Sources of Bias in Mobile Phone Surveys in Developing Countries

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Abstract

This study analyses three surveys carried out to measure food security in the poorest regions of Nepal: a baseline face-to-face (F2F) survey and two dual-mode surveys where respondents received either a F2F or a mobile phone interview.

The goal of the analysis was to investigate whether mobile phone surveys could replace traditional F2F surveys without compromising the accuracy of data.

Across all three surveys, households not owning mobile phones were found to be less food secure than households owning mobile phones: they consumed less food, had poorer diets and lower levels of food stocks. These findings reflected the results from analyses of demographic and socio-economic indicators which indicated that households not owning phones were poorer and less educated than households owning mobile phones.

The mode of interview (mobile phone or F2F) was analysed for one survey. It appeared that responses about food security do not differ if given in a F2F interview or a mobile phone interview.

In the two dual-mode surveys, non-response was analysed for those assigned a mobile phone interview. The results were contradictory: in one survey, mobile phone respondents were found to be more food-secure (also better educated and wealthier) than non-respondents while, in the other survey, they were found to be less food-secure (also poorer and less educated) than non-respondents.

It is concluded that food security estimates from mobile phone surveys are biased with systematic differences between respondents of mobile phone surveys and the population. The overall bias is comprised of coverage bias and non-response bias. It is expected that coverage bias will decrease over time as mobile phone ownership increases, but that non-response bias will continue to affect food security estimates.

Due to the contradictory results of the non-response analysis, it was not possible to consider bias correction techniques such as post-stratification.

It was therefore concluded that reliable food security estimates cannot yet be obtained from mobile phone surveys in Nepal, and the continuation of dual-mode surveys was recommended.

List of Abbreviations

CATI	Computer-Assisted Telephone Interview
DDS	Dietary Diversity Score
F2F	Face-to-Face
FCS	Food Consumption Score
GLM	Generalized Linear Model
Hhld	Household
IVR	Interactive Voice Response
MobPh	Mobile Phone
mVAM	mobile Vulnerability Analysis and Mapping
NeKSAP	Nepal Khadhya Surakshya Anugaman Pranali (Nepal Food Security Monitoring System)
NoMobPh	No Mobile Phone
Non-Resp	Non-Response
NoPh	No Phone
NPR	Nepali Rupees
Ph	Phone
PPS	Probability Proportional to Size
RDD	Random Digit Dialling
Resp	Response
Rpt	Repeat
SMS	Short Messaging Service
WFP	World Food Programme

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1. Introduction

Given the rapidly growing penetration of mobile phones in developing countries, the huge potential of their use in collecting data is becoming evident. National and development agencies, which have traditionally used face-to-face (F2F) surveys to collect data, are becoming increasingly interested in supplementing or even replacing F2F surveys with mobile phone surveys. These enable large cost savings and enormously faster data collection; however, the main challenge is the potential bias in mobile phone surveys due to not all households owning a mobile phone, a higher level of non-response in phone surveys than in F2F surveys, and a possible interview mode bias where responses may differ when sought F2F or by phone.

Together with the Nepal Food Security Monitoring System (Nepal Khadhya Surakshya Anugaman Pranali: NeKSAP), the World Food Programme (WFP) has been implementing household surveys to monitor food security in Nepal since 2002. Earlier surveys comprised solely F2F interviews; however, since 2017, surveys have comprised a mixture of F2F and mobile phone interviews with a long-term aim of possibly moving to purely mobile phone surveys.

If mobile phone surveys are able to provide reliable information, the replacement of F2F surveys with mobile phone surveys has the potential to lead to considerable cost savings and to data being available almost instantaneously. The possibility of real-time tracking of data in terms of levels, changes and trends would have considerable implications for policy makers, particularly so in times of crises, such as natural disasters or political instability, when food security may deteriorate rapidly and when some hard-to-reach areas may be even more difficult than usual to access.

2. Aim

The aim of this study is to estimate the potential bias in food security indicators for the mid-western and far-western mountains of Nepal if surveys were to be carried out solely by mobile phone.

We then discuss whether or not it is possible to obtain reliable food security estimates by adjusting estimates from biased mobile phone data.

3. Mobile Phone Bias

Mobile phone bias occurs when estimates from a mobile phone survey differ systematically from population parameters. The population in this study is households located in the mid-western and far-western mountains of Nepal, and the variables of interest are food security indicators, including food consumption, dietary diversity and levels of food stocks.

Figure 1: Theoretical Break-down of a Mobile Phone Survey

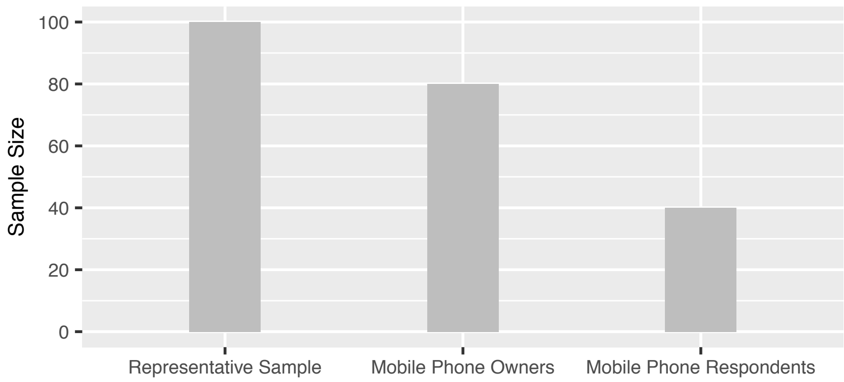


Figure 1 illustrates how mobile phone bias might occur. Let us suppose 80% of the population own mobile phones, and that the response rate for mobile phone surveys is 50%. We start with a representative sample of 100 people, 80 of whom own a mobile phone. We decide to carry out the interviews by mobile phone rather than F2F - this excludes 20 people from being interviewed. We carry out the survey but, of the 80 people we attempt to phone, 40 are not able to be contacted. Mobile phone bias will result if there are systematic differences in characteristics and responses between the 40 people successfully interviewed and the 60 people not interviewed. The bias is calculated as the difference between estimates for the representative sample and estimates for the mobile phone respondents.

There is one further potential source of mobile phone bias not captured in the figure above - it is possible that people may give different responses when interviewed by phone or F2F.

The three potential sources of bias in mobile phone surveys are defined as follows:

- Coverage Bias occurs when a portion of the population does not own a mobile phone, and results from systematic differences between those owning and not owning mobile phones. There is also coverage bias when an incomplete list frame is used (see Section 4) or subscribers own more than one mobile phone.

- Non-Response Bias occurs when a portion of the sample is not able to be contacted by mobile phone or declines to be interviewed, and results from systematic differences between those responding and not responding to the survey. It should be noted that non-response for mobile phone surveys is often considerably higher than for F2F surveys.

- Interview Mode Bias occurs when an individual gives a different response when interviewed by mobile phone or F2F. A possible reason for this is the ability of an interviewer physically present in an interview to 'probe further' to obtain an accurate response. Another reason suggested by Dillon (2011) is that phone interviews are less confidential than F2F interviews which are generally conducted in private to ensure confidentiality. He suggests that responses in a phone interview may be influenced by others in the vicinity of the respondent while being interviewed, and hypothesises that "the one-sided privacy of a phone conversation is likely not sufficient protection for truly sensitive personal data, but for other topics it may be enough". Lamanna et al (2019) discuss a "social desirability bias" initially hypothesising that the presence of an interviewer may induce the respondent to give information which they perceive to be more socially acceptable to the interviewer.

> This suggests a possible F2F bias; however, their analysis found that, for indicators where there was a mode bias, the directionality of the bias was opposite to that predicted - they suspect that "discomfort with receiving calls on mobile phones might have led to respondents giving more socially-desirable answers via CATI compared to F2F" (Lamanna et al, 2019, pp13-14).

In this study, we analyse each source of bias for the Nepal surveys, and then combine these to estimate the overall mobile phone bias.

4. Mobile Phone Surveys: Sample Selection and Method of Interview

There are two main approaches to obtaining a sample of phone numbers for a mobile phone survey: sampling from lists of active mobile phone numbers obtained from mobile network providers; or Random Digit Dialling (RDD) which involves the random generation of numbers conforming to a country's mobile phone number formations, discarding unassigned or non-working numbers until the desired sample size is reached.

In developing countries, the main challenge in using a list approach is that mobile phone providers seldom maintain accurate directories of active mobile phone numbers and users. A challenge for both a list approach and RDD is that owning multiple mobile subscriptions is common in developing countries leading to unequal (but unknown) probabilities of selection from a population.

A third approach, which is used in the Nepal surveys, is to obtain mobile phone numbers from a F2F survey for use in subsequent mobile phone surveys. This overcomes the challenges mentioned above,[1] but obviously incurs an expensive F2F survey round which mobile phone surveys are generally trying to avoid.

In terms of conducting a mobile phone interview, Conrad et al (2017) identifies four methods based on combinations of either a human or an automated interviewer, and using either a voice or SMS text interview: Human Voice (generally referred to as CATI, a computer-assisted telephone interview), Human Text, Automated Voice (generally referred to as IVR, interactive voice response) and Automated Text.[2] SMS interviews appear to be uncommon in developing countries where literacy levels may be low, and CATI appears to be more commonly used than IVR.

Mobile phone interviews in the Nepal surveys were all CATI interviews, with the interviewer reading questions aloud and recording spoken answers.

5. Studies of Mobile Phone Bias in Developing Countries

With mobile phone surveys being a recent phenomenon in developing countries, there is limited information about such surveys and their potential bias. Where studies have been carried out, we found that they were based on a variety of survey types: a F2F survey, a mobile phone survey or a dual mode F2F/mobile phone survey.

[1] Assuming the F2F sample is representative of the population, this ensures that the mobile phone sample is representative of the population owning mobile phones.

[2] Other methods are possible with smartphones, such as a mobile web survey implemented in a smartphone browser, or specialised survey apps; however, in developing countries, non-smartphones are far more common than smartphones (Pew Research Report, 2015) so these methods are rarely used.

Most studies were based on a mobile phone survey, involving a mobile phone sample selected using a list approach or generated by RDD, and interviews carried out solely by mobile phone. The overall mobile phone bias is able to be estimated from such surveys by comparing mobile phone data with census data or data from a national household survey. However, there is no mechanism to investigate the sources of bias (coverage, non-response and interview mode). In addition, if the comparison is with census data, investigation of the overall bias is restricted to indicators collected in a census.

One such study carried out in Ghana in 2017 analysed the bias in a national mobile phone Communicate for Health (C4H) survey (L'Engle et al, 2018). The C4H survey used RDD and comprised demographic, media exposure and health behaviour questions. To measure the mobile phone bias, C4H responses were compared to data collected in the Ghana Demographic and Health Survey and the National Population and Housing Census.

The C4H survey had a response rate of 31.3% which the report claims is "comparable to other national health surveys" conducted on mobile phones using RDD.

The study concluded that C4H (mobile phone) respondents were more likely to be young, male, to live in urban areas and to be better educated than the general population, more likely to listen to the radio and to view television, but less likely to have been exposed to health messages than the general population. The sources of the overall bias were unable to be investigated further.

Even more limited are studies based on a F2F survey where mobile phone owners are compared with those not owning mobile phones. This restricts the analysis to coverage bias, with no mechanism to estimate bias from non-response or other sources.

One such study was recently carried out by the Australian Department of Foreign Affairs in partnership with World Vision in 2018 to investigate whether mobile phone surveys could be potentially used to collect unbiased data about food system resilience in rural Papua New Guinea (Benson, 2019).

The study used a two-stage stratified cluster design, with districts as strata and communities as clusters, to select a sample of 1,026 households. The clusters were selected by convenience as being a pre-specified distance from specific aid projects; the sample is consequently not representative of PNG, but this is a survey design rather than a survey mode issue. All interviews were F2F and, along with demographic indicators, information about food security, diet and nutritional status was collected. The analysis compared indicators for households owning a mobile phone and households without a phone.

The study concluded that "across rural PNG, the food security-related characteristics of mobile phone-owning households in the 2018 survey are not statistically different from those of households that do not own a mobile phone. Consequently, a relatively good indication of the food security and related conditions of communities across rural PNG can be obtained using mobile phones to conduct such surveys" (Benson, 2019, p1). This conclusion is based on the finding that for food security, diet and nutritional status indicators, there were "no significant differences between mobile phone-owning households and those without phones" (Benson, 2019, p6).

However, because the survey was carried out solely using F2F interviews, the mobile phone bias is solely comprised of coverage bias, and the conclusion is based on the assumption that all mobile phone owners will respond to a mobile phone survey (also that there is no difference in responses whether questions are asked by mobile phone or F2F). We know from mobile phone studies that there is likely to be a sizeable proportion of non-respondents in which case the bias is likely to be greater than stated in the study and could well lead to a different conclusion.

For mobile phone bias to be properly investigated, a dual mode F2F/mobile phone survey must be used. This provides the only mechanism for investigating whether or not the mode of interview affects responses, and for differentiating between coverage and non-response bias.

One of the few studies we found which used a dual mode survey was carried out in Kenya in 2018 (Lamanna et al, 2019) to estimate mobile phone bias in nutrition data. The study used a one-week test-retest design on a sample of 1,821 households.[3] Households owning mobile phones were divided into three groups: one group was interviewed F2F and then re-interviewed by mobile phone (CATI); another received a mobile phone and then a F2F interview; and a third group received a F2F followed by a second F2F interview. A fourth group, comprising households not owning mobile phones, received a single F2F interview.

Demographic and nutritional status information of women and of children aged between 6 months and two years in the household was collected. Questions included which food groups the women had consumed food from in the past 24 hours and the number of times infants had been breastfed, or had consumed milk or other foods in the past 24 hours. Responses for various questions were then combined to give overall nutrition scores for women and for their infants.

Responses for those owning and not owning mobile phones were compared to estimate the coverage bias. The study had a non-response rate of 24% (participants who did not participate in both interviews, largely due to unsuccessful phone interviews) - demographic information was compared for the response and non-response groups to estimate the non-response bias. The test-retest design enabled estimation of the survey mode bias by comparing the paired F2F and mobile phone responses for each participant. Prior to the study being carried out, it was hypothesised that interviews conducted by phone would be "less subject to social-desirability bias than those conducted via F2F interviews" on the basis that the less anonymous the interview process, the more likely the participant is to give a socially acceptable response.

In terms of coverage bias, women without access to mobile phones were younger, had fewer assets and were less educated than women from households with mobile phones, and had slightly lower self-reported nutrition scores resulting in a small non-coverage bias of 1-7%.

In terms of non-response bias, women who did not participate in both survey rounds were younger and less likely to live in a household where the male head was employed. There was no significant difference in self-reported nutrition scores for women who did and did not respond; but the infants of non-respondents had lower nutrition scores than respondents.

In terms of the survey mode bias, there was no difference in women's own nutrition scores if they were interviewed by mobile phone or F2F. However, when asked about the nutrition of their infants, the prevalence of an adequate diet for infants was 17% higher when women were interviewed via mobile phone than F2F. This suggests that women were truthful when giving information about their own dietary intake whichever mode of interview was used. However, when an interview was carried out by phone, there was a positive social desirability bias with women over-stating the dietary intake of infants in their care. Interestingly, the social desirability

[3] A combination of purposeful and random sampling of administrative units was used to obtain the sample, and it is assumed that households were visited prior to the study to seek information about mobile phone ownership and to obtain mobile phone numbers.

bias was the opposite of the expectation that giving a more socially acceptable answer would occur in the less anonymous F2F interviews. The study suspects that "discomfort with receiving calls on mobile phones might have led to respondents giving more socially-desirable answers via CATI [mobile phone] compared to F2F" and makes the point that security concerns, such as calls from unknown numbers and harassment, are the third largest barrier to mobile phone use in Kenya after cost and network access.

The study concludes that "collecting nutrition data from rural women in Africa with mobile phones may result in 0% to as much as 25% higher nutrition estimates than collecting that information in face-to-face interviews".

The test/retest design of the Kenya study is one method of implementing a dual F2F/mobile phone survey. The Nepal surveys follow a different approach: a F2F survey was used to obtain information about mobile phone ownership, and then those with mobile phones were randomly allocated either a F2F or a mobile phone interview in subsequent surveys (discussed in more detail below).

6. Mobile Phone Ownership Worldwide and in Nepal

We start the analysis with a study of trends in mobile phone ownership worldwide and in Nepal.

A Pew Research Center study (Pew Research Center, 2015) analysed access to communications technology in 32 emerging and developing nations (Nepal was not one of the countries included in the study). The report commented on the fast growth of mobile phone ownership in developing countries, and the phenomenon of phone leapfrogging, where landlines are bypassed for mobile phones. The report states that "while cell phone ownership has increased drastically over the past decade ... landline connections have remained relatively low – likely due to the lack of infrastructure required for reliable connections" and that "instead of waiting for landline access, many in emerging and developing nations have bypassed fixed phone lines in favor of mobile technology."

We suggest that the leapfrogging is also due to comparatively high fixed costs of installing a landline compared with the far lower costs of buying a mobile phone (in particular, a non-smartphone) and subscription.

Interestingly, the leapfrogging is so great that some emerging and developing countries have comparable mobile phone ownership levels to the USA while retaining low landline levels as can be seen from the figures for Egypt, Jordan, Malaysia, Thailand and South Africa in the following table:

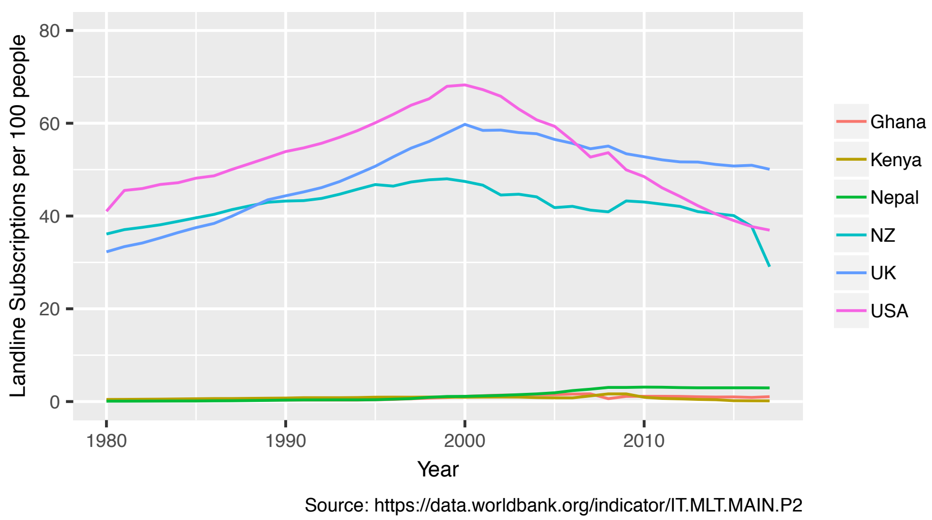
Table 1: Landline and Mobile Phone Ownership in 2014 for a selection of developing countries compared with USA
Source: Pew Research Center, 2015

Country	Working Landline in House	Mobile Phone Ownership
USA	60%	90%
Egypt	29%	91%
Jordan	21%	97%
Malaysia	14%	92%
Thailand	12%	92%
South Africa	6%	90%

In terms of potential mobile phone coverage bias,[4] the report indicates that those with higher education levels and higher incomes were more likely to own mobile phones.

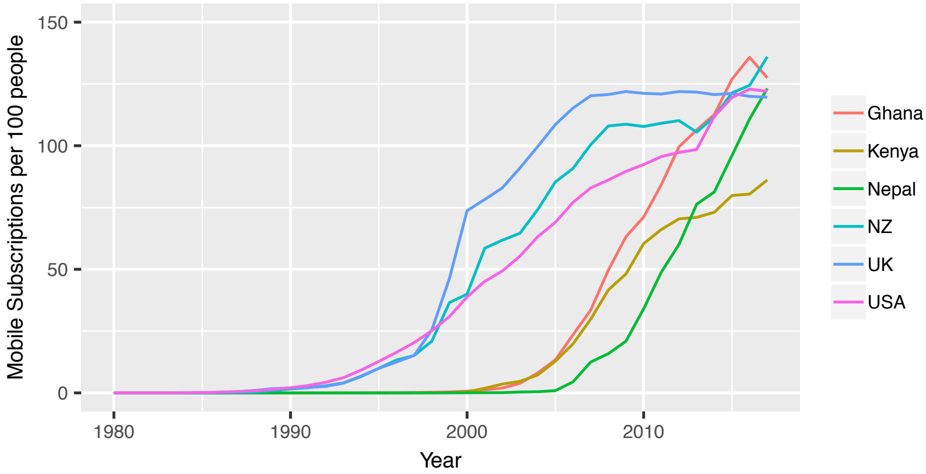
The World Bank has been collecting phone data for countries worldwide in terms of the number of subscriptions per 100 people since 1960 for landlines, and since 1980 for mobile phones. We compare the number of landline subscriptions and the number of mobile phone subscriptions per 100 people for Nepal, Kenya and Ghana (developing countries) with New Zealand, UK and USA (high-income countries) in the following graphs:

Figure 2: Number of Landline Subscriptions per 100 head of population for Nepal, Kenya, Ghana, NZ, UK and USA: 1980 to 2017



[4]"Coverage bias" is related to ownership of mobile phones, not to be confused with "mobile phone coverage" which generally describes the geographical area or the population living in an area covered by a mobile phone network. We note that, according to GSMA estimates (Shah, 2015), in terms of network coverage, "90% of Nepal's population was covered by GSM networks" in 2015, but "only about 40% of its area was covered".

Figure 3: Number of Mobile Phone Subscriptions per 100 head of population for Nepal, Kenya, Ghana, NZ, UK and USA: 1980 to 2017



The leapfrogging effect is clearly evident in the graphs above. While the number of landline subscriptions per 100 people remained at minimal levels for the three developing countries, the number of mobile phone subscriptions rose dramatically from 2005, with mobile phone subscriptions for Nepal and Ghana being similar to levels for New Zealand, UK and USA by 2017.

We see from Figure 3 that mobile phone ownership in the three developing countries initially lagged the three high income countries by roughly ten years.[5] Mobile phone ownership levels flattened from 2010 in the high-income countries, but continued to increase in the three developing countries allowing for the 'catch-up' to have occurred by 2017.

Interestingly, the number of landline subscriptions for the three high income countries peaked at around the year 2000, with landline ownership decreasing as mobile phone ownership has taken hold.

We speculate that landlines will eventually become obsolete and that there will be near universal ownership of mobile phones; however, developing countries will have largely bypassed landlines to reach the same endpoint.

The most recent figures available for Nepal (International Telecommunications Union, https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx) indicate that the number of landline subscriptions has remained stable at around 3 subscriptions per 100 people, but that mobile phone subscriptions have risen to 139 per 100 people in 2018. From 2016 onwards, there was more than one mobile phone subscription per person - this is due to those owning mobile phones often subscribing to several providers. Shah (2015) reports that, in 2015, each unique subscriber in Nepal had approximately two SIM cards. Multiple SIM cards are very common in developing countries, enabling users to switch between different providers to make use of the best call quality in certain locations and to take advantage of discounts and promotions offered by different providers (Rizatto, 2017).

[5] Levels for the high-income countries in 1990 were similar to levels for the developing countries in 2000, and levels for the high-income countries in 2000 were similar to levels for the developing countries in 2010.

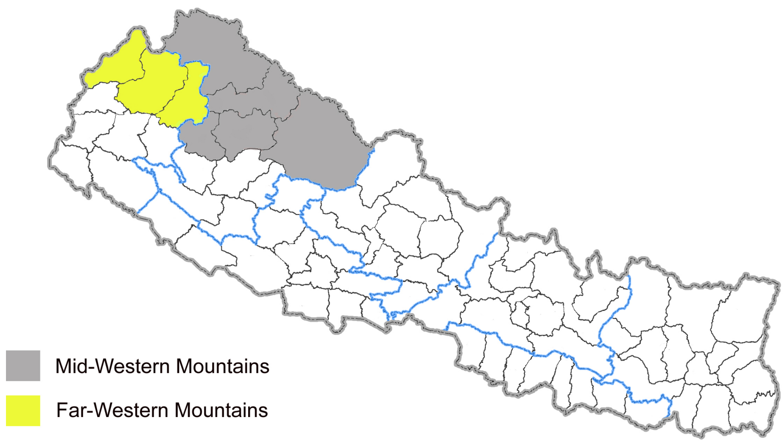
7. Food Security Surveys in Nepal

Surveys of poverty, nutrition, food security and health indicators such as wasting (low weight-for-height) and stunting (low height-for-age) in children are crucial in developing countries in order to allocate resources and to plan, monitor and evaluate programmes designed to alleviate poverty and to improve food security, nutrition and health.

The Nepal Food Security Monitoring System (Nepal Khadhya Surakshya Anugaman Pranali: NeKSAP), in collaboration with the World Food Programme (WFP), has been carrying out household surveys to monitor food security in Nepal since 2002 with particular emphasis on regions which are the least food-secure.

In November 2016, NeKSAP and WFP Nepal carried out a baseline NeKSAP Survey to measure food security in the two most food-insecure regions in Nepal: the Mid-Western Mountains and Far-Western Mountains (NeKSAP, 2016). The area covered by the survey is shown in Figure 4.

Figure 4: Map of Nepal: Regions covered by NeKSAP Survey in November 2016 and mVAM Surveys in June 2017, December 2017 and April 2018



The NeKSAP survey involved a two-stage stratified cluster design. In the first stage of the survey, 49 wards (the primary sampling unit) were selected using probability proportional to size from each of the two regions. The second stage of the survey involved the random selection of 15 households from each of the 98 wards. This resulted in a sample of 1,470 households from two strata (regions) with 98 clusters (wards).

All NeKSAP survey interviews were F2F. Respondents[6] were asked a range of demographic and socio-economic questions, and questions relating specifically to food security. The latter enabled the calculation of measures for overall dietary diversity, food consumption and food security for each household.

Respondents were also asked whether one or more household member owned a mobile phone and, if so, mobile phone numbers were obtained so that future survey rounds could be carried out by mobile phone.

[6] The terms “respondent” and “household” are used interchangeably in this report. One adult was interviewed per household: the household head if available, otherwise another adult.

Following the baseline NeKSAP survey, mVAM[7] surveys have been conducted two to three times each year using purely mobile phone interviews or dual-mode F2F/mobile phone interviews.

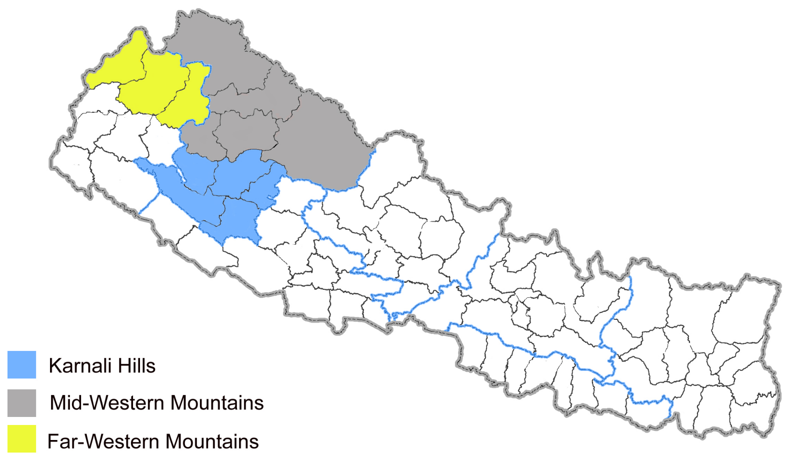
The first mVAM survey was carried out in June 2017, and involved re-interviewing all households from the NeKSAP survey. Households owning mobile phones (according to the NeKSAP survey) were randomly assigned either a F2F interview or a mobile phone interview. If a household in the latter group could not be contacted by mobile phone,[8] a F2F interview was conducted. Households not owning mobile phones received F2F interviews.

In the second mVAM survey (December 2017), only those with mobile phones were interviewed, and all interviews were carried out by mobile phone.

The third mVAM survey (April 2018) comprised 50% repeat and 50% new households. This was done according to a rotation design (Haslett, 2017) where the April 2018 survey retained 50% of households from the NeKSAP survey and selected 50% new households, preserving the survey design of balance between the two strata in terms of both the number of wards and number of households. The newly-selected households were all interviewed F2F, with a mobile phone number being obtained for households owning at least one mobile phone which could be used in subsequent surveys. The 50% repeated households were assigned interviews in the same manner as the first mVAM survey.

Subsequent mVAM surveys were carried out in September 2018, January 2019 and June 2019. The September 2018 survey, while using rotation, selected the new households from the hill districts of Karnali Province rather than from the mid-western and far-western mountains. The two surveys which followed involved those with mobile phones (from all three regions) being interviewed purely by mobile phone. Regions covered by the September 2018 and subsequent surveys are shown in Figure 5.

Figure 5: Map of Nepal: Regions covered by mVAM Surveys in September 2018, January 2019 and June 2019



[7]WFP's mVAM (mobile Vulnerability Analysis and Mapping) project was launched in 2013, beginning in DRC and Somalia. mVAM uses mobile technology to track food security trends in real-time, providing "high-frequency data that supports humanitarian decision-making" (https://vam.wfp.org/sites/mvam_monitoring/).

[8]We note that many households had multiple SIMs due to more than one household member owning a mobile phone and to some individuals owning more than one phone or SIM. We also note that, in the period between the NeKSAP baseline survey in November 2016 and the first mVAM survey in June 2017, mobile phone numbers were obtained if acquired by households not owning a mobile phone in the baseline survey. In attempting to contact a household by mobile phone, interviewers tried all available mobile phone numbers.

We excluded the purely mobile phone surveys from the analysis, since they have no mechanism for estimating bias.

Although the new households in the September 2018 survey were not from the same population as the other surveys and therefore could not be included in the analysis, we initially considered analysing the repeat households. However, it was discovered that around 35% of the repeat households were from the far-western mountains and 65% from the mid-western mountains - the survey design was such that, if implemented correctly, there should have been roughly equal numbers from the two strata. We therefore doubted that the survey design had been followed, and opted not to include the September 2018 survey in the analysis.

Therefore the analysis in this study is restricted to the baseline survey and to the two dual-mode mVAM surveys, summarised as follows:

- November 2016 baseline NeKSAP survey (Nov16): 1,468 newly selected households interviewed F2F

- June 2017 mVAM survey (Jun17): Nov16 households re-interviewed by either F2F or MobPh

- April 2018 mVAM survey (Apr18): 50% of Nov16 households re-interviewed by either F2F or MobPh; 50% newly sampled households interviewed F2F

Table 2 shows sample sizes and types of interview for the three surveys, and Table 3 summarises the five interview types.

Table 2: Breakdown of Interview Type for each survey

Survey	Ph-Ph	NoPh-F2F	Ph-F2F	Ph(NoResp)-F2F	New-F2F	TOTAL
Nov16	0	0	0	0	1468	1468
Jun17	270	498	258	367	0	1393
Apr18	299	152	0	258	711	1420

Table 3: Description of Interview Type

Interview Type	Description
Ph-Ph	Repeat household owning a MobPh: assigned a MobPh interview
NoPh-F2F	Repeat household not owning a MobPh: F2F interview
Ph-F2F	Repeat household owning a MobPh: assigned a F2F interview
Ph(NoResp)-F2F	Repeat household owning a MobPh, assigned a MobPh interview but could not be contacted by phone: F2F interview
New-F2F	New household: F2F interview

8. Methodology

As described earlier, the Nepal surveys involved both stratification (regions) and clustering (wards) resulting in complex samples (as opposed to a simple random sample).

For estimates from a complex sample to be correctly calculated, the design of the survey must be accounted for in the analysis. Failure to account for the design features can lead to incorrect estimates of population parameters, incorrect standard error estimates (generally too small), incorrect confidence intervals (generally too narrow) and misleading conclusions.

In analysing the Nepal surveys, as well as stratification and clustering, design weights are needed to account for the different probabilities that households in the sample had of being selected.

Although equal numbers of households were sampled from each stratum, the population in the far-western mountains is higher than in the mid-western mountains. Within each stratum, the 49 wards were supposedly selected using probability proportional to size (PPS). It was therefore expected that there would be two design weights: a higher weight for all households in the far-western mountains and a lower weight for all households in the mid-western mountains.

Figure 6: Design Weight by Intended Design Weight for each Ward in Nov16 Dataset

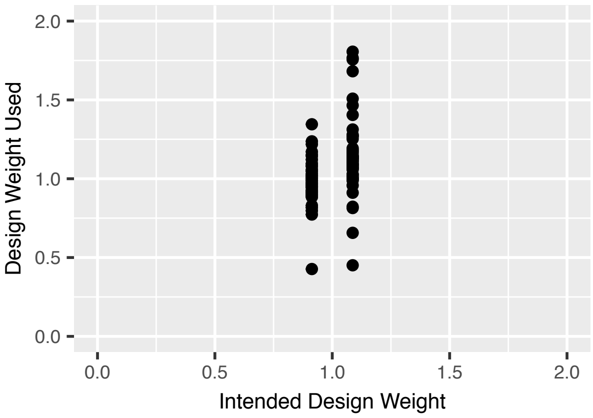


Figure 6 plots the design weights used for households in each of the 98 wards in the Nov16 dataset against the intended design weights. We see that the weights actually used were, in fact, different for each ward with wide variation of weights within each stratum. This is partly due to the fact that, although the survey design was for 15 households to be surveyed in each ward, there were 6 wards where 14 households were interviewed and 4 wards where 16 households were interviewed. However, this alone is a minor deviation from the intended design, and it is therefore assumed that PPS was not used in selecting wards and that the design weights take into account both the population of the stratum and the population of the ward.

We incorporate the clustering, stratification and design weights into the analysis to ensure that estimates are accurate and valid. All analysis in this study is done with R (R Core Team, 2015) using the 'srvyr' package where appropriate. The 'srvyr' package is similar to the 'survey' package but enables weighted confidence interval limits to be included in graphs (https://cran.r-project.org/web/packages/srvyr/vignettes/srvyr-vs-survey.htmp). Standard errors were calculated using the default "linearization". We note that the linearization method accounts for the clustering in the calculation of standard errors.

The crux of this study is to ascertain whether there are any significant differences between food security indicators for respondents in a mobile phone survey and food security estimates for the population.

If differences do exist, it is possible that these are due to underlying demographic and socio-economic differences. We therefore start the analysis by comparing demographic and socio-economic variables for those owning a mobile phone and those not owning a mobile phone, and for those responding and not responding to a mobile phone survey. We start with a univariate approach where we analyse each indicator individually comparing confidence intervals for MobPh/NoMobPh and Response/Non-Response and carrying out t-tests for numerical indicators and F-tests of association for categorical indicators.[9] We then carry out a multivariate approach where we compare regression models for different groups of indicators with MobPh/NoMobPh or Response/Non-Response as the response variable.[10] We compare the 'best' model with the findings from the univariate analysis.

We then investigate the effects of coverage (MobPh/NoMobPh), interview mode (MobPh/F2F) and non-response (Response/Non-Response) on food security indicators. We attempt to quantify each component of bias and finally combine these to estimate the overall mobile phone bias in food security estimates for June 2017 and April 2018.

We are able to explore the effects of coverage using data from all three surveys. For the Nov16 baseline survey, we analyse the complete sample comparing households owning and not owning at least one mobile phone. For the Apr18 baseline survey, we do the same comparison for new households. For the Jun17 survey, we compare the households with a mobile phone who were randomly assigned a F2F interview with households not owning a mobile phone who received a F2F interview.

The Jun17 survey is the only survey where the design enables us to analyse the effects of interview mode as this is the only survey where those owning a mobile phone were randomly assigned either a mobile phone or a F2F interview.

Both the Jun17 and Apr18 surveys allow us to investigate the effects of mobile phone non-response. For each survey, we take all households randomly assigned a mobile phone interview, and compare those successfully interviewed by mobile phone (respondents) with those who could not be contacted by mobile phone and received a F2F interview instead (non-respondents). We note that these findings could be confounded by interview mode if such an effect exists.

Tables 4, 5 and 6 summarise the surveys used to analyse each source of bias, and the sub-samples used to carry out comparisons.

[9] Lumley (2010) discusses the complications in tests for association in complex surveys. The approach he suggests is to "treat the sample as if it came from an infinite superpopulation, and simply ignore the finite-population corrections in inference". The "svychisq" command has options for four test statistics; Lumley suggests that the F-statistic (which we use) is the most accurate.

[10] Since the response variables are binary (MobPh/NoMobPh; Response/Non-Response), we use generalized linear models (GLMs) with a logit (the logarithm of the odds of owning a mobile phone or responding to an interview) link function.

Table 4: Surveys and Sub-Samples used to Analyse Coverage Bias

Survey	Subset of Sample	Owns MobPh	No MobPh
Nov16	Whole Sample	Owns a MobPh	Does not own a MobPh
Jun17	No MobPh; or MobPh and assigned a F2F interview	Ph-F2F	NoPh-F2F
Apr18	New Households	Owns a MobPh	Does not own a MobPh

Table 5: Surveys and Sub-Samples used to Analyse Interview Mode Bias

Survey	Subset of Sample	F2F Interview	MobPh Interview
Jun17	Owns a MobPh	Ph-F2F	Ph-Ph

Table 6: Surveys and Sub-Samples used to Analyse Non-Response Bias

Survey	Subset of Sample	Respondents	Non-Respondents
Jun17	Assigned a MobPh Interview	Ph-Ph	Ph(NoResp)-F2F
Apr18	Assigned a MobPh Interview	Ph-Ph	Ph(NoResp)-F2F

9. Analysis of Demographic and Socio-Economic Indicators

We note that, throughout this study, the population is the mid-western and far-western mountains of Nepal. All proportions, means, confidence interval limits and standard errors are design-based, taking into account the stratified cluster design of the surveys. Confidence intervals (including those shown in graphs) are all 95% CIs.

Although the objective of this study is to analyse the potential mobile phone bias in estimating food security indicators, such biases may be due to underlying biases in demographic and socio-economic indicators. We therefore start the analysis by examining the effects of a selection of demographic and socio-economic variables on phone ownership, interview mode and non-response.

The following variables were selected as being indicators of a household's wealth and socio-economic status:[11]

- Ethnicity: Brahmin, Chhetri, Dalit, Janajati, Other
- Education Level of Head of Household: None, Primary, Secondary, Higher

[11] Other variables were considered but not included. For example, Sex of Household Head was initially included - in the past, a female head of house in Nepal has been associated with a poorer household; however, with the growth of the migrant worker sector, this is no longer the case, as many female heads of house are now due to the male head of house migrating for work leading to higher household incomes.

- Area of Land Owned (hectares)
- Livestock Ownership (Yes/No)
- Ownership of Household Assets (Yes/No): Radio, TV, Table/Chairs, Bed/Sofa/Cupboard
- Roofing: Basic (straw, earth, planks), Improved (iron, concrete, tiles)[12]
- Household has at least one Migrant Worker (Yes/No)
- Remittances received from migrant workers in past year (Nepali Rupees, NPR)

a. Coverage

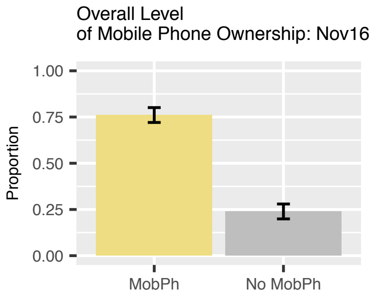
As noted earlier, coverage bias occurs in mobile phone surveys when a portion of the population does not own a mobile phone and there are differences between those owning and not owning mobile phones.

Nov16: Coverage (See Appendix 1 for numerical results)

We recall that the Nov16 survey comprised a representative sample solely interviewed F2F. We use the response for the question about mobile phone ownership to divide the sample into households owning at least one mobile phone and households not owning a mobile phone. For each demographic and socio-economic indicator, we compare these two groups using the methodology described in Section 8: a graphical comparison of confidence intervals for means and proportions; t-tests for differences in numerical indicators and tests of association for categorical indicators; and multivariate regression using MobPh/NoMobPh as the response variable.

We first estimate the proportion of households owning a mobile phone (MobPh) or not owning a mobile phone (No MobPh).

Figure 7: Proportion of households owning at least one mobile phone in November 2016

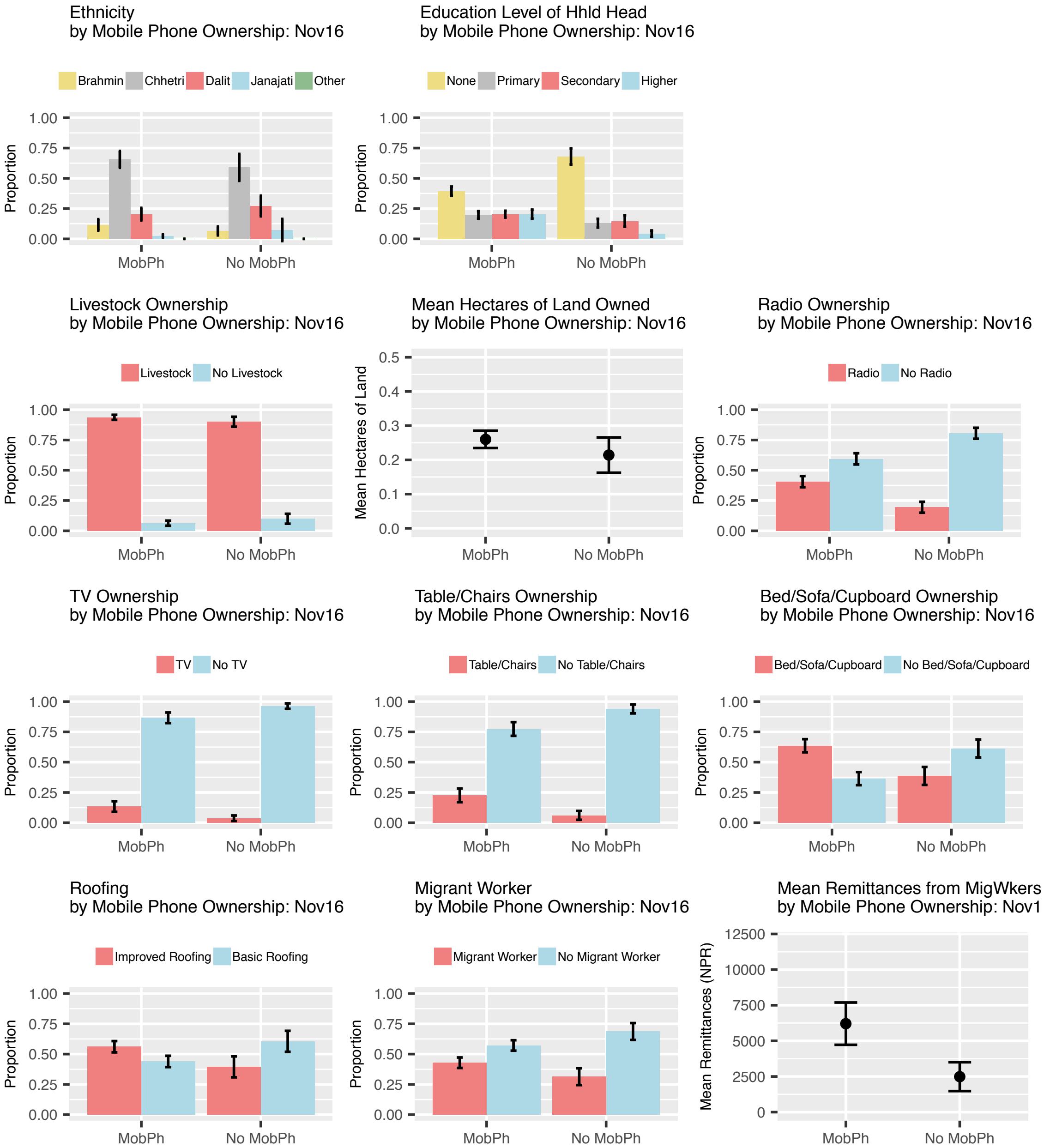


It is estimated that 76% of households owned at least one mobile phone in November 2016.

We next investigate whether or not each demographic and socio-economic indicator differs for the 76% of households owning a mobile phone and the 24% not owning a mobile phone.

[12] According to Lau et al (2019), housing structure (based on roof or shelter type) is a commonly used indicator of socioeconomic status in Africa.

Figure 8: Demographic and Socio-Economic Indicators for MobPh vs No MobPh: Nov16



The 95% confidence intervals in the graphs enable visual comparisons to be made for differences between those owning and not owning mobile phones. Non-overlapping confidence intervals imply significant differences between the two groups, as does a small overlap of confidence intervals.[13] The t-tests and F-tests of association shown in Appendix 1 provide the means of formally testing for statistical significance where it is not obvious in the graphs.

Overall, the graphs above and tests in Appendix 1 indicate that households not owning a mobile phone were poorer (owned less land, less livestock and had fewer assets) and were less educated than households owning a mobile phone.

For households not owning mobile phones, there were higher proportions of the lower-class Dalit

[13] Van Belle (2002, Rule 2.6) says that if confidence intervals overlap by up to 25% we should "assume statistical significance".

and Janajati ethnic groups and lower proportions of the higher-class Brahmin and Chhetri ethnic groups than for households owning mobile phones (significant at the 0.05 level).

Education levels attained by the household head were lower (higher proportions with no education or primary education and a lower proportion with higher education) for households not owning mobile phones than for households owning mobile phones (highly significant).

Households not owning mobile phones were less likely to own livestock than households owning mobile phones, but there was no significant difference in the mean number of hectares of land owned. We note that the survey area was almost completely rural, so a rural/urban breakdown did not aid the analysis.

The proportion of households living in a house with an improved roof (made of iron, concrete or tiles rather than straw, earth or planks) was lower for households not owning a mobile phone (highly significant) suggesting that households without phones had poorer quality houses.

Households not owning mobile phones had fewer household assets: smaller proportions owned a radio, TV, table/chairs or bed/sofa/cupboard than households with mobile phones (all highly significant).

Households without mobile phones were significantly less likely to have a migrant worker and had significantly lower mean remittances from migrant workers than households owning mobile phones.

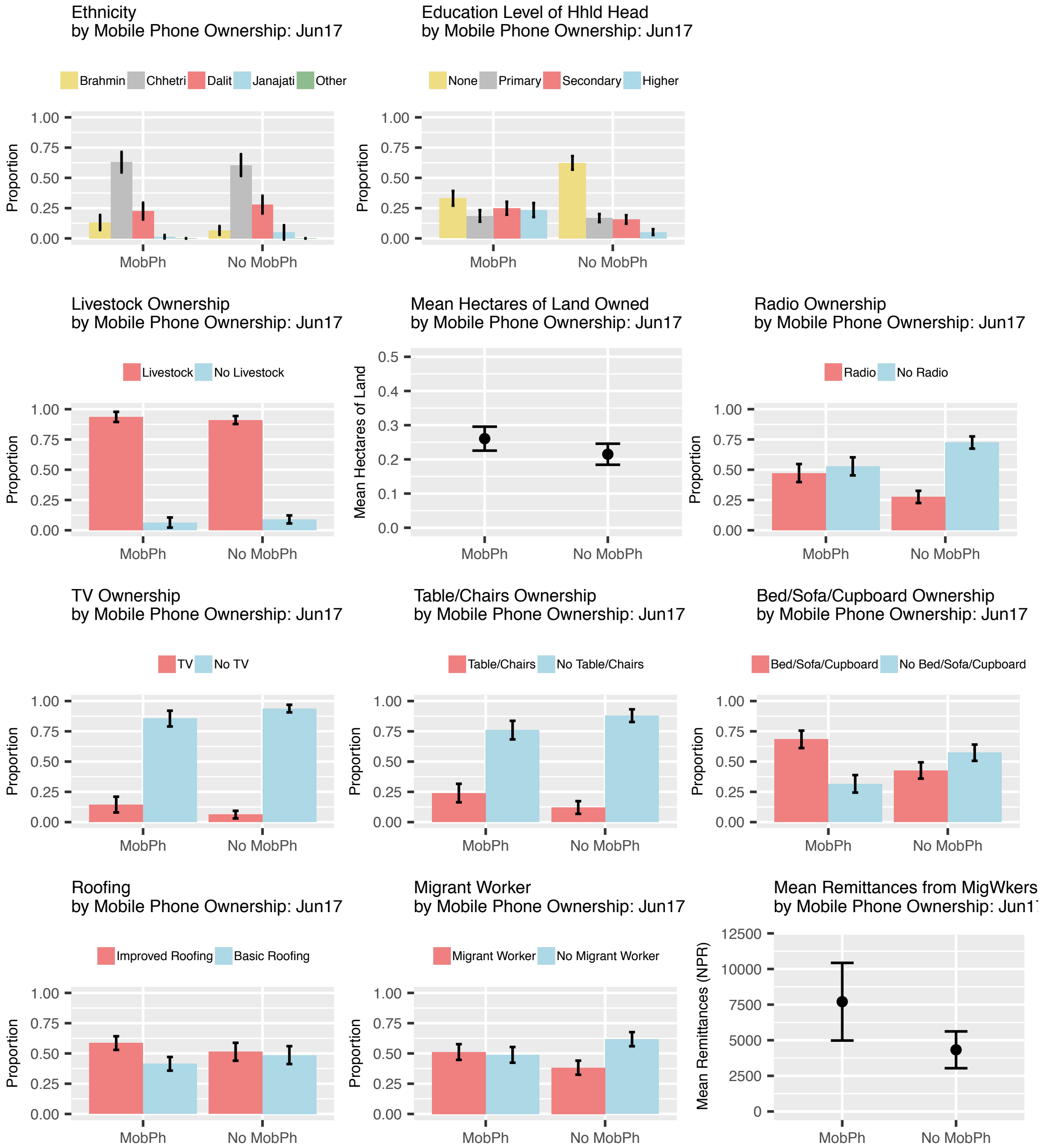
The graphs above essentially contain a separate analysis for the effect of each indicator on mobile phone ownership. We compare this univariate approach with a multivariate approach in Appendix 7 where we investigate regression models with Mobile Phone ownership as the response variable and different groups of possible explanatory variables. The 'best' model suggests that mobile phone ownership can be explained by education level, radio ownership, bed/sofa/cupboard ownership and the level of remittances received from migrant workers. These were all very highly significant (p-values less than 0.001) in the univariate analysis; however, we note that some of the variables which were significant in the univariate approach are not included in the preferred regression model. This is due to high levels of association between a number of variables (for example, radio ownership is strongly associated with table/chair ownership and with an improved roof, and bed/sofa/cupboard ownership is correlated with the household having a migrant worker) so that not all variables are needed in a model explaining mobile phone ownership. In fact, if we view radio and bed/sofa/cupboard as representing asset ownership, the multivariate regression analysis suggests that owning assets, higher education levels and higher incomes all increase the odds of mobile phone ownership, supporting the findings from the univariate analysis.

Jun17: Coverage (See Appendix 2 for numerical results)

We recall that the Jun17 survey involved the sample from the Nov16 baseline survey being re-interviewed. Although the question "Does your household own a mobile phone?" was not asked in the Jun17 survey round, it appears that mobile phone information had been sought and updated between survey rounds and that this was used when assigning different types of interview.

Thus, we do not analyse coverage for Jun17 using the MobilePh variable. We instead compare households owning a mobile phone who were randomly assigned a F2F interview (Ph-F2F) and those in the sample without mobile phones (NoPh-F2F). These groups are assumed to be representative of those owning a mobile phone and not owning a mobile phone and, as interviews were F2F for both groups, there is no possibility of confounding due to interview mode.

Figure 9: Demographic and Socio-Economic Indicators for MobPh vs No MobPh: Jun17



The graphs above and accompanying tests of significance in Appendix 2 indicate that households not owning mobile phones were less educated and poorer than households owning mobile phones. They owned less land, had fewer assets, were less likely to have a migrant worker and received lower remittances from migrant workers than mobile phone-owning households.

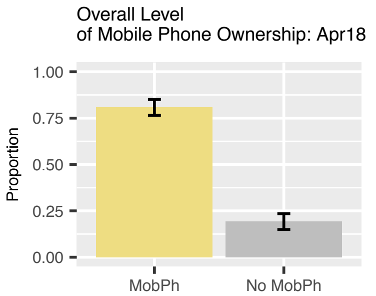
Although there were some slight differences in the results for individual assets in Nov16 and Jun17 (e.g. ethnicity, livestock ownership and roofing were significant in Nov16 but not in Jun17 and the amount of land owned was not significant in Nov16 but significant in Jun17), the overall conclusion that those not owning phones were poorer and less educated was the same in both surveys. In addition, the 'best' regression model for Jun17 (shown in Appendix 7b) suggests that higher education levels, owning a radio, owning a bed/sofa/cupboard and having a migrant worker all increase the odds of owning a mobile phone, and is very similar to the preferred model for Nov16.

Apr18: Coverage (See Appendix 3 for numerical results)

We recall that the Apr18 survey comprised 50% repeat and 50% new households. We restrict the coverage analysis to new households, using the MobilePh variable to divide the sample into households owning at least one mobile phone and households not owning a mobile phone. We note that new households were all interviewed F2F.[14]

We first estimate the proportion of households owning a mobile phone (MobPh) or not owning a mobile phone (No MobPh).

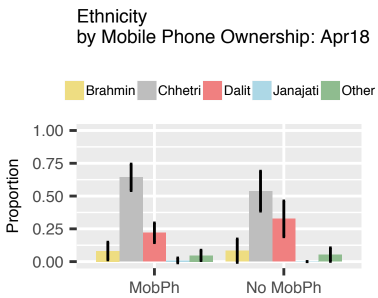
Figure 10: Proportion of households owning at least one mobile phone in April 2018

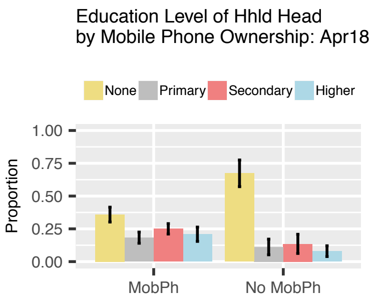


We see that 81% of households owned at least one mobile phone in April 2018, an increase of 5% from November 2016. Although the increase was not significant, we would expect mobile phone ownership to have increased given our earlier observation that the number of mobile phone subscriptions per 100 people had increased during the same period.

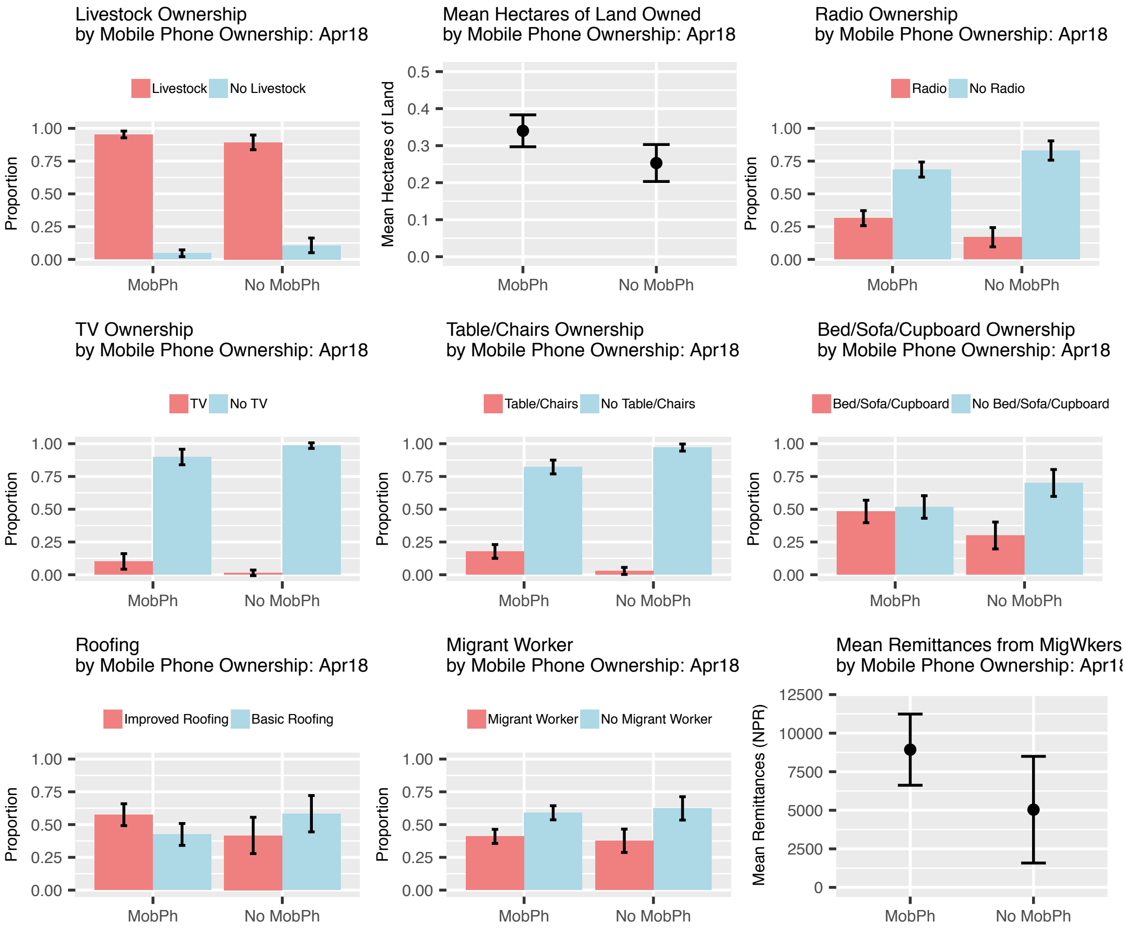
We compare demographic and socio-economic indicators for those owning and not owning a mobile phone.

Figure 11: Demographic and Socio-Economic Indicators for MobPh vs No MobPh: Apr18





[14]It should be noted that we are unable to analyse coverage for repeat households in Apr18 since, unlike Jun17, all households owning a mobile phone were assigned a mobile phone interview, so there were no respondents in the Ph-F2F category and therefore no mechanism to analyse mobile phone ownership for the repeat households.



Once again, we see from the graphs that households not owning mobile phones were less educated, and owned less land and fewer assets than households with mobile phones. This is confirmed by tests of significance in Appendix 3, and by the multivariate regression analysis in Appendix 7c which suggests that higher education levels, and ownership of livestock, bed/sofa/cupboard and table/chairs all increase the odds of owning a mobile phone.

The analyses of coverage across the three surveys suggest that, although ownership of mobile phones increased over the 18 months from November 2016 to April 2018, the attributes of households owning and not owning a mobile phone appear to be reasonably constant across the same period. In general, we observe in all three surveys that households not owning mobile phones are less likely to own livestock, own less land and have fewer assets than households owning mobile phones. The heads of households not owning mobile phones are less educated than in households owning phones, and remittances from migrant workers are lower for households not owning a phone.

b. Interview Mode

Interview mode bias occurs when an individual gives a different response when interviewed by mobile phone or F2F. It is only measurable for respondents that have mobile phones, and only able to be measured using a dual mode survey - either by interviewing each respondent twice, once by mobile phone and once F2F, as in the Kenya study (Lamanna et al, 2019), or by randomly assigning mobile phone owners either a mobile phone or a F2F interview, as in the

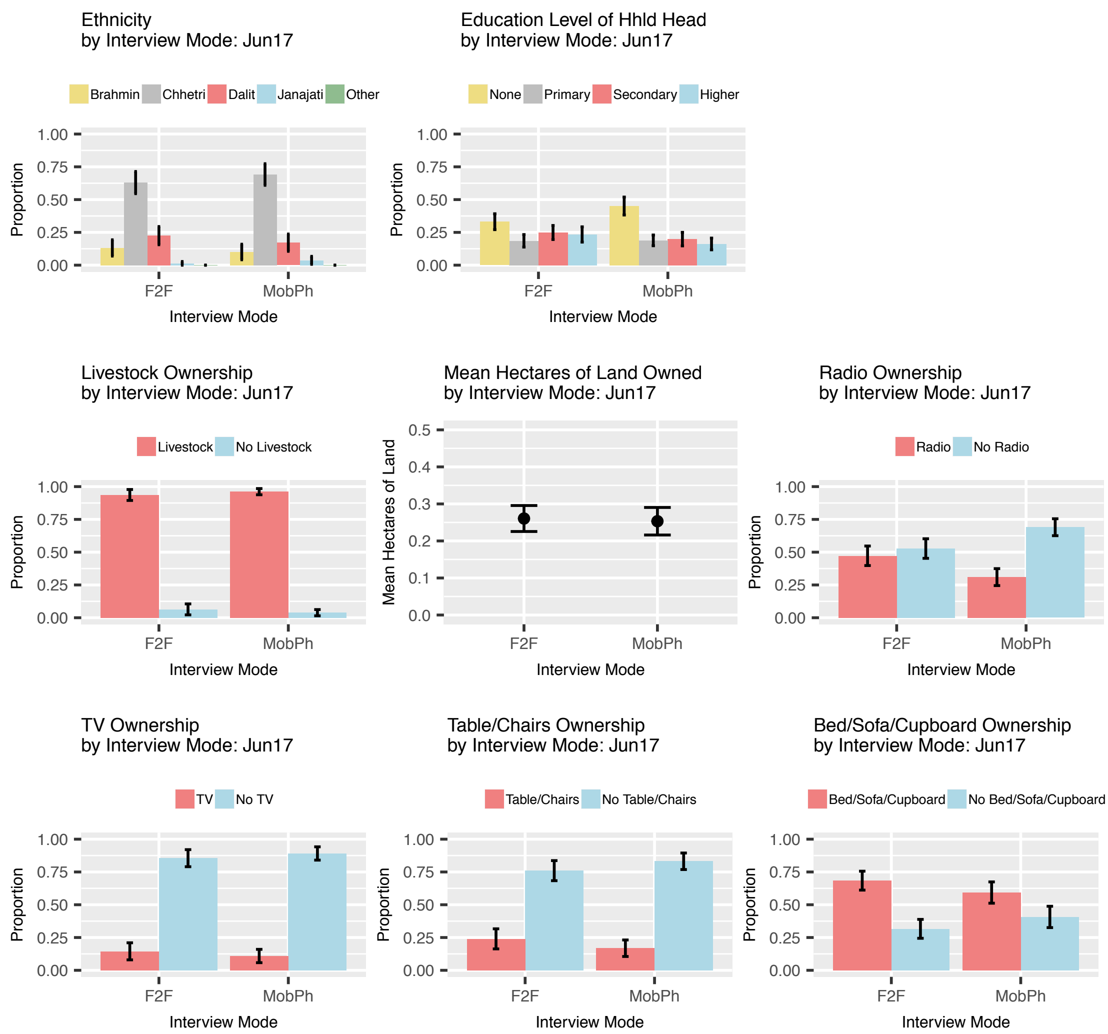
Jun17 mVAM survey.

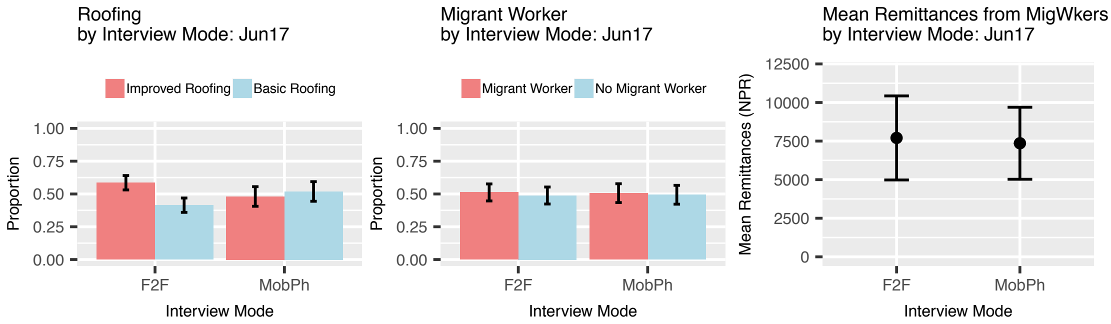
Jun17: Interview Mode (See Appendix 4 for numerical results)

Jun17 was the only survey carried out in such a way where it is possible to investigate the effect of interview mode. Households owning mobile phones were randomly assigned a F2F or a mobile phone interview - to analyse interview mode, we compare indicators for those with mobile phones who were assigned and received a mobile phone interview (Ph-Ph) and those with mobile phones who were assigned and received a F2F interview (Ph-F2F).

We note that demographic and socio-economic information was copied from Nov16 where all interviews were F2F. This means that, in theory, there should be no difference in demographic and socio-economic indicators between the two groups (in contrast with food security indicators which were sought independently in Jun17 and are potentially subject to interview mode bias). The following analysis is carried out to check that randomisation of interview mode took place.

Figure 12: Demographic and Socio-Economic Indicators for MobPh vs F2F interviews: Jun17





In terms of ethnicity, livestock ownership, land ownership, TV ownership, migrant workers and remittances from migrant workers, the graphs above and tests of significance shown in Appendix 4 suggest that there is no significant difference between mobile phone owners interviewed F2F or by MobPh.

We would expect some differences due to sampling error and multiple testing, so the one or two variables where there are significant differences (radio ownership, education and roofing) do not give cause for concern, and we accept that there was randomisation in assigning a mobile phone or F2F interview to mobile phone owners.

c. Non-Response

We continue the analysis by examining the effects of demographic and socio-economic variables on mobile phone non-response. We recall that non-response bias occurs in mobile phone surveys when a portion of the sample (of mobile phone owners) is not able to be contacted by mobile phone or declines to be interviewed, and results if there are differences between respondents and non-respondents.

We note that non-response for the Nepal surveys could more accurately be referred to as 'additional mobile phone non-response': 95% of Nov16 households were re-interviewed in Jun17 rather than the desired 100%, indicating an underlying non-response level of 5% due to non-response in F2F interviews. There is also presumably a non-response level prior to this in the selection of the sample for the November 2016 baseline survey.

Interviews in Nov16 were all carried out F2F, so we confine our non-response analysis to the sub-samples of the Jun17 and Apr18 surveys where mobile phone owners were assigned a mobile phone interview. Apart from Migrant Worker and Remittances, information for demographic and socio-economic indicators was copied from Nov16 rather than being sought again. For these indicators, there is no possibility of the differences between respondents and non-respondents being confounded by interview mode.[15]

Jun17: Non-Response (See Appendix 5 for numerical results)

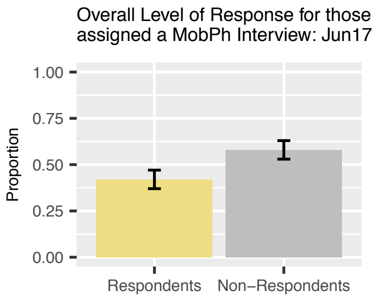
For the Jun17 survey, we first investigate the overall level of non-response, and then compare demographic/socio-economic indicators for respondents and non-respondents.

[15]The copying of responses does raise the question about accuracy - however, variables such as ethnicity, education level of the household head and the amount of land owned by the household are highly unlikely to change.

We analyse households with mobile phones who were assigned a mobile phone interview: respondents are those for whom a mobile phone interview was successfully carried out (Ph-Ph), and non-respondents are those who could not be contacted by mobile phone and who instead received a F2F interview (Ph(NoResp)-F2F).

We first look at overall levels of response and non-response.

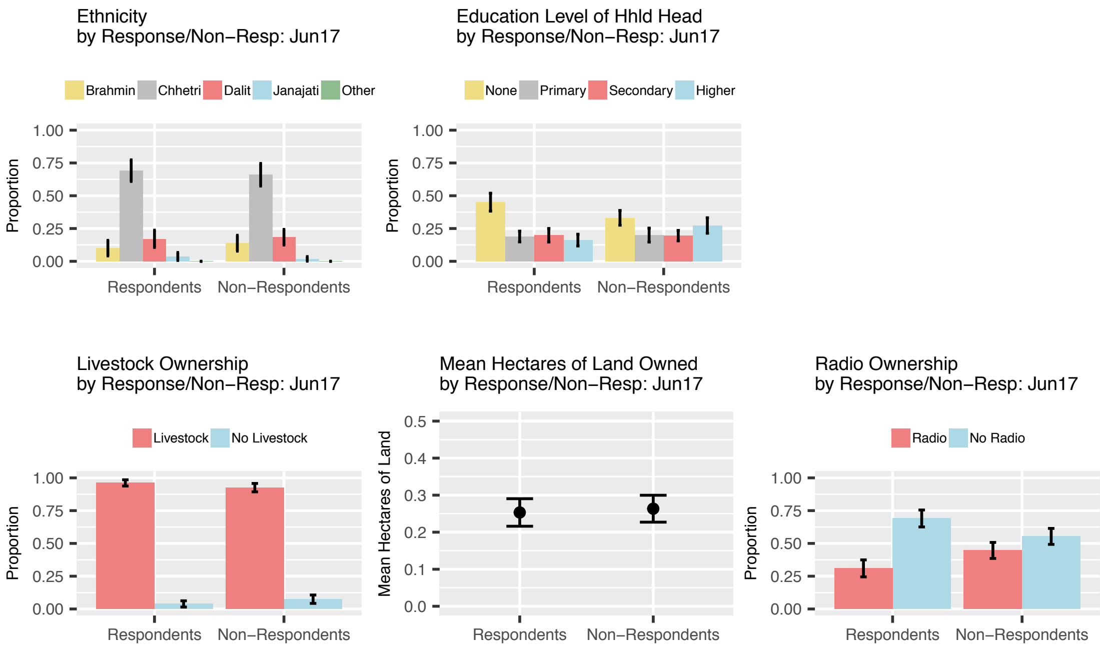
Figure 13: Proportion of Mobile Phone Non-Response for those assigned a mobile phone interview in Jun17 survey

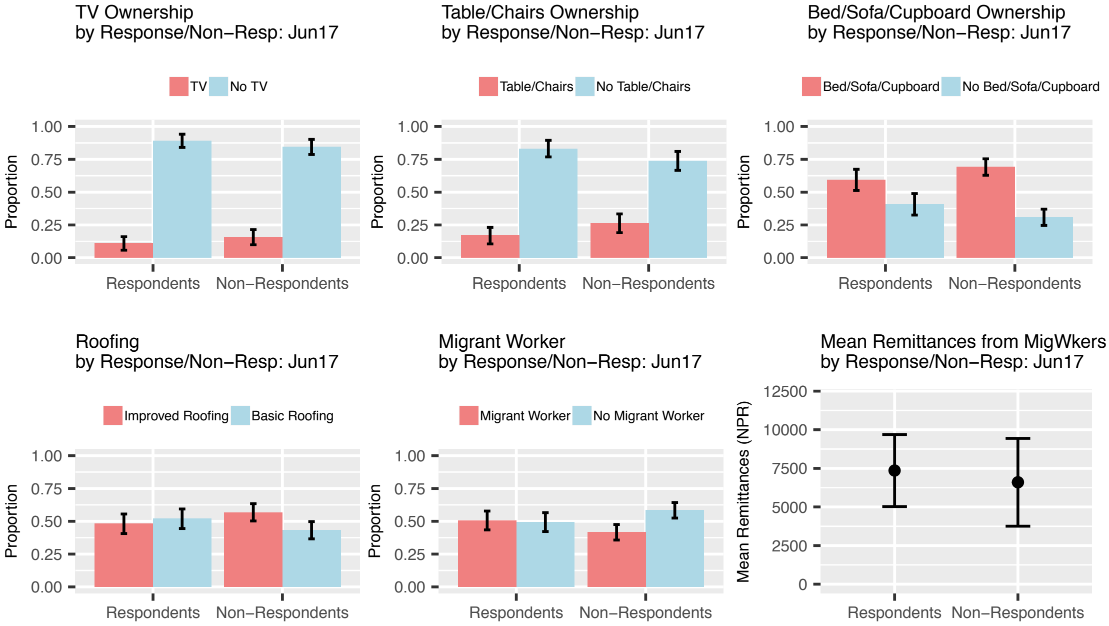


We see that, in June 2017, of those who were assigned a mobile phone interview, a large proportion (58%) did not respond.

We next investigate whether demographic and socio-economic indicators differ for respondents and non-respondents.

Figure 14: Demographic and Socio-Economic Indicators for Mobile Phone Response vs Non-Response: Jun17



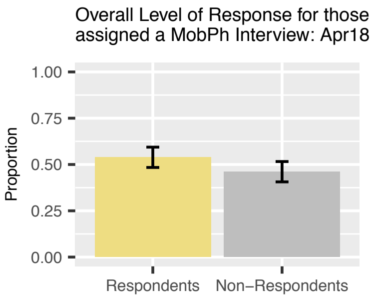


It was expected that mobile phone non-respondents (but contacted F2F) would be poorer and have lower levels of education than respondents. Contrary to expectations, it seems from the graphs above and accompanying tests of significance in Appendix 5 that non-respondents were better educated and had higher levels of asset ownership than respondents.

Apr18: Non-Response (See Appendix 6 for numerical results)

We carry out a similar analysis for the April 2018 survey.

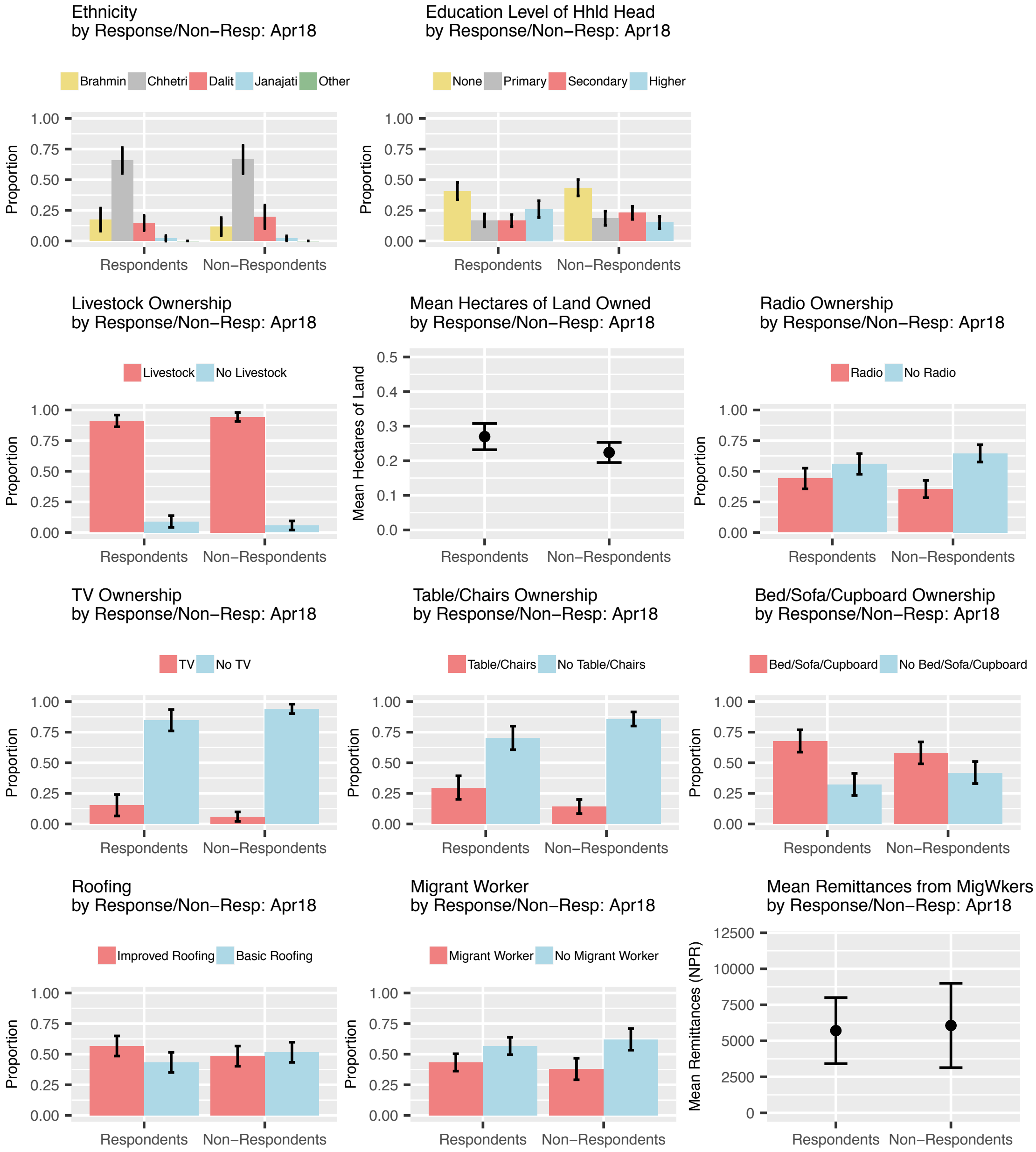
Figure 15: Proportion of Mobile Phone Non-Response for those assigned a mobile phone interview in Apr18 survey



We see that, of those assigned a mobile phone interview, 46% did not respond in April 2018. Although the non-response level was high, it was significantly lower than the 58% in June 2017. This raises questions about the mechanisms for following up phone interviews, and will be discussed later.

We next compare demographic and socio-economic indicators for respondents and non-respondents.

Figure 16: Demographic and Socio-Economic Indicators for Mobile Phone Response vs Non-Response: Apr18



The graphs above and figures in Appendix 6 suggest that mobile phone non-respondents in the Apr18 survey were less educated and poorer (significantly lower levels of radio, TV, table/chairs and land ownership) than respondents. This is the complete opposite of the findings from the Jun17 survey.

So, although both surveys suggest that respondents and non-respondents have different characteristics, the inconsistency of the differences is puzzling: non-respondents appear to be better educated and wealthier than respondents in the Jun17 survey, and the opposite in the Apr18 survey.[16]

[16] Assuming wealthier households have more SIMs, we hypothesised that, if only one SIM had been obtained per household in the Nov16 baseline survey, and that, if a special offer had been made by one of the mobile phone providers prior to the Jun17 survey, this could have led to wealthier households switching SIMs to take advantage of the special deal leading in turn to a higher non-response rate of wealthier households in the Jun17 survey. However, multiple SIMs do appear to have been obtained and used when attempting to contact a household. We

We note that the Apr18 results are more consistent with expectations: in general, we would expect non-respondents in a mobile phone survey to be poorer and less educated than respondents (Lamanna et al, 2019; L'Engle et al, 2018), given that some of the reasons for non-response (such as running out of phone credit) are financial.

10. Analysis of Food Security Indicators

The analysis to this point has explored demographic and socio-economic differences between those with and without mobile phones and for respondents and non-respondents.

In terms of coverage, we were able to analyse all three surveys. Phone ownership has increased over the 18-month span of the surveys. There are clear differences between households owning and not owning mobile phones, and the differences appear to be fairly constant across the three surveys.

The only survey which followed a design enabling us to analyse interview mode is the Jun17 survey. The analysis of demographic and socio-economic indicators confirm that there was randomisation in assigning a mobile phone or a F2F interview for those owning mobile phones.

Both the Jun17 and Apr18 surveys enable us to analyse mobile phone non-response. Non-response appears to be high for both surveys, and respondents appear to have different characteristics from non-respondents; however, the differences are puzzling with non-respondents appearing to be wealthier than respondents in the Jun17 survey, but poorer in the Apr18 survey.

We now come to the crux of the investigation - whether or not mobile phone ownership, interview mode and non-response affect food security indicators.

Five food security indicators are available from the data collected. The following definitions apply to the surveys in this study (NeKSAP, 2016, pp 14-16) - we note that definitions for each of these food indicators can differ among countries and even among surveys within the same country.

- Food Consumption Score (FCS): A composite indicator which combines dietary diversity, food frequency and the nutritional level of food groups into a single score ranging from 1 to 112. It should be noted that Haslett (2013) suggests that FCS is an imperfect measure and that it has "some undesirable statistical properties".[17] However, it is the most commonly-used measure of food security by WFP Nepal, the best measurement available in the datasets provided, and throughout this study is being used comparatively meaning that any issues with imperfections in absolute measurements are immaterial.

- Adequacy of FCS: Households with an FCS above 42 are classified as having an adequate food consumption level.

also note that mobile phone numbers were obtained between survey rounds if acquired by a household formerly without a mobile phone, and it is assumed that changes in phone numbers and additional SIMs acquired between surveys were also obtained. We therefore felt that this explanation was unlikely.

[17] One of these is that FCS is not additive. For example, "adding the seven day counts for all items in a food group does not equal the food group value. An extreme example is that if there were four items in a group and they each had been eaten all seven days, the total would be 28 rather than the actual maximum of seven days out of seven for the food group as a whole" (Haslett, 2013, p 37).

- Dietary Diversity Score (DDS): The number of food groups consumed out of 8 food groups by the household in the 7 days preceding the survey.

- Adequacy of DDS: Households with a DDS of 5 and above are classified as having adequate dietary diversity.

- Food Stocks: The number of days that cereal stocks (rice, wheat, maize, millet, barley etc) would last the household.[18]

We note that the first four indicators are not independent - DDS is a component of FCS, and FCS Adequacy and DDS Adequacy are binary groupings of FCS and DDS.

a. Coverage

For the three surveys, we analyse whether or not each food security indicator differs between households owning a mobile phone and households not owning a mobile phone.

The Nov16 analysis compares MobPh with No MobPh for the complete sample; the Apr18 analysis compares MobPh with No MobPh for the 50% newly selected sample; and the Jun17 analysis compares households owning a mobile phone who were randomly assigned a F2F interview (Ph-F2F) and those in the sample without mobile phones (NoPh-F2F).

Table 7: Effect of Coverage on Food Security Indicators for the Nov16, Jun17 and Apr18 Surveys

	Mean FCS	Prop of hhlds with Adequate FCS	Mean DDS	Prop of hhlds with Adequate DDS	Mean Days of Food Stocks
NOV16					
Owns a MobPh	54.7	0.71	5.7	0.8	141
	(52.3-57)	(0.66-0.77)	(5.5-5.9)	(0.76-0.84)	(126-157)
No MobPh	44.6	0.48	4.9	0.59	106
	(41.9-47.3)	(0.39-0.56)	(4.7-5.1)	(0.51-0.67)	(92-119)
JUN17 Ph-F2F & NoPh-F2F					
Owns a MobPh	49.5	0.59	5.5	0.76	89
	(46.7-52.2)	(0.52-0.66)	(5.3-5.7)	(0.7-0.82)	(79-99)
No MobPh	43.9	0.46	5.1	0.64	83
	(41.8-46.1)	(0.39-0.52)	(4.9-5.3)	(0.58-0.71)	(75-92)

[18] For Nov16 and new households in Apr18, food stocks were recorded as kg of cereal in possession of each household at the time of the survey - figures were converted to days of food stocks based on the size of the household and "the standard cereal requirement of 0.5kg per person per day" (NeKSAP, 2016, p14). We note that the '0.5kg per person' was applied to both adults and children.

	Mean FCS	Prop of hhlds with Adequate FCS	Mean DDS	Prop of hhlds with Adequate DDS	Mean Days of Food Stocks
APR18 New Hhlds					
Owns a MobPh	49	0.61	5.5	0.75	76
	(46.1-51.8)	(0.53-0.69)	(5.3-5.7)	(0.7-0.81)	(62-91)
No MobPh	38	0.34	4.5	0.48	45
	(33.2-42.7)	(0.22-0.46)	(4.1-4.9)	(0.35-0.61)	(31-60)

Figure 17: Food Security Indicators for MobPh vs No MobPh: November 2016

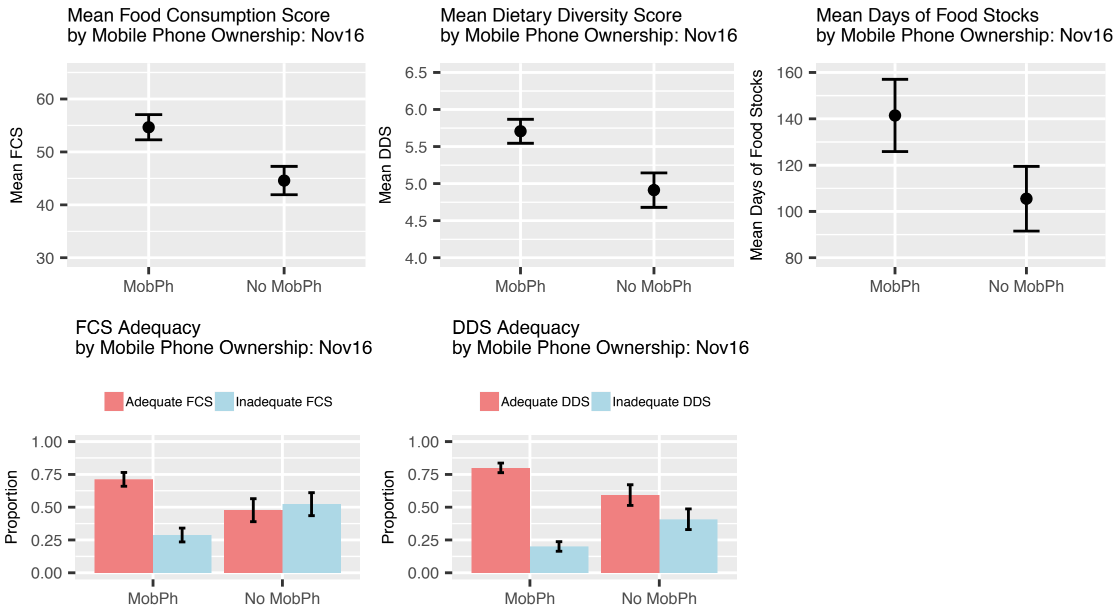


Figure 18: Food Security Indicators for MobPh vs No MobPh: June 2017

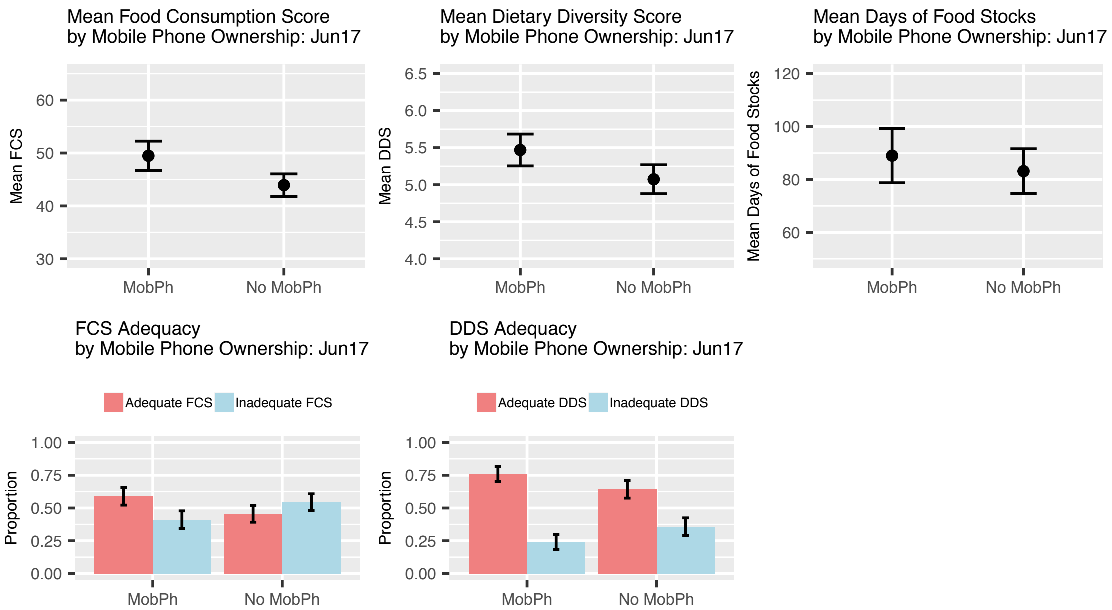


Figure 19: Food Security Indicators for MobPh vs No MobPh: April 2018

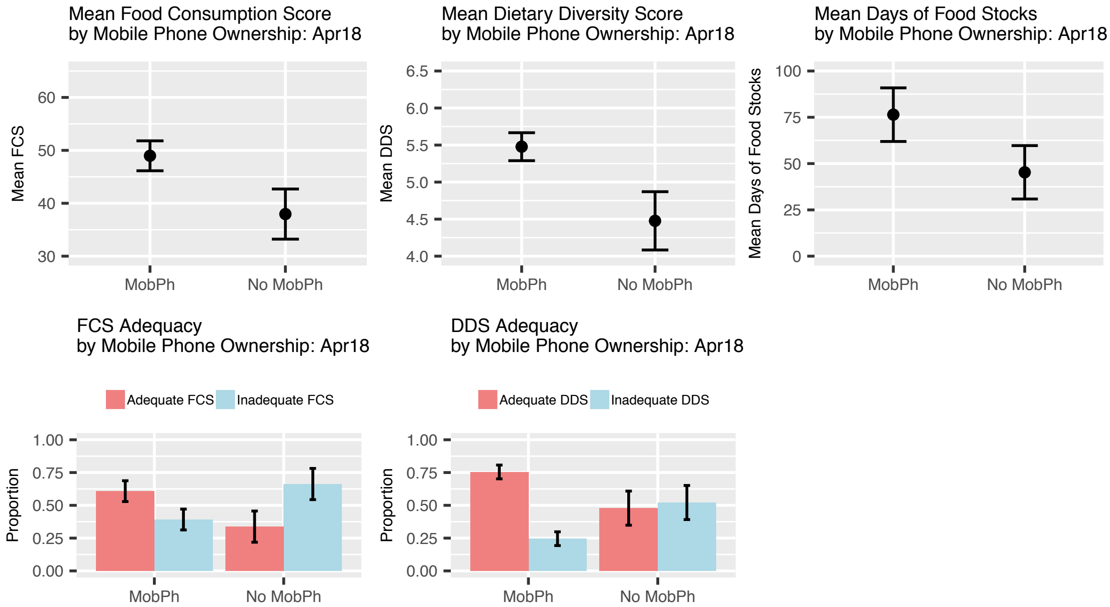


Table 7 and Figures 17, 18 and 19 show clearly that, for all three surveys, households not owning mobile phones are less food secure than households owning mobile phones: they have lower FCSs, a higher proportion of households with an inadequate FCS, lower DDSs, a higher proportion of households with an inadequate DDS and lower food stocks than households owning mobile phones. With the exception of food stocks in Nov16, all differences appear to be highly significant. These findings are not unexpected, given the earlier analysis of demographic and socio-economic indicators which indicated that households not owning phones were significantly poorer than households owning mobile phones.

Potential Magnitude of Coverage Bias

The differences in food security indicators for households owning a mobile phone and households not owning a mobile phone remain significant across the three surveys; however, it is expected that, as the level of mobile phone ownership increases, food security estimates will get closer and closer to the population values. That is, once mobile phone ownership is ‘high enough’, the small portion of the population not owning a phone will not significantly affect overall food security estimates.

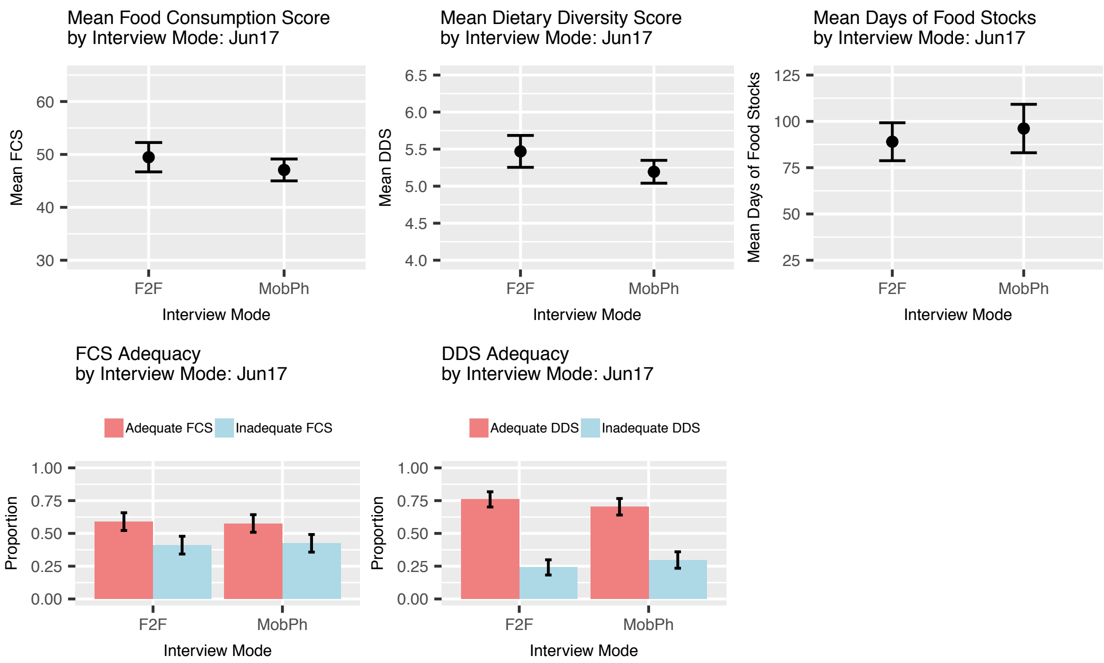
b. Interview Mode

We next investigate whether the interview mode affects food security indicators. We recall that this analysis can only be carried out for the June 2017 survey, where those owning mobile phones were randomly allocated a F2F or a mobile phone interview.

Table 8: Effect of Interview Mode on Food Security Indicators for Mobile Phone Owners in the Jun17 Survey

	Mean FCS	Prop of hhlds with Adequate FCS	Mean DDS	Prop of hhlds with Adequate DDS	Mean Days of Food Stocks
JUN17 MobPh Owners					
F2F Interview	49.5	0.59	5.47	0.76	89
	(46.7-52.2)	(0.52-0.66)	(5.25-5.68)	(0.7-0.82)	(79-99)
MobPh Interview	47.1 (45-49.1)	0.58 (0.51-0.64)	5.19 (5.04-5.35)	0.7 (0.64-0.77)	96 (83-109)

Figure 20: Food Security Indicators for MobPh interview vs F2F interview: June 2017



In terms of FCS and DDS, those interviewed F2F score slightly higher than those interviewed by mobile phone, with a higher mean FCS, a higher mean DDS, and higher proportions of households with adequate food consumption and adequate dietary diversity; however, none of these differences are significant (CIs overlap by at least 30%, and p-values for tests of association between interview mode and indicators are not significant). Although those interviewed by mobile phone have higher levels of food stocks, the difference is not statistically significant.

Potential Magnitude of Interview Mode Bias

The analysis above indicates that there is no evidence to suggest that the mode of interview affects food security indicators. As discussed, we can only carry out this analysis for the June

2017 survey, so cannot be sure that this holds across surveys.

However, for two reasons, we could expect the interview mode bias to be minimal or non-existent. Firstly, the Kenya study (Lamanna et al, 2019) was one of the few studies found which analysed interview mode bias - it concluded that interview mode had no effect on general household nutrition indicators, but did affect questions about the nutrition of the respondents' children. Based on this, and since the food security questions in the Nepal surveys were household-specific, we would not expect interview mode to have an effect.

Secondly, in the Nepal surveys, by design, mobile phone interviews were only carried out for repeat households when a F2F interview had already been carried out - the interviewer and the surveys were therefore already known to the respondent (quite different from the scenario of a respondent receiving a 'cold call' from an unknown person requesting participation in an unknown survey), and in fact respondents had given permission during the Nov16 survey to be contacted by phone for subsequent survey rounds. Lamanna's (2019) hypothesis that "discomfort with receiving calls on mobile phones might have led to respondents giving more socially-desirable answers" about the nutrition of their children than if interviewed F2F is unlikely to apply in the Nepal surveys.

c. Non-Response

We analyse the effect of non-response on food security indicators for the Jun17 and Apr18 surveys, comparing indicators for those who were assigned and received a MobPh interview (Respondents) with those assigned a MobPh interview but could not be contacted and were instead interviewed by MobPh (Non-Respondents).

As noted earlier, if interview mode has an effect on food security indicators, then we have the possibility of the effects of non-response being confounded by interview mode. However, the section above suggests that there is no significant interview mode effect so that the different modes of interview for the two groups should not greatly affect the results.

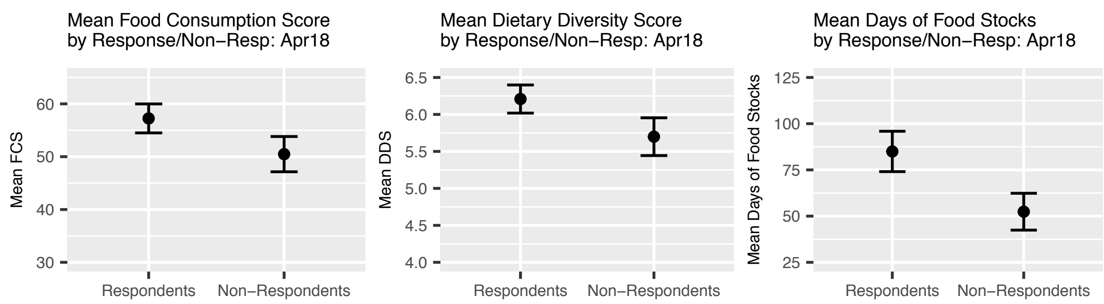
Table 9: Effect of Non-Response on Food Security Indicators for MobPh owners assigned a MobPh interview in the Jun17 and Apr18 Surveys

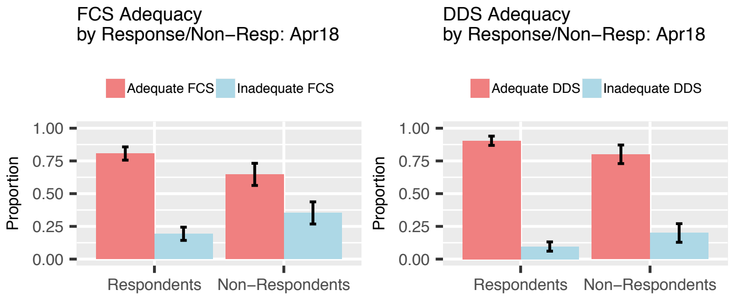
	Mean FCS	Prop of hhlds with Adequate FCS	Mean DDS	Prop of hhlds with Adequate DDS	Mean Days of Food Stocks
JUN17 MobPh Interview					
Respondents	47.1 (45-49.1)	0.58 (0.51-0.64)	5.2 (5-5.3)	0.7 (0.64-0.77)	96 (83-109)
Non-Respondents	60.1 (58-62.2)	0.79 (0.74-0.83)	6.1 (6-6.3)	0.85 (0.81-0.89)	109 (99-119)

	Mean FCS	Prop of hhlds with Adequate FCS	Mean DDS	Prop of hhlds with Adequate DDS	Mean Days of Food Stocks
APR18 MobPh Interview					
Respondents	57.2 (54.5-60)	0.81 (0.76-0.86)	6.2 (6-6.4)	0.9 (0.87-0.94)	85 (74-96)
Non-Respondents	50.5 (47.1-53.8)	0.65 (0.56-0.73)	5.7 (5.4-6)	0.8 (0.73-0.87)	52 (42-62)

Figure 21: Food Security Indicators for Mobile Phone Respondents vs Non-Respondents: June 2017

Figure 22: Food Security Indicators for Mobile Phone Respondents vs Non-Respondents: April 2018





We saw in the analysis of mobile phone non-response for demographic and socio-economic indicators that in Jun17 non-respondents were wealthier and better educated than respondents, but that in Apr18 non-respondents were poorer and less educated than respondents.

The analysis of non-response on food indicators in Table 9 and Figures 21 and 22 reflect these contradictory findings.

Non-respondents appear to be more food-secure than respondents in Jun17: non-respondents have higher FCSs, DDSs and Food Stocks than respondents, and higher proportions of non-respondents have an Adequate DDS and Adequate FCS (all highly significant apart from Food Stocks).

However, in Apr18, the reverse was found with non-respondents being less food-secure (highly significant for all indicators).

Potential Magnitude of Non-Response Bias

We recall that overall non-response (for those allocated a MobPh interview) was 58% in June 2017 and 46% in April 2018.

There are two issues of concern in terms of mobile phone non-response bias. The first is the high levels of non-response potentially leading to a high non-response bias. The second and perhaps more serious concern is that, from the two surveys analysed, we have conflicting findings. The Jun17 survey suggests that non-respondents are more food secure than respondents, but the Apr18 survey suggests the opposite. This means that, not only is there a potentially high level of non-response bias in future mobile phone surveys, but that we cannot predict the direction of the bias.

11. Overall Mobile Phone Bias in Food Security Indicators

We recall that the main aim of this study is to estimate the potential bias in food security indicators if we were to move to surveys with interviews carried out solely by mobile phone. The bias is essentially the difference between indicators for the population and indicators for mobile phone owners who respond to surveys.

To calculate the overall bias, we start with population estimates, then exclude those not owning mobile phones from the sample and investigate the change in estimates (coverage bias), then exclude non-respondents and investigate the further change in estimates (non-response bias).[19] The overall difference constitutes the mobile phone bias.

[19] We concluded in Section 10 that the mode of interview (MobPh or F2F) did not significantly affect people's responses so assume that there is no interview mode bias.

This can be expressed mathematically as follows. If we let:

$$
\begin{aligned}
&\theta = Food\ Indicator\ Mean/Proportion\ for\ the\ Population\\
&p = Proportion\ of\ Respondents\\
&(1-p) = Proportion\ of\ NonRespondents\\
&\theta_{Resp} = Food\ Indicator\ Mean/Proportion\ for\ MobPh\ Respondents\\
&\theta_{NonResp} = Food\ Indicator\ Mean/Proportion\ for\ MobPh\ NonRespondents
\end{aligned}
$$

then the overall mobile phone bias can be defined as:

$$Bias_{MobPh} = \theta_{Resp} - \theta \qquad [1]$$

We note that an alternative expression[20] for the bias is:

$$Bias_{MobPh} = (1-p)(\theta_{Resp} - \theta_{NonResp}) \qquad [2]$$

since $\theta = p(\theta_{Resp}) + (1-p)(\theta_{NonResp})$

Using Equation [1] above, we use survey estimates for θ and θ_{Resp} to estimate the overall bias (shown in Table 11) using:

$$B\hat{ias}_{MobPh} = \hat{\theta}_{Resp} - \hat{\theta} \qquad [3]$$

We recall from Section 10 that there were significant differences in food security indicators between households owning and not owning mobile phones indicating that estimates will be affected by coverage bias. To estimate the coverage bias, we calculate the difference between estimates for the population and estimates for MobPh owners.

We also observed in Section 10 that, for those owning mobile phones, there were significant differences between respondents and non-respondents, indicating non-response bias. To estimate the non-response bias in food security indicators from the Jun17 and Apr18 surveys, we calculate the difference between estimates for all MobPh owners and estimates for MobPh respondents.

Mathematically, if we let:

$$\theta_{MobPh} = Food\ Indicator\ Mean/Proportion\ for\ MobPh\ Owners$$

then the Coverage Bias and Non-Response Bias can be estimated as follows:

$$B\hat{ias}_{Cov} = \hat{\theta}_{MobPh} - \hat{\theta} \qquad [4]$$

$$B\hat{ias}_{Resp} = \hat{\theta}_{Resp} - \hat{\theta}_{MobPh} \qquad [5]$$

We note that:

$$B\hat{ias}_{MobPh} = B\hat{ias}_{Cov} + B\hat{ias}_{Resp} \qquad [6]$$

For this part of the analysis, for the Apr18 survey, we treat the 50% repeat and 50% new

[20]This expression is needed if we were to calculate a standard error for the bias, and also in the case where the proportion p is estimated from one dataset and θ_{Resp} and $\theta_{NonResp}$ estimated from another dataset.

households as separate surveys,[21] referring to them as Apr18New and Apr18Repeat. We do this because the coverage analysis carried out in Section 10 was based on new households, but the non-response analysis was based on repeat households. This means that the group of phone owners (and the resulting indicators) is different for the coverage and the non-response analyses. In fact, we could have analysed coverage for the repeat households comparing the Ph-Ph/Ph(NoResp)-F2F interview types with NoPh-F2F, and we do so in Table 11 in order to be able to calculate overall bias for the Apr18 survey.[22]

Coverage, non-response and overall biases for each of the five food security indicators are shown in the following table.

Table 10: Estimates of Mobile Phone Bias for Food Security Indicators

	Whole Sample	Owns a MobPh	**Coverage Bias**	Owns a MobPh	Respond-ents	**Non-Response Bias**	**OVERALL MOBPH BIAS**
Mean FCS							
Nov16	52.2	54.7	**2.4**				
Jun17	49.8	53.1	**3.3**	53.1	47.1	**-6.1**	**-2.7**
Apr18 New	46.9	49	**2.1**				
Apr18 Rpt	52.2	54.1	**1.9**	54.1	57.2	**3.1**	**5**
Prop of Hhlds with Adequate FCS							
Nov16	0.66	0.71	**0.06**				
Jun17	0.59	0.67	**0.08**	0.67	0.58	**-0.09**	**-0.02**
Apr18 New	0.56	0.61	**0.05**				
Apr18 Rpt	0.69	0.73	**0.04**	0.73	0.81	**0.07**	**0.11**
Mean DDS							
Nov16	5.5	5.7	**0.19**				
Jun17	5.4	5.7	**0.21**	5.7	5.2	**-0.5**	**-0.3**
Apr18 New	5.3	5.5	**0.19**				
Apr18 Rpt	5.8	6	**0.15**	6	6.2	**0.2**	**0.4**

[21] We note that the survey design was such that they are effectively two separate representative samples.

[22] It is concerning that, apart from Food Stocks, food security indicators for the repeat sample are all significantly higher than for the new sample. This calls into question the implementation of the Apr18 survey. However, because we are interested in biases and differences rather than absolute measurements, this may not affect our analysis too much as long as we treat the new and repeat households as separate samples.

	Whole Sample	Owns a MobPh	**Coverage Bias**	Owns a MobPh	Respond-ents	**Non-Response Bias**	**OVERALL MOBPH BIAS**
Prop of Hhlds with Adequate DDS							
Nov16	0.75	0.8	**0.05**				
Jun17	0.73	0.78	**0.05**	0.78	0.7	**-0.08**	**-0.03**
Apr18 New	0.7	0.75	**0.05**				
Apr18 Rpt	0.81	0.86	**0.04**	0.86	0.9	**0.05**	**0.09**
Mean Days of Food Stocks							
Nov16	132.8	141.4	**8.6**				
Jun17	93.6	99.5	**5.9**	99.5	96.1	**-3.4**	**2.5**
Apr18 New	70.4	76.4	**6**				
Apr18 Rpt	63.6	70	**6.4**	70	85	**15**	**21.4**

Coverage Bias

Table 10 shows a positive coverage bias for all food security indicators across the surveys. That is, if we include only those owning mobile phones in our sample, FCS, DDS, the proportion of households with adequate FCS and with adequate DDS will all be over-stated. This is synonymous with the findings in the analysis of food security indicators in Section 10.

We see that coverage bias for the two FCS indicators increased in the six months from Nov16 to Jun17 and then decreased over the next year from Jun17 to Apr18[23] (to levels below Nov16). Coverage bias for the two DDS indicators remained constant from Nov16 to Jun17 and then decreased to Apr18, and coverage bias for Food Stocks decreased across the 18-month span of the three surveys.

Although it appears that coverage bias is decreasing as levels of mobile phone ownership increase, the decrease may not be significant.[24] With surveys only available for three points in time, we cannot analyse trends in coverage bias - however, as more surveys are carried out, time series analysis will enable trends in coverage bias over time to be investigated.

[23] taking an average coverage bias for Apr18New and Apr18Repeat

[24] A rigorous investigation would involve calculating the standard error for the change in bias using Equation [2] on page 34 - however, the biases are likely to be correlated, which causes difficulties with the linearisation method. The Jackknife Method could be used, but is beyond the scope of this study.

Non-Response Bias

We next investigate the non-response bias for Jun17 and Apr18Repeat by calculating the difference in indicators for mobile phone owners with indicators for those who responded to a mobile phone interview.

For Jun17, we see that there is a negative non-response biases for all food security indicators. This suggests that, for the population of mobile phone owners, non-response will lead to food security indicators being understated. For Apr18, we see the opposite: the non-response biases are all positive, with non-response leading to food security indicators being overstated. These findings are synonymous with the earlier comparisons between respondents and non-respondents.

Because we have only two surveys where we are able to measure non-response bias, and since these give conflicting results, it is impossible to consider trends or to make generalisations.

Overall Bias

In the Jun17 survey, we see that, for FCS, FCS Adequacy, DDS and DDS Adequacy, the positive coverage bias is more than offset by the negative non-response bias. For these indicators, a mobile phone survey would understate food security indicators suggesting that households are less food secure than they really are. For Food Stocks, the positive coverage bias is only partially offset by the negative non-response bias, resulting in a positive overall bias, suggesting that a mobile phone survey would overstate food stocks.

For Apr18, the positive coverage biases are compounded by positive non-response biases: if the sample excludes those without mobile phones, food security estimates will be overstated, but they will then be overstated even further because of non-response. A mobile phone survey would have resulted in mean FCS being overstated by around 10%, the proportion of households with Adequate FCS by around 17%, mean DDS by around 7%, the proportion of households with Adequate DDS by around 11% and Days of Food Stocks by 34%. That is, if the survey were to have been carried out solely by mobile phone, we would have considerably over-estimated food security concluding that households are more food secure than they really are.

Once again, due to the conflicting contribution of non-response bias to the total bias, we cannot comment on trends in overall bias or predict what the bias might be in future surveys.

12. Adjusting Food Security Estimates to Correct for Mobile Phone Bias

We finally return to the question of whether reliable food security estimates could be obtained from purely mobile phone surveys in Nepal.

If the biases across the surveys had been constant or had at least followed a steady trend, we would next explore bias correction techniques to see whether unbiased estimates could have been obtained from the surveys analysed (and then applied to future surveys). However, the biases in food security estimates calculated from the Jun17 and Apr18 surveys were so different that there would be little point in this exercise.

We note that there are a number of methods for adjusting estimates to reduce bias. Post-stratification is the most common of these and involves adjusting the sampling weights (usually by demographic variables) to account for households not owning mobile phones and non-respondents.[25] We note that the surveys in Nepal were conducted in the poorest rural areas: this means that, even if we had had more predictable biases, post-stratification using variables such as geographical area or urban/rural is unlikely to improve estimates. However, if future surveys show more predictable biases, we would suggest exploring post-stratification (or other bias correction techniques) based on some of the common variables included in the preferred regression models in Appendix 7 (e.g. Education, Radio, Bed/Sofa/Cupboard, Table/Chairs) to see whether the bias is able to be corrected to an extent where food security estimates from mobile phone surveys reflect population estimates.[26]

13. Recommendations

Based on the analysis above, it is strongly recommended that surveys used to measure food insecurity in Nepal do not yet move to purely mobile phone surveys. These would lead to biased food security estimates, unable to be sufficiently corrected due to the magnitude and direction of the bias being unpredictable. Biased estimates have the potential to lead to poorly-informed policies and poorly-allocated resources.

The continuation of dual-mode surveys is recommended: this will enable bias to continue to be monitored until it is relatively predictable, at which stage a move to mobile phone surveys could be considered.

The analysis broke down potential mobile phone bias into three components.

Coverage bias was significant and reasonably constant across the three surveys; however, it was noted that, as mobile phone ownership increases, coverage bias is likely to decrease to to a level where it is not significant in the coming years.

Although there was no evidence of interview mode bias, this was based on the results from a single survey and should therefore be investigated for at least another dual-mode survey before confirming this finding.

Non-response bias was highly significant in the two surveys where it could be measured but, worryingly, was negative in one survey and positive in the other.

With coverage bias becoming less and less of a concern given future high levels of mobile phone ownership, and assuming the confirmation of no interview bias, non-response bias will be the main concern in future mobile phone surveys. Unlike mobile phone ownership, which is completely determined by outside factors, survey implementers have some control over non-response and it is recommended that everything possible is done to reduce this in the Nepal surveys. Non-response in Jun17 was significantly higher than in Apr18. This suggests that there may not have been strict adherence in both surveys to the specified number of phone rings, number of attempts to reach a number and the timing of day for calls, as outlined in the survey scope and requirements

[25] Other methods include raking, an iterative process involving "post-stratifying on each set of variables in turn, and repeating the process until the weights stop changing", and generalized regression (GREG) estimation which involves calibrating a sample to the marginal totals of variables in a linear regression model (Lumley, 2010).

[26] We note, however, that bias correction techniques are not a panacea for non-response, and every effort should first be made to reduce non-response through the survey design and implementation.

(World Food Programme, 2016). The fact that the non-response bias was positive in one survey and negative in the other also suggests differences in survey implementation. We suspect that there may have been problems with the Jun17 survey implementation since the negative bias (respondents being poorer, less educated and less food secure than non-respondents) contradicts expectations and the results from many other studies.

14. Conclusions

This study analysed three surveys carried out to measure food security in the poorest regions of Nepal. The aims of the study were to estimate the bias in mobile phone surveys and to investigate whether it is possible to obtain reliable food security estimates from biased mobile phone data.

Across all three surveys, households not owning mobile phones were found to be less food secure than households owning mobile phones: they consumed less food, had poorer diets and lower levels of food stocks. These findings reflected the results from analyses of demographic and socio-economic indicators which indicated that households not owning phones were poorer and less educated than households owning mobile phones.

The mode of interview (mobile phone or F2F) was analysed for one survey. It appeared that responses about food security do not differ if given in a F2F interview or a mobile phone interview.

In the two dual-mode surveys, non-response was analysed for those assigned a mobile phone interview. The results were contradictory: in one survey, mobile phone respondents were found to be more food-secure (also better educated and wealthier) than non-respondents while, in the other survey, they were found to be less food-secure (also poorer and less educated) than non-respondents.

The study concluded that food security estimates from mobile phone surveys are biased with systematic differences between respondents of mobile phone surveys and the population. The overall bias is comprised of coverage bias and non-response bias. It is expected that coverage bias will decrease over time as mobile phone ownership increases, but that non-response bias will continue to affect food security estimates.

Due to the contradictory results of the non-response analysis, it was not possible to consider bias correction techniques such as post-stratification.

It was therefore concluded that reliable food security estimates cannot yet be obtained from mobile phone surveys in Nepal, and the continuation of dual-mode surveys was recommended.

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Appendix 1: Indicators for Hhlds owning a MobPh vs Hhlds not owning a MobPh in November 2016

Population: Households in Mid-Western and Far-Western Mountains of Nepal
Sample: Nov16 Survey, Whole Sample (n=1,468)
Comparison: MobilePh=MobPh vs MobilePh=NoMobPh

Figures are proportions unless otherwise indicated.
For categorical variables, the p-value is from an F-test of association between the indicator and MobPh/NoMobPh.
For numerical variables, the p-value is from a t-test for a difference between means for MobPh and NoMobPh.

	MobPh (95% CI)	NoMobPh (95% CI)	P-value
HHLD OWNS A MOBILE PHONE	0.76 (0.72-0.8)	0.24 (0.2-0.28)	
DEMOGRAPHIC AND SOCIO-ECONOMIC INDICATORS			
Ethnicity			0.026
Brahmin	0.12 (0.07-0.16)	0.07 (0.03-0.1)	
Chhetri	0.66 (0.59-0.73)	0.59 (0.48-0.7)	
Dalit	0.2 (0.15-0.26)	0.27 (0.19-0.36)	
Janajati	0.02 (0.01-0.04)	0.07 (-0.02-0.16)	
Educ of Hhld Head			<0.001
None	0.39 (0.36-0.43)	0.68 (0.61-0.75)	
Primary	0.2 (0.17-0.23)	0.13 (0.09-0.17)	
Secondary	0.2 (0.18-0.23)	0.15 (0.1-0.19)	
Higher	0.2 (0.17-0.24)	0.04 (0.02-0.07)	
Owns Land			0.797
Yes	0.97 (0.95-0.98)	0.97 (0.94-1)	
No	0.03 (0.02-0.05)	0.03 (0-0.06)	
Total Land Owned			0.090
Mean no. of hectares	0.26 (0.23-0.29)	0.21 (0.16-0.27)	
Owns Livestock			0.049
Yes	0.94 (0.92-0.96)	0.9 (0.86-0.94)	
No	0.06 (0.04-0.08)	0.1 (0.06-0.14)	
Owns Radio			<0.001
Yes	0.41 (0.36-0.45)	0.19 (0.15-0.24)	
No	0.59 (0.55-0.64)	0.81 (0.76-0.85)	
Owns TV			<0.001
Yes	0.13 (0.09-0.18)	0.04 (0.01-0.06)	
No	0.87 (0.82-0.91)	0.96 (0.94-0.99)	
Owns Table/Chairs			<0.001
Yes	0.23 (0.17-0.28)	0.06 (0.02-0.1)	
No	0.77 (0.72-0.83)	0.94 (0.9-0.98)	

	MobPh (95% CI)	NoMobPh (95% CI)	P-value
Owns Bed/Sofa/Cupboards			<0.001
Yes	0.64 (0.58-0.69)	0.39 (0.31-0.46)	
No	0.36 (0.31-0.42)	0.61 (0.54-0.69)	
Roofing			0.002
Improved	0.56 (0.51-0.61)	0.39 (0.31-0.48)	
Basic	0.44 (0.39-0.49)	0.61 (0.52-0.69)	
Hhld has a Migrant Worker			0.003
Yes	0.43 (0.39-0.47)	0.31 (0.24-0.38)	
No	0.57 (0.53-0.61)	0.69 (0.62-0.76)	
Remittances from Migrant Workers			<0.001
Mean remittances in past year (NPR)	6,210 (4,720-7,690)	2,490 (1,480-3,500)	
FOOD SECURITY INDICATORS			
Food Consumption Score			<0.001
Mean FCS (ranges from 1 to 112)	54.7 (52.3-57)	44.6 (41.9-47.3)	
Inadequate FCS			<0.001
Adequate ($FCS > 42$)	0.71 (0.66-0.77)	0.48 (0.39-0.56)	
Inadequate ($FCS \leq 42$)	0.29 (0.23-0.34)	0.52 (0.44-0.61)	
Dietary Diversity Score			<0.001
Mean DDS (ranges from 0 to 8)	5.7 (5.5-5.9)	4.9 (4.7-5.1)	
Inadequate DDS			<0.001
Adequate ($DDS \geq 5$)	0.8 (0.76-0.84)	0.59 (0.51-0.67)	
Inadequate ($DDS < 5$)	0.2 (0.16-0.24)	0.41 (0.33-0.49)	
Food Stocks			<0.001
Mean stock of cereal foods (days)	141 (126-157)	106 (92-119)	

Appendix 2: Indicators for Hhlds owning a MobPh vs Hhlds not owning a MobPh in June 2017

Population: Households in Mid-Western and Far-Western Mountains of Nepal
Sample: Jun17 Survey, SurveyType=2/3 (n=756)
Comparison: SurveyType=3 (MobPh) vs SurveyType=2 (NoMobPh)

Figures are proportions unless otherwise indicated.
For categorical variables, the p-value is from an F-test of association between the indicator and MobPh/NoMobPh.
For numerical variables, the p-value is from a t-test for a difference between means for MobPh and NoMobPh.

	MobPh (95% CI)	NoMobPh (95% CI)	P-value
DEMOGRAPHIC AND SOCIO-ECONOMIC INDICATORS			
Ethnicity			0.062
Brahmin	0.13 (0.07-0.19)	0.07 (0.03-0.1)	
Chhetri	0.63 (0.55-0.71)	0.61 (0.52-0.7)	
Dalit	0.23 (0.16-0.29)	0.28 (0.21-0.35)	
Janajati	0.01 (0-0.03)	0.05 (-0.01-0.11)	
Educ of Hhld Head			<0.001
None	0.33 (0.27-0.39)	0.62 (0.57-0.68)	
Primary	0.19 (0.14-0.23)	0.17 (0.13-0.2)	
Secondary	0.25 (0.2-0.3)	0.16 (0.12-0.19)	
Higher	0.23 (0.18-0.29)	0.05 (0.03-0.08)	
Owns Land			0.957
Yes	0.96 (0.94-0.98)	0.96 (0.94-0.98)	
No	0.04 (0.02-0.06)	0.04 (0.02-0.06)	
Total Land Owned			0.016
Mean no. of hectares	0.26 (0.23-0.3)	0.22 (0.18-0.25)	
Owns Livestock			0.317
Yes	0.94 (0.89-0.98)	0.91 (0.88-0.94)	
No	0.06 (0.02-0.11)	0.09 (0.06-0.12)	
Owns Radio			<0.001
Yes	0.47 (0.4-0.55)	0.28 (0.22-0.33)	
No	0.53 (0.45-0.6)	0.72 (0.67-0.78)	
Owns TV			0.004
Yes	0.14 (0.08-0.21)	0.06 (0.03-0.09)	
No	0.86 (0.79-0.92)	0.94 (0.91-0.97)	
Owns Table/Chairs			0.002
Yes	0.24 (0.16-0.32)	0.12 (0.07-0.17)	
No	0.76 (0.68-0.84)	0.88 (0.83-0.93)	
Owns Bed/Sofa/Cupboards			<0.001
Yes	0.68 (0.61-0.76)	0.43 (0.36-0.49)	
No	0.32 (0.24-0.39)	0.57 (0.51-0.64)	

	MobPh (95% CI)	NoMobPh (95% CI)	P-value
Roofing			0.116
Improved	0.59 (0.53-0.64)	0.51 (0.44-0.59)	
Basic	0.41 (0.36-0.47)	0.49 (0.41-0.56)	
Hhld has a Migrant Worker			0.002
Yes	0.51 (0.45-0.58)	0.38 (0.32-0.44)	
No	0.49 (0.42-0.55)	0.62 (0.56-0.68)	
Remittances from Migrant Workers			0.020
Mean remittances in past year (NPR)	7,700 (4,980-10,430)	4,330 (3,040-5,620)	
FOOD SECURITY INDICATORS			
Food Consumption Score			0.001
Mean FCS (ranges from 1 to 112)	49.5 (46.7-52.2)	43.9 (41.8-46.1)	
Inadequate FCS			0.002
Adequate ($FCS > 42$)	0.59 (0.52-0.66)	0.46 (0.39-0.52)	
Inadequate ($FCS \leq 42$)	0.41 (0.34-0.48)	0.54 (0.48-0.61)	
Dietary Diversity Score			0.003
Mean DDS (ranges from 0 to 8)	5.5 (5.3-5.7)	5.1 (4.9-5.3)	
Inadequate DDS			0.004
Adequate ($DDS \geq 5$)	0.76 (0.7-0.82)	0.64 (0.58-0.71)	
Inadequate ($DDS < 5$)	0.24 (0.18-0.3)	0.36 (0.29-0.42)	
Food Stocks			0.298
Mean stock of cereal foods (days)	89 (79-99)	83 (75-92)	

Appendix 3: Indicators for Hhlds owning a MobPh vs Hhlds not owning a MobPh in April 2018

Population: Households in Mid-Western and Far-Western Mountains of Nepal
Sample: Apr18 Survey, New Hhlds (n=711)
Comparison: MobilePh=MobPh vs MobilePh=NoMobPh

Figures are proportions unless otherwise indicated.
For categorical variables, the p-value is from an F-test of association between the indicator and MobPh/NoMobPh.
For numerical variables, the p-value is from a t-test for a difference between means for MobPh and NoMobPh.

	MobPh (95% CI)	NoMobPh (95% CI)	P-value
HHLD OWNS A MOBILE PHONE	0.81 (0.77-0.85)	0.19 (0.15-0.23)	
DEMOGRAPHIC AND SOCIO-ECONOMIC INDICATORS			
Ethnicity			0.396
Brahmin	0.08 (0.01-0.15)	0.08 (-0.01-0.17)	
Chhetri	0.64 (0.54-0.74)	0.54 (0.39-0.69)	
Dalit	0.22 (0.14-0.29)	0.33 (0.19-0.46)	
Janajati	0.01 (-0.01-0.03)	0 (0-0)	
Other	0.05 (0.01-0.09)	0.05 (0-0.1)	
Educ of Hhld Head			<0.001
None	0.36 (0.3-0.42)	0.67 (0.57-0.78)	
Primary	0.18 (0.14-0.23)	0.11 (0.05-0.17)	
Secondary	0.25 (0.21-0.29)	0.14 (0.06-0.21)	
Higher	0.21 (0.15-0.26)	0.08 (0.04-0.12)	
Owns Land			0.702
Yes	0.98 (0.96-0.99)	0.97 (0.94-1)	
No	0.02 (0.01-0.04)	0.03 (0-0.06)	
Total Land Owned			0.004
Mean no. of hectares	0.34 (0.3-0.38)	0.25 (0.2-0.3)	
Owns Livestock			0.031
Yes	0.95 (0.93-0.98)	0.89 (0.84-0.95)	
No	0.05 (0.02-0.07)	0.11 (0.05-0.16)	
Owns Radio			0.003
Yes	0.31 (0.26-0.37)	0.17 (0.1-0.24)	
No	0.69 (0.63-0.74)	0.83 (0.76-0.9)	
Owns TV			0.003
Yes	0.1 (0.04-0.16)	0.01 (-0.01-0.04)	
No	0.9 (0.84-0.96)	0.99 (0.96-1.01)	
Owns Table/Chairs			<0.001
Yes	0.18 (0.13-0.23)	0.03 (0-0.06)	
No	0.82 (0.77-0.87)	0.97 (0.94-1)	

	MobPh (95% CI)	NoMobPh (95% CI)	P-value
Owns Bed/Sofa/Cupboards			0.002
Yes	0.48 (0.4-0.57)	0.3 (0.2-0.4)	
No	0.52 (0.43-0.6)	0.7 (0.6-0.8)	
Roofing			0.030
Improved	0.58 (0.49-0.66)	0.42 (0.28-0.56)	
Basic	0.42 (0.34-0.51)	0.58 (0.44-0.72)	
Hhld has a Migrant Worker			0.417
Yes	0.41 (0.36-0.46)	0.38 (0.29-0.47)	
No	0.59 (0.54-0.64)	0.62 (0.53-0.71)	
Remittances from Migrant Workers			0.060
Mean remittances in past year (NPR)	8,930 (6,620-11,240)	5,040 (1,580-8,490)	
FOOD SECURITY INDICATORS			
Food Consumption Score			<0.001
Mean FCS (ranges from 1 to 112)	49 (46.1-51.8)	38 (33.2-42.7)	
Inadequate FCS			<0.001
Adequate ($FCS > 42$)	0.61 (0.53-0.69)	0.34 (0.22-0.46)	
Inadequate ($FCS \leq 42$)	0.39 (0.31-0.47)	0.66 (0.54-0.78)	
Dietary Diversity Score			<0.001
Mean DDS (ranges from 0 to 8)	5.5 (5.3-5.7)	4.5 (4.1-4.9)	
Inadequate DDS			<0.001
Adequate ($DDS \geq 5$)	0.75 (0.7-0.81)	0.48 (0.35-0.61)	
Inadequate ($DDS < 5$)	0.25 (0.19-0.3)	0.52 (0.39-0.65)	
Food Stocks			0.002
Mean stock of cereal foods (days)	76 (62-91)	45 (31-60)	

Appendix 4: Indicators for Mode of Interview (F2F vs MobPh) for Hhlds owning a MobPh in June 2017

Population: Households owning a MobPh in Mid-Western and Far-Western Mountains of Nepal
Sample: Jun17 Survey, SurveyType=1,3 (n=528)
Comparison: SurveyType=1 (MobPh Interview) vs SurveyType=3 (F2F Interview)

Figures are proportions unless otherwise indicated.
For categorical variables, the p-value is from an F-test of association between the indicator and Interview Mode.
For numerical variables, the p-value is from a t-test for a difference between means for F2F Interview and MobPh Interview.

	F2F Interview (95% CI)	MobPh Interview (95% CI)	P-value
DEMOGRAPHIC AND SOCIO-ECONOMIC INDICATORS			
Ethnicity			0.144
Brahmin	0.13 (0.07-0.19)	0.1 (0.04-0.16)	
Chhetri	0.63 (0.55-0.71)	0.69 (0.61-0.77)	
Dalit	0.23 (0.16-0.29)	0.17 (0.11-0.24)	
Janajati	0.01 (0-0.03)	0.04 (0.01-0.07)	
Educ of Hhld Head			0.012
None	0.33 (0.27-0.39)	0.45 (0.38-0.52)	
Primary	0.19 (0.14-0.23)	0.19 (0.15-0.23)	
Secondary	0.25 (0.2-0.3)	0.2 (0.15-0.25)	
Higher	0.23 (0.18-0.29)	0.16 (0.12-0.21)	
Owns Land			0.319
Yes	0.96 (0.94-0.98)	0.98 (0.96-1)	
No	0.04 (0.02-0.06)	0.02 (0-0.04)	
Total Land Owned			0.740
Mean no. of hectares	0.26 (0.23-0.3)	0.25 (0.22-0.29)	
Owns Livestock			0.168
Yes	0.94 (0.89-0.98)	0.96 (0.94-0.99)	
No	0.06 (0.02-0.11)	0.04 (0.01-0.06)	
Owns Radio			<0.001
Yes	0.47 (0.4-0.55)	0.31 (0.25-0.37)	
No	0.53 (0.45-0.6)	0.69 (0.63-0.75)	
Owns TV			0.246
Yes	0.14 (0.08-0.21)	0.11 (0.06-0.16)	
No	0.86 (0.79-0.92)	0.89 (0.84-0.94)	
Owns Table/Chairs			0.050
Yes	0.24 (0.16-0.32)	0.17 (0.11-0.23)	
No	0.76 (0.68-0.84)	0.83 (0.77-0.89)	
Owns Bed/Sofa/Cupboards			0.022
Yes	0.68 (0.61-0.76)	0.59 (0.51-0.67)	
No	0.32 (0.24-0.39)	0.41 (0.33-0.49)	

	F2F Interview (95% CI)	MobPh Interview (95% CI)	P-value
Roofing			0.011
Improved	0.59 (0.53-0.64)	0.48 (0.41-0.56)	
Basic	0.41 (0.36-0.47)	0.52 (0.44-0.59)	
Hhld has a Migrant Worker			0.898
Yes	0.51 (0.45-0.58)	0.51 (0.43-0.58)	
No	0.49 (0.42-0.55)	0.49 (0.42-0.57)	
Remittances from Migrant Workers			0.839
Mean remittances in past year (NPR)	7,700 (4,980-10,430)	7,360 (5,030-9,690)	
FOOD SECURITY INDICATORS			
Food Consumption Score			0.111
Mean FCS (ranges from 1 to 112)	49.5 (46.7-52.2)	47.1 (45-49.1)	
Inadequate FCS			0.727
Adequate ($FCS > 42$)	0.59 (0.52-0.66)	0.58 (0.51-0.64)	
Inadequate ($FCS \leq 42$)	0.41 (0.34-0.48)	0.42 (0.36-0.49)	
Dietary Diversity Score			0.018
Mean DDS (ranges from 0 to 8)	5.5 (5.3-5.7)	5.2 (5-5.3)	
Inadequate DDS			0.164
Adequate ($DDS \geq 5$)	0.76 (0.7-0.82)	0.7 (0.64-0.77)	
Inadequate ($DDS < 5$)	0.24 (0.18-0.3)	0.3 (0.23-0.36)	
Food Stocks			0.258
Mean stock of cereal foods (days)	89 (79-99)	96 (83-109)	

Appendix 5: Indicators for Respondents vs Non-Respondents for Hhlds owning a MobPh in June 2017

Population: Households owning a MobPh in Mid-Western and Far-Western Mountains of Nepal
Sample: Jun17 Survey, SurveyType=1,4 (n=637)
Comparison: SurveyType=1 (Respondents) vs SurveyType=4 (Non-Respondents)

Figures are proportions unless otherwise indicated.
For categorical variables, the p-value is from an F-test of association between the indicator and Response/Non-Response.
For numerical variables, the p-value is from a t-test for a difference between means for Respondents and Non-Respondents.

	Respondents (95% CI)	Non-Respondents (95% CI)	P-value
OVERALL LEVEL OF RESPONSE	0.42 (0.37-0.47)	0.58 (0.53-0.63)	
DEMOGRAPHIC AND SOCIO-ECONOMIC INDICATORS			
Ethnicity			0.390
Brahmin	0.1 (0.04-0.16)	0.14 (0.08-0.2)	
Chhetri	0.69 (0.61-0.77)	0.66 (0.57-0.75)	
Dalit	0.17 (0.11-0.24)	0.18 (0.12-0.24)	
Janajati	0.04 (0.01-0.07)	0.02 (0-0.04)	
Educ of Hhld Head			0.003
None	0.45 (0.38-0.52)	0.33 (0.28-0.39)	
Primary	0.19 (0.15-0.23)	0.2 (0.15-0.25)	
Secondary	0.2 (0.15-0.25)	0.2 (0.16-0.24)	
Higher	0.16 (0.12-0.21)	0.27 (0.21-0.33)	
Owns Land			0.493
Yes	0.98 (0.96-1)	0.97 (0.95-0.99)	
No	0.02 (0-0.04)	0.03 (0.01-0.05)	
Total Land Owned			0.677
Mean no. of hectares	0.25 (0.22-0.29)	0.26 (0.23-0.3)	
Owns Livestock			0.043
Yes	0.96 (0.94-0.99)	0.93 (0.89-0.96)	
No	0.04 (0.01-0.06)	0.07 (0.04-0.11)	
Owns Radio			0.002
Yes	0.31 (0.25-0.37)	0.45 (0.39-0.51)	
No	0.69 (0.63-0.75)	0.55 (0.49-0.61)	
Owns TV			0.095
Yes	0.11 (0.06-0.16)	0.16 (0.1-0.21)	
No	0.89 (0.84-0.94)	0.84 (0.79-0.9)	
Owns Table/Chairs			0.008
Yes	0.17 (0.11-0.23)	0.26 (0.19-0.33)	
No	0.83 (0.77-0.89)	0.74 (0.67-0.81)	

	Respondents (95% CI)	Non-Respondents (95% CI)	P-value
Owns Bed/Sofa/Cupboards			0.019
Yes	0.59 (0.51-0.67)	0.69 (0.63-0.75)	
No	0.41 (0.33-0.49)	0.31 (0.25-0.37)	
Roofing			0.076
Improved	0.48 (0.41-0.56)	0.57 (0.5-0.63)	
Basic	0.52 (0.44-0.59)	0.43 (0.37-0.5)	
Hhld has a Migrant Worker			0.055
Yes	0.51 (0.43-0.58)	0.42 (0.36-0.48)	
No	0.49 (0.42-0.57)	0.58 (0.52-0.64)	
Remittances from Migrant Workers			0.664
Mean remittances in past year (NPR)	7,360 (5,030-9,690)	6,600 (3,760-9,440)	
FOOD SECURITY INDICATORS			
Food Consumption Score			<0.001
Mean FCS (ranges from 1 to 112)	47.1 (45-49.1)	60.1 (58-62.2)	
Inadequate FCS			<0.001
Adequate ($FCS > 42$)	0.58 (0.51-0.64)	0.79 (0.74-0.83)	
Inadequate ($FCS \leq 42$)	0.42 (0.36-0.49)	0.21 (0.17-0.26)	
Dietary Diversity Score			<0.001
Mean DDS (ranges from 0 to 8)	5.2 (5-5.3)	6.1 (6-6.3)	
Inadequate DDS			<0.001
Adequate ($DDS \geq 5$)	0.7 (0.64-0.77)	0.85 (0.81-0.89)	
Inadequate ($DDS < 5$)	0.3 (0.23-0.36)	0.15 (0.11-0.19)	
Food Stocks			0.070
Mean stock of cereal foods (days)	96 (83-109)	109 (99-119)	

Appendix 6: Indicators for Respondents vs Non-Respondents for Hhlds owning a MobPh in April 2018

Population: Households owning a MobPh in Mid-Western and Far-Western Mountains of Nepal
Sample: Apr18 Survey, SurveyType=1,4 (n=557)
Comparison: SurveyType=1 (Respondents) vs SurveyType=4 (Non-Respondents)

Figures are proportions unless otherwise indicated.
For categorical variables, the p-value is from an F-test of association between the indicator and Response/Non-Response.
For numerical variables, the p-value is from a t-test for a difference between means for Respondents and Non-Respondents.

	Respondents (95% CI)	Non-Respondents (95% CI)	P-value
OVERALL LEVEL OF RESPONSE	0.54 (0.48-0.59)	0.46 (0.41-0.52)	
DEMOGRAPHIC AND SOCIO-ECONOMIC INDICATORS			
Ethnicity			0.181
Brahmin	0.17 (0.08-0.27)	0.12 (0.04-0.19)	
Chhetri	0.66 (0.55-0.76)	0.67 (0.55-0.78)	
Dalit	0.15 (0.08-0.21)	0.2 (0.1-0.29)	
Janajati	0.02 (0-0.04)	0.02 (0-0.04)	
Educ of Hhld Head			0.027
None	0.41 (0.34-0.48)	0.43 (0.37-0.5)	
Primary	0.17 (0.11-0.22)	0.19 (0.13-0.24)	
Secondary	0.17 (0.12-0.21)	0.23 (0.18-0.28)	
Higher	0.26 (0.19-0.33)	0.15 (0.1-0.2)	
Owns Land			0.502
Yes	0.97 (0.94-0.99)	0.96 (0.93-0.98)	
No	0.03 (0.01-0.06)	0.04 (0.02-0.07)	
Total Land Owned			0.006
Mean no. of hectares	0.27 (0.23-0.31)	0.22 (0.19-0.25)	
Owns Livestock			0.166
Yes	0.91 (0.86-0.96)	0.94 (0.91-0.98)	
No	0.09 (0.04-0.14)	0.06 (0.02-0.09)	
Owns Radio			0.046
Yes	0.44 (0.36-0.53)	0.35 (0.28-0.42)	
No	0.56 (0.47-0.64)	0.65 (0.58-0.72)	
Owns TV			<0.001
Yes	0.15 (0.07-0.24)	0.06 (0.02-0.1)	
No	0.85 (0.76-0.93)	0.94 (0.9-0.98)	
Owns Table/Chairs			<0.001
Yes	0.3 (0.2-0.39)	0.14 (0.08-0.2)	
No	0.7 (0.61-0.8)	0.86 (0.8-0.92)	

	Respondents (95% CI)	Non-Respondents (95% CI)	P-value
Owns Bed/Sofa/Cupboards			0.097
Yes	0.68 (0.59-0.77)	0.58 (0.49-0.67)	
No	0.32 (0.23-0.41)	0.42 (0.33-0.51)	
Roofing			0.110
Improved	0.57 (0.49-0.65)	0.48 (0.4-0.57)	
Basic	0.43 (0.35-0.51)	0.52 (0.43-0.6)	
Hhld has a Migrant Worker			0.305
Yes	0.43 (0.36-0.5)	0.38 (0.29-0.47)	
No	0.57 (0.5-0.64)	0.62 (0.53-0.71)	
Remittances from Migrant Workers			0.793
Mean remittances in past year (NPR)	5,710 (3,410-8,000)	6,070 (3,140-8,990)	
FOOD SECURITY INDICATORS			
Food Consumption Score			0.001
Mean FCS (ranges from 1 to 112)	57.2 (54.5-60)	50.5 (47.1-53.8)	
Inadequate FCS			0.001
Adequate ($FCS > 42$)	0.81 (0.76-0.86)	0.65 (0.56-0.73)	
Inadequate ($FCS \leq 42$)	0.19 (0.14-0.24)	0.35 (0.27-0.44)	
Dietary Diversity Score			0.001
Mean DDS (ranges from 0 to 8)	6.2 (6-6.4)	5.7 (5.4-6)	
Inadequate DDS			0.009
Adequate ($DDS \geq 5$)	0.9 (0.87-0.94)	0.8 (0.73-0.87)	
Inadequate ($DDS < 5$)	0.1 (0.06-0.13)	0.2 (0.13-0.27)	
Food Stocks			<0.001
Mean stock of cereal foods (days)	85 (74-96)	52 (42-62)	

Appendix 7: Analysis of Regression Models

a. MobPh/NoMobPh, Nov16

We explore regression models with MobilePh as the response variable and a number of different explanatory variables. Since the response variable is binary (MobPh or NoMobPh), we use generalized linear models[1] with a logit (the logarithm of the odds of owning a mobile phone) link function.

To explore different models, we use a backward stepwise approach. This involves starting with the "full" model containing all variables analysed in Section 9. We drop the least significant variable (highest p-value) and refit the model. We continue until all variables are significant (p-value<0.05) and then test the resulting "reduced/best/preferred" model against the full model.

Table 11: Full Model for MobPh/NoMobPh, Nov16

svyglm(formula = MobilePh ~ Ethnicity + EducHeadGroup + LandArea + Livestock + Radio + TV + TableChairs + BedSofaCupboard + ImprovedRoofing + MigrantWorker + Remittances, design = Nov16Cov.design, family = quasibinomial())

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-3.256e+00	5.915e-01	-5.504	4.23e-07	***
EthnicityChhetri	3.655e-01	2.693e-01	1.357	0.178453	
EthnicityDalit	3.628e-01	2.946e-01	1.232	0.221695	
EthnicityJanajati	1.459e+00	7.916e-01	1.843	0.069005	.
EducHeadGroupPrimary	-8.578e-01	1.855e-01	-4.625	1.40e-05	***
EducHeadGroupSecondary	-6.069e-01	2.201e-01	-2.757	0.007202	**
EducHeadGroupHigher	-1.656e+00	3.291e-01	-5.032	2.88e-06	***
LandArea	2.470e-01	5.464e-01	0.452	0.652522	
Livestock NoLivestock	5.548e-01	2.918e-01	1.901	0.060811	.
Radio NoRadio	7.457e-01	1.838e-01	4.057	0.000114	***
TV NoTV	6.074e-01	3.948e-01	1.538	0.127830	
TableChairs NoTableChairs	4.870e-01	3.247e-01	1.500	0.137510	
BedSofaCupboard NoBedSofaCupboard	5.691e-01	1.695e-01	3.357	0.001202	**
ImprovedRoofing BasicRoofing	1.985e-01	2.144e-01	0.926	0.357240	
MigrantWorker NoMigrantWorker	2.707e-01	1.768e-01	1.531	0.129639	
Remittances	-1.165e-05	7.245e-06	-1.607	0.111869	

Of the variables with p>0.05, LandArea is the least significant (highest p-value). We drop LandArea and refit the next model. We continue dropping variables (ImprovedRoofing, TV, MigrantWorker, Ethnicity, Table/Chairs, Livestock) until we have following reduced model where all variables are significant.

[1] GLMs are an extension of linear regression models that allow the dependent variable to be non-normal.

Table 12: Reduced Model for MobPh/NoMobPh, Nov16

svyglm(formula = MobilePh ~ EducHeadGroup + Radio + BedSofaCupboard + Remittances, design = Nov16Cov.design, family = quasibinomial())

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.577e+00	2.085e-01	-7.560	3.26e-11	***
EducHeadGroupPrimary	-8.877e-01	1.813e-01	-4.897	4.25e-06	***
EducHeadGroupSecondary	-7.052e-01	2.256e-01	-3.126	0.00238	**
EducHeadGroupHigher	-1.784e+00	3.360e-01	-5.311	7.83e-07	***
Radio NoRadio	8.567e-01	1.794e-01	4.775	6.93e-06	***
BedSofaCupboard NoBedSofaCupboard	6.752e-01	1.644e-01	4.108	8.78e-05	***
Remittances	-2.022e-05	7.528e-06	-2.686	0.00861	**

We test the full model against the reduced model using "regTermTest" (rather than the usual "anova") - this is appropriate because maximum likelihood has not been used (Lumley, 2010).

Wald test for dropping LandArea ImprovedRoofing TV MigrantWorker Ethnicity TableChairs Livestock from Full Model
F = 1.837567 on 9 and 81 df: p= 0.073816

The p-value for the Wald Test is greater than 0.05, indicating that the dropped variables together do not significantly improve the reduced model.

The model fitted is a log linear model, so we need to take care when interpreting coefficients. Negative coefficients correspond to the odds of owning a mobile phone being less than 1, that is, Prob(MobPh) > Prob(NoMobPh) and positive coefficients to Prob(MobPh) < Prob(NoMobPh).

We note that the baseline indicator is households where the head has no education, and which own a radio and a bed/sofa/cupboard. The coefficients above suggest that higher levels of education and higher remittances increase the odds of owning a mobile phone, as do owning a radio or owning bed/sofa/cupboards.

b. MobPh/NoMobPh, Jun17

Table 13: Reduced Model for MobPh/NoMobPh, Jun17

svyglm(formula = Cov ~ EducHeadGroup + Radio + BedSofaCupboard + MigrantWorker, design = Jun17Cov.design, family = quasibinomial())

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.2737	0.2285	1.198	0.234179	
EducHeadGroupPrimary	-0.6732	0.2350	-2.864	0.005199	**
EducHeadGroupSecondary	-0.9390	0.2093	-4.487	2.13e-05	***
EducHeadGroupHigher	-1.7733	0.3134	-5.658	1.80e-07	***
Radio NoRadio	0.5961	0.2013	2.961	0.003920	**
BedSofaCupboard NoBed/Sofa/Cupboard	0.6787	0.1959	3.465	0.000814	***
MigrantWorker NoMigrantWorker	0.4651	0.1975	2.355	0.020671	*

Wald test for dropping LandArea ImprovedRoofing TV Ethnicity TableChairs Livestock Remittances from Full Model
F = 1.26541 on 9 and 80 df: p= 0.2687

c. MobPh/NoMobPh, Apr18

Table 14: Reduced Model for MobPh/NoMobPh, Apr18

svyglm(formula = MobilePh ~ EducHeadGroup + Livestock + TableChairs + BedSofaCupboard, design = Apr18Cov.design, family = quasibinomial())

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.4575	0.5534	-4.441	6.90e-05	***
EducHeadGroupPrimary	-1.0794	0.3357	-3.216	0.002578	**
EducHeadGroupSecondary	-1.1841	0.2984	-3.968	0.000293	***
EducHeadGroupHigher	-1.3634	0.3003	-4.541	5.05e-05	***
Livestock NoLivestock	1.1141	0.4135	2.694	0.010266	*
TableChairs NoTable/Chairs	1.2731	0.4793	2.656	0.011290	*
BedSofaCupboard NoBed/Sofa/Cupboard	0.5693	0.2257	2.523	0.015727	*

Wald test for dropping LandArea ImprovedRoofing MigrantWorker Radio TV Ethnicity2 Remittances from Full MNodel
F = 1.664234 on 9 and 31 df: p= 0.14057

d. Response/NoResponse, Jun17

Table 15: Reduced Model for Response/NoResponse, Jun17

svyglm(formula = Resp ~ EducHeadGroup + Radio + MigrantWorker, design = Jun17Resp.design, family = quasibinomial())

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.1777	0.2067	0.860	0.392189	
EducHeadGroupPrimary	0.3319	0.2366	1.403	0.164187	
EducHeadGroupSecondary	0.2703	0.2372	1.139	0.257625	
EducHeadGroupHigher	0.8223	0.2223	3.699	0.000379	***
Radio NoRadio	-0.5829	0.1785	-3.266	0.001562	**
MigrantWorker NoMigrantWorker	0.4090	0.1872	2.186	0.031537	*

Wald test for dropping LandArea ImprovedRoofing TV BedSofaCupboard Ethnicity TableChairs Livestock Remittances from Full Model
F = 1.233019 on 10 and 77 df: p= 0.28395

e. Response/NoResponse, Apr18

Table 16: Reduced Model for Response/NoResponse, Apr18

svyglm(formula = Resp ~ EducHeadGroup + LandArea + TableChairs, design = Apr18Resp.design, family = quasibinomial())

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.67186	0.24892	-2.699	0.00997	**
EducHeadGroupPrimary	0.04559	0.28035	0.163	0.87161	
EducHeadGroupSecondary	0.39493	0.24554	1.608	0.11524	
EducHeadGroupHigher	-0.40137	0.24264	-1.654	0.10555	
LandArea	-0.67180	0.31959	-2.102	0.04158	*
TableChairs NoTable/Chairs	0.85505	0.18310	4.670	3.09e-05	***

We initially dropped Education from the model above; however the resulting Wald Test has a p-value below 0.05 suggesting that at least one of the omitted variables would improve the model.

Wald test for dropping Ethnicity EducHeadGroup Livestock Radio TV BedSofaCupboard ImprovedRoofing MigrantWorker Remittances from Full Model
F = 3.022584 on 13 and 32 df: p= 0.0053751

We added Education (the last dropped variable) back into the model with the resulting Wald Test indicating that the model could not be significantly improved by including further variables.

Wald test for dropping Ethnicity Livestock Radio TV BedSofaCupboard ImprovedRoofing MigrantWorker Remittances from Full Model
F = 0.8332242 on 10 and 32 df: p= 0.6008