (6) of Table 2 show that both owning at least one phone and owning two or more mobile phones have a positive and statistically significant effect on HDDS12. When the HDDS with nine food groups is considered (columns 7 and 8), only owning two or more mobile phones approaches statistical significance; the coefficient for owning at least one mobile phone is positive but insignificant.[2]

A possible explanation for the difference in significance levels between HDDS12 and HDDS9 for low utilization frequencies lies in the food groups not included in HDDS9. 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 less perishable than most of the foods in the other food groups. HDDS9 therefore mostly consists of foods that perish relatively fast such as meat, milk, vegetables, fruit, or eggs. While rare mobile phone use might induce better access to foods that last longer, it might not be frequent enough to increase access to more perishable foods. The same argument can be made to explain the insignificant effect of owning one mobile phone on HDDS9: if

[2] To understand how sensitive the results are with regard to attrition, we ran the same models but only including those households for whom we have complete observations for all six rounds ($N = 4{,}512$). The results are shown in Table S2 in Supporting Information; they are nearly identical to those in Table 2. While these estimates with the balanced panel do not provide a perfect counterfactual for the scenario without non-random attrition, the similarity of the results suggests that the magnitude of any potential attrition bias is small.

TABLE 2 Effects of mobile phones on household dietary diversity scores (fixed effects panel models)

	Mobile phone use				Mobile phone ownership			
	HDDS12		HDDS9		HDDS12		HDDS9	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily MP use	0.306^{***}	0.289^{***}	0.261^{***}	0.243^{***}				
	(0.075)	(0.075)	(0.077)	(0.078)				
Weekly MP use	0.021	0.011	−0.060	−0.071				
(excluding daily use)	(0.070)	(0.068)	(0.063)	(0.061)				
At most monthly MP use	0.142^{*}	0.138^{*}	0.122	0.118				
	(0.071)	(0.069)	(0.077)	(0.075)				
Owning at least one MP					0.192^{*}	0.186^{*}	0.120	0.115
					(0.097)	(0.096)	(0.103)	(0.102)
Owning two or more MPs					0.248^{**}	0.233^{*}	0.211^{*}	0.195^{*}
					(0.111)	(0.111)	(0.107)	(0.109)
Income		2.321^{***}		2.484^{***}		2.362^{***}		2.515^{***}
(million KES)		(0.438)		(0.447)		(0.434)		(0.444)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Division × year dummies	YES	YES	YES	YES	YES	YES	YES	YES
Model statistics								
R^2	0.587	0.591	0.584	0.589	0.567	0.572	0.565	0.570

Note. Estimates are based on an unbalanced panel data set with 5,506 observations and 1,062 groups. Standard errors shown in parentheses are robust and clustered at the sublocation level. HDDS = household dietary diversity score. MP = mobile phone. Control variables are nomadic status, radio possession, cooking source, land farmed, herd size, education, gender, age, household size. Full results with all control variables are shown in Table S3 in Supporting Information.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

households only own a single mobile phone, the device might be more likely to be used for other purposes or by other household members.

Columns (1), (3), (5), and (7) in Table 2 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), (6), and (8) even after controlling for income, suggests that income gains are not the only mechanism of the mobile phone effects on dietary diversity.

Given the positive and statistically significant effects of the mobile phone variables in Table 2, we confirm Hypotheses 1 and 2. The partially different results for HDDS12 and HDDS9 imply that the effects of mobile phones may depend on the food group classification. To deepen the analysis we now look at the effects of mobile phones on the households' food sources. Table 3 shows regression results of the two models explained in Equation (3). Columns (2) and (4) show that all specifications for the mobile phone ownership and use variables have positive and statistically significant effects on the number of food groups consumed from purchases. This confirms that mobile phones facilitate the acquisition of food through markets. Columns (1) and (3) of Table 3 show the same models with the number of food groups from self-production as dependent variable. All mobile phone coefficient estimates are statistically insignificant. This suggests that improved access to purchased foods is indeed the main mechanism how mobile phones improve diets and nutrition in the pastoral communities. We therefore also confirm Hypotheses 3 and 4.

As a robustness check, we now look at the individual time trends in the years before, during, and after mobile phone adoption, as explained in Equation (2). We consider the three outcome variables for which we found statistically significant effects of mobile phones, namely HDDS12, HDDS9, and the number of food groups coming from purchases. Table 4 shows that none of the 24 coefficients for the years prior to first mobile phone access is statistically significant. This supports the validity of our identification strategy and suggests that households adopting mobile phones were not already on a different trajectory than other households before they adopted.

The coefficients concerned with the years after first access to a mobile phone give insights on the duration of the positive effects on dietary diversity. Mobile phone use has a positive effect from the very first round for all three nutritional indicators. These effects last at least as long as the time span covered by the data. Mobile phone ownership approaches

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE

TABLE 3 Effects of mobile phones on dietary diversity obtained from self-production and food purchases (fixed effects panel models)

	Mobile phone use		Mobile phone ownership	
	Food groups from self-production	Food groups from purchase	Food groups from self-production	Food groups from purchase
	(1)	(2)	(3)	(4)
Daily MP use	−0.019	0.384***		
	(0.047)	(0.089)		
Weekly MP use (excluding daily use)	−0.072	0.235**		
	(0.042)	(0.093)		
At most monthly MP use	−0.013	0.236**		
	(0.040)	(0.090)		
Owning at least one MP			0.008	0.307***
			(0.050)	(0.092)
Owning two or more MPs			0.042	0.276***
			(0.070)	(0.086)
Income (million KES)	0.568**	2.302***	0.556**	2.366***
	(0.231)	(0.465)	(0.233)	(0.472)
Control variables	YES	YES	YES	YES
Division × year dummies	YES	YES	YES	YES
Model statistics				
R^2	0.443	0.607	0.442	0.606

Note. Estimates are based on an unbalanced panel data set with 5,506 observations and 1,062 groups. The dependent variable for columns (1) and (3) is the number of food groups that the household consumed coming from self-production. The dependent variable for the columns (2) and (4) is the number of food groups that the household consumed coming from food purchases. Standard errors shown in parentheses are robust and clustered at the sublocation level. MP = mobile phone. Control variables are nomadic status, radio possession, cooking source, land farmed, income, herd size, education, gender, age, household size. Full results with all control variables are shown in Table S4 in Supporting Information.
$^{***}p < 0.01$, $^{**}p < 0.05$.

statistical significance when HDDS12 is considered, but only in the very first year of access. Treatment effects for later rounds are not statistically different from the round prior to first access. Ownership does not have a positive effect on HDDS9. The positive effect of mobile phone ownership on the food groups from purchases is more sustainable.

This analysis with individual time trends has certain limitations that deserve further discussion. Since the data cover six rounds, we can only estimate the *before 5* coefficient based on the households that adopted mobile phones in the last survey round. Similarly, the *before 4* coefficient can only be identified from households that adopted in the last or second to last survey round and so on. The *before* coefficients are therefore not representative of the respective pre-trend of all mobile phone adopters, but only capture households that adopted mobile phones later during the period. This does not render the results in Table 4 invalid, but means that the finding of absence of pre-trends is restricted to certain groups. We cannot rule out potential pre-trends of households that adopted relatively early. Similarly, the *after* coefficients can only be based on relatively early adopters and are therefore also not representative of the entire sample.[3]

That said, if we assume that potential pre-trends would become apparent especially in the years directly preceding the adoption decision, the *before 1*, *before 2*, and *before 3* coefficients would be the ones particularly important for this analysis. These coefficients are identified by a large share of the sample and therefore more representative. As a robustness check, we estimate Equation (2) only with dummies for the time span from 3 years before individual mobile phone adoption to 3 years after mobile phone adoption. These additional estimates, which are shown in Table S6 in Supporting Information, do not produce any positive and statistically significant coefficients that would indicate the existence of pre-trends as well.

One of the three identification assumptions formalized by Abraham and Sun (2019) requires treatment effect homogeneity across different cohorts. In the context of this study, it is plausible that cohorts react differently to the treatment. For example, early adopters might be wealthier than late adopters and therefore benefit more from easier access to

[3] This could explain why some of the after 5 coefficients are particularly large in Table 4.

TABLE 4 Effect duration of mobile phone access on dietary outcomes (fixed effects panel model)

	Mobile phone usage			Mobile phone ownership		
	HDDS12	HHDS9	Food groups from purchase	HDDS12	HHDS9	Food groups from purchase
	(1)	(2)	(3)	(4)	(5)	(6)
Before 5	0.162	0.199	0.127	0.022	0.084	−0.280
	(0.162)	(0.146)	(0.218)	(0.102)	(0.118)	(0.225)
Before 4	0.116	0.132	0.121	−0.070	−0.004	−0.180
	(0.143)	(0.143)	(0.201)	(0.107)	(0.096)	(0.129)
Before 3	0.089	0.113	−0.013	0.006	0.039	0.082
	(0.093)	(0.095)	(0.115)	(0.101)	(0.113)	(0.107)
Before 2	0.058	0.073	0.013	0.055	0.100	0.063
	(0.059)	(0.079)	(0.089)	(0.074)	(0.070)	(0.090)
Before 1	Reference year					
After 0	0.214^{**}	0.188^{**}	0.258^{***}	0.136^{*}	0.094	0.264^{***}
	(0.076)	(0.077)	(0.087)	(0.073)	(0.084)	(0.085)
After 1	0.192^{*}	0.112	0.197	0.077	0.035	0.252^{**}
	(0.095)	(0.095)	(0.135)	(0.072)	(0.086)	(0.096)
After 2	0.226^{**}	0.229^{***}	0.337^{**}	0.042	−0.040	0.243^{*}
	(0.102)	(0.071)	(0.127)	(0.145)	(0.157)	(0.134)
After 3	0.252^{**}	0.234^{**}	0.330^{***}	−0.080	−0.112	0.233
	(0.087)	(0.080)	(0.104)	(0.210)	(0.199)	(0.154)
After 4	0.289^{**}	0.262	0.393	0.019	0.024	0.094
	(0.124)	(0.174)	(0.314)	(0.267)	(0.299)	(0.389)
After 5	0.433^{**}	0.467^{**}	0.818^{***}	−0.010	0.109	0.375^{*}
	(0.169)	(0.178)	(0.216)	(0.253)	(0.228)	(0.204)
Control variables	YES	YES	YES	YES	YES	YES
Division × year dummies	YES	YES	YES	YES	YES	YES
Model statistics						
R^2	0.590	0.570	0.605	0.589	0.570	0.606

Note. Estimates are based on an unbalanced panel data set with 5,506 observations and 1,062 groups. The dependent variable for columns (1) and (4) is household dietary diversity score with 12 food groups. The dependent variable for columns (2) and (5) is the dietary diversity score with nine food groups. The dependent variable for columns (3) and (6) is the number of food groups that the household consumed coming from food purchases. The independent variables shown here refer to the number of rounds before or after a household first gained access to a mobile phone relative to the year before first access. Standard errors shown in parentheses are robust and clustered at the sublocation level. Full results with all control variables are shown in Table S5 in Supporting Information. Control variables are nomadic status, radio possession, cooking source, income, land farmed, herd size, education, gender, age, household size.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

food purchases. However, Abraham and Sun (2019) show that a violation of this assumption does not invalidate the estimation, but rather complicates the interpretation of the coefficients.

Since we do not have data for the year of adoption before 2009, we do not know in which year households that already owned/used mobile phones in the first survey round had actually adopted the technology. Consequently, we cannot assign proper *after* dummies for these households. For the estimations in Table 4, all of the *after* and *before* dummies for these households were attributed a value of zero. Since we are mostly interested in pre-trends, this simplified assumption should be acceptable. It does however mean that the *after* coefficients in general should be interpreted with some caution.

To further analyze the effects of mobile phones on dietary quality from food purchases, we split HDDS12 into its 12 food groups and estimate a linear probability model for each of these groups. The dependent variable indicates whether or not a household consumed a certain food group in the 7 days prior to the survey and mentioned purchase as the main source of acquirement.

Table 5 shows that daily mobile phone use helps procure foods that are particularly perishable such as *white roots and tubers*, *vegetables*, *meat*, *eggs*, and *fish*. These products spoil relatively fast, especially in the absence of cooling devices.

TABLE 5 Linear probability models for the consumption of each food group when purchase was the main source of acquiring the food group

	Cereals (1)	white roots and tubers (2)	legumes, nuts, and seeds (3)	vegetables (4)	Fruits (5)	Meat (6)	Eggs (7)	Fish and seafood (8)	Milk and milk products (9)	Sweets and sugars (10)	Oils and fats (11)	Spices, condiments, and beverages (12)
Daily MP use	0.000	0.054**	0.039	0.048*	0.004	0.081**	0.020**	0.043***	0.035	0.028**	0.018	0.013
	(0.016)	(0.021)	(0.030)	(0.025)	(0.006)	(0.030)	(0.009)	(0.013)	(0.029)	(0.012)	(0.026)	(0.009)
Weekly MP use	0.034**	−0.019	0.019	−0.022	−0.020**	0.043**	0.013	0.012	0.101***	0.034**	0.014	0.025***
(excluding daily use)	(0.014)	(0.022)	(0.030)	(0.023)	(0.008)	(0.019)	(0.010)	(0.013)	(0.022)	(0.014)	(0.032)	(0.007)
At most monthly MP use	0.022	0.030	0.029	0.011	0.001	0.047**	0.004	0.013	0.026**	0.019	0.019	0.014
	(0.019)	(0.020)	(0.019)	(0.022)	(0.009)	(0.021)	(0.009)	(0.013)	(0.011)	(0.011)	(0.020)	(0.009)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Division × year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Model statistics												
R^2	0.304	0.574	0.367	0.607	0.350	0.368	0.301	0.369	0.412	0.247	0.389	0.242

Note. Estimates are based on an unbalanced panel data set with 5,506 observations and 1,062 groups. It is important to note that the items included in the two food groups *meat* and *fish and seafood* are slightly altered. 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. Standard errors shown in parentheses are robust and clustered at the sublocation level. MP = mobile phone. TLU = Tropical Livestock Unit. Control variables are nomadic status, radio possession, cooking source, income, land farmed, herd size, education, gender, age, household size. Full results with all control variables are shown in Table S7 in Supporting Information.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Statistically significant coefficient estimates lie between 0.02 and 0.08. Daily mobile phone users are therefore 2% to 8% more likely to have consumed such food groups in the last 7 days with purchase being the main source than non-users.

Less frequent mobile phone use increases the probability to purchase foods that can typically be bought at markets such as *cereals*, *milk & milk products*, *sweets and sugars*, and *spices, condiments, and beverages.* These findings are in line with our argument that mobile phones help to better coordinate procurement of foods from distant markets. For instance, mobile phones allow people in the local setting to organize alternating travels to the market, which reduces transport and transaction costs significantly. The rather odd negative effect of weekly mobile phone use on the probability to have consumed fruits from purchase is difficult to explain.

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 regions of developing countries. Mobile phones thus present a promising instrument to improve social welfare in such areas. This article focused on nutrition as one essential social welfare dimension. We analyzed whether and how the mobile phone technology translates 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 use. Dietary diversity was measured at the household level using two dietary diversity indicators. We further analyzed how mobile phones affect the number of food groups acquired through food purchases as well as the duration of the effects.

The results indicate that mobile phones are associated with higher levels of dietary diversity for households living in Kenya's ASAL 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, could represent an important mechanism through which mobile phones improve dietary diversity.

When dietary diversity is measured using the HDDS with 12 food groups, mobile phone use is associated with higher dietary diversity for high and low usage frequencies. However, when dietary diversity is measured with a score that excludes three calorie-rich but micronutrient-poor food groups, only daily mobile phone use seems to improve dietary diversity. Results also show that mobile phones do not affect the consumption of self-produced foods, but are associated with increased consumption of foods obtained from purchases. This effect can be seen for all usage frequencies. 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 were 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 could be plausible.

We further looked into the duration of the positive effects that mobile phones have on dietary diversity. While dietary improvements based on mobile phone use seem to be sustainable and can be traced back at least 5 years after first access to mobile phones, the effects of mobile phone ownership on dietary diversity are weaker and much less sustainable.

There are a few limitations to our study, three 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. Hence, causal interpretation should be made with some caution, although the effects described 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 to settings with very dissimilar conditions. In locations with more food crop production and better market access the effects of mobile phones on dietary diversity and nutrition may be different. Third, the analyses are based on an unbalanced panel, since some observations dropped out of the survey. However, the attrition rate is relatively low, so we do not expect strong attrition bias in the estimates, which was also supported by an additional robustness check.

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 is worthwhile from a gender perspective. Further research on how mobile phones can be used to improve nutrition is 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 could help improve diets and nutrition in such areas, we draw several policy implications. First, we recommend policy makers to further facilitate the use of mobile phones in rural areas. Beyond helping to improve nutrition, mobile phones can have many other positive effects to spur rural development, as earlier research showed (Aker & Mbiti, 2010; Kikulwe et al., 2014). While many of the direct investments in ICT infrastructure are made by the private sector, public policies can facilitate access to mobile phones through enabling infrastructure (e.g., electricity) and conducive regulation. The households living farthest away from urban areas are the ones with the highest opportunity costs of reaching markets and thus can benefit most 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 and text messages remain affordable. Many households in Kenya's ASAL are poor (Mburu et al., 2017), so that increases in communication costs could quickly diminish the benefits. Policies or interventions that keep such costs low could thus be beneficial to many households in pastoral communities. Although we cannot provide any estimates for the cost-effectiveness of such policies, we are confident that they could be justified, given the widespread food insecurity and poverty in the study region.

ACKNOWLEDGMENTS

This research was financially supported by the German Research Foundation (DFG) through grant number RTG1666 (GlobalFood). The publication was made possible by access to data for which we thank the Index Based Livestock Insurance Project, a collaborative effort of the International Livestock Research Institute, Cornell University, Syracuse University, the BASIS Research Program at the University of California at Davis, and the Foreign Affairs and Trade, the Agriculture and Rural Development Sector of the European Union, the United States Agency for International Development, the World, and the CGIAR Research Programs on Climate Change, Agriculture and Food Security and Dryland Systems. All views expressed in this publication are those of the authors and not necessarily those of the supporting institutions. The authors thank three anonymous reviewers and Ashok Mishra for very useful comments.

REFERENCES

Abraham, S., & Sun, L. (2019). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Working Paper (No. SSRN 3158747).

Aker, J. C., & Ksoll, C. (2016). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *Food Policy*, *60*, 44–51.

Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *Journal of Economic Perspectives*, *24*(3), 207–232.

Akombi, B. J., Agho, K. E., Merom, D., Renzaho, A. M., & Hall, J. J. (2017). Child malnutrition in sub-Saharan Africa: A meta-analysis of demographic and health surveys (2006–2016). *PLoS One*, *12*, e0177338.

Arimond, M., Wiesmann, D., Becquey, E., Carriquiry, A., Daniels, M. C., Deitchler, M., … Torheim, L. E. (2010). Simple food group diversity indicators predict micronutrient adequacy of women's diets in 5 diverse, resource-poor settings. *The Journal of Nutrition*, *140*(11), 2059S–69S.

Bauer, J. M., & Mburu, S. (2017). Effects of drought on child health in Marsabit District, Northern Kenya. *Economics and Human Biology*, *24*, 74–79.

Bester, C. A., & Hansen, C. B. (2016). Grouped effects estimators in fixed effects models. *Journal of Econometrics*, *190*(1), 197–208.

Beuermann, D. W., McKelvey, C., & Vakis, R. (2012). Mobile phones and economic development in Rural Peru. *The Journal of Development Studies*, *48*(11), 1617–1628.

Blauw, S., & Franses, P. H. (2015). Off the hook: Measuring the impact of mobile telephone use on economic development of households in Uganda using Copulas. *The Journal of Development Studies*, *52*(3), 315–330.

Butt, B. (2015). Herding by mobile phone: Technology, social networks and the "transformation" of pastoral herding in East Africa. *Human Ecology*, *43*(1), 1–14.

Davies, J., & Bennett, R. (2007). Livelihood adaptation to risk. Constraints and opportunities for pastoral development in Ethiopia's Afar region. *The Journal of Development Studies*, *43*(3), 490–511.

Debsu, D. N., Little, P. D., Tiki, W., Guagliardo, S. A. J., & Kitron, U. (2016). Mobile phones for mobile people: The role of information and communication technology (ICT) among livestock traders and Borana pastoralists of Southern Ethiopia. *Nomadic Peoples*, *20*(1), 35–61.

Development Initiatives. (2017). *Global nutrition report 2017: Nourishing the SDGs*. Bristol, UK: Development Initiatives.

Development Initiatives. (2018). *2018 Global nutrition report: Shining a light to spur action on nutrition*. Bristol, UK: Development Initiatives. https://doi.org/10.1111/agec.12543

D'Souza, A., Mishra, A. K., & Hirsch, S. (2019). Enhancing food security through diet quality. The role of non-farm work in rural India. *Agricultural Economics*, *51*, 95–110. https://doi.org/10.1111/agec.12543

Fongar, A., Gödecke, T., Aseta, A., & Qaim, M. (2019). How well do different dietary and nutrition assessment tools match? Insights from rural Kenya. *Public Health Nutrition*, *22*(3), 391–403.

Grace, K., Brown, M., & McNally, A. (2014). Examining the link between food prices and food insecurity. A multi-level analysis of maize price and birthweight in Kenya. *Food Policy*, *46*, 56–65.

Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *Econometrics Journal*, *7*(1), 98–119.

Hirvonen, K., & Hoddinott, J. (2017). Agricultural production and children's diets. Evidence from rural Ethiopia. *Agricultural Economics*, *48*(4), 469–480.

Ikegami, M., & Sheahan, M. (2017). Index based livestock insurance (IBLI) Marsabit household survey codebook. ILRI and Cornell University. Available at: http://data.ilri.org/portal/dataset/ibli-marsabit-r1

Jack, W., & Suri, T. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review*, *104*(1), 183–223.

Jones, A. D., Shrinivas, A., & Bezner-Kerr, R. (2014). Farm production diversity is associated with greater household dietary diversity in Malawi: Findings from nationally representative data. *Food Policy*, *46*, 1–12.

Kikulwe, E. M., Fischer, E., & Qaim, M. (2014). Mobile money, smallholder farmers, and household welfare in Kenya. *PLoS One*, *9*(1), e109804.

Koppmair, S., Kassie, M., & Qaim, M. (2017). Farm production, market access and dietary diversity in Malawi. *Public Health Nutrition*, *20*(2), 325–335.

Lio, M., & Liu, M.-C. (2006). ICT and agricultural productivity: Evidence from cross-country data. *Agricultural Economics*, *34*, 221–228.

Luckett, B. G., DeClerck, F. A. J., Fanzo, J., Mundorf, A. R., & Rose, D. (2015). Application of the nutrition functional diversity indicator to assess food system contributions to dietary diversity and sustainable diets of Malawian households. *Public Health Nutrition*, *18*(13), 2479–2487.

Mburu, S., Otterbach, S., Sousa-Poza, A., & Mude, A. (2017). Income and asset poverty among pastoralists in Northern Kenya. *The Journal of Development Studies*, *53*(6), 971–986.

Mude, A., Ouma, R., & Lentz, E. (2012). Responding to food insecurity: Employing the market information and food insecurity response analysis framework in rural Northern Kenya. *The Journal of Development Studies*, *48*(12), 1731–1749.

Muto, M., & Yamano, T. (2009). The impact of mobile phone coverage expansion on market participation: Panel data evidence from Uganda. *World Development*, *37*(12), 1887–1896.

Nakasone, E., & Torero, M. (2016). A text message away. ICTs as a tool to improve food security. *Agricultural Economics*, *47*(11), 49–59.

Nakasone, E., Torero, M., & Minten, B. (2014). The power of information. The ICT revolution in agricultural development. *Annual Review of Resource Economics*, *6*(1), 533–550.

Neyman, J., & Scott, E. (1948). Consistent estimates based on partially consistent observations. *Econometrica*, *16*(1), 1–32.

Ng'ang'a, S. K., Bulte, E. H., Giller, K. E., Ndiwa, N. N., Kifugo, S. C., McIntire, J. M., … Rufino, M. C. (2016). Livestock wealth and social capital as insurance against climate risk. A case study of Samburu County in Kenya. *Agricultural Systems*, *146*, 44–54.

Opiyo, F., Wasonga, O., & Nyangito, M. (2014). Measuring household vulnerability to climate-induced stresses in pastoral rangelands of Kenya: Implications for resilience programming. *Pastoralism: Research, Policy and Practice*, *4*(10), 1–15.

Opiyo, F., Wasonga, O., Nyangito, M., Schilling, J., & Munang, R. (2015). Drought adaptation and coping strategies among the turkana pastoralists of Northern Kenya. *International Journal of Disaster Risk Science*, *6*(3), 295–309.

Sekabira, H., & Qaim, M. (2017). Can mobile phones improve gender equality and nutrition? Panel data evidence from farm households in Uganda. *Food Policy*, *73*, 95–103.

Sibhatu, K. T., Krishna, V. V., & Qaim, M. (2015). Production diversity and dietary diversity in smallholder farm households. *Proceedings of the National Academy of Sciences USA*, *112*(34), 10657–10662.

Sibhatu, K. T., & Qaim, M. (2018a). Farm production diversity and dietary quality: Linkages and measurement issues. *Food Security*, *10*(1), 47–59.

Sibhatu, K. T., & Qaim, M. (2018b). Review: Meta-analysis of the association between production diversity, diets, and nutrition in smallholder farm households. *Food Policy*, *77*, 1–18.

Sife, A. S., Kiondo, E., & Lyimo-Macha, J. (2010). Contribution of mobile phones to rural livelihoods and poverty reduction in Morogoro region, Tanzania. *The Electronic Journal on Information Systems in Developing Countries*, *42*(3), 1–15.

Silvestri, S., Bryan, E., Ringler, C., Herrero, M., & Okoba, B. (2012). Climate change perception and adaptation of agro-pastoral communities in Kenya. *Regional Environmental Change*, *12*(4), 791–802.

Snapp, S. S., & Fisher, M. (2015). "Filling the maize basket" supports crop diversity and quality of household diet in Malawi. *Food Security*, *7*(1), 83–96.

Swindale, A., & Bilinksy, P. (2006). Household dietary diversity score (HDDS) for measurement of household food access. Indicator Guide. 2nd ed. Washington, DC: Food and Nutrition Technical Assistance Project (FANTA), Academy for Educational Development; 2006.

Tadesse, G., & Bahiigwa, G. (2015). Mobile phones and farmers' marketing decisions in Ethiopia. *World Development*, *68*, 296–307.

Upton, J. B., Cissé, J. D., & Barrett, C. B. (2016). Food security as resilience: Reconciling definition and measurement. *Agricultural Economics*, *47*, 135–147.

Vigan, A., Lasseur, J., Benoit, M., Mouillot, F., Eugène, M., Mansard, L., … Dutilly, C. (2017). Evaluating livestock mobility as a strategy for climate change mitigation: Combining models to address the specificities of pastoral systems. *Agriculture, Ecosystems & Environment*, *242*, 89–101.

Zanello, G. (2012). Mobile phones and radios: Effects on transactions costs and market participation for households in Northern Ghana. *Journal of Agricultural Economics*, *63*(3), 694–714.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Parlasca MC, Mußhoff O, Qaim M. Can mobile phones improve nutrition among pastoral communities? Panel data evidence from Northern Kenya. *Agricultural Economics*. 2020;51:475–488. https://doi.org/10.1111/agec.12566