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Ryo Takahashi, Yasuyuki Todo, Yu Ri Kim and Yuzuka Kashiwagi

Waseda INstitute of Political EConomy
Waseda University
Tokyo, Japan

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Ryo Takahashi[a], Yasuyuki Todo[a], Yu Ri Kim[b], Yuzuka Kashiwagi[c]

[a] Graduate School of Economics, Waseda University

[b] School of International Studies, Hanyang University

[c] National Research Institute for Earth Science and Disaster Resilience

Abstract

Using a randomized experiment targeting wheat producers in Ethiopia, this study examines the impact of providing market price information through Facebook on farmers' selling prices of wheat. In addition, to identify how homogeneity of informant affects the information use provided via social media, we distinguished the informant's nationality as either Ethiopian or foreign. We find that only information provided by Ethiopian informant increases the wheat selling price in the final transaction by approximately 14%. It is because farmers use the price information to delay the time of sale to the high price period, and does not affect farmers' negotiations with traders during the low-price period. Furthermore, our heterogeneity analysis suggests that the effect of information from the domestic informant is larger for older, poorer, socially more isolated, and female farmers, most likely because they have less access to information before our experiment. Our findings suggest that the use of social media has great potential for efficiently disseminating price information, while homogeneity of informant is still an important determinant of information flows through social media.

Keywords: social media, homogeneity, Facebook, market information, RCT

JEL codes: O13, O33, Q11, Q13, O55

1 Introduction

Considering that many of the poor are agricultural producers in developing countries, increasing selling prices of agricultural products is important for poverty alleviation. However, because of incomplete markets of agricultural products in developing countries, selling prices to farmers are often lower than prices that would be determined in complete markets. A notable reason for the low selling prices is information asymmetry. Because farmers are not accessible to reliable information on prices in different markets over time due to poor infrastructure and monopolistic markets, they tend to sell their products to intermediaries at below-market prices (Goyal, 2010; Mérel et al., 2009; Negi et al., 2018) immediately after harvesting (Kadjo et al., 2018).

Therefore, provision of price information can be an important factor for increasing selling prices. Provision of information may increase farmers' bargaining power and facilitate price negotiations with intermediaries. In addition, farmers may delay the timing of crop sales when they realize that current market prices are low but that future prices are likely to increase through the information provision.

To disseminate market information efficiently, information and communication technologies (ICTs), such as the internet, mobile phones, and short message services (SMS), have attracted attention from both the academia and development agencies (Fabregas et al., 2019; Jensen, 2007; World Bank, 2016). As ICTs enable producers to communicate with traders and agricultural extension agents regardless of physical distance and the level of transportation infrastructure, ICTs have a great advantage of reducing the cost of information acquisition, expecting to facilitate the dissemination of price information in developing countries (Aker and Mbiti, 2010). The potential of ICTs has been particularly increasing in developing countries in recent years due to the rapid diffusion of ICTs (Fabregas et al., 2019; Hjort and Poulsen, 2019; Paunov and Rollo, 2016). However, the empirical evidence on the effectiveness of ICTs is mixed as summarized in Aker et al. (2016) and Spielman et al. (2021).

In this study, we examine the impact of providing market price information through social media on the agricultural product sales price. In addition, we explore the mechanisms by which farmers use the information to negotiate prices or adjust the timing of their sales. For this purpose, we conducted a randomized controlled trial using Facebook, a popular social media service, in Ethiopia. In this experiment, we provided weekly market price information of wheat during the three-month period immediately following wheat harvest, when selling price is at its lowest.

This study contributes to the literature on ICTs and information diffusion in agriculture. Previous empirical literature reported that agricultural prices increased due to the introduction of ICTs, such as mobile phones (Aker, 2010), SMS (Courtois and Subervie, 2015), and radio (Svensson and Yanagizawa, 2009). In addition, the adoption of agricultural technologies was also enhanced by mobile phones (Gupta et al., 2020), voice messaging (Cole and Fernando, 2021; Dzanku et al., 2021), and video messaging (Dzanku et al., 2022; Gandhi et al., 2007; Van Campenhout, 2021; Van Campenhout et al., 2021; Van Campenhout et al., 2017). However, the empirical evidence on the effectiveness of ICTs on the diffusion of agricultural information in developing countries is mixed (Aker et al., 2016; Spielman et al., 2021). Several studies found that the impact of ICTs, such as mobile phones (Aker and Fafchamps, 2015; Muto and Yamano, 2009) and SMS (Camacho and Conover, 2019; Fafchamps and Minten, 2012), on agricultural prices was either insignificant or partial. Therefore, despite the great potential of ICTs to promote the diffusion of agricultural information, whether it is a practically efficient approach for developing countries remains unclear.

In this regard, this study contributes to the literature on ICTs in developing countries by providing new empirical evidence on the effects of social media as a means of agricultural information dissemination. The number of users of social media, such as Facebook and Twitter, is rapidly increasing in developing countries (Pew Research Center, 2018). For example, in Africa, the penetration of Facebook is approximately 19% of the total population, accounting for 42% of the total internet users (Internet World Stats, 2021). Furthermore, the power of social media on diffusing information in developing countries was well recognized during the Arab Spring in 2011, when people actively shared information about protests through social media (Khondker, 2011). However, social media has received relatively little attention in previous studies in the context of agricultural development.

Social media has several advantages in disseminating information compared to other ICTs that have been focused in previous studies (i.e., mobile phones and SMS). First, especially compared with SMS, informants can easily distribute agricultural information to a large number of people with a single post. Second, informants can post information on social media along with images and videos, which helps people's understanding of the distributed information (Van Campenhout et al., 2021). Third, social media allows users to easily share and discuss information with other users, both publicly and privately. For example, users can have public discussions by commenting directly on posts, or they can communicate with others through private direct messages. In fact, Lee and Suzuki (2020) found that shrimp farmers were actively exchanging information in a private Facebook group. Finally, users can learn about informants by accessing the informants' account pages, which is expected to improve the credibility of the information sources. Given the great advantages of social media for information sharing, understanding how social media can be utilized to diffuse agricultural technologies in developing countries is an important policy consideration. However, to the best of our knowledge, no study has examined the impact of social media on the diffusion of information on agricultural prices.

Finally, this study contributes to a literature on learning effects and informant characteristics (Krishnan and Patnam, 2014). Although agricultural extension agents play an important role in disseminating agricultural information in developing countries (Adegbola and Gardebroek, 2007; Moser and Barrett, 2006), producers' decision to use information depends on the agents' characteristics, such as trust (Aker et al., 2016; Buck and Alwang, 2011), social connection (Abdulai and Huffman, 2005; Maertens and Barrett, 2013), and gender (BenYishay et al., 2016; Kondylis et al., 2016). In this study, we particularly focused on whether information use differed depending on the homogeneity between senders and receivers of information. More precisely, we estimated how the impact of information provision through Facebook changed depending on whether the informant was Ethiopian or non-Ethiopian. Whether the use of information is affected by the homogeneity of the informants has substantial policy implications. If homogeneity is irrelevant, what matters most is the establishment of a social media platform for information sharing. By contrast, the establishment of platform alone is insufficient when producers consider homogeneity with informants. In the latter case, although one advantage of social media is the ability to share information without being limited by physical distance, it is important to select informants based on their social distance from the producers.

2 Experimental Design and Data Collection

The Ethiopian government made significant efforts to disseminate agricultural information through extension services (Buehren et al., 2019; Krishnan and Patnam, 2014; Takahashi et al., 2015; Todo and Takahashi, 2011). However, most extension services are provided in the conventional face-to-face style in the field, while the use of ICTs is fairly limited (Birke et al., 2019).

In this study, we selected two districts (Hitosa and Diggerna-Tiyo) in the Tiyo region, located in southern Ethiopia. There are a total of 46 villages in the two study districts. Out of 46 villages in the two districts, we randomly selected 16 villages (584 households) and examined how the provision of market information through Facebook affected the selling prices of wheat, which is one of the major crops in the region. Since most producers harvest wheat in January, the market price of wheat is the lowest of the year from January to March (hereafter, "the low-price period"). Figure 1 shows the monthly average retail price of wheat in the capital city of Ethiopia, Addis Ababa, from 2014 to 2018, with the average price in January set at 100. The five-year average in the bold line shows that the retail price of wheat from January to March is lower than in other months and tends to increase from April onward, although there were no price fluctuations in 2016 due to severe drought. Data for 2019, the year of the experiment, are missing, but there were no major shocks affecting agricultural prices during the period of our analysis.

2.1 Experimental design

In this experiment, there are three treatment arms: two groups receiving the market information via Facebook (hereafter, "the treatment groups") and one control group without the intervention. The two control groups are different in that the information source is an Ethiopian in one group while it is a foreigner in the other, as explained in detail later, in order to examine the familiarity of information sources to farmers affects the treatment effect.

We created two "communities" for information sharing and discussion in Facebook, one for each treatment group, and invited farmers in the treatment groups to the communities. Participation in each private Facebook community required invitation and approval from the research team, allowing us to strictly limit the participation of those who were not invited. In the private Facebook communities, we posted weekly price information on major crops (i.e., wheat, barley, and fava beans) in key markets in the region. To provide accurate weekly market information, we hired local experts from the Oromia Trade and Market Development Bureau, the local government agency in charge of collecting market information. Participants in the two treatment groups received the same market information in the local language (Oromo), except that the nationalities of the informants were different.

In the first treatment group (hereafter, "the domestic-informant treatment"), the market price information was always posted from an account with an Ethiopian name and profile photo. By contrast, the participants in the second treatment group (hereafter, "the foreign-informant treatment") received the information from a non-Ethiopian account using an Asian name and profile photo. To avoid deception, we created Ethiopian and non-Ethiopian Facebook accounts using the real names and photos of Ethiopian and non-Ethiopian members of the research team. Because both Ethiopian and non-Ethiopian accounts are new accounts created for the experiment, the only information displayed on each account's page is the name and one face photo. Further, to avoid the influence of characteristics other than the informant's nationality, the two informants were males of similar age with formal clothes.

We first randomly selected 10 villages out of 16 study villages (hereafter, "the treatment villages"). In December 2018, all 357 households in the treatment villages were invited to participate in a lottery to determine the participants who received our interventions. Through the lottery, 120 households (34% of the lottery participants) were randomly selected as the treatment groups for this study, with 60 households in 5 villages receiving information from an Ethiopian informant and the rest from a non-Ethiopian. Hence, the assignment of whether to receive information was done by a lottery at the household level, while the assignment of treatments by an Ethiopian and a foreigner was done at the village level to avoid contamination between the two treatments within the same village. Furthermore, the essential condition for this experiment is that the treatment households need to have both a Facebook account and an internet connection. Thus, after a lottery selection, we donated one smartphone to each of the treatment households and helped them create their Facebook accounts.

From January to March 2019, the weekly market information was provided to the 120 treated households through the private Facebook communities. As mentioned, this intervention period corresponds to a period of falling selling prices for the main crops (wheat, barley, and fava beans). After April, the distribution of market price information ceased, while the private Facebook communities continued to exist. Prior to the experiment, participants were informed that market price information would be distributed only for a certain period of time. However, since the specific end date was unknown, the distribution ended at an unexpected time for participants.

During the intervention, we did not restrict participants from posting to the private Facebook community or sharing information with others. Although some participants made political posts in the community, we did not observe any posts from participants regarding agricultural prices or agricultural technology. In contrast, there is a possibility of spillover effects from the intervention. The 237 households in the treatment villages who were not selected in the lottery did not receive any information from the research team. Therefore, it is possible that the treated households may pass the market information from the Facebook community to these unselected households in the same village.

In the experiment, the take-up ratio of treated farmers was 100%. In other words, all of the households who won the lottery received a smartphone, most likely because it was free, created a Facebook account, and received information through Facebook. However, it is unclear whether the treated households read or utilized the information sent through Facebook.

2.2 Data collection

To evaluate the impact of the Facebook intervention, we conducted two types of surveys. First, the baseline and endline face-to-face surveys were conducted in August 2018 and 2019, respectively, to establish panel data on participants' demographic characteristics, selling prices of three major crops in the region (i.e., wheat, barley, and fava bean), Facebook usage, and perceptions of trust to local and foreign people. A total of 522 households from 16 villages (approximately 89% of the total) participated in both the baseline and endline surveys. Our benchmark analysis relies on the panel data to estimate the longer-term effect of the information provision on selling prices.

Second, an additional telephone survey was undertaken in January 2019, two weeks following the information provision via the Facebook groups to capture the immediate effect. A total of 369 households responded to the telephone survey, which asked about the selling prices and quantities sold of the three crops. The participation in the telephone survey is lower than in the face-to-face survey possibly because of smaller social pressure in the telephone survey. We did not merge this round of telephone survey into the panel since the time of the telephone survey is different from that of the face-to-face surveys; instead, we separately analyzed the selling prices from the telephone survey as cross-sectional data.

In 2018, 370 households which are approximately 70% of surveyed households, produced and sold wheat at the local markets. Of these, 41 and 46 households received the domestic- and foreign-informant treatments, respectively. However, the proportion of barley and fava bean sellers was fairly limited, at 4% and 9%, respectively. Therefore, this study only focuses on wheat producing households.

2.3 Variable construction and summary statistics

Summary statistics of the pre-treatment demographic characteristics of the wheat producing households are presented in Table 1, whereas those of the full sample including barley and fava bean producers are in the Appendix Table A. Prior to the experiment, 71-76% of our observations owned at least one mobile phone in their household, while the average penetration rate of Facebook was low at 8%. Furthermore, people rarely used Facebook to communicate about agricultural commodity prices or agricultural technology. We compare the average of each indicator by using t-test and find no statistically significant differences between the treatment and control groups for all indicators.

3 Method

3.1 Benchmark estimation

To identify how the information provision through Facebook affects the selling price of wheat, this study employed the following difference-in-differences (DID) models with two-way fixed effects (TWFE), one for households and the other for years:

$$Y_{it} = \alpha + \beta Treat_i \times \tau_t + \delta X_{it} + \rho_i + \tau_t + \varepsilon_{it}, \tag{1}$$

$$Y_{it} = \alpha + \gamma_1 DomesticTreat_i \times \tau_t + \gamma_2 ForeignTreat_i \times \tau_t + \delta X_{it} + \rho_i + \tau_t + \varepsilon_{it}, \qquad (2)$$

where Y_{it} is the outcome of interest (i.e., selling price of wheat, Facebook usages, and trust perceptions) for household i in year t (t = 2018, 2019) $Treat_i$ in equation (1) is a dummy variable that takes a value of 1 when household i received information through Facebook from either the domestic or foreign informant. *DomesticTreat* and *ForeignTreat* in equation (2) are the dummy variables for receiving information from the domestic and foreign informant, respectively. X_{it} indicates a set of observable demographic characteristics of household i shown in the upper part of Table 1, including the size of the household, education level, total income, number of oxen, and a measure of risk preferences. Controlling for total income and the number of oxen is particularly important, because the level of income and wealth may affect the ability to collect information and liquidity constraints and, thus selling prices of the household. ρ_i is the household-specific fixed effect for household i, which reduces the unobserved time-invariant differences between households. τ_t represents a time dummy. Because the take-up ratio is 100%, and because the pre-treatment attributes were balanced (Table 1), we simply estimate equations (1) and (2) using ordinary least squares (OLS) estimations. Standard errors are clustered at the village level to account for correlations in the error term ε_{it} within the same village.

If farmers take advantage of market information distributed through Facebook, the wheat selling price and Facebook usage are likely to increase. Hence, the parameters β and γs in equations (1) and (2) are expected to be positive. Furthermore, by comparing the coefficients of the two treatment dummies in equation (2), we can test whether the homogeneity of informants to farmers influences the usage of information even in online communities. If farmers trust and utilize information from the local informant more than from the foreign informant, the coefficient of the domestic-informant treatment should be larger than that of the foreign-informant treatment ($\gamma_1 > \gamma_2$).

In addition, we also performed the estimation to check the spillover effects of our interventions. As indicated earlier, 66% of households in the 10 villages selected for the lottery did not have the opportunity to receive the market information through the Facebook community directly. However, they may have received the same information indirectly from their peers in the treatment group. The spillover effects were also observed in prior literature in Uganda, where treatment farmers shared the agricultural information distributed by the video intervention with control farmers in the same village (Van Campenhout et al., 2021). To examine the spillover effects, we include the additional two dummy variables in equation (2) that take a value of 1 if household i belongs to the control group in the village receiving the domestic- and foreign-informant treatments, respectively and 0 if the household is in one of the treatment groups or in a village with no treated household.

3.2 Mechanisms

There are two potential mechanisms for farmers to increase the selling price through market information provision: negotiating over prices and postponing selling to a later period when prices are expected to be higher. To empirically test the potential mechanisms, we use cross-sectional telephone survey data conducted immediately after the provision of market information when wheat prices are generally low (Figure 1) and estimate its immediate effect on the selling price and sales volume. The independent variables in the models are similar to those in equations (1) and (2), except that household and year fixed effects are replaced by village fixed effects because of the cross-sectional nature of the data from the telephone survey.

When producers use the market information to negotiate selling price, the treatment dummies are expected to have a positive effect on wheat selling price during the low-price period. In contrast, if producers delay the timing of sales in response to market information, we expect the effect on wheat selling price is expected to be close to zero while our interventions would reduce the volume of wheat sales volume during the low-price period.

4 Results

4.1 Impact on Facebook usage

We start with the DID estimation of equations (1) and (2) with TWFE, using several variables that indicate the usage of Facebook as outcome variables, and show the results in Table 2. The odd columns in Table 2 show the impact of receiving market information from either an Ethiopian or foreign informant, while the even columns are the results when we distinguish between the two types of treatments. As expected, the treatment dummy in column (1) had a positive effect on the probability of having a Facebook account at the one percent significance level. Consistently, the coefficients in column (2) indicate that participants in both treatment groups are 15-19% more likely to have a Facebook account than participants in the control group.

Next, we tested whether our intervention encouraged participants to obtain agricultural price information through Facebook. The effects of the treatment dummy in column (3) and the domestic-informant treatment in column (4) are positive and statistically significant at the one percent level, while the effect of treatment by the foreign informant is found to be insignificant. These results indicate that the effect of treatment on the use of Facebook to obtain price information is driven by information provision by an Ethiopian but not by a foreigner. Similarly, we find in column (6) that only the domestic-informant treatment had a significant impact on obtaining agricultural technology information through Facebook.

The difference between the effects of domestic- and foreign-informant treatments on receiving agricultural information may simply come from that households received information by a foreign informant did not use Facebook after the treatment. To check this, we estimate the effect of each type of treatment on receiving political information through Facebook, which were not provided by the informants of the experiment. Columns (7) and (8) of Table 2 show that both effects of domestic- and foreign-informant treatments are positive and significant at the 10-percent level, suggesting that households who received agricultural information from the foreign informant used Facebook.

Another possibility of the difference is that farmers did not trust information from the foreign informant and thus ignored Facebook posts from the foreign informant. In a separate regression, we estimate the effect of the treatments on the level of respondents' trust in various types of people and find a positive and weakly significant ($p = 0.07$) effect of the foreign-informant treatment on trust in foreigners (Appendix Table A2). The result suggests that the exposure to a foreigner that is quite rare in the rural areas of our examination in Ethiopia promoted general trust in foreigners. However, our earlier results in columns (4) and (6) imply that despite the improvement in the general trust in foreigners, farmers are still skeptical about the quality of the agricultural information provided by the foreign informant. In columns (9) and (10), we further check the treatment effect on whether farmers share information to other farmers through Facebook and find a positive and significant effect of the domestic-informant treatment but an insignificant effect of the foreign-informant treatment. This result also supports our conjecture that farmers did not trust information from the foreign informant.

4.2 Impact on selling prices

To identify how the provision of information on prices in the market affects farmers' selling price of wheat, we begin with the TWFE DID estimates based on our panel data collected in August 2018 and 2019. The results in column (1) of Table 3 reveal that the average selling price of wheat significantly increased by the provision of information. However, column (2) shows that we only observe a positive significant effect of the treatment by the Ethiopian informant but no significant effect of the treatment by the foreign informant. The coefficient in column (2) indicates that the information provision by the Ethiopian increases the selling price by 14.2%, which is consistent with the results in Ghana, where the provision of price information by SMS increased the selling price of maize by 10% (Courtois and Subervie, 2015). These results are also consistent with the findings from the results on Facebook usage presented in Table 2, which show that only farmers in the domestic-informant treatment groups obtained price information from Facebook.

In addition, we test spillover effects of the treatments and present the results in column (3) of Table 3. As mentioned, 66% of the villagers in the treatment villages did not receive treatment as a result of the lottery. However, those villagers could have obtained information on market price from treated participants in the same village. Therefore, we incorporate the possibility of treatment spillovers by including two dummy variables representing non-treatment households in the treatment villages. The results in column (3) show that the effect of spillovers from households who received information from the domestic or foreign informant to others is not significant at the 10% level. Meanwhile, even after controlling for spillover effects, we consistently find a significantly positive effect of the domestic-informant treatment. Overall, these results suggest that only when the homogeneity between farmers and informants is high, the provision of information on market prices through Facebook increases the farmers' selling price.

4.3 Mechanism

To examine the potential mechanisms of the effect of the provision of price information on the increase in farmers' selling prices, we further examine its effect based on cross-sectional data from the telephone survey. As we mentioned in Section 2.2, selling prices that we used so far were those in the last transaction between the harvest in January and the data collection in August, while selling prices collected in the telephone survey were those in January, immediately after the harvest.

The results from estimating the immediate effect of the treatments on the selling price of wheat are presented in columns (1) and (2) of Table 4. Unlike the baseline specification, the coefficients of all the treatment variables are close to zero and insignificant. In contrast, we found that the treatment by the

Ethiopian informant significantly reduced the sales volume of wheat by 13.6%, while the treatment by the foreign informant was not significant, as shown in column (4) of Table 4.

These findings suggest that the price information from the Ethiopian informant was not useful in selling their crips at higher prices in January when prices were the lowest (Figure 1). Even if a farmer knew the price, individual bargaining power would not increase due to the massive volume of supply of wheat on the market and the intense competition among farmers shortly following the harvest. Instead, they have reduced the sales volume during the low-price period and delayed the timing of sales, expecting that they could sell their crops at a higher price later with the help of Facebook price information.

To confirm this conjecture, we estimated the impact of the treatments on the sales volume and frequency of sales reported by respondents at the endline survey in August. The results for sales volume at the endline in column (6) indicate that the coefficient of treatment by the Ethiopian informant was negative but insignificant. These results imply that participants provided information by the Ethiopian informant sold less only during the low-price period (column (4)) but not later (column (6)). Furthermore, when farmers received information from the Ethiopian informant, the frequency of sales in the market or to traders declined significantly, as shown in column (8) of Table 4, most likely because they delayed the timing of sales after harvesting.

It is important to note that these results do not negate the possibility of price negotiation through information provision as indicated in previous studies. In this experiment, since information provision ended in March, only the effect of information provision in the low-price period was examined. Therefore, if information provision is continued after April, farmers may use the information to negotiate prices with intermediaries. Meanwhile, the results of this study also suggest that the effect of price negotiation through information provision in previous studies may be overestimated by not accounting for price increase due to sales delay.

4.4 Robustness

To check the robustness of the results above, we apply alternative specifications in which the key independent variable is the dummy variable for obtaining price information through Facebook. However, whether farmers received price information through Facebook is endogenously determined even when they were provided information by our experiment, as we found in column (4) of Table 2 that the treatment by the foreign informant did not significantly affect the receipt of the information. Therefore, we employ instrumental variable (IV) estimations, using the dummy variables for the domestic- and foreign-informant treatments as IVs for the receipt of information. The results in the Appendix Table A3 are consistent with the results from the baseline specifications in Tables 3 and 4. However, although the first stage of the IV estimations find that the domestic-informant treatment is significantly correlated with the endogenous variable, the Kleibergen-Paap F statistics are mostly low, as shown in Appendix Table A3. Therefore, the instruments may be weak, and thus we rely more on the baseline results than the IV results.

4.5 Heterogeneity

In this section, we investigate possible heterogeneity in the effects of the treatments for the baseline specification presented in Table 3. More precisely, we evaluate how the effects of the treatments vary across different subsamples based on six demographic variables: age, education level of the household head, gender, wealth (number of oxen), income, and social networks of the household. For estimation, we created subsample dummy variables for each demographic variable (e.g., below median dummy and above median dummy) and interacted them with each of the treatment dummies (the domestic- and foreign-informant treatments). Figure 2 only shows the effect estimates for the domestic-informant treatment (Table A4 in Appendix reports the regression table).

First, to assess whether participants at different age are differently affected by the treatments, we split the observations into subsets based on the median age of the household head (40 years). The results in Figure 2 show that older household heads increase their selling price more than younger heads when the market price information is provided through Facebook. Prior literature also confirms that the impact of ICTs is greater for older household heads (Dzanku et al., 2021). One potential reason for this result is that the benefit of information provision through Facebook is greater for older household heads due to their limited use of ICTs prior to the experiment (Nakasone and Torero, 2016). Therefore, teaching how to create a Facebook account and improving access to price information through Facebook by our experiment may have led to a greater effect on older farmers.

Second, we construct the subsamples by the education level of the household heads, with grade 6 as the threshold education level (less than 40% have graduated from elementary school, as shown in Table 1). The coefficients of domestic-informant treatment were positive and significant for both subsamples below and above grade 6, while the regression estimate was slightly higher for the low-education subsample. These findings suggest that the effect of the information provision through Facebook may not be affected by the education level.

Third, we divide the sample by the gender of household heads. The results suggest that female participants are more positively affected by the information provision by the Ethiopian informant. Although the number of female household heads was limited to approximately 20% of the total, we also found that the estimated coefficients of the domestic-informant treatment differ significantly between female- and male-headed households at the 10% level. In general, female farmers in developing countries are isolated from local social networks, resulting in a low adoption rate and knowledge level of agricultural technologies (Beaman and Dillon, 2018). Potential explanation for the larger effect among women could be that the Facebook intervention reduced social isolation and provided access to market price information.

Fourth, we explore heterogeneity in the treatment effects by the economic level, such as the number of oxen and household income. Although there was no observable impact of liquidity constraints on selling price prior to the experiment, there remains concern that liquidity constraints may dilute the effectiveness of information provision through Facebook. If liquidity constraints affect the effect of information provision through Facebook, the estimated coefficients of treatment are expected to be smaller for households with lower levels of livestock and income. However, we find that the domestic-informant treatment significantly increased the selling price for households with lower than median number of oxen and household income.

Finally, we examine whether the treatment effects vary across the strength of participants' social networks. As mentioned, farmers isolated from social networks are less likely to have access to agricultural information (Beaman and Dillon, 2018). If our intervention creates online networks among isolated farmers and increases their access to information, we expect to observe a greater impact among farmers with fewer helping networks. To examine this, we create a variable that measures the strength of social networks of each household, applying principal component analysis to responses to nine questions regarding social networks shown in Appendix Table A5. The results show that the effect of the domestic-informant treatment is significantly positive only for farmers with lower strength of social network. In addition, we find that the estimated coefficient is significantly larger for farmers with lower network strength than those with higher strength at the 10% level.

Overall, the heterogeneity analysis above implies that when farmers have less access to agricultural information because of the age, gender inequality, poor economic situation, and weak social ties, information provision is helpful to increase the selling price of their agricultural products. However, information provision to farmers who already have access to sufficient information is less likely to have an additional effect on their selling prices.

5 Conclusion

By conducting a randomized experiment targeting wheat producers in Ethiopia, this study investigates the impact of providing information on market prices of agricultural products through social media, specifically Facebook, on the smallholder farmers' selling price of wheat. We find that although the interventions promoted Facebook use among farmers in the treatment groups, the information was used only when the informant was from the same country as farmers but not when the informant was a foreigner. Consistently, the provision of price information from a domestic informant increased the wheat selling price in the last transaction after harvest by approximately 14%, while that from a foreign informant has no such effect possibly because farmers do not trust information from foreigners. Furthermore, the results from our heterogeneity analysis suggest that the effect of information provision by a domestic informant is larger for older, poorer, socially more isolated, and female farmers, most likely because they have less access to information prior to our experiment. In other words, if farmers are already accessible to sufficient information, provision of additional information through social media has little impact on their selling prices.

In contrast, we do not find evidence that our interventions increased sales price immediately after harvest when prices are quite low because of competition among farmers. Instead, there was a significant decrease in the sales volume of farmers who obtained information from a domestic informant in the low-price period. Combined with the prior results, this result implies that while information on market prices is not helpful to farmers' negotiations with traders in the low-price period, farmers use the price information to delay the timing of their sales to a later period when prices are higher.

Our findings provide useful policy implications for agricultural development in developing countries. First, the use of social media has great potential for efficiently disseminating price information in developing countries. Our results show that information provision via social media is particularly effective to marginalized farmers. Second, despite the effectiveness of information provision, policy makers may need to be careful about who provides the information, as we find ineffectiveness of information provision by foreigners possibly because of lack of trust in foreigners. Although social media eliminates the constraints of physical distance and thus enables to provide information from anywhere without any additional cost, social distance is still an important determinant of information flows through social media. Therefore, simply building an online social media platform is not expected to be effective in increasing farmers' income and reducing poverty. Finally, to increase the selling price of agricultural products, it is important to intensively provide market price information during the period of lowest selling prices, immediately after harvest. Especially when financial constraints limit the ability to collect information, it may be more efficient to concentrate resources for information collection during periods of low prices.

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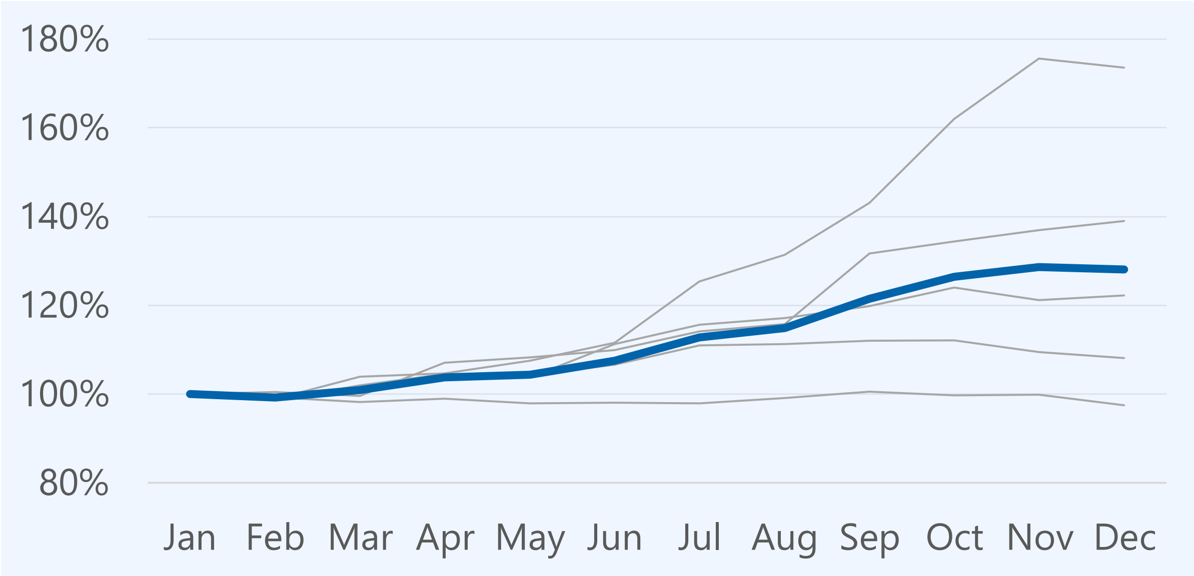

Figure 1. Average monthly retail price of wheat in Addis Ababa from 2014 to 2018. The values on the vertical axis indicate the price change in each month when the January price is set to 100. The light gray line in the figure is the average for each year, while the thick blue line shows the five-year average. Data obtained from USDA (2019).

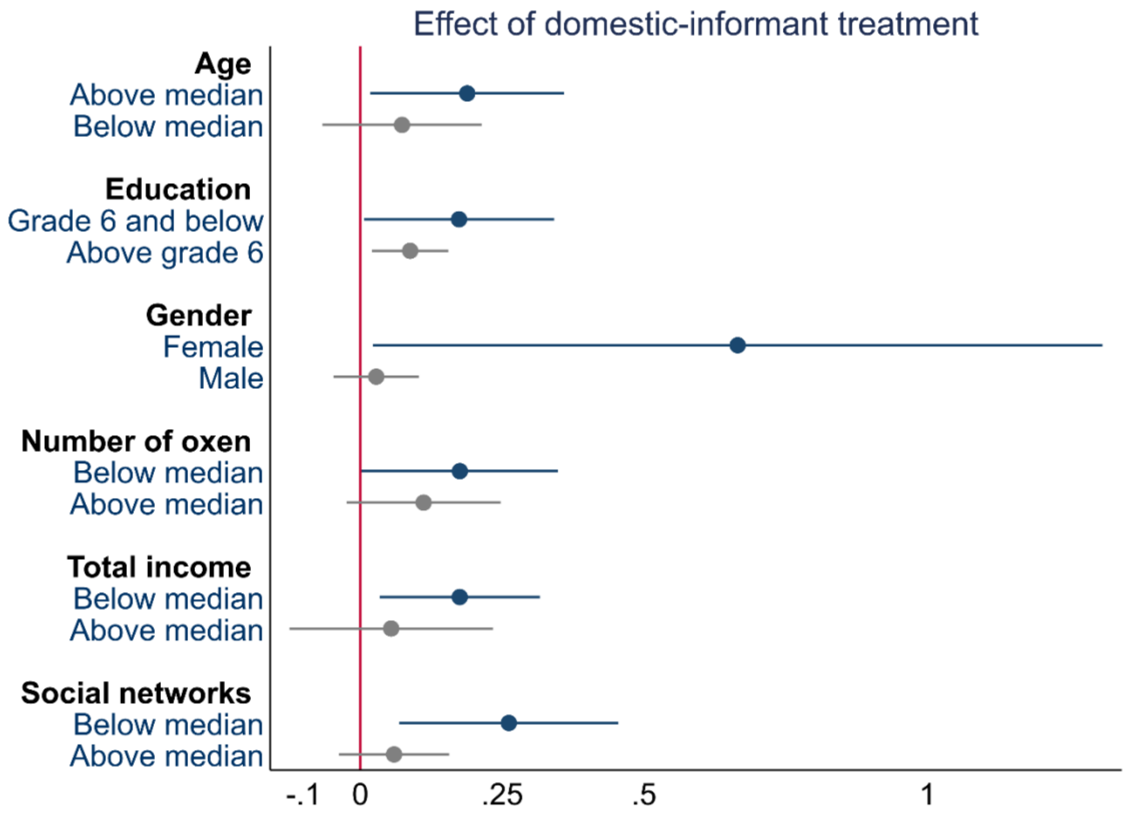

Figure 2. Heterogeneity. For the demographic variables shown in the header, dummy variables were created for each subsample (e.g., below median, above median) and interacted with the domestic-informant treatment. Regression estimates with 90% confidence intervals based on cluster-robust standard errors are reported. Although not shown in the figure, the interaction terms with the foreign-informant treatment are included in the estimation.

Table 1: Summary statistics before the experiment

		Treatment			
	Treatment	Domestic	Foreign	Control	Total
Number of observations	88	41	47	282	370
Age	45.33	45.81	44.92	42.60	43.25
	(13.64)	(12.02)	(15.03)	(14.78)	(14.54)
Female household head	0.17	0.22	0.13	0.21	0.20
	(0.38)	(0.42)	(0.34)	(0.41)	(0.40)
Education above grade 6	0.31	0.24	0.36	0.39	0.37
	(0.46)	(0.44)	(0.49)	(0.49)	(0.48)
Number of household members	6.73	6.95	6.53	6.19	6.32
	(2.86)	(2.85)	(2.87)	(2.92)	(2.91)
Total size of cultivated land (ha)	1.65	1.56	1.72	1.60	1.61
	(1.09)	(0.91)	(1.23)	(1.45)	(1.37)
Households with mobile phones	0.76	0.81	0.72	0.71	0.72
	(0.43)	(0.40)	(0.45)	(0.46)	(0.45)
Risk lover	0.34	0.40	0.28	0.27	0.29
	(0.48)	(0.50)	(0.46)	(0.45)	(0.45)
Total household income (10 thousand birr)	0.71	0.48	0.92	0.45	0.51
	(1.94)	(1.10)	(2.44)	(1.25)	(1.44)
Number of oxen	3.84	3.93	3.77	3.73	3.75
	(3.09)	(3.45)	(2.78)	(2.82)	(2.88)
Facebook usage					
Facebook user	0.08	0.05	0.11	0.08	0.08
	(0.27)	(0.22)	(0.31)	(0.26)	(0.27)
Getting agricultural price information	0.01	0	0.02	0.02	0.02
	(0.11)		(0.15)	(0.13)	(0.13)
Getting agricultural technology information	0.03	0.05	0.02	0.01	0.02
	(0.18)	(0.22)	(0.15)	(0.10)	(0.13)
Getting political information	0.06	0.05	0.06	0.05	0.05
	(0.23)	(0.22)	(0.25)	(0.21)	(0.22)
Sharing the information	0.07	0.05	0.09	0.05	0.05
	(0.25)	(0.22)	(0.28)	(0.22)	(0.23)

Note: Standard deviations in parentheses. There is no statistically significant difference in any variable between the groups.

Table 2: Treatment effect on Facebook usage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Outcome									
	Holding a Facebook account		Receiving through Facebook information on						Sharing information through Facebook	
			agricultural prices		agricultural technology		political information			
Treatment * year	0.162***		0.115**		0.060		0.155**		0.085	
	(0.044)		(0.038)		(0.038)		(0.054)		(0.053)	
Domestic-informant treatment * year		0.176**		0.155***		0.088*		0.168*		0.130***
		(0.066)		(0.042)		(0.046)		(0.081)		(0.026)
Foreign-informant treatment * year		0.150**		0.081		0.036		0.144*		0.047
		(0.052)		(0.067)		(0.064)		(0.070)		(0.088)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Household fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	718	718	722	722	722	722	722	722	722	722
R-squared	0.596	0.596	0.536	0.538	0.552	0.553	0.591	0.591	0.620	0.622

Note: The treatment dummy represents whether the participant received one of the two Facebook interventions. The domestic- and foreign-informant treatments indicate provision of information by an Ethiopia and foreign informant, respectively. Standard errors clustered at the village level are in parentheses; ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively.

Table 3: Effect of the information provision on selling prices

	(1)	(2)	(3)
	Outcome: selling price of wheat (log)		
Treatment * year	0.085*		
	(0.045)		
Domestic-informant treatment * year		0.142**	0.162**
		(0.065)	(0.073)
Foreign-informant treatment * year		0.036	0.055
		(0.048)	(0.056)
Spillover of domestic-informant treatment			0.051
			(0.044)
Spillover of foreign-informant treatment			0.022
			(0.051)
Controls	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Number of observations	724	724	724
R-squared	0.640	0.643	0.644

Note: The treatment dummy represents whether the participant received one of the two Facebook interventions. The domestic- and foreign-informant treatments indicate provision of information by an Ethiopia and foreign informant, respectively. Standard errors clustered at the village level are in parentheses; ** and * indicate statistical significance at the 5% and 10% levels, respectively.

Table 4: Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Data	Telephone survey				Endline survey		Panel data	
Dependent variable	Selling price (log)		Sales volume (log)		Sales volume (log)		Frequency of sales	
Treatment * year	-0.001		-0.151		0.105		-0.065	
	(0.008)		(0.103)		(0.441)		(0.134)	
Domestic-informant treatment * year		-0.007		-0.152**		-0.460		-0.249*
		(0.008)		(0.061)		(0.478)		(0.130)
Foreign-informant treatment * year		0.007		-0.149		0.574		0.093
		(0.012)		(0.214)		(0.599)		(0.184)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes		
Time fixed effects							Yes	Yes
Household fixed effects							Yes	Yes
Number of observations	231	231	230	230	370	370	714	714
R-squared	0.285	0.296	0.419	0.419	0.200	0.207	0.632	0.634

Note: The treatment dummy represents whether the participant received one of the two Facebook interventions. The domestic- and foreign-informant treatments indicate provision of information by an Ethiopia and foreign informant, respectively. Standard errors clustered at the village level are in parentheses; ** and * indicate statistical significance at the 5% and 10% levels, respectively.

Declaration of competing interest:
The authors declare that they have no competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Appendix Tables

Table A1: Average demographic characteristics of the full sample before the experiment

	Treatment	Treatment: Domestic	Treatment: Foreign	Control	Total
Number of observations	115	59	56	407	522
Age	44.76	46.19	43.25	42.56	43.05
	(13.96)	(12.96)	(14.92)	(14.72)	(14.57)
Female household head	0.17	0.15	0.18	0.21	0.20
	(0.37)	(0.36)	(0.39)	(0.41)	(0.40)
Education above grade 6	0.32	0.31	0.34	0.36	0.35
	(0.47)	(0.46)	(0.48)	(0.48)	(0.48)
Number of household members	6.65	6.97	6.32	6.28	6.36
	(2.98)	(3.07)	(2.88)	(2.90)	(2.92)
Total size of cultivated land (ha)	1.61	1.65	1.57	1.45	1.48
	(1.16)	(1.12)	(1.20)	(1.34)	(1.30)
Households with mobile phones	0.77	0.78	0.77	0.67	0.69
	(0.42)	(0.42)	(0.43)	(0.47)	(0.46)
Risk lover	0.33	0.37	0.29	0.27	0.28
	(0.47)	(0.49)	(0.46)	(0.44)	(0.45)
Total household income (10 thousand birr)	0.57	0.38	0.77	0.39	0.43
	(1.72)	(0.94)	(2.26)	(1.11)	(1.27)
Number of oxen	3.68	3.98	3.36	3.47	3.51
	(3.11)	(3.40)	(2.77)	(2.83)	(2.89)
Facebook usage					
Facebook user	0.06	0.03	0.09	0.05	0.06
	(0.24)	(0.18)	(0.29)	(0.23)	(0.23)
Getting agricultural price information	0.01	0	0.02	0.01	0.01
	(0.09)		(0.13)	(0.11)	(0.11)
Getting agricultural technology information	0.03	0.03	0.02	0.01	0.01
	(0.16)	(0.18)	(0.13)	(0.09)	(0.11)
Getting political information	0.04	0.03	0.05	0.03	0.04
	(0.21)	(0.18)	(0.23)	(0.18)	(0.18)
Sharing the information	0.05	0.03	0.07	0.04	0.04
	(0.22)	(0.18)	(0.26)	(0.19)	(0.20)

Note: Standard deviations in parentheses. There is no statistically significant difference in any variable between the groups.

Table A2: Effect of the Facebook information provision on perceptions of trust

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Based on dictator game		Based on questionnaire							
	Altruism to people outside the village		General trust (GSS)		Trust in people meeting for the first time		Trust in people of another religion		Trust in people of another nationality	
Treatment * year	-0.113		0.079		-0.036		0.029		0.081	
	(1.860)		(0.075)		(0.061)		(0.068)		(0.051)	
Domestic-informant treatment * year		0.503		0.227**		-0.049		-0.020		0.041
		(2.771)		(0.086)		(0.108)		(0.121)		(0.070)
Foreign-informant treatment * year		-0.637		-0.050		-0.025		0.071		0.117*
		(2.109)		(0.077)		(0.044)		(0.049)		(0.066)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	718	718	702	702	724	724	718	718	698	698
R-squared	0.590	0.591	0.503	0.507	0.535	0.535	0.569	0.569	0.544	0.545

Note: The treatment dummy represents whether the participant received the treatment by Ethiopian or foreigner. Standard errors are clustered at the village level in parentheses; ** and * indicate statistical significance at the 5% and 10% levels, respectively.

Table A3: Results of instrumental variable estimates

	(1)	(2)	(3)	(4)
Data	Panel	Mobile survey		Endline
Dependent variable (Panel A)	Selling price (log)	Selling price (log)	Sales volume (log)	Sales volume (log)
Panel A: IV estimates				
Use of Facebook to obtain price information	0.820*	-0.048	-1.062**	0.346
	(0.468)	(0.047)	(0.504)	(4.152)
Dependent variable (Panel B)	Use of Facebook to obtain price information			
Panel B: First-stage estimates				
Domestic-informant treatment * year	0.155**	0.146**	0.146**	0.110***
	(0.061)	(0.063)	(0.064)	(0.026)
Foreign-informant treatment * year	0.081	0.006	0.010	0.085
	(0.096)	(0.046)	(0.053)	(0.065)
Kleibergen-Paap *F*-statistic	3.97	2.71	2.68	9.01
Controls (for all panels)				
Demographic variables	Yes	Yes	Yes	Yes
Time dummy	Yes			
Household fixed effect	Yes			
Village fixed effect		Yes	Yes	Yes
Number of observations (for all panels)	731	231	230	370

Note: Obtaining price information via Facebook is a dummy variable that takes 1 if participant obtain the market price information through Facebook. Standard errors are clustered at the village level in parentheses; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Demographic variable	Age	Education	Gender	Number of oxen	Total income	Social networks
Group 1	Above median	6th grade and below	Female	Below median	Below median	Below median
Group 2	Below median	Above 6th grade	Male	Above median	Above median	Above median
*Domestic-informant treatment * year **						
Group 1 dummy	0.188*	0.174*	0.665*	0.175*	0.175**	0.262**
	(0.096)	(0.095)	(0.363)	(0.098)	(0.080)	(0.109)
Group 2 dummy	0.073	0.088**	0.028	0.111	0.054	0.059
	(0.079)	(0.038)	(0.042)	(0.077)	(0.101)	(0.055)
*Foreign-informant treatment * year **						
Group 1 dummy	0.055	0.005	0.011	0.006	0.035	0.055
	(0.068)	(0.064)	(0.086)	(0.043)	(0.035)	(0.067)
Group 2 dummy	0.015	0.111	0.044	0.070	0.039	0.018
	(0.034)	(0.091)	(0.046)	(0.069)	(0.074)	(0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	724	724	724	724	724	724
R-squared	0.644	0.644	0.665	0.644	0.644	0.647

Note: The results of heterogeneity shown in Figure 1 are reported. For the demographic variables shown in each column, we created dummy variables for each subsample (i.e., groups 1 and 2) and interacted them with each treatment dummy. Standard errors are clustered at the village level in parentheses; ** and * indicate statistical significance at the 5% and 10% levels, respectively.

Table A5: Nine indicators related to social network used for a principal component analysis

No	Questions	Mean
1	Can ask the village leader for help in times of trouble. (1=Yes)	0.414
2	Can ask the local agricultural extension agent for help in times of trouble. (1=Yes)	0.395
3	Can ask the local institution for help in times of trouble. (1=Yes)	0.443
4	Can ask the federal government for help in times of trouble. (1=Yes)	0.219
5	Can ask the other public institution for help in times of trouble. (1=Yes)	0.246
6	Receiving any support from Ethiopian institution during past drought (1=Yes)	0.319
7	Receiving any support from foreign institution during past drought (1=Yes)	0.032
8	Using the agricultural extension hotline at least once a month (1=Yes)	0.027
9	Number of people asking for help when faced with some difficulty (e.g., illness, accidents, crimes, and disasters)	1.389

Note: Questions 1 to 8 were answered with either "Yes" or "No". The agricultural extension hotline is a service provided by the Agricultural Transformation Agency (ATA) of Ethiopia in which farmers can receive agricultural advice through mobile phones.