Mobile Phones and Farmers' Marketing Decisions in Ethiopia[1]

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Abstract

This paper examines the impact of mobile phones on farmers' marketing decisions (spatial arbitrage, buyer's choice, frequency of selling, and size of transaction) and prices they receive based on household and village level information collected from rural Ethiopia. It explains the reason for the weak impact of mobile phones observed in this study as well as in previous studies in Africa. We argue that even though many farmers participate in information searching, the number of farmers who use mobile phones for information searching is very small. The reason for such low use of mobile phones for information searching seems lack of quality information that can be accessed through mobile phones.

Key words*: mobile phones, agricultural marketing, producer prices, smallholder farmers, Ethiopia*

Introduction

Access to information, an important input for making agricultural decisions in production, marketing and finance, has historically been very costly in Africa South of the Sahara. Farmers who want to sell their products have to search for the right price, the right buyer, the right standards and grades of the product. All these searches are costly. Farmers need to do frequent travel, repeated loading and unloading to showcase their produce to buyers and brokers. Typical farmers in Ethiopia sell produce to traders either in their village or in distant markets which entails substantial transportation and labor costs. The village markets are characterized by asymmetric information in which traders are more informed than farmers about the prices in the central or regional markets (Tadesse & Shively, 2013) that makes information searching very costly. Besides the searching cost for price information from the central market, farmers have to incur substantial searching cost to compare prices of different buyers in local markets. Prices also vary within days and weeks which forces farmers to search for information every time they want to sell.

Excessive market searching cost causes smallholders to produce very limited range of goods and services. In the extreme case, it leads to households to produce only for home consumption. It also constrains them to apply low levels of external input and become less responsive to market changes(Holden, Shiferaw, & Pender, 2001; Sadoulet & Janvry, 1995). Hence, farmers do not realize the gains from trade and are unable maximize annual farm income through specialization according to long term comparative advantages.

Expansion of mobile phones coverage is considered one of the remedies for such an information problem. The percentage of the world's population with mobile phone coverage rose from around 12% in 1999 to around 76% in 2009. Almost three-fourths of the world's mobile phones in 2010 were in developing countries (Donovan, 2011). In many developing countries, more people have access to mobile phones than to older technologies like telephone landlines, newspapers, and radio(Aker, 2011). Improved regulatory environments, technological innovations, and payment options attractive to poor people such as pre-pay plans have all enabled the rapid uptake of mobile phones (Donovan, 2011). As a result, mobile phone coverage is widely expanding in Africa (Aker & Mbiti, 2010). For example, Ethiopia, one of the lowest ICT penetrated countries in Africa, had more than 17.26 million mobile subscribers in 2012 (TeleGeography, 2012). Although many of

the subscribers are in urban centers and small towns, the penetration to rural areas is also remarkable and growing very fast over time (Figure 1). According to Minten, Stifel, and Tamru (2012), in 2005 almost all rural agricultural wholesale markets had access to mobile phones. With the expansion of rural electrification, many farmers have got access to mobile telephone services in recent periods although the network coverage is still very poor.

Many studies, with few exceptions, have confirmed that mobile phones are indeed improving farmers' production practices and adoption of new practices. Lio and Liu (2006) found that the adoption of new ICTs increases overall agricultural productivity, perhaps because ICT infrastructure facilitates the adoption of modern agricultural inputs. Mittal, Gandhi, and G.Tripathi (2010) interviewed Indian farmers and fisherman who stated that information delivered via mobile phone allowed them to increase yields. However, an experiment on the effect of the Reuters Market Light (RML) information service in India failed to find significant effects of the information service on crop varieties grown or on production practices (Fafchamps & Minten, 2012).

Mobile phone coverage has also improved market efficiency and reduced consumer prices for certain commodities. According to Jensen (2007) mobile phone coverage improved market functioning in Kerala, India. Aker and Fafchamps (2013) assessed the impact of mobile phones on agricultural price dispersions in Niger. The study found that while mobile phone coverage reduced the spatial dispersion of producer prices for semi perishable commodities like cowpeas; it had no impact on non-perishable commodities such as millet and sorghum at all. The study further found that farmers owning mobile phones obtained more price information but did not receive higher prices. The explanation given was non-participation of farmers in spatial arbitrage. In Ethiopia, access to mobile phones has improved traders and brokers' business communication for negotiating prices and settling payments (Minten et al., 2012).

However, studies assessing the impact of cell phone on producers marketing decisions are few. The existing studies that assessed the link between ICT and farmer's market participation have found that access to mobile phone did not significantly improve farmers' market participation and spatial arbitrage (Alene et al., 2008; Fafchamps & Minten, 2012; Muto & Yamano, 2009). The reason for such insignificant impact is not yet well explained. For mobile phones to influence

3

farmers' decision and generate economic benefits, farmers' marketing decision should first be guided by market information. Smallholders may sell when they are in need of cash or when they have surplus output beyond their home consumption irrespective of what is going on in the market. In this case, having a mobile phone may not necessarily matter for farmers marketing decisions. Second, farmers must use mobile phones for information searching. This is contingent upon the presence of an information source that can deliver reliable, trusted and understandable information to address specific needs and create awareness on different uses of mobile phones including call-in and SMS-services. Third, the cost of using mobile phones should be within the capacity of smallholders who have limited access to electricity and air-time credits.

The objective of this paper is to examine the effect of mobile phones expansion in rural Ethiopia on farmers' marketing decisions and prices they receive. It is aimed at providing farm level evidence to translate technological opportunities into economic benefits. Specifically, the paper responds to the following research questions: 1) Do farmers with mobile phones make different marketing decisions (place of selling (spatial arbitrage), frequency of selling and quantity of selling) than those who do not have access to mobile phones? 2) Do farmers with mobile phones access receive higher prices than those who have no access to mobile phones? 3) Do smallholder farmers really search information before making marketing decisions? 4) Do farmers use mobile phone for searching information? By addressing these questions, the paper contributes to the growing literature on the impact of mobile phones on smallholders' marketing decision and the price they receive. It also presents new insights on why mobile phone impact is weak in farm households marketing decisions in Africa.

These insights are derived from a series of econometric models estimated using household survey data collected from central and southern Ethiopia. The first model estimated the effect of mobile phones access on the probability of selling to different market places including village market, district market and central market. The second model estimated the impact of mobile phones access on frequency and quantity of output sold and price received by farmers. We also studied whether farmers really use mobile phones for information searching or not. We find that the impact of mobile phone access on farmers marketing decision (market arbitrage) and the price they receive is very weak, which is similar to the findings of previous studies in other countries (Aker & Fafchamps, 2013; Fafchamps & Minten, 2012). However, the explanation is less likely to relate to

non-participation of farmers in spatial or temporal arbitrage at least in the Ethiopian context. Even though many farmers participate in information searching (and market arbitrage), the number of farmers who use mobile phones for information searching is very small. The reason for such low use of mobile phones for information searching seems to be lack of quality information that can be accessed through mobile phones. The results are further discussed to shed light on the need for organized and trusted institutions that can deliver information to farmers through ICT.

The paper is organized as follows. The next section presents the conceptual framework, which lays the theoretical foundation of the paper. This section is followed by a brief explanation of the data used to test the hypotheses presented in the conceptual framework. The empirical models are explained in the subsequent estimation strategy section. Then, we present the results and discussion of the main findings of the paper. Finally, we conclude by highlighting key policy and research recommendations.

Conceptual Framework

To ascertain the importance of mobile phones for smallholder farmers, we must first understand how famers make marketing decisions and how information plays a role in these decisions. The literature on farm households marketing decision behavior is very diverse and usually relates to production, marketing or trade analysis. In a neoclassical economic theory where markets are assumed to be perfect and competitive, marketing decisions are not separable from production decisions because in these markets prices are competitive and differ across places, times and forms only to the extent of the competitive cost that requires the product to move from one place to other, or across time, or to convert from one form to another. However, in many cases markets are not perfect or competitive. In this case, prices become endogenous (deJanvry, M.Fafchamps, & Sadoulet, 1991; Singh, Squire, & Strauss, 1986). Farm households have to make a calculated decision on where to sell, when to sell, how much to sell and to whom to sell in order to receive the highest price possible to maximize their revenue.

According to the new farm household economics, the net price farmers receive from the market depends on the extent of market imperfection which is measured in terms of transaction costs. What determines transaction costs is a subject thoroughly studied by many authors. Summarizing

5

the major studies indicates that transaction costs depend on the nature of transaction (Williamson, 1979) and the extent of information asymmetry and searching (Fafchamps, 2004; Stiglitz, 1986). Transaction costs depend on asset specificity, frequency of transaction and uncertainty of transaction, which mainly stems from information uncertainty (Williamson, 1985). Information searching is costly in Africa(Fafchamps, 2004). It surges the level of transaction costs, thereby reducing the net price farmers receive. In general, information searching cost is an important component of transaction costs in an economy where markets are characterized by imperfections, implying that reducing information searching cost is an important development goal to improve farm households marketing and commercialization.

Many institutional and technological innovations have been evolved to reduce transaction cost in general information searching in particular. Mobile phone is one of the technological innovations that have been praised for reducing information costs not only in industrial sectors but also in agriculture and social sectors(Aker & Mbiti, 2010). In rural communities, mobile phones help in facilitating social and business communications. With the advent of mobile phones, many rural communities can easily communicate on social affairs such as funeral services, wedding ceremonies and religious matters. Similarly, access to mobile phones eases the process of farmers' market information searching at a lower cost than other mechanisms (Aker, 2011; Jensen, 2010). With the help of mobile phones, farmers can decide on where, to whom and when to sell their products and purchase inputs more easily than without mobile phones. Therefore, access to mobile phones can build farmers confidence (reduce information uncertainty) on transactions, reduce marketing costs and help them to receive higher prices.

In summary, having mobile phones reduces information searching cost that prompts farmers to relax their choices over different alternatives of marketing. By properly assessing such alternatives, farmers can receive higher prices. However, such high price or market arbitrage will surely be attributed to mobile phones access if farmers do search information while packing for sale and are actually using the mobile phones for searching. This logical framework allows us to distinguish three sets of empirically testable variables. The first group includes intermediate (outcome) variables representing marketing decisions such as: 1) farmers choice of market places; 2) frequency of selling and 3) quantity sold. The second group is the impact variables represented by prices received by farmers for different commodities. The third is a conditioning variable that

represents the use of mobile phone for information searching. Estimating all these variables along the impact pathway helps to ascertain the impact of mobile phone on marketing decisions due to easing information searching.

Data

The data used in this paper are extracted from a household survey conducted in 2012 in central Ethiopia where farmers are considered as surplus producers. The survey was conducted as a baseline study for a project that aimed at empowering smallholder farmers through organizing cooperatives and introducing ICTs for agricultural marketing. A multi-stage sampling technique was used to select sample households. In the first stage, we selected six districts from the four administrative zones of the Oromia regional state, which is the largest region in Ethiopia. The districts (locally called *Woredas*) were randomly selected from the list of districts where the project operates. The sample districts were Sinana*, Shashemene, Arsi Negele, Sedden Soddo, Becho* and *Jeldu*. These districts have different agro-ecologies and farming systems. While *Sinana* is located in the eastern highlands of Ethiopia where barley and wheat are the two most important cropping systems, *Sedden Soddo, Becho and Jeldu* districts are located in the central highlands of Ethiopia where *teff* is a dominant cropping system. The other two districts –*Arsi Negelle* and *ShaShemene* are located in the southern highlands of the country where farmers mainly grow maize and wheat.

In the second stage, we selected sample villages, locally known as *Kebeles*, from each district. To select sample villages, we grouped villages within a district based on the presence of a cooperative in the village. Sample villages were randomly selected from each group. The number of villages selected from each district depended on the number of villages which have cooperatives. In total, 24 (16 with cooperatives and 8 without cooperatives) villages were selected. The number of sample villages with cooperative is higher than the number of sample villages without cooperatives because of larger number of villages with cooperatives than villages without cooperatives.

Sampling of households was done differently in villages with and without cooperatives. In a village where there is a cooperative, we chose both members and nonmembers of the producer cooperatives. In a village where there no cooperative, all the samples are non-members. Samples are randomly drawn from the list of cooperative members and from the list of residents of a village for non-members. We chose a larger number of samples from a village with a cooperative than

from a village without a cooperative. A total of 1023 households were selected for interviews. However, the sample size used to estimate each model is different due to missing values and inappropriateness of some variables for certain farmers.

Sample households were interviewed by experienced and well-trained enumerators who were hired for this purpose using a structured and pretested questionnaire. The questionnaire used to collect the data was very rich and contained many variables related to market access, information searching, marketing practices and total value sold for different crops. The use of mobile phone for information searching was specifically asked in order to understand the role of ICTs for accessing markets. Other demographic and socioeconomic information were also collected. The major characteristics of sample households used for this study are presented in Table 1.

Estimation procedures

Informed by the conceptual framework outlined above, our empirical estimation follows step-wise procedures to test several hypothesis along the change pathway. We first estimated the effect of mobile phone access on outcome variables representing market arbitrage and frequency and size of transaction such as farmers' choice of marketplaces, frequency of selling and quantity sold. Then, we estimated the impact of mobile phone ownership and access on prices received. Finally, we estimated determinants of mobile phone use for information searching. This is helpful to understand the reason behind the presence or absence of empirical link between mobile phone access and farm gate prices. The dependent variables take different values, calling for different types of econometric models to be estimated. Depending on the type of dependent variables, we used the following four types of estimation methods:

1: Bivariate probit for estimating where-to-sell and whom-to-sell. Both conceptually and empirically, farmers' choice of selling a commodity either to the village market or distant market and selling to the cooperative or private trader are contemporaneously correlated. As a result we estimated them together to improve the efficiency of the parameters estimates.

2: Ordered probit for estimating the frequency of transaction (selling) in which the dependent variable takes ordered values as once per year, twice per year and more than twice per year

3: Ordinary Least Square (OLS) for estimating the average price received and size of transaction (quantity sold) by farmers.

4: Binary probit for estimating farmers' use of mobile phone for information searching: In this model, the dependent variable takes a binary value of 1 if the household uses mobile phones for information searching and 0 if not.

These estimations are made for different treatment variables, set of control variables and agricultural commodities. Two treatment variables are alternatively used to measure the impact of mobile phone access on different outcome variables. The first one is household level mobile phone ownership. However, information is not always a private good. A household that owns a mobile phone and obtains information through the mobile phone may share the information with neighboring households. Therefore, it may not be possible to observe differences between households who own mobile phones and those who do not in the same village. To overcome this problem, we estimated a second variable which is the village level mobile phone penetration rate that indicates the density of mobile phones coverage in the village computed as the percentage of households who own mobile phones in the village. The major assumption is that the average village level decision is affected by access to information at village level through network effect. According to the network economics, which is widely applied in business (Nagurney, 1999) and recently in development (Mckenzie & Rapoport, 2007), a network effect is present if the use of a good or service by someone has effect on the value of that product to other people. The effect of village level mobile density is meant to capture such network effect in rural areas of Ethiopia. Information sharing, especially market information, among village residents is very common in Ethiopia. This is particularly the case in areas where village residents are uniform in terms of socio-cultural factors such as religion and ethnicity. Our sample areas are uniform with regard to these

factors. They are drawn from the same region. This uniformity may allow farmers to share information generated through mobile phones.

Control variables (covariates) are included in all the models to control for observable heterogeneity within the samples. Many of the variables   listed in Annex 1 are taken as controls, except the endogenous variables for example total crop sale. Some of the control variables are included in all of the models. These are household head characteristics such as sex, age and years of schooling to control for heterogeneity in households' skill and access to information. Market access variables such as physical distance from the nearest market, transportation means and ownership of back animals are included to control for differences in households' access to markets.   Gender disaggregated labor endowment is also included to control for differences in the shadow wage which is an important component of information searching cost. The size of total cultivated land is included to control for the total quantity of crop production that may affect households' ability to market differently. Other explanatory variables are included depending on the nature of the dependent variables. For example, in a model that estimates farmers' decision to sell to a cooperative, we included variables that distinguish households as member and non-members of farmers' organizations and the physical distance of the households to cooperative centers. The probability of generating non-farm income is included in models that estimate quantity sold, frequency of selling, and price received. Access to electricity is included while estimating the use of mobile phones for information searching. The lists of control variables included in each model are noted under each table presenting the results.

Many of the models are independently estimated for each crop type. Estimating them jointly or pooling them together would have increased efficiency of estimates. However, two major reasons hinder us from doing so. First, the crops are not grown by similar farmers. Farmers who produce barley are different from farmers who produce *teff*. Hence, we do not have the same observation for the crops. Second, the market structure of the crops are completely different. For example, *teff* market is different from say, maize and vegetable markets in terms of number of traders involved, price certainty and seasonality. These differences will inflate heterogeneity and undermine the consistency of the estimates. Therefore, we estimate each of the above models for each commodity separately.

Endogeneity tests

Since mobile phone ownership by itself is an outcome variable that may depend on households' socio-economic conditions, it could be correlated with the error term of the dependent variables. To check the robustness of the estimates, we tested for endogeneity of mobile phone ownership using Control Function (CF) approach. CF is selected for two reasons: 1) it is efficient even for weak instruments, 2) its special application proposed by Wooldridge (2007), is efficient for binary outcome endogenous variables which other IV (Instrumental Variable) methods (2SLS, GMM, or ivprobit) do not estimate efficiently. We followed Wooldridge (2007) two-stage endogeneity test. First, we run a probit function that estimated owning a mobile phone as a function of many exogenous variables. These variables are of two types. The first group of variables are control variables that are included in the second-stage estimation. The second group of variables are instruments that satisfy the orthogonality condition of IVs. Finding an appropriate instrument especially in cross-sectional data is always a challenge. We chose four instrumental variables we think strongly affect mobile phone ownership but not significantly affect the outcome variables. These are whether a household head and spouse have basic education or not, whether the household has access to electricity or not and cattle ownership to proxy wealth. Basic numeric, reading and writing literacy is an important precondition for a household to own and use mobile phone. Similarly, electric power is very essential to charge mobile phones regularly. Access to electric power is both village and household dependent. In rural Ethiopia, some villages have access to electric power from the national hydropower system. However, many do not have this access but they can access solar power. Solar power access is not uniform, some households own solar power equipment and others do not.

From the first-stage estimation we predicted the generalized residual, which is the inverse Mills ratio of the predicted value of owning a mobile phone. Then, the generalized residual is included in the second-stage estimation that estimated the outcome variables (price, place of sell, and quantity sold) against observed mobile ownership and other control variables other than the instruments. Endogeneity is detected if the generalized residual is statistically significant in the second stage regressions. The result is shown in Table 2. Of the 28 cases over different type of dependent variables and commodities, the generalized residual is only statistically significant for 8 cases. Endogeneity is detected mainly in a model estimating size of transaction or quantity sold

at time of sale. It is also detected for selling wheat and barley to cooperatives. Whenever we detected an endogeneity problem, we used the results of the control function estimation. However, for models where endogeneity is not detected we used non-IV estimations. In the absence of endogeneity, performing IV estimation inflates the asymptotic variance of the estimators (Wooldridge, 2003).

Results and discussion

Mobile phones coverage and ownership in the study areas

The use of mobile phones is rapidly expanding in rural Ethiopia. All the study areas have access to mobile phone coverage. We did not find a village without a mobile phone. Close to half of the households own at least one mobile phone (Table 3). Some households own as many as 6 mobile phones. However, the extent of network coverage and the rates of mobile phones penetration are different across locations. In some districts, three-quarters of the total households own a mobile phone. In others, only one-quarter of the households own a mobile phone.   Village level penetration rate ranges from 23 to 88   percent.

To further shed light on the distribution of mobile phones across households, we estimated determinants of mobile phone ownership using a probit function. The results are shown in table 4. All the variables included show the expected sign. Age and education are found as significant variables for owning a mobile phone. As expected, young and educated household heads have higher probability of owing mobile phone than old and uneducated household heads. Wealth as indicated by livestock size is also significant. Better-off farmers are more likely to afford a mobile phone. Access to electric power has significant effect because many of the mobile phones owned by farmers have short-lived batteries and frequent charging is necessary. More interestingly, market access is found to be an important determinant. Famers who are far from the local market and all-weather roads have higher probability of owning mobile phones than farmers who are close to these centers.

Market arbitrage

Market arbitrage is broadly defined as a practice of taking advantage of price differences across market places, times, and buyers/sellers of different kind. In this paper, it includes spatial arbitrage

as well as choice of buyers by smallholder producers. In areas where markets are imperfect, prices vary not only across markets but also across traders (buyers). Hence, farmers have to search and choose the higher price among the different buyers in the markets. The buyers could be cooperatives or private traders or consumers. In the study areas, farmers have access to many markets including village, district and to some extent regional markets. Village markets are very near markets where village assemblers (similar to retailers) purchase agricultural produce for wholesaling in primary and secondary markets. Primary markets are markets located at the center of the district. They are farther than village markets but nearer than secondary markets. Secondary markets are markets whereby regional wholesalers buy grains for transporting to distant consumer markets. In some places the distinction of these markets is subtle. However, one can find at least two marketplaces in a given locality that the farmer has to choose from in deciding where to sell. Table 5 summarizes the number of farmers selling to the different markets. Farmers' choice of marketplaces varies across commodities. While low value (maize, wheat and barley) and bulky (vegetables) commodities are sold at nearest markets, high value commodities (*teff*, peas and beans) are being sold at distant markets. Animal products are usually sold at nearest markets.

Spatial arbitrage in the study area is done by farmers as well as traders. The role of traders depends on where the transaction is taking place and the type of commodity. We consider only the grain market in this paper. Many previous studies(Gabre-Madhin & Amha, 2005; Minten et al., 2012) indicate that the role of traders in Ethiopian grain marketing varies across spatially disaggregated markets. In the village market, they are assemblers who determine price and other terms of trade based on negotiation with farmers. They exchange based on payment on delivery. They do not provide credit. The number of buyers in the village market is very small but farmers do have also option to sale to a bigger district market which is not h far from their villages. In this market, the buyers are wholesalers, still they do not provide credit for food grains. The number of buyers is large. Pricing is made through bilateral negotiations, however, the farmer has the option to move to the next trader if the negotiation fails. This implies that farmers do really engage in arbitrage between village and district markets and between buyers in each market.

To test the impact of mobile phone on marketplace choice, we grouped markets into two: village and distant markets. Farmers' market choice together with buyers (cooperatives vs. private traders)

choice was regressed against household and community specific variables including access to mobile phones measured in terms of household and village level ownership. The results are presented in table 4. An important hypothesis we wanted to test is whether there is a statistical difference in spatial market choice between farmers with mobile phone and farmers without mobile phones. The sign depends on the efficiency of the markets. If the village market is efficient, farmers who have information about all the markets will tend to sell to the village market. If the village market is inefficient, they will tend to sell to the distant markets. What the mobile phone does is to reveal the efficiency of the market. Thus, the sign of mobile access is inconsequential. In fact, farmers with mobile phone access tends to sell more likely to the village for many of the commodities except for barley (Table 6). However, household level mobile phone ownership has no statistically significant effect on spatial market choice of farmers except for pulses.   In contrast, village level mobile phone access has significant and strong impact on marketplace choices for many of the commodities studied. Those farmers who live in highly penetrated villages have higher probability of selling to the village market compared to farmers in less penetrated villages. This indicates a strong network effect in which private mobile phones are generating village public goods or owning mobile phone has positive externality for the village. However, the result have to be interpreted cautiously in a sense that   highly penetrated villages might be those villages which are located in a well-developed markets so that farmers sell to that market not because of mobile phones but because of the development of the market and the fact that a market is close to them.

Table 6 also shows the impact of mobile phone access on selling to cooperatives or to private trader.   Here we tested if there is any variation in buyer choice due to mobile phone access. For many commodities the impact is insignificant. It is significant and negative only for maize and wheat. Farmers who have access to mobile phones are less likely to sell to the cooperative. This is in line with our expectation that farmers sell to cooperatives because they lack adequate information about open (traders') markets. If they get enough information from the open market via mobile phones, there is little incentive for famers to sell to the cooperative market.

Frequency and size of transaction

Table 7 summarizes the average quantity per transaction and the frequency of selling for the different commodities. The results reveal that farmers who own mobile phones seem selling higher quantity per transaction than farmers who do not have mobile phones for most of the commodities studied. It is also observed that perishable and bulk products such as animal products and vegetables are sold more frequently than storable commodities (Table 7).

However, there seems to be significant difference among farmers on the frequency of selling the same commodity requiring extra explanations other than storability and perishability. One such explanation is searching cost which includes substantial amount of sunk costs that have to be incurred per sale. Thus, if searching cost is pervasive, farmers prefer to sell less frequently than the case where searching cost is less important. In a situation where searching cost is low, one can sell or buy products at any time when he/she wants to do so. The opposite is true if the searching cost is high. If the searching cost is large and that cost is incurred each time of transaction, a rational market operator plans to transact less frequently.

However, this conceptual argument is not supported by the empirical statistical tests (Table 8). Table 8 presents the results of ordered probit that estimated the probability of selling frequencies against household level mobile phone ownership and village penetration rate. Even though many of the commodity specific models predicted positive effect of mobile phone ownership on selling frequency, they are not statistically significant. Similarly, village level mobile phone penetration rates have shown a statistically significant impact on the probability of frequent selling only in two commodities (Wheat and Barley). An increase in mobile density at village level increases the probability of frequent selling (more than twice per year) for these commodities. In general, it seems that the difference in selling frequency among farmers is not due to mobile phone access. Mobile phone access has little effect on frequency of selling.

The traditional way of market information searching is through face-to-face contact with potential buyers. This method requires carrying the product by the person searching for prices. To make the searching process easy and less costly, farmers prefer to carry small quantities per time of selling. Such a strategy will no longer be required in the presence of mobile phones that reduce

the cost of information searching and hence farmers tend to pack larger quantity per time of sale. We tested this hypothesis by regressing size of transaction (quantity sold per sale) against mobile phone access at household and village level separately. The result revealed that mobile phone has indeed statistically significant positive effect on average quantity per transaction for four commodities (*teff*, wheat, maize and vegetables) out of six commodities (Table 8). In a risky market, farmers prefer to sell piecemeal. Access to mobile phone reduces information risk and hence encourages farmers to sell larger quantities per transaction.   Unlike other marketing decisions, the effect of household level mobile phone access is wider than village level mobile phone access for this decision. This could be due to the fact that the decision on quantity of transaction is made based on household specific (private) information unlike others like where or who to sell, which can be decided by publicly available information. Generally, the effect of mobile phone access is relatively stronger in quantity of transactions than frequency of transaction.

Producer prices

Farmers receive different prices for the same crop. Table 7 shows the significant difference among farmers' prices as implied by large coefficient of variation that ranges from 27% to 67%. This variation could be attributed to access to price information. We disaggregated the mean prices by mobile ownership to examine how information through mobile phone helps in obtaining a better price (Table 9). Farmers with mobile phones receive higher prices in only two of the four crops.

However, this descriptive result is not sufficient to attribute mobile phone ownership to price differences. An econometric model is used to estimate the actual effect of mobile phone ownership on prices of different crops. The model is specified as

$$\ln P_i = \alpha_0 + \alpha_1 L_i + \alpha_2 M_i + \alpha_3 Q_i + \varepsilon_i$$

Where $\ln P$ is the logarithmic transformation of the nominal prices and the right hand variables are the different explanatory variables. Farmers receive different prices for many reasons. First, they are located in different places where prices are different due to distance to central markets. This effect is controlled by L. Second, the time of selling might be different. Third, the place of selling and the type of buyer could be different causing significant difference in prices received. These variables: time of selling, place of selling, and type of buyer are endogenous to mobile phone

ownership. Farmers with mobile phones can sell at time where they fetch higher price, from a buyer who offers higher price and to the market that has a higher net price through intensive price searching and negotiation. Thus, the effects of these variables are instrumented by mobile phone ownership, M. Fourth, the total quantity a farmer supplied to the market in a year, represented by Q. Finally, the quality of grain supplied by the different farmers could be different. Unfortunately, we did not have quality information in our data set and hence unable to include it as an explanatory variable.

The results indicate that mobile phone ownership has no statistically significant effect on the level of price that the farmers received except for wheat (Table 10). The elasticity of wheat price is significant and positive. This could be due to the fact that wheat is being traded by Ethiopian Government as a strategy to stabilize food price volatility and hence price information for wheat can easily be accessed through mobile phones. The effect of village level mobile phone access is totally insignificant. This result is consistent with the findings of previous studies (Aker & Fafchamps, 2013; Fafchamps & Minten, 2012).

This analysis and the previous ones showed that the effect of mobile phone access on farmers marketing decision and price received is either nil or very minimal. The three possible reasons may explain these findings: 1) farmers may not need information at all because they do not do spatial and temporal arbitrage. 2) Farmers may not use the mobile phones for information searching; and 3) the information obtained through mobile phones is not relevant. We assessed the first two of these possibilities. Our data does not allow us to verify the last hypotheses.

Do farmers search price information for marketing decision?

Previous studies which have more or less similar findings attribute the absence of mobile phone's impact on smallholders' decision to farmers' inability to engage in spatial arbitrage. In other words, it seems that farmers' marketing decisions are not guided by price information rather by other structural problems such as immediate need of cash, availability of transportation and others. This prompted us to ask whether famers need information for making marketing decisions. We specifically asked farmers whether they search for price information before packing their outputs for sale. The result indicated that about 90% of the farmers indeed search for market information

before selling their produce. This implies that market arbitrage is a common practice among smallholder farmers. Farmers search prices of different local and central markets and different buyers. The major sources of market information are traders, media and development agents (Table 11.). Of the farmers who seek market information, close to 72% search from traders and development agents which can be communicated with either through mobile phones or face-to-face interaction. Such information searching either improves their bargaining power or provides alternative markets from which they can choose from to obtain higher prices. The quantity farmers' supply to the market might be very small and uneconomical to arbitrage between central and local markets. However, smallholder farmers access several local and regional markets to arbitrage. If they do not arbitrage, searching information is meaningless.

Use of mobile phones for market information searching

We also asked whether farmers who search price information use mobile phones or not. The results indicate that the use of mobile phone for acquiring business information is very limited. Only 43% of farmers who own mobile phones use them to search for market information (Table12). Surprisingly, some farmers who have no mobile phone obtain market information through mobile phones. Possible explanation would be the use of neighbors' mobile phones or sharing information from neighbors who own mobile phones. This is consistent with the higher effect of village level mobile phones density on different marketing decisions presented earlier.

The use of mobile phones for information searching depends on demand and supply side factors of accessing information. The demand for information relates to the quantity of product the farmers supply to the market, farmer's awareness about the importance of information, the ability of getting information through other means and access to mobile phones. It also relates to the technical ability of the farmer in using mobile phones. The supply side factors relate to the presence of an information source which provides reliable and accessible information. All these variables were represented by different proxy variables and a probit model was estimated to investigate the relative importance of the demand and supply side factors.

The results clearly indicate that farmers who are close to an institutional center, be it the open market, cooperative or the village center, have a higher probability of using mobile phones for

information searching than farmers who are far from such centers (Table 13). Farmers closer to markets might have better access to information sources from which they obtain reliable information about current and expected prices as they might have better social ties with traders and institutions in the market than distant farmers, which has been proved in previous studies (Tadesse & Shively, 2013). Therefore, availability of an information source is more important than lack of information for driving farmers' decisions to use mobile phones for information searching. This implies that the demand for information is less strong than the supply of information in explaining the use of ICT for agricultural decisions. A mere existence of mobile phones in the village may not necessarily mean farmers are using the technology to solve information problems. Only those who have access to an information source and know where to search for information are using the technology to facilitate information access.

As expected, younger households are more likely to use mobile phones for information searching than older households. Access to electric power robustly explains the use of mobile phones for better market information.

Conclusion and recommendations

Translating technological opportunities into economic benefits has always been a development challenge in smallholder agriculture. Sometimes, the adoption of a new technology may not necessarily mean farmers are optimally using the technology and maximizing the benefit of the potential of that technology. Mobile phone is a case in point. Many farmers own mobile phones but to what extent this mobile phone is helping farmers in making marketing decisions is an important concern that many researchers and development practitioners want to understand more. This paper assessed the impact of the mobile phone access both at household and village levels on marketing decisions and prices received by farmers in Ethiopia. The results are mixed. However, in general, the impact is not strong enough to believe that mobile phones are really helping farmers marketing decisions.   The empirical analyses on farm gate prices clearly indicate that the impact is almost always insignificant. These findings suggest that cell phones may be useful for certain farmers in certain types of circumstances but in the study area mobile phones do not seem to be a suitable means by which to provide price information. The absence of mobile phones as an

effective means of price discovery suggests that there exists scope for alternative means of providing price information.

Furthermore, the explanation for absence of mobile phones as an effective means of accessing price information could be the limited use of mobile phones for searching agricultural information. Only few of the farmers use mobile phones to reduce information searching costs. This seems to be due to lack of information sources that can deliver relevant information to farmers. We, therefore, recommend establishing information centers either at farmers' cooperative centers or at local agricultural development centers that serves farmers as a reliable source of information and knowledge.

References

Aker, J. C. (2011). Dial A for Agriculture: Using ICTs for Agricultural Extension in Developing Countries. *Agricultural Economics, 42*(6).

Aker, J. C., & Fafchamps, M. (2013). *Mobile Phone Coverage and Producer Markets: Evidence from West Africa*. CSAE Working Paper, WPS/2013-09.

Aker, J. C., & Mbiti, I. M. (2010). Mobile Phones and Economic Development in Africa. *Journal of Economic Perspectives*(summar).

Alene, A. D., Manyong, V. M., manya, G., Mignouna, H. D., Bokanga, M., & G.Odhiambo. (2008). Smallholder market participation under transactions costs: Maize supply and fertilizer demand in Kenya. . *Food policy, 33*(4), 318-328.

deJanvry, A., M.Fafchamps, & Sadoulet, E. (1991). Peasant household behaviour with missing markets: some paradoxes explained. . *Economic Journal, 101*, 1400-1417.

Donovan, K. (2011). Anytime, anywhere: Mobile devices and services and their impact on agriculture and development. Module 3 in ICT in Agriculture: Connecting Smallholders to Knowledge, Networks, and Institution: The World Bank Report No. 64605.

Fafchamps, M. (2004). *Market institutions in Sub-Saharan Africa: Theory and Evidence* London The MIT Press.

Fafchamps, M., & Minten, B. (2012). Impact of SMS-Based Agricultural Information on Indian Farmers. *The World Bank Economic Review, 26*(3), 383-414.

Gabre-Madhin, E., & Amha, W. (2005). *Characterizing Grain Traders*. Paper presented at the Policies for Improved Land Management and Agricultural Market Development in the Ethiopia Highlands, Addis Ababa, Ethiopia

Holden, S., Shiferaw, B., & Pender, J. (2001). Market imperfections and land productivity in the Ethiopian Highlands. *Journal of Agricultural Economics, 52*(3), 53-70.

Jensen, R. (2007). The Digital Provide: Information (Technology), Market Performance and Welfare in the South Indian Fisheries Sector. *Quarterly Journal of Economics, 122*(3), 879-924.

Jensen, R. (2010). Information, Efficiency and Welfare in Agricultural Markets. *Agricultural Economics, 41*(S1), 203-216.

Lio, M., & Liu, M. (2006). ICT and agricultural productivity: Evidence from cross-country data. . *Agricultural Economics, 34*(3), 221-228.

Mckenzie, D., & Rapoport, H. (2007). Network effects and the dynamics of migration and inequality: Theory and evidence from Mexico. *Journal of Development Economics 84*, 1-24.

Minten, B., Stifel, D., & Tamru, S. (2012). Structural Transformation in Ethiopia: Evidence from cereal markets: IFPRI- ESSP II Working Paper 39 : http://essp.ifpri.info/publications/#sthash.0cb1gig3.dpuf.

Mittal, S., Gandhi, S., & G.Tripathi. (2010). Socio-Economic Impact of Mobile Phones on Indian Agriculture. Indian Council for Research on International Economic Relations *Working Paper No. 246.*: http://www.eaber.org/sites/default/files/documents/Socio-economic%20Impact%20of%20Mobile%20Phones%20on%20Indian%20Agriculture.pdf

Muto, M., & Yamano, T. (2009). The Impact of Mobile Phone Coverage Expansion on Market Participation: Panel Data Evidence from Uganda. *World Development., 37*(12), 1887-1896.

Nagurney, A. (1999). *Network Economic: A Variational Inequality Approach* (second and revised ed.). Dordrecht, The Netherlands Kluwer Academic Publishers.

Sadoulet, E., & Janvry, A. d. (1995). *Quantitative Development policy Analysis:* : The Johns Hopkins university press.

Singh, I., Squire, L., & Strauss, J. (1986). A Survey of Agricultural Household Models - Recent Findings and Policy Implications. *World Bank Economic Review, 1*(1), 149-179.

Stiglitz, J. E. (1986). The New Developement Economics *World Development, 14*(2), 257-265.

Tadesse, G., & Shively, G. (2013). Repeated Transaction in Rural Grain Markets of Ethiopia *Journal of Development Studies, 49*(9), 1172-1187.

TeleGeography. (2012). Ethio Telecom mobile base tops 17.26m at end-June, *http://www.telegeography.com/products/commsupdate/articles/2012/09/20/ethio-telecom-mobile-base-tops-17-26m-at-end-june/*.

Williamson, O. (1979). Transaction-Cost Economics: The Governance of Contractual Relations *Journal of Law and Economics, 22*(2), 233-261.

Williamson, O. (1985). *The Economic Institutions of Capitalism*. New York: The Free Press.

Wooldridge, J. (2003). *Econometric Analysis of Cross Section and Panel Data*. London: The MIT Press.

Wooldridge, J. (2007). *What's New in Econometrics? Control Functions and Related Methods*.

Figure 1. Mobile cellular subscribers in Ethiopia both rural and urban
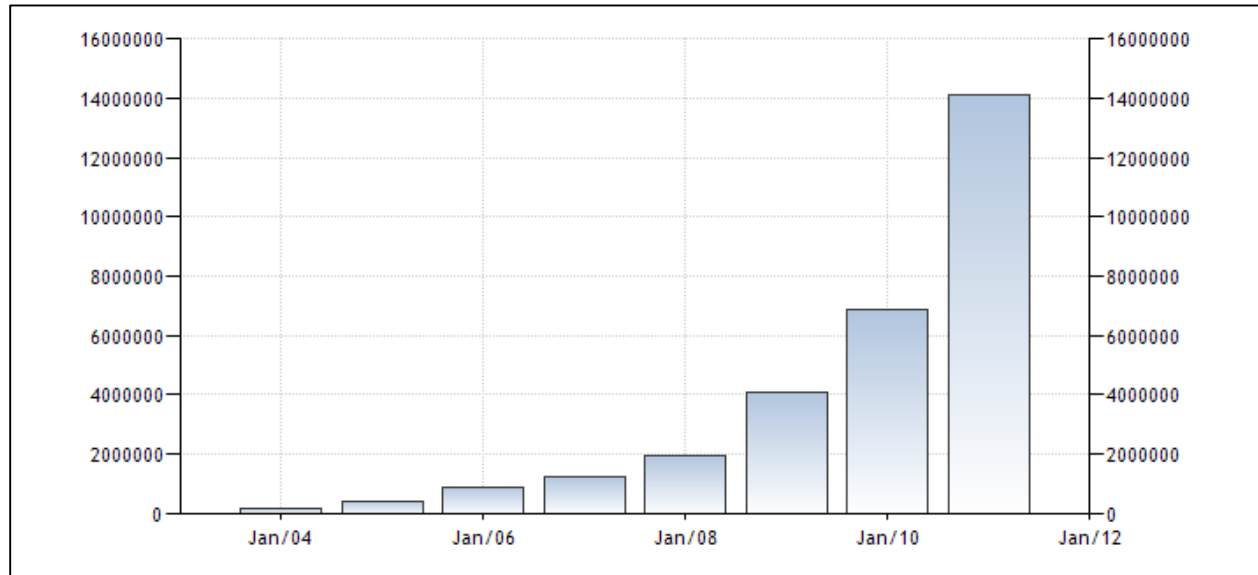
Source: http://www.tradingeconomics.com/ethiopia, Last Accessed March 2014.

Table 1: Characteristics of sample households

Characteristics	Descriptive statistics	Values
Human capital indicators		
Family size	Mean (Std. Dev.)	6.6 (2.3)
Male labor	Mean (Std. Dev.)	1.5 (0.9)
Female labor	Mean (Std. Dev.)	1.7 (1.1)
Sex of household head (% male headed)	Percentage of male headed	92.2
Age of household	Mean (Std. Dev.)	43.7 (12.6)
Education of household heads	Percentage who had basic education	65.0
Education of household heads spouse	Percentage who had basic education	43.9
Wealth and income indicators		
Land size	Mean (Std. Dev.)	1.8 (2.0)
Cultivated land per person in ha	Mean (Std. Dev.)	0.73 (13.9)
Total household asset value in 1000 ETB	Mean (Std. Dev.)	26.5 (45.4)
Total livestock size (cattle)	Mean (Std. Dev.)	4.3 (4.7)
Total small ruminant size	Mean (Std. Dev.)	2.2 (4.9)
Total annual crop sale in 1000 ETB	Mean (Std. Dev.)	7.2 (22.1)
Households participated on non-farm activities	Percentage	30.5
Access to market indicators		
Distance from markets in Km	Mean (Std. Dev.)	6.2 (5.4)
Distance from village center in Km	Mean (Std. Dev.)	1.5 (1.5)
Distance from all-weather road in Km	Mean (Std. Dev.)	7.1 (35.6)
Availability of cooperatives in the village	Percentage with access to cooperative	75.0
Distance from cooperative	Mean (Std. Dev.)	2.3 (5.0)
Cooperative membership	Percentage who are member	52.5
Access to vehicle to transport farm products	Percentage who use vehicle	5.2
Back animal	Mean (Std. Dev.)	1.3 (2.1)
Access to electricity	Percentage own electrical power	16.3

Source: Authors estimation form survey data,

Table 2: Endogeneity tests of mobile ownership using Control Function approach

	Coefficient (St.err) of generalized residual in each model				
	Price	**Selling to village market**	**Selling to cooperative**	**Frequency of transaction**	**Size of transaction**
Teff	-226.41	0.057	-0.54	-0.20	-0.68**
	(174.84)	(0.42)	(0 .43)	(0.28)	(0.31)
Wheat	-19.43	0.35	0.82**	-0.32	-0.72***
	(26.40)	(0.29)	(0.32)	(0.21)	(0.23)
Maize	-38.63	0.64	2.27*	-0.54	-0.38
	(56.49)	(0.98)	(1.14)	(0.64)	(0.42)
Barley	-64.83	1.48**	2.2***	0.33	-0.93*
	(82.45)	(0.69)	(0.74)	(0.45)	(0 .53)
Pulses	NA	0.13	NA	-0.08	-1.28
		(0 .77)		(0 .66)	(0.96)
Vegetables	NA	(0.46)	NA	0.33	-1.8**
		(0.73)		(0.63)	(0 .86)
Animal products	NA	0.04	NA	-0.73	NA
		(0.66)		(1.99)	

Source: Authors estimation form survey data,

Notes: (1) NA=data not available. (2) The values are estimated in two-stage procedure. In the first stage, mobile phone ownership is regressed against several instruments and the generalized residual is estimated from this regression following Woodridge (2007). Then the generalized residual is included in the second-stage regression that estimates the dependent variables listed here for each commodity together with mobile ownership and other explanatory variables.

Table 3. Mobile phones coverage in rural areas of Ethiopia

Districts (Woredas)	Percentage of households owning
Sinana	72
Jeldu	45
Seddan sodo	38
Dewo	26
Arsi negele	52
Shashemene	42
Total	46

Authors estimation form survey data

Table 4: Determinants of owning a mobile phone in rural areas of Ethiopia

Determinants	Marginal effects	Std. Err.
Age of the household head	-0.004***	0.002
Market distance in KM	-0.006**	0.003
Distance from the village center in Km	0.014	0.010
Distance from all-weather road in Km	-0.001**	0.000
Availability of cooperatives in the village	-0.044	0.039
Per capita cultivated land holding	-0.002	0.004
Participation in non-farm activities	0.025	0.036
Livestock holding (cattle)	0.032***	0.005
Basic education of the household head	0.194***	0.041
Basic education of household head spouse	0.127***	0.038
Access to electric power	0.185***	0.049

Source: Authors estimation form survey data
Note: N=758. * p<0.10, ** p<0.05, *** p<0.01

Table 5: Percentage of farmers selling their outputs in village, primary and secondary markets

Commodity	Village market	Primary market	Secondary market
Teff	15.8	65.6	18.7
Wheat	34.8	51.3	13.9
Maize	33.7	61.2	5.1
Barley	39.0	55.3	5.7
Peas	2.4	67.1	30.5
Beans	16.7	35.2	48.2
Vegetables	30.7	41.6	27.7
Eggs	31.3	56.7	11.9

Source: Authors estimation form survey data

Table 6: The effect of mobile phone on market arbitrage   (marginal values and robust standard errors derived from biprobit estimation)

Commodities	N	Marginal effects on the probability of selling to the village market (1)		Marginal effects on the probability of selling to cooperatives (2)	
		Household ownership (3)	*Village level penetration rate (3)*	*Household ownership (3)*	*Village level penetration rate (3)*
Teff	298	0.06	0.49***	-0.05	0.08
		(0.05)	(0.17)	(0.04)	(0.16)
Wheat	478	0.05	0.42***	-0.20**	-0.07
		(0.05)	(0.13)	(0.10)	(0.11)
Maize	85	-0.05	-0.28	-0.66	-0.64*
		(0.37)	0.46	(0.46)	(0.35)
Barley	132	0.07	0.92***	-0.08	0.38
		(0.08)	(0.25)	(0.07)	(0.31)
Pulses(4)	186	0.10*	0.82***	NA	NA
		(0.05)	(0.16)		
Vegetables	96	0.0001	0.74**	NA	NA
		(0.10)	(0.30)		
Animal products	82	0.07	0.77**	NA	NA
		(0.11)	(0.26)		

Source: Authors' estimation from survey data

Notes: (1) control variables included are household head characteristics (sex, age and years of schooling), per capita cultivated land holding, number of female adults, number of male adults, distance from the nearest market, transportation means, number of back animals and availability of cooperative in the village or not. (2) In addition to the variables listed in (1), membership to cooperative is included. (3) While *households' ownership* measures whether a household owns a mobile phones or not, *village level penetration rate* measures percentage of farmers who own mobile phones in the village. It is meant to account for village level information flow. (4) The number of farmers selling pulses, animal products and vegetables to cooperatives is very few and hence unable to make any regression. (4) Pulses include peas and beans (5) numbers in the parentheses are standard errors (6) NA implies not applicable because the commodity is not sold to cooperatives.   (7) * p<0.10, ** p<0.05,   *** p<0.01

Table 7: Frequency and quantity of transactions by smallholder farmers

Commodities	N	Percentage of farmers who sold			Average quantity per transaction in 100kg	
		Once per year	*Twice per year*	*more than twice a year*	*who own mobile phone*	*Not own mobile phone*
Teff	306	16.3	42.2	41.5	1.8	1.2
Wheat	545	21.8	35.8	42.4	16.5	10.6
Maize	98	23.5	29.6	46.9	5.4	3.2
Barley	135	17.8	40.0	42.2	5.3	10.7
Pulses	81	32.1	25.9	42.0	1.1	2.6
Vegetables	100	22.0	15.0	63.0	14.6	4.7
Eggs	68	1.5	4.4	94.1	7.1	1.2

Source: Authors survey

Note: Quantity sold per time of sale is derived by dividing the total annual sale to the frequency of selling per year.

Table 8: The effect of mobile phone access on frequency and size of transaction

Commodities	Marginal effects on the probability of selling more frequently per year (1, 2)		Elasticity of quantity supply to mobile access (2)	
	Household ownership	*Village level penetration rate*	*Household ownership*	*Village level penetration rate*
Teff	0.005	0.011	1.154**	-2.177***
	(0.06)	(0.22)	(0.53)	(0.80)
Wheat	-0.001	0.233*	1.632***	4.620***
	(0.04)	(0.14)	(0.37)	(0.36)
Maize	0.018	0.215	0.491***	0.604
	(0.10)	(0.39)	(0.19)	(0.87)
Barley	0.094	0.678**	1.119	0.980
	(0.08)	(0.34)	(0.72)	(0.80)
Pulses	0.113	1.854	-0.506	0.884
	(0.10)	(1.18)	(0.40)	(1.56)
Vegetables	-0.075	-0.367	3.291**	-0.837
	(0.10)	(0.37)	(1.25)	(1.97)
Animal products	(0.03)	0.084	NA	NA
	(0.08)	(0.20)		

Source: Authors' estimation.

Note: (1) Frequency of transaction is defined as 1= if a farmers sells only once a year; 2 if a farmer sells twice a year; 3 if a farmer sells more than twice a year. It is estimated using ordered probit. The marginal effects reported here are the marginal effects of the highest order, that is, the marginal effects of owning mobile phone and an increase in village level penetration rate on frequent selling (more than twice a year). For example, 0.094 under household ownership for barley is interpreted as owning mobile phone increases the probability of selling more than twice a year by about 0.094. Similarly 0.678 under village level penetration rate, it is interpreted as an increase in penetration rate by one, increases the probability of selling more than twice per year by about 0.678. (2) Control variables included are household head characteristics (sex, age and years of schooling), per capita cultivated land holding, distance from the nearest market, and distance from village center, transportation means, and households' participation in non-farm income generation. (3) Numbers in the parentheses are standard errors (4) NA implies not applicable because the commodity is not sold to cooperatives.   (5) * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 9: variation in producer prices among farmers

Crops	Coefficient of variation	Mean price in ETB/100kg			
		Total	*Do not own mobile phone*	*own mobile phone*	*Difference*
Teff	0.67	1,106	1,078	1,161	82
Wheat	0.27	663	666	661	-5
Maize	0.32	460	442	482	40
Barley	0.42	609	621	597	-23

Source: Authors' computation from survey data.

Note: We reported only for the four crops because the other three commodities such as vegetables, animal products and pulses represent group commodities. They do not have single price life wheat. For example, in pulses you find chickpea and haricot bean, we pooled together because of their similarity in production and marketing practices but their prices are different. The sample size is very small to estimate for each commodity in the group.

Table 10: The effect of mobile phone ownership on producer prices

Mobile phone access	Logarithm of prices (elasticity and stad.err)			
	Teff	*Wheat*	*Maize*	*Barley*
Household ownership	0.012 (0.04)	0.071* (0.04)	0.155 (0.12)	0.024 (0.09)
Village penetration rate	0.192 (0.21)	-0.069 (0.20)	-0.111 (0.50)	0.235 (0.78)

Source: Authors' computation from survey data. The numbers in the parenthesis are standard errors.
Note: (1) control variables included are district dummies and total quantity sold per year, (2) * p<0.10, ** p<0.05,
   *** p<0.01

Table 11: Sources of market information

Sources	Frequency	Percentage
Traders	423	50.5
Radio and TV	222	26.5
Development Agents	181	21.6
Cooperatives	5	0.6
Neighboring Farmers	4	0.5
Others	2	0.2

Source: Authors' computation from survey data

Table 12: Percentage of households using mobile phone for market information searching

Owning mobile phone	Percentage	% of farmers use mobile phone for market information searching
Farmers who own mobile phones	46 (464)	43 (200)
Farmers who do not own mobile phone	54 (548)	6 (32)
Total	100 (1012)	23 (232)

Source: Authors' estimation. Numbers in the parentheses are number of farmers

Table 13: Determinants of the probability of using mobile phone for market information searching (marginal effects and standard errors)

Explanatory variables	The whole sample	Mobile owners only
Owning mobile	0.4002***	
	(0.0890)	
Market distance	-0.0094***	-0.0118**
	(0.0029)	(0.0053)
Distance from village center	-0.0154*	-0.0316*
	(0.0084)	(0.0169)
Distance form all-weather road	0.0004	0.0025
	(0.0002)	(0.0023)
Availability of cooperative in the village	0.0570*	0.0755
(*Kebele*)	(0.0313)	(0.0602)
Per capita cultivated land holding	-0.0007*	0.0195
	(0.0004)	(0.0704)
Age of the household head	-0.0009	-0.0020
	(0.0012)	(0.0025)
Years of schooling of the household head	-0.0049	-0.0027
	(0.0045)	(0.0085)
Access to electricity	-0.0373	-0.0054
	(0.0406)	(0.0734)
Generalized Residual /IMR (1)	-0.0454	0.0000
	(0.0575)	(0.1052)
N	736	347

Source: Authors' estimation

Note: (1) generalized residual is used in the first model that estimates for the whole sample and inverse mills ratio (IMR) is used in the second equation for only to mobile owners. While the generalized residual is meant to control endogeneity, IMR is to control for selection bias. (2) Numbers in the parentheses are standard errors (3) *** $p < 0.01$, **$p < 0.05$ *$P < 0.1$