Mobile phones and radios: effects on transactions costs and market participation for households in northern Ghana

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Abstract

The literature on agricultural markets suggests that transactions costs are the main obstacles preventing households from participating in agricultural markets. We examine the impact of the recent massive penetration of ICTs (Information Communication Technologies, particularly mobile phones and radios) in developing countries to investigate the role of information in economic transactions and participation in food crop markets. To fully capture market participation behaviours, the current theoretical framework on market participation and transactions costs is extended to include those households that sell and buy in the same time period. We correct for endogeneity and selectivity throughout our models. We used a novel dataset of 393 households in northern Ghana with detailed information on market transactions and ICTs usage. Results show that receiving market information via mobile phones has a positive and significant impact on market participation, with a greater impact for households with a surplus of food crops. We find that radios have larger impact on the quantity traded. This may reflect the nature of mobiles in reducing searching costs, while radios provide an updated and regular flow of information which affect the patterns of crops consumed and sold. We also emphasise that the most significant factor is how ICTs are used, rather than their ownership.

Keywords: market participation, transaction costs, information technologies, mobile phones, radios, food crops, household food balances.

JEL Classification: D10, D83, O12, O55, Q12.

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1 Introduction

The recent spread of mobile phones and radios in rural areas of developing countries, where previously communication was impossible and the transportation infrastructure often poor, poses an important question: is this spread of new technologies just part of the modernization process of rural areas or can it also be an important development tool? There is limited empirical evidence on the impact of communication technologies used as marketing tools by smallholders. The current paper explores the possible effects and the impact their use — not the simply ownership — in enhancing market participation in food crop markets among smallholders in northern Ghana. Our results should inform policy makers, since mobile phones are becoming available and affordable for the 5 billion people living in emerging and developing economies. To date, 61 percent of the world's mobile phones are in developing countries and Africa is currently the fastest growing mobile market worldwide with more than 400 million subscribers and over 41 percent mobile phone penetration in 2009 (ITU; 2010).

Analysing data for four countries in Sub-Saharan Africa, Winters *et al.* (2010) estimate that more than half of the households are farming orientated, but only a quarter are market-orientated with the remainder being largely subsistence farmers. The figures drop in the case of Ghana, where less than ten percent of the farm households are market-orientated. Evidence from the literature suggests that transactions costs are the main obstacle that prevents a household from participating in markets, with information as an important factor affecting transactions costs. In rural environments, where inadequate infrastructure and transportation bring delays and storage losses, market information can help farmers to reduce transactions costs and increase participation in food crop markets. Benefits of participating in markets are immediate to farm households. From the sale of marketable surplus, they may earn enough to make some savings, invest further in improved technologies and personal assets, and pay taxes to government authorities.

In recent years, numerous studies have investigated the impact of ICTs (Information Communication Technologies, namely mobile phones and radios) in the areas of education, gender, health, credit, empowerment, and at social and cultural levels, but only a small number follow a quantitative approach (Aker and Mbiti; 2010). However, none examine transactions costs and mobile phone usage with a household model approach. Econometric studies on the evidence of microeconomic impacts of mobile telephony encompass panel studies on market performance and welfare in India (Jensen; 2007), grain markets in Niger (Aker; 2010), and market participation in cash food crops (Muto and Yamano; 2009) and migration (Muto; 2009) in Uganda. These studies find that the advent of mobile phones is associated with a reduction of price dispersion and waste of fish caught on the coast of Kerala; reduction in price dispersion of grains between Nigerian markets by at least 6.5 percent; and increased market participation of banana growers in Uganda, though not for maize. The impact of market information through radios is investigated by Svensson and Yanagizawa (2009). They exploited a natural experiment in Uganda and concluded that in the areas where radio is used to receive price information, farm gate prices increased by 15 percent. Notably, they had data only on radio ownership and not on the actual use of radio. Chowdhury (2006) looked at the impact of fixed line phones in

Bangladesh, finding increased market participation for households that used phones, though without correcting for endogeneity.

Our current work encompasses two strands of literature: the first focuses on transactions costs and market participation in development economics; a more recent second strand concerns the impact of information technologies in developing countries. Our contribution is twofold: first, we extend the current theoretical framework on market participation and transactions costs to include pure sellers and buyers, in addition to those households that sell and buy in the same period of time (net-sellers and net-buyers). Second, we investigate the potential role of mobile phones and radios as tools to reduce transactions costs and increase market participation, focusing on the actual uses of the ICT by the users rather than the mere ownership as in previous studies.

The paper is structured as follows. Based on Key *et al.* (2000) and Bellemare and Barrett (2006), we begin by expanding the current theoretical framework on household market participation and transaction costs to include pure sellers and buyers, as well as net-sellers and net-buyers. We then develop the empirical model, which is followed by description of the data and study area. Results are analysed in two sub-sections, the first dealing with the households with a potential marketable surplus, the second for those with a potential deficit of food crop. The final section concludes.

2 Theoretical framework

Our model is based on Key *et al.* (2000) and Bellemare and Barrett (2006). From the first, the concepts of fixed and proportional transaction costs are adopted to explore the role of ICTs; from the latter, the dynamic generalization estimation is used. To better reflect smallholders' market behaviour in northern Ghana, these models are extended to include households which both buy and sell food crops in the same period. In addition, we include net-sellers (those who sold more food crop than purchased) and net-buyers (those who bought more food crop than sold).

Consider, first, an economy where there are no transaction costs. A given household can be represented as maximising utility (1) subject to a series of constraints (2-4). This household's utility is a function of production output (X_a), purchases of goods (X_m), sales (X_n), and leisure time (X_l). The household faces a cash constraint, where the expenditure on all purchases cannot exceed the revenue from sales, other income (T) (off-farm income, remittances etc.), and savings (S). Specifically, n_i is the quantity and p^n_i is the market price of the i^{th} crop sold; equally pm is the market price of the i^{th} crop purchased and mi the quantity. The production technology depends on the crop produced (q_i) and the input used (x_i), based on z_q which acts as a production shifter representing the fixed production factors. The resource balance (4) states that for each crop the total that is consumed (c_i), sold, and used as input by an household, must be equal to what is produced, purchased, and the endowment (Ai) which includes stocks from previous seasons. Each constraint requires non negative production, consumption and input for the i^{th} crop (5).

$$max\, U\,(X_a, X_m, X_n, X_l;\; z_u) \tag{1}$$

Subject to:

$$\sum_{i=1}^{N} p_i^n n_i - \sum_{i=1}^{N} p_i^m m_i + T - S = 0 \tag{2}$$

$$G(q_i, x_i; z_q) \tag{3}$$

$$q_i - x_i + A_i + n_i - m_i - c_i = 0; \qquad i = 1, ..., N \tag{4}$$

$$c_i, q_i, x_i \geq 0 \tag{5}$$

The Lagrangian multiplier resulting from 1-4 is:

$$\mathcal{L} = U(X_a, X_m, X_n, X_l; z_u) + \sum_{i=1}^{N} \mu_i(q_i - x_i + A_i + n_i - m_i - c_i) + \phi G(q, x; z_q) \\ + \lambda(\sum_{i=1}^{N} p_i^n n_i - \sum_{i=1}^{N} p_i^m m_i + T - S)$$

Now, we introduce transactions costs to Equation 2. Expanding Key *et al.* (2001), we include the proportional[2] (t_p) and fixed transactions costs (t_f) but keep the buying ($.^b$) and selling ($.^s$) transactions separate. The cash constraint (2) now becomes:

$$\sum_{i=1}^{N} \left[(p_i - t_p^s(z_t^s))n_i - t_f^s(z_t^s)\right] \delta_i^s - \sum_{i=1}^{N} \left[(p_i + t_p^b(z_t^b))m_i + t_f^b(z_t^b)\right] \delta_i^b + T - S = 0$$

The variable transaction costs raise the price effectively paid by a buyer and lower the price effectively received by a seller. The price received by the seller is lower than the market price pi, by the unobservable amount tsp, and the price paid by the buyer is greater than p_i by the unobservable amount $t^b{}_p$; $t^s{}_f$ and $t^b{}_f$ are the unobservable fixed transaction costs when selling and buying the ith crop, respectively. The transaction costs are a function of the observed exogenous characteristics z_t^s for sellers, and z_t^b for buyers. The dummies δ_i^s and δ_i^b denote if a household is a seller and/or a buyer of the ith crop.

The Lagrangian multiplier that includes the transactions costs, both proportional and fixed is:

$$\mathcal{L} = U(X_a, X_m, X_n, X_l; z_u) + \sum_{i=1}^{N} \mu_i(q_i - x_i + A_i + n_i - m_i - c_i) + \phi G(q, x; z_q) \\ + \lambda \sum_{i=1}^{N} \left[\left[(p_i - t_p^s(z_t^s))n_i - t_f^s(z_t^s)\right] \delta_i^s - \left[(p_i + t_p^b(z_t^b))m_i + t_f^b(z_t^b)\right] \delta_i^b + T - S\right] \tag{6}$$

[2] Hereinafter we use the notion of proportional and variable transaction costs interchangeably.

Therefore rational farmers will decide on their market participation by comparing the utility obtained from selling or buying the i^{th} crop, selling and buying the i^{th} crop with a surplus or a deficit, or remaining self-sufficient.

Within the household framework, the different nature of ICTs could have different impacts on transactions costs, *viz.* mobile phones are bi-directional technologies (where the users can talk and listen), while radios are uni-directional. Given the nature of mobile phones, we expect their use to mainly influence the fixed transactions costs, since they can be used to find buyers (or sellers) and get information on prices which help peoples' decisions to trade. In contrast, a regular flow of information, such as market information from a radio bulletin, may have more influence on the patterns of consumption, purchases and sales. Distance to markets and transportation means affect the variable transactions costs. Unlike previous studies focusing on transactions costs (such as Goetz; 1992; Chowdhury; 2006; Alene *et al.*; 2008), we include not only the ownership of ICTs but also their actual use by households. Since the ownership of ICTs by itself does not indicate their use, we do not expect ownership (*per se*) to affect transaction costs.

Smallholders can trade, buying and selling within the same period of time, based on their needs and price fluctuations. For example, if households are constrained by liquidity, they may need to sell their crop after harvest and buy back at higher prices at the end of the agricultural season. If not so constrained, they may buy food crops at the beginning of the season and sell it back with a profit when prices rise. For these reasons, in addition to sellers and buyers, we have included the categories of net-sellers, net-buyers, and neutral households, in the case where the amount purchased of i^{th} crop is the same as the amount sold of i^{th} crop. Based on Equation 6, the decision price pi > 0 assumes the values:

$$p_i \begin{cases} p_i^m + t_p^b & if\ n_i = 0,\ m_i > 0,\ \delta_t^s = 0,\ \delta_t^b = 1;\ \Rightarrow buyer \\ (p_i^n - t_p^s), (p_i^m + t_p^b) & if\ n_i > 0,\ m_i > 0,\ \left[(p_i^n - t_p^s)n_i - t_f^s\right] < \left[(p_i^m + t_p^b)m_i + t_f^b\right];\ \Rightarrow net-buyer \\ \tilde{p} = \mu/\lambda & if\ n_i = m_i = 0;\ \Rightarrow autarchy \\ (p_i^n - t_p^s), (p_i^m + t_p^b) & if\ n_i > 0,\ m_i > 0,\ \left[(p_i^n - t_p^s)n_i - t_f^s\right] = \left[(p_i^m + t_p^b)m_i + t_f^b\right];\ \Rightarrow neutral \\ (p_i^n - t_p^s), (p_i^m + t_p^b) & if\ n_i > 0,\ m_i > 0,\ \left[(p_i^n - t_p^s)n_i - t_f^s\right] > \left[(p_i^m + t_p^b)m_i + t_f^b\right];\ \Rightarrow net-seller \\ p_i^n - t_p^s & if\ n_i > 0,\ m_i = 0,\ \delta_t^s = 1,\ \delta_t^b = 0;\ \Rightarrow seller \end{cases}$$

where $\tilde{p}$ is the shadow price.

The first order of conditions of Equation 6 yield the reduced forms of the supply and demand (8-9), conditional on market participation (7):

- Market participation determinants as a seller and/or buyer of i^{th} crop:

$$\theta_i = f(p_i^n, p_i^m, t_f^b, t_f^s, t_p^b, t_p^s, Q^s, Z) \tag{7}$$

- Output marketed supply ith crop:

$$n_i = f(p_i^n, p_i^m, t_p^b, t_p^s, Q^s, Z) \tag{8}$$

- Market purchase demand ith crop:

$$m_i = f(p_i^n, p_i^m, t_p^b, t_p^s, Q^s, Z) \tag{9}$$

where Q^s represents the production surplus if positive (deficit, otherwise) and a vector of household characteristics. The definition of production surplus (deficit) is the excess (shortfall) of production over household nutritional requirements. As a consequence the production status of a household determines the observed purchases (m_i) and sales (n_i). We now turn to the econometric models used to estimate Eq. 7-9.

3 Empirical model

Figure 1 provides an overview of the overall model. An initial probit (y_1, referred to as the "selectivity probit") estimates the determinants of producing a potential surplus (or potential deficit) of food crop. We define a farm household to have a potential surplus (deficit) whenever farm production exceeds (falls short of) household nutritional requirements, implying that the quantity sold is larger (smaller) than the quantity purchased. In addition, there are non-traders (autarchy), for whom we have no observed sales or purchases. However, non-traders may have being in surplus (or deficit), but not be able/willing to sell (buy), because of transactions costs or other constraints. For these reasons, our selectivity probit models share the non-trading observations.[3] Let Q^s_i be the potential surplus of the i^{th} food crop when $Q^s_i=(q_i-c_i)\geq 0$ (or the potential deficit $Q^s_i=(q_i-c_i)\leq 0$). In case of household with a potential surplus, we observe

$$y_1 = \begin{cases} 1\ if\ Q_i^s \geq 0 \\ 0\ otherwise \end{cases}$$

With y_2 denoting the categories of households with a marketable surplus, we can order the marketing intensity as:

$$y_2 = \begin{cases} 1\ [n_i = 0,\ m_i = 0] \Rightarrow autarchy \\ 2\ [n_i > 0,\ m_i = 0] \Rightarrow seller \\ 3\ [n_i > m_i > 0] \Rightarrow net-seller \end{cases} \quad . \tag{10}$$

Net-sellers are considered more active in the market than the sellers since in the same period of time they both buy and sell the same crop. The log-likelihood for the selectivity ordered probit estimator is:

[3] As a consequence we expect the estimations of the selectivity probit of having a potential surplus or a potential deficit to have slightly different coefficients.

$$
\begin{aligned}
\ell(\theta) = {} & \\
& 1[y_1 = 0]log[1 - \Phi(x^{'}\beta)] + 1[y_1 = 1]\{log[\Phi(x^{'}\beta)] + 1[y_2 = 1]\left(log[\Phi(\alpha_1 - x^{'}\beta)]\right) \\
& + 1[y_2 = 2]\left(log[\Phi(\alpha_2 - x^{'}\beta) - \Phi(\alpha_1 - x^{'}\beta)]\right) + 1[y_2 = 3]\left(log[\Phi(\alpha_2 - x^{'}\beta)]\right)\}, \quad (11)
\end{aligned}
$$

where x is a vector of characteristics specific to the household that influence the production activities, β the vector of parameters, α_1 and α_2 the cut-points or thresholds of the ordered model, and $\Phi(.)$ the standard normal cumulative distribution function that characterizes the probit model.

In case of a potential deficit (buyers), the selectivity specification (y'_1) and the ordered categories (y'_2) are respectively:

$$
y_1' = \begin{cases} 1 \ if \ Q_i^s \leq 0 \\ 0 \ otherwise \end{cases}
$$

$$
y_2' = \begin{cases} 1 \ [n_i = 0, \ m_i = 0] \Rightarrow autarchy \\ 2 \ [n_i = 0, \ m_i > 0] \Rightarrow buyer \\ 3 \ [m_i > n_i > 0] \Rightarrow net - buyer \end{cases} . \quad (12)
$$

A final stage uses a tobit model to estimate the determinants of quantity traded and aims to capture the fixed transactions costs. The rationale for using a tobit rather than a linear model is that the decision to not participate into the market is a rationale choice by households, based on their expected utility between participating vs. non-participating and the transactions costs they may face. The quantity traded by sellers (y_3), net-sellers (y_4), buyers (y_5), and net-buyers (y_6) is respectively computed as:

$$
\begin{cases} y_3 = n_i \ \ if \ n_i > 0, \ m_i = 0, \ Q_i^s > 0 & \Rightarrow sellers \\ y_4 = (n_i - m_i) \ \ if \ n_i > 0, \ m_i > 0, \ Q_i^s > 0 & \Rightarrow net - sellers \\ y_5 = m_i \ \ if \ n_i = 0, \ m_i > 0, \ Q_i^s < 0 & \Rightarrow buyers \\ y_6 = (m_i - n_i) \ \ if \ n_i > 0, \ m_i > 0, \ Q_i^s < 0 & \Rightarrow net - buyers \end{cases} .
$$

For each $k \in \{3, 4, 5, 6\}$, the underlying latent variable is expressed as

$$
y_k = \begin{cases} y_k^* = x^{'}\beta + \epsilon \ if \ y_k > L \\ L \ if \ y_k = L \end{cases} ,
$$

and the latent variable y_k^* satisfies the linear model assumption, and it implies the observed variable y_k to be equal to y_k^* when $y_k^*>0$.

The overall model allows the estimation of the determinants of fixed and proportional transactions costs as follows: from the ordered probit the effect of fixed and proportional transactions costs are determined based on the intensity of market participation, while the tobit is used to assess the proportional transactions costs based on the quantity traded.

4 Data description

The geographical focus of the analysis is Ghana, specifically the dry land savannah zones of northern regions (Northern, Upper East, and Upper West region) where primary data for the agricultural season 2008-2009 were collected by the author from November 2009 to March 2010. A household survey capturing detailed information on mobile phone usage and economic transactions was administered in three districts (Lawra in Upper West, Bongo in Upper East and Bunkpurugu-Yunyoo in Northern region).[4] We used a multi-stage sampling procedure, where within each district, five communities were randomly selected and thirty households surveyed in each community based on a proportional sampling approach. For this analysis, we used a sub-sample of 393 households that produce only grains and/or legumes, which are the main food crops in the region. Small-scale farmers in the study area are used to growing different crops to mitigate risk, as a consequence it would not have been sensible to focus on a single specific crop. Due to similar characteristics (non perishability) of grains and legumes, we aggregate them and treat them as a single output, aggregating on the crops' calorie contents.[5] The market position of each household is based on the quantity sold and purchased: where sales aggregate the quantity sold for each transaction, and purchases are estimated from the typical weekly purchases recorded in the survey. The total sample comprises buyers (31%), net-buyers (8%), autarchies (27%), sellers (16%), and net-sellers (19%). There are no neutral households in the survey.

Table 1 describes the variables used in the models. The household average size is almost eight people, and over 90 percent of the households are male-headed, with an average dependency ratio[6] of 0.87. Most of the households surveyed have at least one mobile phone, mainly used to communicate with relative and friends. Batteries, one of the main constraints where electricity is not available, are usually recharged from local entrepreneurs that for a small fee use automobile batteries to do the charging. Radios are slightly more common than cell phones, being present in six out of ten households surveyed. Over 60 percent of the respondents stated that they receive information on prices, with 40 percent seeking information by travelling to the source ("word of mouth") and less than 10 percent listening to the governmental market information bulletin on a radio. Approximately a third of the mobile users use it to received information on prices of agricultural commodities.[7] Interestingly, only 2 percent of the households used text messages to receive information, perhaps reflecting the low literacy among the sample (overall, individuals in schooling age have an average of less than 6 years of education), and the preferences of farmers in the study area, who appear to prefer personal interaction to more impersonal text messages. The most common sources of information are: neighbours (52%) followed by extension agents

[4] For the survey purposes, we define a household as a group of people living together, sharing common cooking arrangements, and pooling their incomes.

[5] We could have alternately aggregated the weight of the different crops, although it would not have considered the different water content and therefore the mass that have an influence in transport costs. The aggregation of values of crops, instead, would have made arduous to separate the transaction costs from the selling cost.

[6] The dependency ratio is the number of inactive individuals (household members under 15 years of age and the number of individuals over 64 years of age) per active member in the household (age 15 to 64 years old).

[7] At the time of the survey, in the study area no comprehensive government or non-governmental programmes of market information diffusion via mobile phone were being implemented. Therefore, farm households that used cell phones to receive price information privately contacted (or had been contacted by) an informant.

(25%). Twenty percent of mobile phone users (51 in the sample) receive information on best agricultural practices. The variables that are thought to explain the fixed transaction costs include the availability of information on prices, the means used, and the source. On the other hand, distance from the market, and bicycle ownership are considered to influence the proportional transaction costs. In the literature, studies have found evidence of the utility of cooperatives to cut transaction costs (Holloway *et al.*; 2000). However in our sample less than 9 percent of the households are associated with a cooperative, which did not allow us to explore its effect in the model. Finally, due to the unreliability on the savings data collected, we were not able to use it, although the economic model incorporates it. The monetary values are all in local currency, the Ghanaian cedis (GH¢)[8].

5 Corrections for sample selection and endogeneity

Two selectivity procedures are employed to correct the potential estimation issues. Since, for the second stage, we only observe households with a potential surplus (deficit), an initial selectivity probit is used to take account of a possible bias and generate consistent and efficient estimates. The probit and the ordered probit models are estimated simultaneously with full-information maximum likelihood (Eq. 11). A second selectivity procedure is deployed between the second and third stage. From the ordered probit a Heckman-Lee selectivity method is used to correct the possibility of bias due to sample selection in the following and last stage, when the intensity of trade is estimated with a tobit regression (Sabates-Wheeler; 2002).[9] Correcting for selectivity bias is justified by the fact that the market behaviour of farmers is not generally a random process, as they self-select into a particular marketing group based at least partly on transactions costs.

Due to the unobserved nature of transactions costs, variables that are thought to affect them may be endogenous in the model. Price information is likely to affect the intensity of market participation and quantity traded, but may also be determined by market participation itself confounding attempts to identify causation. In particular, the use of the mobile phone to receive price information by the household can be correlated (or otherwise not independent) with unobserved factors that affect the market participation, and thus be endogenous. Equally, households that are more active in the market may have the incentive to seek price information via mobiles and therefore the two variables influence each other. Based on the study area and discussions with the farmers, we judge that the use of the mobile phones to obtain price information can be related to the extent to which mobile phones are shared within the household (since the younger generation may be more likely to own one), and the intensity of their use. Since it is unlikely that these two characteristics affect the dependent variables (quantity traded, market participation status/group), we instrument the use of mobile phone to receive market information using whether the households spend more than GH¢ 3 each month in calls

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[8] The average exchange rate in 2009 was GH¢ 2.202/£ and GH¢ 1.413/$.

[9] The two inverse Mills ratios (IMRs) are constructed from a truncated bivariate normal distribution of the full probability function of the ordered probit. Following Sabates-Wheeler (2002), let $\theta_{\mu 1} = \alpha_1 - x'\beta$ and $\theta_{\mu 2} = \alpha_2 - x'\beta$, $IMR_1 = [\varphi(\theta_{\mu 1}) - \varphi(\theta_{\mu 2})]/[(\Phi(\theta_{\mu 1}) - \Phi(\theta_{\mu 2})]$ and $IMR_2 = -\varphi(\theta_{\mu 2})/[1 - (\Phi(\theta_{\mu 2})]$, where φ is the standard normal density function and Φ the cumulative standard normal distribution. This two-stage procedure gives unbiased estimates of the parameters.

(this amount would enable them to talk on average for half an hour, depending on the different cell phone carriers) and the degree of decision making within the household. We found the latter as the best variable that can proxy for the share of the mobile phones within the household. The rationale behind this choice is that since the mobile phones are more likely to be owned by the younger generation, in case the decision making process is collective they may also be used by older generation.

We used a two-stage procedure: in the ordered probit and tobit models we test whether receiving price information via mobile phone is indeed endogenous (Durbin-Wu-Hausman test), check that the instruments chosen are valid (Sargan-Hansen J-Test) and not weak (Wald test based on Stock and Yogo significance levels), and replace the predicted values into the model of interest. Since the potential endogenous variable is dichotomous, we run the instrumental regression within a probit model (Table 8 in Appendix 1). In the estimation of market participation of households with a potential marketable surplus, the Durbin-Wu-Hausman test could not reject the exogeneity of the use of mobile phone to get price information (suggesting an endogeneity issue), therefore we used the Sargan-Hansen which confirmed the validity of the instruments followed by the weak instrument test based on Stock and Yogo (2002). For the households in deficit, the variable did not appear to be endogenous. In the tobit models, only in the case of sellers did we confirm our suspicions of endogeneity. In all cases where we have a confirmation of endogeneity, we use IV estimates. The results of the tests for each model are reported in Table 9 in Appendix 1.

6 Results and analysis

This section presents and comments on the estimation of the economic model. The initial selectivity probit assesses the determinants of producing a surplus (or deficit) of food crops. The ordered probit that follows highlights the determinants of market intensity and the impact of the fixed and proportional transactions costs on market participation, in particular the impact of ICTs. The final tobit determines the intensity of quantity traded, emphasizing the roles of proportional transactions costs. For clarity, the section is divided in two parts, first analysing the households with a positive marketable surplus, followed by the households with a food deficit.

6.1 Households with a potential food surplus

Table 2 reports the estimates from the selectivity probit model. The results are as expected, where the probability of having a potential marketable surplus of food crop is positively related to the distance to the market and negatively to the availability of off-farm income. More remote households are more likely to focus the economic activities on agricultural production and rely on auto-consumption. Farmers with more experience are also more likely to produce a surplus; likewise the age of the head of household positively affects the probability of being in surplus (although increasing at a decreasing rate). Receiving best practices via mobile phone has a significant and negative impact, decreasing by 0.13 the probability of having a surplus. A possible explanation may be on the fact that households more in need of receiving best practices have less favourable land and for that reason less likely to have a surplus. This is supported by the fact that when we model the probability to have a deficit of food crop (Table 5), the best practice variable has a positive sign although not significant at 10 percent. On the other hand, we could have expected that households that receive best practices are more likely to produce a surplus. More detailed analysis are needed in this area to better understand and isolate the effect the use of mobile may have on the production activities. Finally, as expected, the calories harvested per capita consumption[10] is positively significant: the larger the harvest relative to the nutritional requirement of the household, the more likely the household will have a potential marketable surplus.

In the second stage, the results from the ordered probit are shown in Table 3. We find evidence that households that receive price information via mobile phones are significantly more active in the market (having corrected for endogeneity). This variable reduces the probability of being a non-trader by 0.58 and increases the probability of being a net-seller by 0.56. It also has a small and positive impact (0.02) for sellers. The effect of listening to price information on the radio has an opposite effect. It significantly decreases the likelihood of being a net-seller or seller. The use of different ICTs may have different influences on the marketing stance of households. Due to the different nature of the technologies, the use of mobiles may lead to a more active approach, where users come across different marketing options and reduce search costs. Instead, the use of radio may provide more limited information and not give exactly the information the users want. Among the different sources of information, extension agents have a strong effect on enhancing market participation, increasing the probability of a household being a net seller by 0.21 and reducing the probability of being a non-trader by 0.19. As in Aker (2011), this finding highlights the role of extension officers in sharing market information via visits or on mobile phones, where the reliability and the trust of the source probably plays an important role.

We do not find that ownership of a mobile phone or a radio to be a significant factor determining the market intensity. The uses to which ICTs are put are more important than the ownership itself. This is an important point, in the context of previous studies where the ownership of ICTs has been used as a variable influencing market participation. In our case proportional transactions costs do not have a significant effect on market participation. The distance to the market is negatively correlated to the market intensity, but is not significant at the 10 percent level. Examining the variables that capture the household characteristics, male heads of households are more likely to participate in the market. Finally, more experienced farmers — often associated with older age — are more likely to have lower market participation, although the impact is very small.

In the last stage, the determinants of the quantity traded by sellers and net-sellers are estimated (Table 4). The proportional transactions costs, which from the theory are meant to influence the intensity of trade, are represented by the distance to the market, the ownership of a bicycles, and indirectly by the use of ICTs. As expected net-sellers that live further away from the market trade significantly lower quantities, but distance to the market is not a significant factor for pure sellers. This suggests that pure sellers are not affected by the distance of the market, being willing

[10] The harvest per capita consumption is computed dividing the total calories harvested by the sum of the estimated calories needed by the household members based on the recommendation in FAO (2001).

(if not forced) to sell their surplus, regardless of the proportional transaction costs. ICTs play a role on the quantity traded by both types of actors. Pure sellers that receive market information via mobile phone are more likely to trade smaller quantities. In northern Ghana, larger quantities are more likely to receive buying offers at the farm-gate from dealers, so that mobiles might tend to be used to search for a buyer when the quantity traded is smaller and farm-gate buyers are not available. In this regard, households that have access to regular flow of information provided by radios are likely to trade larger quantities. On the other hand, for net-sellers the use of radio significantly reduces the ratio between sales and purchases and therefore change the pattern of crop sold and consumed. An inexpensive and regular flow of information may allow farmers to make best use of their money and possibly take advantage of price volatility in the market. The ownership of radios or mobile phones has no apparent effect, as with marketing intensity above.

Among sellers, we found that wealthier households (where they have livestock bigger herd) are inclined to sell more of staple food crop; any additional Tropical Livestock Unit (TLU) increases the quantity traded by 20.000 calories (equivalent to six kilograms of maize). Generally wealthier households are more likely to afford the use of inputs (fertilizers and hired labour) and likely to be willing to participate in the market as a cash buyer of food. Finally, the fact that sales prices are negatively correlated with the quantity traded should not be surprising given the environment of the study area. Price variation in the sample closely reflects spatial price differences, being prices higher in net-deficit areas (such as some communities in Upper East region). Additionally, among subsistence smallholders market participation may be aimed at achieving a fixed level of income in order to meet other needs. Once the target level of income is reached, they may decide to consume the remaining part of the own production. Similar behaviour has been shown in Martin (1992), where the supply curve is backward bending. Prices elasticity is then negative, with a magnitude of -1.35 for the sellers supply.

6.2 Households with a potential food deficit

Results from the probit model are shown in Table 5 and their interpretation is intuitive with the directions of the variables substantially the reverse of the food surplus model (Table 2). As expected, households that invest more in inputs are less likely to be potentially deficit in food crops. On the other hand, smallholders with a deficit of family labour (captured by the land per adult variable) are less likely to be sellers or net-sellers. Equally, income generated from off-farm activities increases the likelihood of being in food deficit. Typically in northern Ghana households with less fertile land tend to have off-farm activities rather than focusing their activity on food production, so both need and are able to buy the food to meet their needs. Regional dummies indicate that the Upper East region is significantly disadvantaged in the production of marketable surplus, while households closer to the market are more likely to rely on purchased food than to produce their own. As expected farm households with larger availability of food (calories harvested per capita consumption) are less likely to participate in the market as buyers.

The results of the second stage ordered probit are reported in Table 6. Receiving information on market prices via mobile phone has a positive impact on the market intensity, as for the sellers above. It reduces the probability of being a non-trader by 0.26, and increases the probability of being a buyer or net-buyer by 0.18 and 0.08 respectively. Likewise, the use of radio has an impact and in this case larger than the use of mobile phones. Households with a food deficit are likely to buy regularly (weekly or fortnight) and in small quantities. For them, radio bulletins provide a regularly updated flow of information at minimal cost, which offers to take advantages of any price volatility and buy more when prices are lower. Although extension officers significantly increase market intensity for food surplus households, their effect is the opposite for food deficit households. Greater use of extension advice might indicate improved household production and hence less likelihood of being deficit. As in the case of households with a potential marketable surplus, the ownership of the mobile phones and radios is not a significant factor. This again emphasises the finding that it is the actual use of the ICT tools rather than ownership which is relevant for market participations. Fixed transactions costs, represented by the distance to the market, do not appear to be significant as a determinant of the probability of being in food deficit.

As expected, off-farm income affects the intensity of market participation; any additional off-farm income increases the probability of being a buyer or net-buyer by 0.04 and 0.01 respectively, since households that focus their resource on off-farm activities are more likely to need to buy food crops from the market and also to income to allow them to rely on purchased food. As in the case of households with marketable surplus, female heads of the households are likely to be less active in the market and farming experience has a negative but small impact on the market intensity, resulting in households being more likely autarky.

The estimates of the determinants of the quantity traded for buyers and net-buyers are shown in Table 7. Focusing first on the role of transaction costs, as expected, the distance to the market has a negative impact on the quantity traded for both buyers and net-buyers, with a bigger impact on the latter where each additional kilometre from the market reduces the quantity traded by 120,500 calories per year (equivalent to around 35 kilograms of maize) . Net-buyers do not seem to change their patterns of consumption due to more comprehensive market information. Instead pure buyers that seek price information via mobile phone and "word of mouth" tend to buy less. Possibly they check for prices to save money and maximize their purchasing power. In addition, households less dependent on food purchases (lower deficits) may not need or find useful to exploit the buying advantages.

As for sellers and net-sellers, we find hints of a possible interconnection of the staples market and the livestock market. Net-buyers are likely to buy more food when their income deriving from sales of livestock increases, suggesting that households with a food deficit tend to be sellers in the livestock market. As expected, higher income from off-farm activities results in higher quantity traded by pure buyers. On the one hand, they may have more income available to meet the demand for food crop; on the other hand less family labour may be allocated to production of food crop and necessitating market purchases. The average purchase price has a negative effect on the quantity purchased, with a price elasticity of -1.27 for the buyers demand. Food demand is typically considered inelastic, however in the study area where most of the households are primarily subsistence farmers, the income constraint is likely to limit opportunities for substitution and adjustment of production (self-supply) is also constrained and not likely to be immediate.

7 Conclusions

We have developed a model to investigate the impact of different ICTs on farmers' market participation in food crop markets in northern Ghana. We find evidence that receiving prices of agricultural product via mobile phones significantly increases market participation for both smallholders with a deficit and with a surplus of food. We also find that different use of technology translates into different marketing intensities. Farm households that rely on mobile phones to receive price information are more likely to trade less, possibly trying to maximize the profit from a small transaction or using the mobile phone to lower the search costs. On the other hand, farmers that both buy and sell food are more likely to increase their purchases if they listen to market information to the radio. Mobile phones seem to be more effective in encouraging entry to the market, reducing search costs, while listening to market information on the radio seems to influence the quantity traded and affect the patterns of purchases and sales.

We find that the ownership of mobile phones and radios are not significant factors in enhancing market participation in any of the models estimated, highlighting the fact that it is the use of ICTs rather than the ownership which matters. This is in contrast to much of the current literature on transaction costs and market participation, where the effect of communication tools have been assessed mainly based on ownership. We identify a weak impact of the use of mobile phones to receive agricultural best practices on the production of surplus. However, implications are difficult to draw and further investigation of this relationship is required.

From these findings, we draw two main lessons to support policy. Firstly, different technologies meet different users' needs. Mobile phones can indeed enhance market participation among smallholders in northern Ghana. However, radio bulletins seem best suited to allow these households to optimise their purchase and sales patterns. Any Market Information System should use the different technologies based on the targeted recipients, taking into account farmers' technological literacy and their ability to write and read text messages. Secondly, the role of extension officers in the diffusion of market information and support of farmers appears to be critical, as found by Aker (2011). Households with a marketable surplus rely strongly on their information to increase market participation, probably seeing them as a trustworthy and reliable source. A more active role of extension officers in this field may be considered, and at the same time the use of technology can also support their work to deliver more accurate and updated advice and information.

Figure 1: Empirical framework

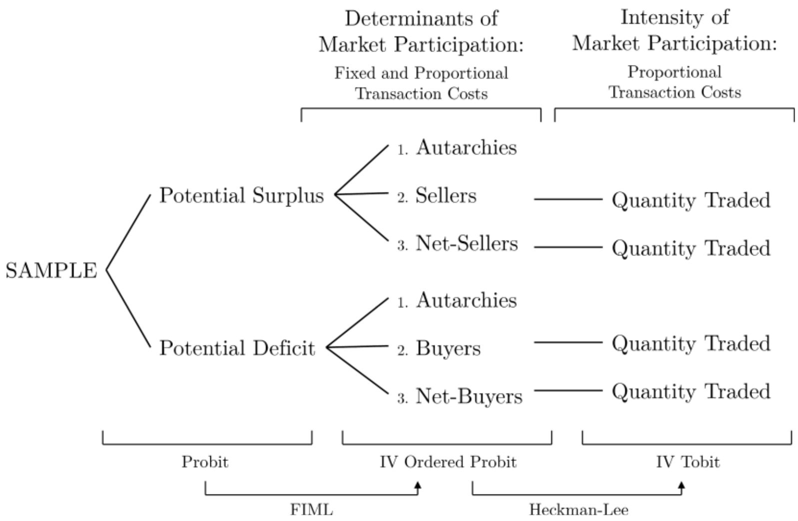

Table 1: Definitions and summary statistics of the variables used in the analysis.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Household characteristics					
Gender of household head (1= male, 0 otherwise)	393	0.91	0.29	0	1
Household head age (years)	393	53.32	15.55	24	95
Household head experience (years of farming)	393	30.21	15.58	2	70
Household head education (years of formal schooling)	393	2.30	4.37	0	20
Dependency ratio	393	0.87	0.69	0	4
Decision making (1=Head alone, 4=Entire Household)	393	1.58	1.02	1	4
Fixed and variable transactions costs determinants					
Receiving information on prices via mobile phone dummy	393	0.18	0.38	0	1
Receiving information on prices via radio dummy	393	0.08	0.27	0	1
Receiving information on prices via "word of mouth" dummy	393	0.40	0.49	0	1
Receiving information on prices from extension agents dummy	393	0.25	0.43	0	1
Receiving information on prices from neighbours dummy	393	0.52	0.50	0	1
Distance to the market (Km)	393	4.84	3.16	0	16
Bike ownership dummy	393	0.77	0.42	0	1
Mobile phone ownership dummy	393	0.55	0.50	0	1
Monthly expenditure on mobile phone calls > GH¢ 3 dummy	393	0.49	0.50	0	1
Radio ownership dummy	393	0.59	0.49	0	1
Production characteristics and assets					
Land per adult (in hectare)	393	0.47	0.34	0.06	2.40
Household and self-help labour (days)	393	586.15	530.63	0	4476
Inputs used (included hired labour) (in GH¢)	393	181.91	217.35	0.33	2015.21
Agricultural best practices received via mobile phone dummy	393	0.13	0.34	0	1
Calories harvested per capita consumption	393	311.56	266.03	7.26	1696.84
Tropical Livestock Unit (TLU)	393	3.07	3.51	0	23.43
Total income from livestock sales (in log GH¢)	393	2.06	2.32	0	7.58
Total income from off-farm activities (in log GH¢)	393	4.08	3.07	0	8.65
Output					
Output for buyers (in 1.000 Calories)	120	834.90	699.48	18.01	3570.49
Output for net-buyers (in 1.000 Calories)	30	492.40	524.26	4.43	2070.64
Output for sellers (in 1.000 Calories)	62	2208.34	2237.33	27.39	9377.70
Output for net-sellers (in 1.000 Calories)	74	3746.49	3072.93	82.06	13226.78
Average price for 1.000 calories purchased (in log GH¢)	224	-1.67	0.31	-2.48	-1.12
Average price for 1.000 calories sold (in log GH¢)	166	-2.35	0.47	-3.40	-1.26
Regional dummies					
North Region dummy	393	0.36	0.48	0	1
Upper West Region dummy	393	0.28	0.45	0	1

Table 2: First stage: Probit model on households with potential marketable surplus of food crop

	Coeff.	Std. Err.	ME
North Region	0.17	0.19	0.06
Upper West	0.95***	0.22	0.31
Household head gender	-0.16	0.27	-0.06
Household head age	0.08**	0.03	0.03
Household head age squared	-1E-03***	0.00	0.00
Dependency ratio	-0.13	0.13	-0.05
Household head education	0.00	0.02	-1E-03
Household head experience	1E-03*	0.01	0.01
Land per adult	0.12	0.38	0.05
Distance to the market	0.04*	0.03	0.02
Inputs	1E-03	5E-06	2E-05
Household and self-help labour	-7E-06	2E-05	-2E-06
Agricultural best practices received via mobile phone	-0.34*	0.21	-0.13
Off-farm income (log)	-0.12***	0.03	-0.04
Calories harvested per capita consumption	0.01**	1E-03	5E-05
Constant	-2.15**	0.97	
Overall correct prediction (%)	77.61		

***, **, * indicate statistical significance at 0.01, 0.05, 0.1 levels respectively, using robust standard errors.

Table 3: Second stage potential marketable surplus of food crop: Ordered probit on market intensity

			Marginal Effect		
	Coeff.	Std. Err.	Autarchies	Sellers	Net-Sellers
North region	1.36***	0.37	-0.43	-0.05	0.48
Upper West region	0.42	0.35	-0.15	-0.01	0.15
Gender of household head	0.45*	0.27	-0.17	0.03	0.14
Household head age	0.01	0.01	-0.01	2E-05	0.01
Dependency ratio	0.03	0.12	-0.01	5E-05	0.01
Household head education	0.01	0.02	-2E-03	1E-05	2E-03
Household head experience	-0.02**	0.01	0.01	-2E-05	-0.01
Mobile phone ownership	-0.17	0.24	0.06	-2E-03	-0.06
Radio ownership	-0.08	0.17	0.03	-1E-03	-0.03
Receiving information on prices via mobile phone (IV)	1.58**	0.69	-0.58	0.02	0.56
Receiving information on prices via "word of mouth"	-0.07	0.22	0.03	-1E-03	-0.02
Receiving information on prices via radio	-0.59*	0.33	0.23	-0.05	-0.18
Receiving information on prices from extension agents	0.58***	0.22	-0.20	-0.02	0.21
Receiving information on prices from neighbours	-0.08	0.21	0.03	-1E-03	-0.03
Bike ownership	0.04	0.20	-0.02	1E-03	0.02
Distance to the market	-0.04	0.03	0.01	-1E-03	-0.01
Off-farm income (log)	-2E-03	0.03	1E-03	-3E-06	-1E-03
Calories harvested per capita consumption	1E-03**	6E-05	-4E-05	1E-06	3E-05
$\rho^{\dagger}$	-0.69*				
α_{11}	1.19*				
α_{12}	2.11***				
Log pseudo-likelihood	-396.32				
Wald $\chi^2(18)$	87.74***				
Overall correct prediction (%)	63.79				

***, **, * indicate statistical significance at 0.01, 0.05, 0.1 levels respectively, using robust standard errors. † The correlation parameter between the first stage probit and the ordered probit.

Table 4: Third stage: Tobit on quantity traded for sellers and net-sellers (in thousands of calories)

	Sellers			Net-sellers		
	Coeff.	Std. Err.	ME‡	Coeff.	Std. Err.	ME‡
Mobile ownership	1120.12	846.46	149.04	1072.02	831.51	91.14
Radio ownership	520.00	595.62	69.19	273.33	629.55	23.24
Receiving information on prices via mobile phone (IV for sellers)	-6775.84**	2953.67	-901.60	30.55	1070.61	2.60
Receiving information on prices via "word of mouth"	-58.42	672.07	-7.77	-91.91	741.16	-7.81
Receiving information on prices via radio	1396.17*	725.53	185.78	-5669.52***	1786.21	-481.99
Bike ownership	-272.11	860.92	-36.21	107.21	810.87	9.11
Distance to the market	78.01	124.54	10.38	-216.83**	107.15	-18.43
Off-farm income (log)	96.41	155.72	12.83	169.22	146.23	14.39
TLU	151.38*	88.29	20.14	-26.31	100.05	-2.24
Income from livestock (log)	65.66	123.39	8.74	19.17	166.95	1.63
Inverted mills ratios (IMRs)	-104.08	1170.74	-13.85	-3122.36**	1542.51	-265.44
Calories harvested per capita consumption	1.77	2.30	0.24	3.30	2.12	0.28
Average price per purchase (log)				-4244.76***	606.10	-360.86
Average price per sales (log)	-2794.38***	350.63	-371.82	-3399.35***	444.70	-288.99
Constant	-8493.31***	2989.37		-9969.83**	4549.07	
σ	3092.11***	327.80		2883.34***	298.02	
Pseudo R^2	0.10			0.17		
Log pseudo-likelihood	-642.57			-722.81		
Likelihood ratio χ^2	5.53***			7.14***		

***, **, * indicate statistical significance at 0.01, 0.05, 0.1 levels respectively, using robust standard errors. ‡The marginal effect has been calculated as the "conditional expectation" at the mean. The estimations include (not shown) household characteristics (age, gender and level of education of the head of the household, and dependency ratio) and regional dummies.

Table 5: First stage: Probit model on households with potential deficit of food crop

	Coeff.	Std. Err.	ME
North Region	-0.99***	0.24	-0.35
Upper West	-1.41***	0.25	-0.51
Household head gender	-0.41	0.33	-0.13
Household head age	-0.05	0.04	-0.02
Household head age squared	5E-05	5E-05	2E-05
Dependency ratio	-0.13	0.12	-0.04
Household head education	0.01	0.02	0.01
Household head experience	-4E-03	0.01	-1E-03
Land per adult	0.89***	0.34	0.31
Distance to the market	-0.04*	0.02	-0.01
Inputs	-2E-03***	4.7E-05	-1.0E-03
Household and self-help labour	1E-03	2E-05	2E-06
Agricultural best practices received via mobile phone	0.12	0.22	0.04
Off-farm income (log)	0.06**	0.03	0.02
Calories harvested per capita consumption	-3E-03***	1E-03	-1E-03
Constant	3.91***	1.13	
Overall correct prediction (%)	80.41		

***, **, * indicate statistical significance at 0.01, 0.05, 0.1 levels respectively, using robust standard errors.

Table 6: Second stage potential deficit of food crop: Ordered probit on market intensity

			Marginal Effect		
	Coeff.	Std. Err.	Autarchies	Sellers	Net-Sellers
North region	0.30	0.25	-0.12	0.09	0.03
Upper West region	-0.86***	0.23	0.31	-0.26	-0.05
Gender of household head	0.46*	0.26	-0.17	0.14	0.03
Household head age	0.01	0.01	-3E-03	2E-03	1E-03
Dependency ratio	0.19*	0.10	-0.07	0.06	0.02
Household head education	-0.02	0.02	0.01	-0.01	-2E-03
Household head experience	-0.02***	0.01	0.01	-0.01	-1E-03
Mobile phone ownership	-0.10	0.15	0.04	-0.03	-0.01
Radio ownership	0.07	0.16	-0.03	0.02	0.01
Receiving information on prices via mobile phone (IV)	0.66**	0.32	-0.26	0.18	0.08
Receiving information on prices via "word of mouth"	-0.09	0.29	0.04	-0.03	-0.01
Receiving information on prices via radio	0.75*	0.46	-0.29	0.19	0.11
Receiving information on prices from extension agents	-0.55*	0.29	0.21	-0.17	-0.04
Receiving information on prices from neighbours	0.14	0.26	-0.06	0.04	0.01
Bike ownership	0.18	0.18	-0.07	0.06	0.01
Distance to the market	-0.04	0.03	0.02	-0.01	-3E-03
Off-farm income (log)	0.11***	0.03	-0.05	0.04	0.01
Calories harvested per capita consumption	-4E-05	1E-03	1E-05	-1E-05	-3E-06
$\rho^{\dagger}$	1.145*				
α_{11}	0.78				
α_{12}	2.383***				
Log pseudo-likelihood	-368.68				
Wald $\chi^2(18)$	105.41***				
Overall correct prediction (%)	61.09				

***, **, * indicate statistical significance at 0.01, 0.05, 0.1 levels respectively, using robust standard errors. † The correlation parameter between the first stage probit and the ordered probit.

Table 7: Third stage: Tobit on quantity traded for buyers and net-buyers (in thousands of calories)

	Buyers			Net-buyers		
	Coeff.	Std. Err.	ME‡	Coeff.	Std. Err.	ME‡
Mobile ownership	159.89	161.85	31.52	-342.46	235.66	-21.57
Radio ownership	232.59	145.16	45.85	-90.81	170.01	-5.72
Receiving information on prices via mobile phone (IV for sellers)	-556.19**	219.13	-109.64	431.27	319.33	27.16
Receiving information on prices via "word of mouth"	-329.19**	146.55	-64.89	-56.25	220.61	-3.54
Receiving information on prices via radio	-188.26	345.52	-37.11	449.56*	272.9	28.31
Bike ownership	73.01	170.39	14.39	385.60*	209.97	24.28
Distance to the market	-46.68*	27.04	-9.20	-120.50***	40.35	-7.59
Off-farm income (log)	94.36***	29.64	18.60	19.47	33.04	1.23
TLU	6.35	20.82	1.25	0.84	26.66	0.05
Income from livestock (log)	-7.79	33.59	-1.54	127.97***	47.68	8.06
Inverted mills ratios (IMRs)	-294.63	248.98	-58.08	88.22	301.61	5.56
Calories harvested per capita consumption	-1.31**	0.64	-0.26	-4.00***	1.36	-0.25
Average price per purchase (log)	-1107.73***	105.67	-218.37	-673.74***	176.26	-42.43
Average price per sales (log)				-762.92***	134.63	-48.04
Constant	-1026.25**	449.81		-2041.23***	663.64	
σ	909.83***	76.06		680.26***	129.97	
Pseudo R^2	0.10			0.17		
Log pseudo-likelihood	-1055.96			-262.52		
Likelihood ratio χ^2	8.29***			2.94***		

***, **, * indicate statistical significance at 0.01, 0.05, 0.1 levels respectively, using robust standard errors. ‡The marginal effect has been calculated as the "conditional expectation" at the mean. The estimations include (not shown) household characteristics (age, gender and level of education of the head of the household, and dependency ratio) and regional dummies.

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Appendix

Table 8: Instrument variable (IV): Probit model

	Coeff	Std Err	ME
North Region	0.74***	0.19	0.14
Upper West Region	0.07	0.24	0.01
Decision making	0.15**	0.08	0.03
Monthly expenditure on mobile phone calls	1.49***	0.21	0.28
Constant	-2.51***	0.27	
Pseudo R^2	0.24		
Log pseudo-likelihood	-139.76		
Likelihood ratio χ^2	61.02***		
Overall correct prediction (%)	83.97		

***, **, * indicate statistical significance at 0.01, 0.05, 0.1 levels respectively, using robust standard errors.

Table 9: Instrument tests

	y_2	y'_2	y_3	y_4	y_5	y_6
H_0: Receiving information on prices via mobile phone is exogenous						
Durbin-Wu-Hausman Test	5.67**	1.86	5.07**	0.13	1.50	0.67
H_0: Instruments are valid						
Sargan-Hansen J-Test	0.58	0.59	1.18	4.14**	0.50	0.08
H_0: Chosen instruments are weak						
Weak instrument	6.77**	4.38**	16.98***	0.31	0.48	0.45

***, **, * indicate statistical significance at 0.01, 0.05, 0.1 levels respectively, using robust standard errors.