

## **Determinants and impact of farmers' participation in social media groups: Evidence from irrigated areas of Kazakhstan and Uzbekistan**

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**CITATION** Tadjiev, A., Kurbanov, Z., Djanibekov, N. Govind, A. and Akramkhanov, A. 2023. Determinants and impact of farmers' participation in social media groups: Evidence from irrigated areas of Kazakhstan and Uzbekistan. Halle (Saale), Germany, IAMO Discussion Paper No. 201, Halle (Saale): IAMO.

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ISSN 1438-2172

ISBN 978-3-95992-159-6

## ABSTRACT

The spread of information and communications technology (ICT) in Central Asia has reached a point where most farmers use smartphones with mobile internet access, providing an opportunity for a cost-effective and timely access to agricultural information and extension services. When extension service provision is poor and does not reflect farmers' immediate needs, farmers often seek other sources of information, such as exchanging knowledge with their peers via social media groups in instant messaging applications (apps). Using the findings of a farm-level survey conducted in 2022 in irrigated areas of Kazakhstan and Uzbekistan, we study behavior and attitudes of farmers in terms of participation in smartphone-based social media groups and its impact of farm performance. We find that in the two country contexts underlying reasons for participation in social groups differ. In Kazakhstan, participation decisions are made by those who have better access to a mobile internet connection, are younger, have agriculture-related education, have a wider communication circle on phone with more than four individuals, cultivate fewer crops, have lands with low soil quality and poor irrigation water access, as well as located in remote areas. In Uzbekistan participation decisions are made by those who see the relevance of mobile internet for their farm business, have own agronomic knowledge, are open to new things, care less about the opinion of other farmers, have higher perception about freedom in crop choice, have off-farm work, as well as poor irrigation water access. These findings suggest farmers' participation in agricultural information-sharing groups (AISG) is influenced less by the type of cultivated crops or farm size, but by their institutional environment. The findings are relevant for developing private strategies and public policies to spread digital technologies among Central Asia's farmers. When introducing smartphone-based digital advisory services policymakers are recommended to start scaling up with younger and more educated farmers who rely on their own knowledge and are more open to embracing new ways of farming and interaction. Farmers' decision-making autonomy will be crucial for converting digital transformation in agriculture into farm benefits.

## KEYWORDS

Extension services, self-help groups, knowledge exchange, participation determinants, Central Asia

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## 1. Introduction

Well-structured agricultural extension services based on participatory methods can stimulate desirable agricultural growth by transferring knowledge, advice and educating farmers about new practices and technologies (Anderson and Feder 2004). The ability of extension service organizations to integrate modern research findings and other relevant information to address new agricultural challenges is a worldwide concern (World Bank 2012). The development of modern agricultural extension and advisory services is of high relevance in Central Asia's agricultural development. For instance, in the context of Uzbekistan, Djuraeva et al. (2022) finds wheat growers' access to extension services can complement the effects of agricultural inputs such as fertilizers, seeds, and irrigation water. Djuraeva et al. (2022) also show that the enhanced frequency of extension visits, improved irrigation technologies, cooperation status among farmers, and participatory extension methods strongly enhance the technical efficiency of wheat producers in Uzbekistan. However, conventional physical approaches in extension services such as Training-and-Visit and Farmer Field Schools may not always yield the intended results of technology adoption or livelihood improvements of farmers (Steinke et al. 2021).

The Central Asian system of knowledge production and knowledge sharing relies on a complex network of agricultural ministry departments, public agricultural universities, and research institutes and international development agencies (de Danieli and Shtaltovna 2016). This traditional way of service provision to farmers by public organizations in a top-down manner without accounting for the farmers' actual needs creates many challenges (Nazarov 2008). For instance, extension services in Uzbekistan are underdeveloped owing to the lack of national policy guidelines and an undefined institutional and organizational structure (Kazbekov and Qureshi 2011). The quality of extension services is being addressed by recent changes in Uzbekistan, i.e. establishment of the Agricultural Knowledge and Innovations System (AKIS) in 2019 as part of the implementation of the Agriculture Development Strategy 2030.

The top-down communication of knowledge is among the major factors hindering the expansion of extension services (de Danieli and Shtaltovna 2016). A lack of representation of farmers' interests through a strong organization or simply because the public organizations have their targets issued by the central ministry makes farmers unable to signal their knowledge needs to policymakers. Due to a lack of access to modern knowledge, poor communication techniques, and conflicting agendas, public agricultural service organizations are insufficient in addressing farmers' knowledge needs (de Danieli and Shtaltovna 2016). Furthermore, small and disadvantaged farmers in remote areas often have restricted access to extension and advisory services. The knowledge dissemination projects run by international development agencies through participatory approaches serve only a relatively small number of farmers with short-lived effects without a wider adoption (Van Assche 2016). Consequently, no efficient system connects and coordinates knowledge transfer from

agricultural education and research organizations to farmers. Because of the ineffective extension systems, farmers often seek other sources of information, such as exchanging knowledge with their peers or relying on public information platforms such as TV, newspapers and radio (Kurbanov et al. 2022).

Information and communication technology (ICT) tools can address issues related to poor physical extension services, such as slow or top-down knowledge supply which does not reflect farmers' needs, or when accessing high-quality information is cumbersome or expensive (World Bank 2011). The use of ICTs, namely smartphones, can offer platforms for agricultural extension services in updating farmers on weather and disease forecasts, output and input markets, farming practices, as well as other information related to farming business such as agricultural credits, veterinary services, and others (Aker 2011; Steinke et al. 2021). Compared to traditional extension services, ICT tools offer timely, relevant, and actionable information to farmers at lower costs (Norton and Alwang 2020). The use of smartphones minimizes transaction costs for farmers and provides them with new ways to search for and learn about solutions to their daily farming issues. In response to these advantages, agriculture extension specialists and research institutes throughout the world have been advocating the enhanced use of ICT to boost agricultural production by facilitating farmer learning, problem-solving, and access to profitable markets (World Bank 2011).

ICT-based extension services can overcome the hurdles of traditional knowledge flow by improving interactions and communications among farmers and experts for information exchange about essential things related to their day-to-day operations (Steinke et al. 2021). Smartphone-based messaging applications (apps) such as WhatsApp and Telegram have become prominent and well-established ICT-based tools for creating knowledge-sharing channels among individuals and complementing conventional communication methods (Ahmed et al. 2019). Such instant messaging apps have recently gained high popularity in agriculture in developing countries (Fabregas et al. 2019) where farmers organize social media communities to share information, ideas, personal messages and other media content and discuss them with peers and experts (Norton and Alwang 2020). The participants of the social media groups include not only farmers but also other actors of value chains such as agricultural advisors and extension agents, researchers, policymakers, processors and retailers. The COVID-19 pandemic and the consequent reduction of in-person meetings enhanced the role of knowledge exchange and information flow through smartphone-based social media groups (Davis et al. 2020).

Despite the increasing use of social media groups in agriculture of developing countries, there is a lack of empirical evidence about factors that explain farmers' participation in social media groups and whether it improves farm performance. Recent empirical studies on farmers' adoption and impact of ICT tools focused on the use of mobile phones, smartphones, mobile internet and internet services (Bounkham et al. 2022; Kaila and Tarp 2019; Ma et al. 2020; Michels et al. 2020a; Michels et al. 2020b; Ogutu et al. 2014; Quandt et al. 2020; Van

Campenhout et al. 2020; Zhu et al. 2021) and do not account for the new global phenomenon of farmers organizing online self-help groups in instant messaging apps. Only a study by Mendes et al. (2023) directly addressed the participation of farmers in social media groups in smartphone-based messaging app. The evidence about how farmers use social groups, what defines their participation in such knowledge exchange platforms, and how this affects farm business can contribute to a better understanding the ways of harnessing the ICT tools for improved extension services. Thus, the study aims to address these gaps by investigating the following three research questions (1) How do farmers perceive the ICT use for their farm business?, (2) What are the determinants of farmers' participation in social media groups?, and (3) What are the impact of participation in social media groups on farm performance?

By doing so, our study contributes to the globally limited empirical literature on farmers' participation in social media groups for knowledge exchange. To address the first research question (i.e., explore the extent and perceptions of farmers' use of ICT tools in farm business) we use a survey data collected in spring 2022 from 901 interviewed farm managers in irrigated areas of Kazakhstan and Uzbekistan. As a farmer-focused digital extension and advisory services are not yet developed in Central Asia, our study intentionally focuses on a narrow class of ICT services, namely on farmers' participation in social groups created in smartphone-based messaging apps such as Telegram and WhatsApp. Despite these two instant messaging apps are used for work-related issues among administration and agricultural extension organizations in Uzbekistan and Kazakhstan, their professional application for farm extension communication activities has been overlooked. In addressing the next two questions, we use a subsample of 526 cotton-growing farmers who owned smartphones and either participated or did not participate in AISG created within instant messaging apps.

Mobile phones and the internet have penetrated Kazakhstan and Uzbekistan to a greater extent. The ratio of mobile cellular subscriptions to the total population is above 1.4. Approximately 85% of people in Kazakhstan and 70% of people in Uzbekistan have internet access, which is expected to increase further as the costs of internet-based technologies will be declining (World Bank 2023). As of January 2022, there were 6.25 million social media users in Uzbekistan, equivalent to 18% of the total population, and 13.8 million social media users in Kazakhstan, equivalent to 72% of the total population<sup>1</sup> (DataReportal 2022). Among social media apps, WhatsApp is the most popular messaging app in Kazakhstan, while in Uzbekistan it is Telegram<sup>2</sup>. As our analysis will show these two apps are widespread among farmers. A major boost to farmers' participation in social media groups comes from increased use of smartphones. For instance, in 2020 the smartphone penetration rate in Kazakhstan was 70%, while in Uzbekistan it is 60% (GSMA 2022). Furthermore, Internet coverage in Kazakhstan and Uzbekistan by cellular network has sharply increased over the last years (ITU and FAO 2020). This numbers will only keep growing and more smartphones and mobile

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<sup>1</sup> Most It is important to note that social media users may not represent unique individuals as people make use of more than one social media sources.

<sup>2</sup> Most Popular Messaging Apps by Country <https://eagernomad.com/most-popular-messaging-apps-by-country/>



internet use will reach remote rural areas. The question now is how best policymakers and agricultural extension and advisory services can tap into this digital take-up for agricultural growth. Kazakhstan and Uzbekistan recognize the power of digitalization in transforming their societies and economies. The COVID-19 pandemic made that transformation essential and speeded it up. In late 2010s, both countries achieved remarkable results in digitalization and ICT development, especially, in provision of digital public services. For instance, Uzbekistan adopted a strategy "Digital Uzbekistan – 2030".

The paper is organized as follows. The next section provides a review of evidences from other studies on farmers' participation in social media groups for exchanging information on farm business. Following this, a section informs about the farm-level data used in this study and its sampling technique. After that, we present the farmers' responses about the use of ICTs in their farm business. We then present a descriptive statistics of group participants and non-participants among cotton growers subsample, which we took for empirical analysis of determinants and impact of social media group participation. A separate section explains the estimation methods used to answer our research questions. Following this, the econometric model results are presented and discussed. Finally, the paper concludes with the presentation of major findings and their implications for policymakers and researchers.

## 2. Impact of E-extension on farmers' outcomes

The instant messaging apps such as WhatsApp and Telegram are among popular ICT-based advisory tools that can improve farmers' communication and decision-making by offering easier and faster information access. They allow users to exchange bilaterally or within groups information through text and voice messages but also more sophisticated media such as documents and photo- and video files. In the recent decade, messaging apps have been transformed into so-called E-extension support system for farmers in developing countries (Fabregas et al. 2019). As E-extension tools, messaging apps complement and improve real-life interaction and knowledge flow between farmers, researchers and extension agents by organizing and disseminating agricultural research results to advisors (Materia et al. 2018).

In combination with offline face-to-face and group-oriented communication, they offer platforms for organizing social media groups that integrate diverse expertise from farmers, researchers, and extension agents to respond to complex challenges (Fabregas et al. 2019; Norton and Alwang 2020; Munthali et al. 2021). Such farmers' agricultural knowledge-sharing groups proved vital in technology diffusion and lowering costs for public and private extension and advisory services (Norton and Alwang 2020). By bringing together different stakeholders into one social media group for real-time communication, these messaging apps offer a platform for a pluralistic extension (Materia et al. 2015). The knowledge in such digital extension groups, e.g. on crop health, output and input prices, soil conditions, water

availability, pest outbreaks, training events, comes not from one particular expert but from multiple fellow farmers and experts. Farmers can address information asymmetries in their access to the input markets through social media groups by exchanging experience with inputs and machinery services and with specific agricultural input dealers (Schroeder et al. 2021).

Furthermore, participants in such social media groups can provide rapid feedback to public and private extension agencies with farmers' assessments and needs for improving the services and thus direct research agenda and participatory technology development (Materia et al. 2015). Using messaging apps, farmers and other actors of value chains, such as intermediaries, processors, and retailers, can exchange information. Producer groups such as agricultural cooperatives can address the problems of smallholders in accessing to both upstream and downstream markets and reduce transaction costs. Through improving member connection, accounting and administrative procedures, value-added services, and collective voice, social media groups can contribute to functionality of producer organizations and better inclusion of smallholders in value chains (World Bank 2011).

The social media groups can empower participating farmers by strengthening the linkages between them, extension workers, and researchers (Davis et al. 2020). Participation in social media groups can boost social cohesion among farmers and improve relationships between farmers, not only among those in the neighborhood or along an irrigation canal but also located at a relative distance and with different social and economic status (Spielman et al. 2021). Farmers will likely be increasingly dependent on messaging apps for rapid advice, including from progressive peers and agricultural experts (Spielman et al. 2021).

Most studies on ICT use in agriculture of developing countries focus on the impacts of mobile phones and Internet on smallholders' outcomes. Quandt et al. (2020) found that mobile phone use increases reported maize yields and agricultural profits and decreases the costs and time investments of farming among smallholders in Tanzania. Empirical studies in China showed that smallholders' Internet use improves technical efficiency in apple (Zhu et al. 2021) and banana production (Zheng et al. 2021), as well as profits of wheat production by 8% by increasing their gross revenue and wheat yields and reducing production costs (Zheng and Ma 2023). In Vietnam, farmers with internet access had 7% higher agricultural output (Kaila and Tarp 2019). The use of mobile phone and Internet technology increases incomes of farmers in Pakistan (Khan et al. 2022).

There is an emerging evidence on the impacts of ICT use on farmers' practices and outcomes. Empirical evidence of the impact of smartphone-based app use and AISG on farm performance is scant. Although e-extension has shown positive effects on farmers' adoption of technology, its impact on crop yields is less certain (Schroeder et al. 2021). Many studies do not find systematic evidence of impact of ICT-based advisory services on farmer

performance and crop yields, although anecdotal evidence suggests that e-extension can improve farm income (Schroeder et al. 2021).

For instance, according to Aker and Ksoll (2016) farmer's improved access to mobile phone technology increased crop diversification in Niger. Digital extension enhanced the adoption of recommended agrochemical inputs and increased farmers' yields by 4% in India and Kenya (Fabregas et al. 2019). These small potential e-extension gains in input efficiency, yields, and profits are substantial when compared to the cost of physical delivery of information in conventional way (Fabregas et al. 2019). ICT-based market information services project in Kenya increased the use of seeds, fertilizer, labor and land productivity, and reduced labor use among participating smallholders (Ogutu et al. 2014). Smartphone-based information intervention reduced the excessive usage of chemical pesticides and fertilizers in China (Ma and Zheng 2022). In Uganda, households that were shown a short video on how to become better maize farmers reported about having 10% increase in yields (Van Campenhout et al. 2020). Information received through smartphones helped Lao farmers improve vegetable production and marketing practices and increased vegetable yields and profits (Bounkham et al. 2022). In China, smartphone use increases farm and off-farm incomes by more than 10% and household income by more than 14% (Ma et al. 2020). Mendes et al. (2023) found that participation in agricultural information-sharing media groups in smartphone-based instant messaging apps positively affects incomes of Brazilian cattle farmers.

### 3. Farm survey data

The dataset comes from the data collected through a survey of farm managers conducted within the framework of the SUSADICA project<sup>3</sup> in Turkistan (Kazakhstan) and Samarkand (Uzbekistan) provinces in April-May 2022. The sample is not random, preventing extrapolation to all farms in South Kazakhstan or Uzbekistan. The farm survey data in the Turkistan province were collected employing stratified 2-step sampling. First, three villages (locally named "Aul") were sampled from each district that was part of the AGRICHANGE farm survey in 2019. Second, 50 farm managers were randomly chosen from each Aul. In Samarkand, farm managers were randomly chosen from the farm list. Maktaaral and Shardara districts in Turkistan and Pastdargam and Payarik districts in Samarkand are specialized in cotton and wheat cultivation. Sariagash district in Turkistan and Jomboy district in Samarkand have diversified non-cotton farming systems. The SUSADICA dataset consists of 901 individual farms (451 in Kazakhstan and 450 in Uzbekistan) registered as owner-operator or fixed tenants specializing in crop production. From this sample, about 71% of respondents engage

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<sup>3</sup> SUSADICA – Structured doctoral programme on Sustainable Agricultural Development in Central Asia: <https://www.iamo.de/en/research/projects/details/susadica/>

in cotton-wheat cultivation, one-fifth engage in wheat-vegetable growing, and the remaining 9% specialize in cultivation of high-value vegetables and melons.

While the section on the farmers' perceptions about ICT use is based on the full sample of interviewed farmers, the section on determinants and impact of participation in social media groups is based on a more homogenous subsample of cotton-growing farmers, i.e. 71% of all respondents. The cotton growers represent the largest share of farmers in irrigated areas of Central Asia.

The interviewed farmers responded to a comprehensive questionnaire on socio-demographic information, behavioral perceptions, farm, field, and geographical factors. The farm survey covered questions on farmers' attitudes about usefulness of mobile internet and social group participation, such as perceived autonomy in the choice of crops, agronomic methods, and marketing channels.

Farmers who use smartphones were asked to answer a question whether they participate in social media groups in instant messenger apps to find out information relevant for their farm business. Based on the answers we divided farmers in Kazakhstan and Uzbekistan samples into two groups, i.e. into participants and non-participants in social media groups. A participant is a farmer who responded "yes" about the participation in social groups. In total, we have 107 farmers in Turkistan province and 145 farmers in Samarkand province who as of survey time participated in social groups in messenger apps for farm business. A non-participant is a farmer who answered "No" in question about participation in social groups in messenger apps for farm business.

## 4. Opinion of farmers in Kazakhstan and Uzbekistan about ICT use and benefits

### 4.1 Adoption of PC, mobile and smart phones and Internet

Table 1 illustrates the composition of ICT technologies used in the context of Central Asia among sampled farmers. In both countries, smartphones appear the most commonly used ICT technology (used by three-fourths of farmers) followed by computer or laptops (around one-third of farmers) and computer-enabled internet (used among 20-27% of farmers) and finally mobile phone (common among less than 20% of farmers). Only few farmers responded about not using any phone device.

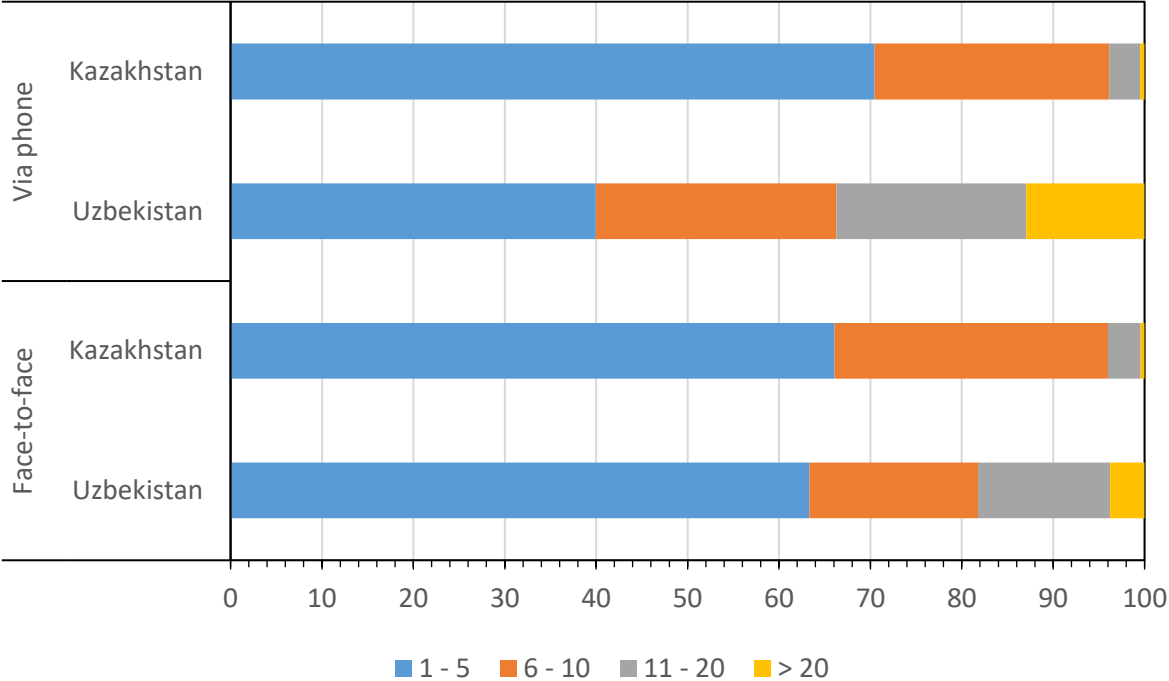
**Table 1** ICT device users among interviewed farmers

ICT device users among farmers	Kazakhstan		Uzbekistan	
	n	% (n/N*100)	n	% (n/N*100)
<i>Mobile device users</i>				
Only smartphone users	344	76.3	290	64.4
Only mobile phone users	76	16.9	95	21.1
Both smartphone and mobile phone users	20	4.4	63	14.0
No phone device	11	2.4	2	0.4
<i>Computer and internet users</i>				
Computer or laptop users	117	25.9	158	35.1
Internet users on desktop/laptop for farm business	94	20.8	121	26.9

Note: In Kazakhstan N=451, in Uzbekistan N=450.

### 4.2 ICT use among farmers

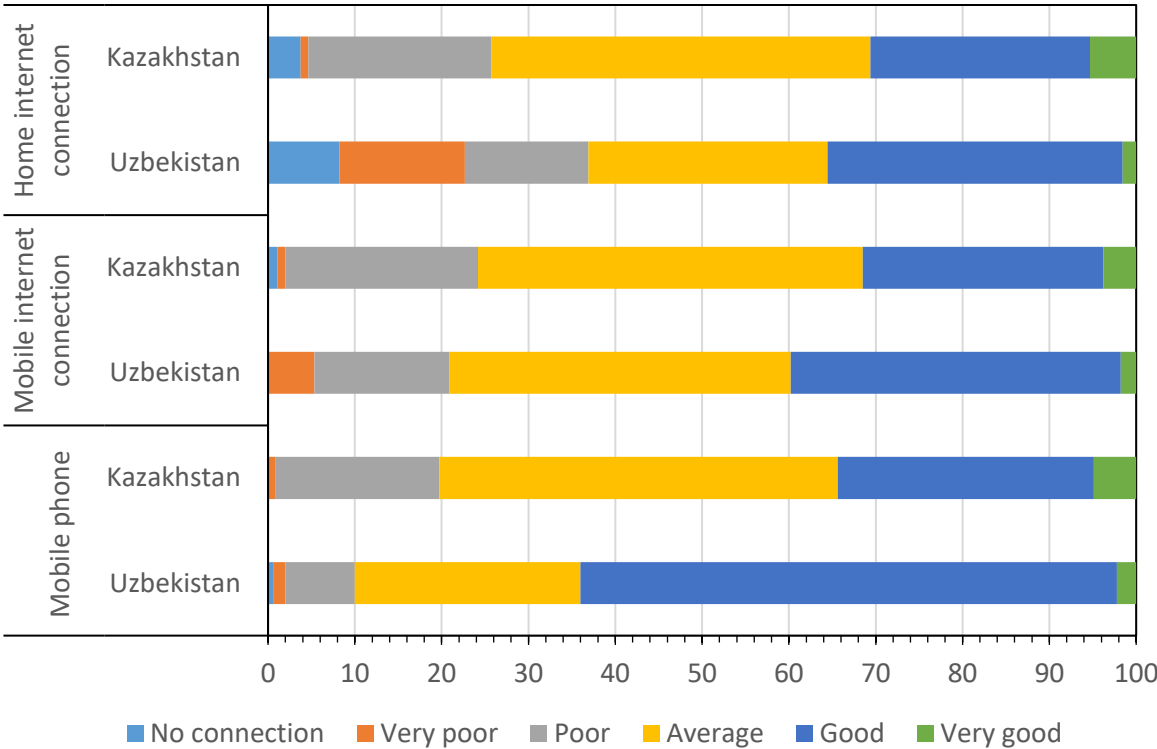
Figure 1 describes the extent of communication circle of interviewed farmers measured as the number of persons the farmers communicate on daily basis via phone and face-to-face. From top two horizontal bars illustrate the communication means via phone while the bottom two bars illustrate face-to-face communication. We can notice that irrespective of communication means (phone or face-to-face) in Kazakhstan the substantial majority of interviewed farmers engage in smaller circle of communication up to 10 persons daily. This is in contrast with the Uzbekistan setting where there are groups of farmers who contact more than 10 people on every working day.



**Figure 1** Characterization of farmers based on the frequency of interactions they make daily via phone and face-to-face, % of all interviewed farmers

Note: In Kazakhstan N=451, in Uzbekistan N=450.

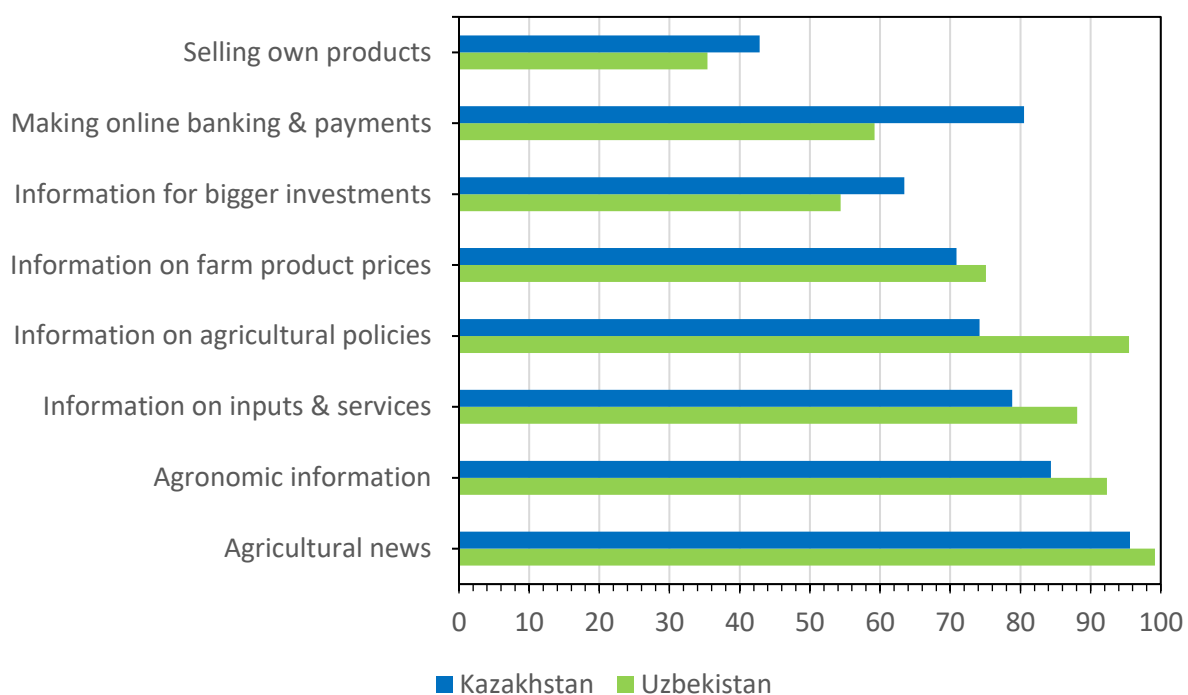
Figure 2 describes farmers’ assessment of internet quality at home (land-based connection) and mobile device as well all communication quality of mobile phone. For three types of ICTs, in Kazakhstan the share of farmers reporting average or poor quality is larger than those who perceived connection quality as good or very good. On the contrary, among the respondents in Uzbekistan the share of farmers reporting good or very good is larger than those who perceive connection low. In addition, in Uzbekistan farmers report higher perceived connection for mobile internet than other two ICTs, while among farmers in Kazakhstan perceived connection to devices do not vary much.



**Figure 2** Characterization of farmers according to assessment of internet quality (home and mobile phone) as well as communication quality of mobile phone, % of all interviewed farmers

Note: In Kazakhstan N=451, in Uzbekistan N=450.

Figure 3 illustrates interviewed farmers' mobile internet use for information search and farm activities. Overall, the pattern of mobile internet is very close in two countries. Specifically, interviewed farmers use mobile internet to access information relevant on agricultural news, agronomy and agricultural policies, input and service and output prices, and to less extent mobile internet is used for finding information on investment and selling own products. In the two countries, we can notice a slight difference in the nature of using mobile internet for activities related to online banking and payments such as monitoring, executing financial transactions. This reflects contrasting arrangements in accessing working capital and credit in two countries, where Uzbekistan cotton and wheat producing farmers have less autonomy over controlling the terms and conditions of farm credits.



**Figure 3** Information search and farm activities mobile internet is used for among interviewed farmers, % of smartphone users

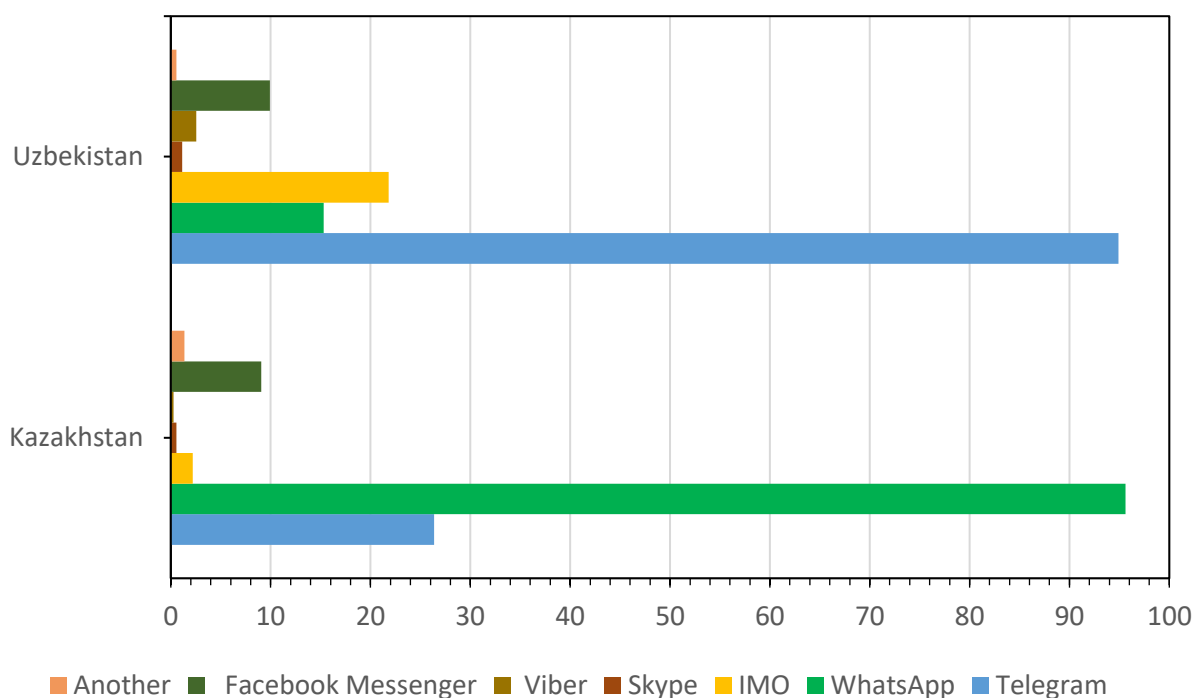
Note: In Kazakhstan N=364, in Uzbekistan N=353.



### 4.3 Use of instant messaging apps among farmers

In Kazakhstan among the 364 interviewed farmers who use smartphones 349 farmers (i.e., 96%) reported to using an instant messenger app. In Uzbekistan among the 353 interviewed farmers who use smartphones, 337 farmers (i.e., 95%), reported using messenger apps. Among the respondents who do not use a messaging app, the main reasons include the lack of trust or knowledge in using a messaging app and low perceived benefits.

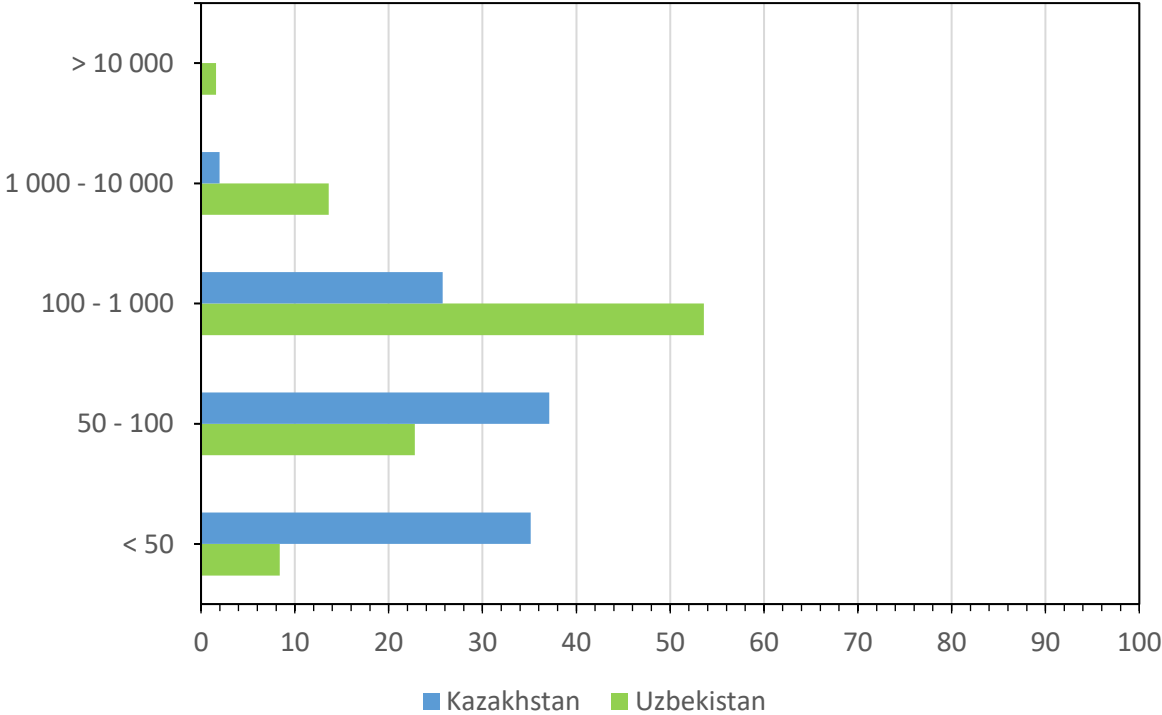
Figure 4 describes the types of instant messaging apps used among smartphone users in the two settings. It is apparent that the most widely used messaging apps among farmers in Kazakhstan and Uzbekistan are WhatsApp and Telegram, respectively. Less than 20% of farmers use other messaging apps such as IMO, Facebook messenger, Viber and Skype.



**Figure 4** Instant messaging apps used by farmers, % of smartphone users

Note: In Kazakhstan N=349, in Uzbekistan N=337.

In Kazakhstan, among 349 farmers who reported about using a messenger app 202 farmers (57%) reported about participation in social media groups as of survey time. In Uzbekistan, among 337 farmers who reported using a messenger app, 250 farmers (74%) reported about participation in social media groups. Figure 5 describes the size of social groups in the messenger apps among farmers who participated in online social groups as of survey time. The pattern observed in this figure is very similar to that observed earlier about the comparable sizes of communication circles in the two settings. Similarly, among interviewed farmers in Kazakhstan it is more common to participate in social groups consisting less than 50 and between 50 and 100 members, while among farmers in Uzbekistan, it is common to be a member in larger groups between 100 and 10 000 members exchanging information.

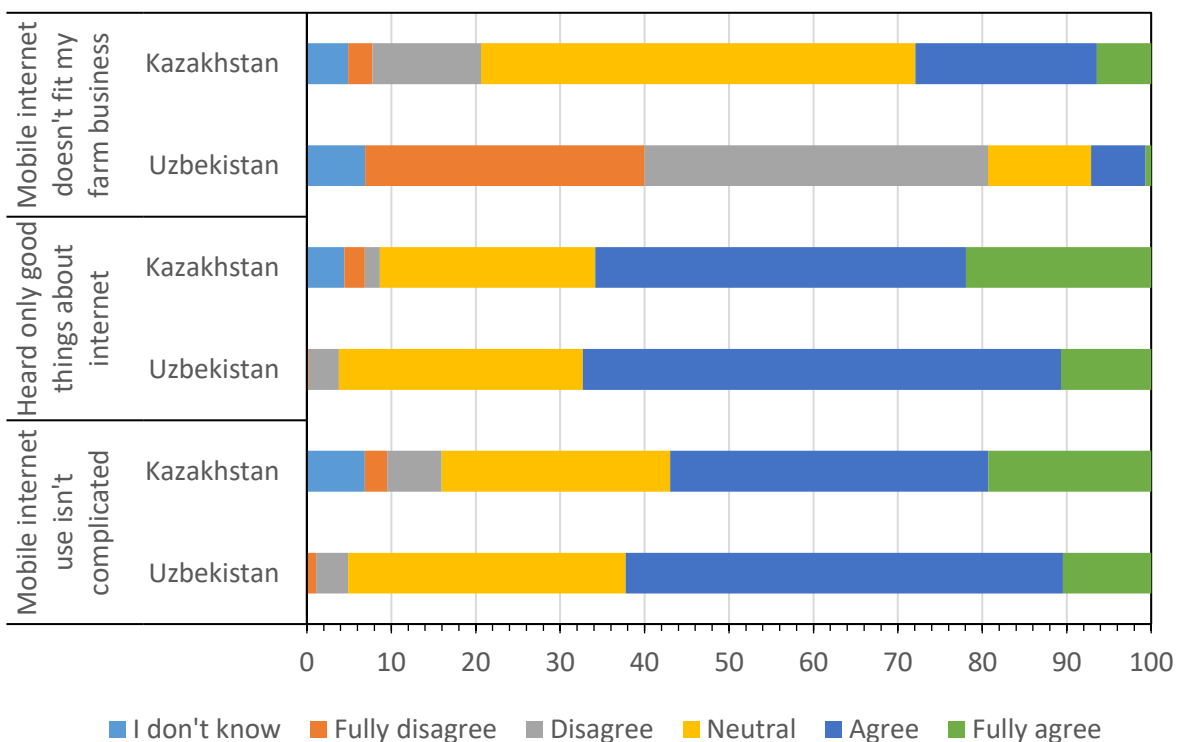


**Figure 5** Distribution of farmers according to average size of social media group, % of social media group participants

Note: In Kazakhstan N=202, in Uzbekistan N=250.

#### 4.4 Farmers' perception about usefulness of ICT tools

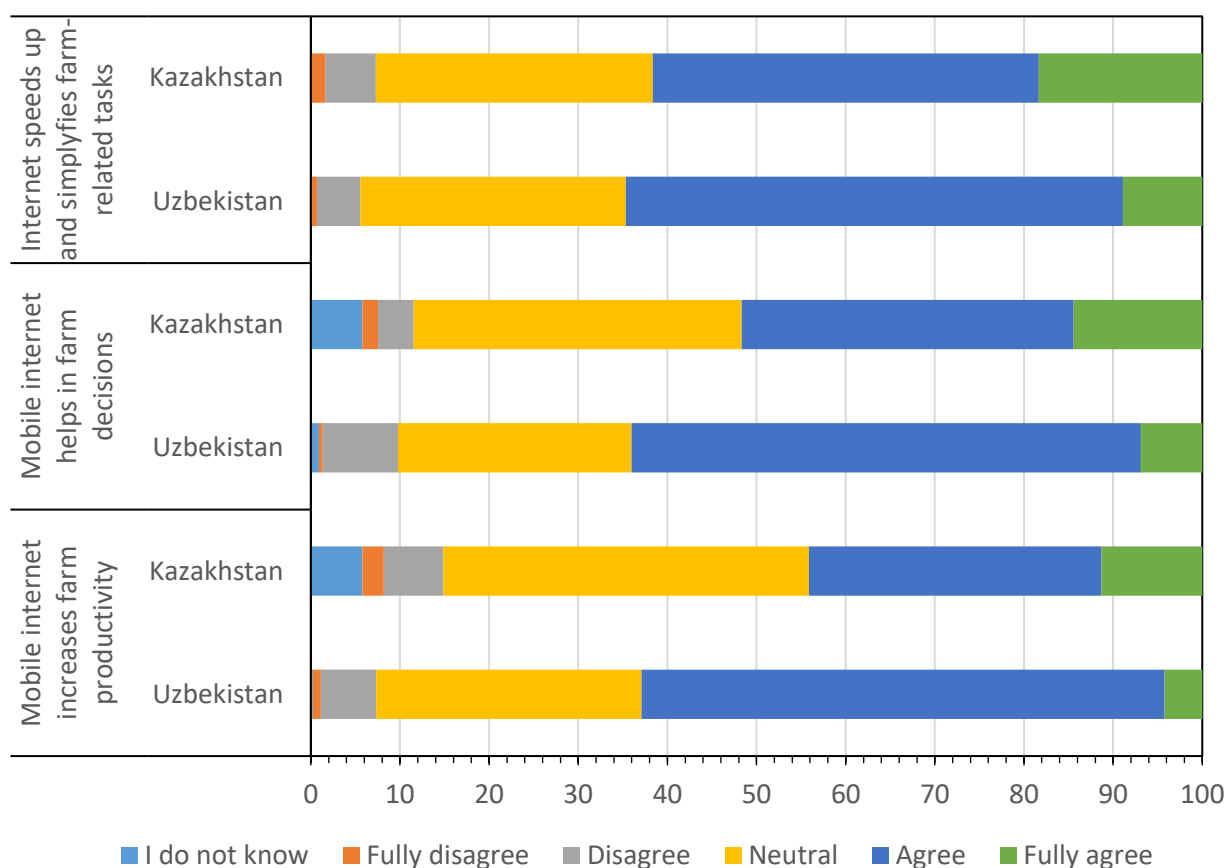
Figure 6 describes farmers' perceptions of general relevance of internet, particularly whether it fits farm business, farmer heard good things about and it is not complicatedness to use. The responses by interviewed farmers to the bottom two questions (what they heard about internet and perceived complexity), all in all, are quite similar in two settings; around 40% of farmers in Kazakhstan and 50% of farmers in Uzbekistan respond that they heard only good things about internet and it is not complicated for them to use. Interestingly, the share of those who disagree with the questions (around 30%) are also similar in two countries. The responses to these questions underscore the fact that in the context of studied countries, and probably at the regional level, farmers' perceptions about internet is generally similar and rather positive. However, the responses to question 1 at the top tend to vary between farmers in two countries. Specifically, in Kazakhstan larger share of farmers agree that mobile internet is not compatible with their farm business than farmers in Uzbekistan. On contrary, the share of those who disagree or neutral with the question, that is, they find mobile internet is relevant for their farm business, is larger in Uzbekistan than the one in Kazakhstan.



**Figure 6** Farmers' perceptions about general relevance of internet, % of all interviewed farmers

Note: In Kazakhstan N=451, in Uzbekistan N=450.

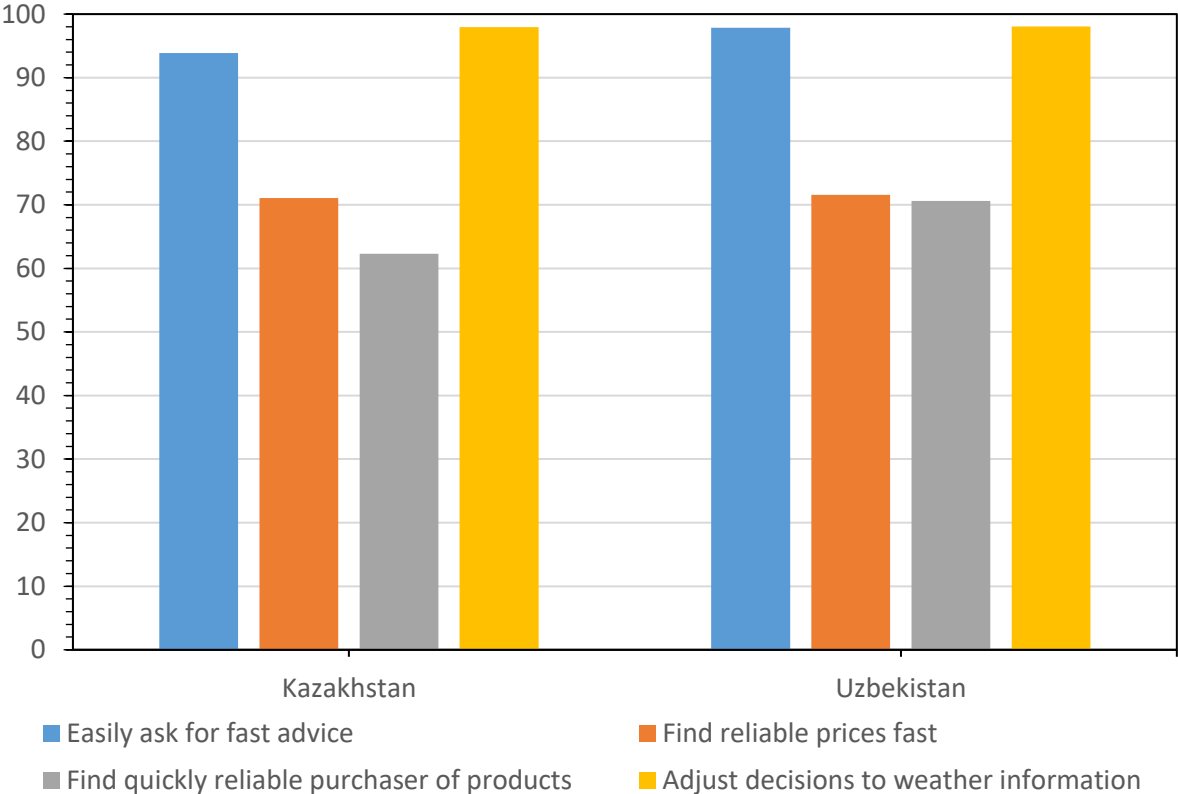
Figure 7 shows farmers' perceptions about specific relevance of internet for their farm businesses. Specifically, it is seen from the data that internet-based information quickens and simplifies tasks, helps to make decisions and finally contributes to increase farm productivity. The responses to these questions overall reflect responses to question 1 in the preceding figure. Specifically, the share of farmers in Uzbekistan who agree with the questions is much larger than the ones in Kazakhstan. For instance, more than 60% of farmers in Uzbekistan agree about the importance of (mobile) internet for their farm business such as in implementing tasks, decision-making and productivity.



**Figure 7** Farmers' perceptions about relevance of internet for farm business, % of all interviewed farmers

Note: In Kazakhstan N=451, in Uzbekistan N=450.

Figure 8 shows farmers opinions about the benefits of mobile internet for farm business in the two countries. The pattern follows what we observed with regard to the types of information and activities farmers use mobile internet for. In both countries, the majority (more than 90%) of interviewed farmers benefited from mobile internet to seek easy and fast advisory as well as to adjust their production decisions in tune with the weather information. A smaller share in the range of 60-70% also reported rapid finding reliable price and customers for agricultural inputs as benefits of mobile internet.



**Figure 8** Farmers’ opinions about benefits of mobile internet for farm business, % of mobile internet users

Note: In Kazakhstan N=342, in Uzbekistan N=415.

## 5. Descriptive statistics of social media group participants and non-participants among cotton growers

For the empirical estimation of the determinants and impacts of social media group participation in two countries, we took a subsample of the cotton growers data we collected in Kazakhstan and Uzbekistan. First of all, the cotton-growing farms represent the largest share of not only our sample (71%), but also in general farmers in the irrigated areas of Central Asia. Furthermore, more homogenous farm specialization in cotton cultivation allows us to control other unobserved factors that might differ depending on cultivated crops. Although, these farms specialize in cotton, they cultivate other crops on part of their irrigated land.

The descriptive statistics of the participants and the non-participants in the online social (interest) groups is given in Table 2. Both in Kazakhstan and in Uzbekistan, participants in the social media groups were 3-6 younger than the non-participants and thus had lesser experience in agriculture. Furthermore, compared to the non-participants, in both the country settings, more of the social group participants had a specialized education in agriculture. The share of Uzbekistan farmers with specialized education in agriculture was higher than among the Kazakhstan respondents. In both countries, the participants in social groups had significantly bigger farms. The interviewed Uzbekistan farmers have farm sizes almost nine times larger than Kazakhstan farmers did (about 94 ha against 12 ha). The social media group participants in Uzbekistan had smaller cotton cultivation area than social-media group non-participants and among Kazakhstan farmers in general. In both countries, participants and non-participants in social media groups cultivated almost the same number of crops. However, farmers in Uzbekistan reported to cultivate twice as many crops as their peers in Kazakhstan.

The sample shows an interesting trend regarding amount of time farmers spent on off-farm businesses. In both the countries, the amount of time spent on off-farm employment was higher among farmers who participated in social media groups than that of farmers who did not participate in social groups. Regarding sectoral effort-hours, due to their farm size, the Kazakhstan farmers spent almost six times more hours on off-farm work than what their Uzbekistan peers did.

In Uzbekistan, participants in social media groups reported about higher autonomy in deciding what crop to cultivate compared to non-participants. In other words, Uzbekistan farmers who perceived higher decision-making freedom participated more in such online social groups as they had higher autonomy in applying new knowledge received from their peers. Furthermore, Uzbekistan's participants in social media groups reported to be less attentive to the opinions of other farmers compared to non-participants. The trend was other way around for Kazakhstan where participants in social media groups perceived to care more about opinions of others farmers than non-participants. Furthermore, in both countries larger

share of participants in social media groups perceived that they were open to new things than non-participants.

As the individual farm sizes in Uzbekistan were much larger (94 ha) than those surveyed in Kazakhstan (12 ha), they were more dependent on the use of external agronomy experts. In Kazakhstan, almost all respondents reported that they relied on own agronomy knowledge to operate their farms. In Uzbekistan, where farm size is larger, this share was twice less. In Kazakhstan, the share of those who took farm trainings within the last three years was much higher among the online social group participants than among non-participants, i.e. 36% against 10%. In Uzbekistan, the share of participants in both sub-samples was about 82% due to the high attention of the state authority to cotton, which it considers a strategic crop. In Kazakhstan, almost equal share (about two-thirds) of participants and non-participants reported about receiving information about agronomy from media sources such as newspapers, radio, TV and the internet. In Uzbekistan, equal share of participants and non-participants in social groups received information on agronomy from newspapers, radio, TV and the internet.

In Kazakhstan, participants in social groups tend to have daily phone talks to significantly more people about their farm business than non-participants. However, in general, farmers in Uzbekistan tend to communicate with much more people than their peers in Kazakhstan. Particularly, in case of phone talks, Uzbekistan respondents had daily conversations with three times more people than Kazakhstan ones. This can be because Uzbekistan farmers have much larger land than farmers in Kazakhstan do. They also specialize less in cotton and have more diverse crop portfolio.

In terms of physical characteristics of farms and surrounding infrastructure, in Kazakhstan a higher share of non-participants than participants in social groups reported having good quality land (68% against 49%). In Uzbekistan, about equal share of respondents in both farm groups reported having good quality land.

Furthermore, in Kazakhstan almost twice higher share of non-participants in social media groups had fields located near irrigation canals and were satisfied with irrigation and drainage system than participants in social media groups. Similar pattern yet not with statistically significant difference was observed among Uzbekistan respondents. However, in both countries, a slightly higher share of non-participants in social groups than participants reported having farm fields at the head of irrigation water source. Furthermore, in Kazakhstan, fields of participants of social media groups were located further away from district centers than fields of non-participants. In both countries, farm fields of participants in social media groups were located further away from their dwellings than farm fields of non-participants. Finally, in both countries, the participants in online social groups reported having higher quality of mobile internet connection compared to non-participants.

The survey data revealed further contrasting differences between farmers in Kazakhstan and Uzbekistan. Participants in social media groups in both countries had higher, yet statistically insignificant, cotton yields and net revenues of cotton compared to non-participants. The mean differences, however, do not account for the effects of other characteristics affecting farmers' participation decisions based on which they can self-select into participants and non-participants of social media groups.



**Table 2** Descriptive statistics of farm-level variables across participants and non-participants in social media groups

Variables	Kazakhstan			Uzbekistan		
	Participants (N=107)	Non-participants (N=138)	mean diff	Participants (N=145)	Non-participants (N=136)	mean diff
Farmer's age (years)	47.477 (12.742)	53.180 (13.688)	-5.703***	46.075 (10.054)	49.532 (9.597)	-3.458***
Farmer's has a special education in agriculture (1/0)	0.206 (0.406)	0.079 (0.271)	0.126***	0.537 (0.500)	0.525 (0.501)	0.012
Amount of time that farmer spends for off-farm work (hours/week)	13.271 (19.699)	8.489 (16.258)	4.782**	2.816 (8.869)	0.705 (3.904)	2.111**
Total currently available land (ha)	12.871 (13.007)	10.804 (14.299)	2.067	107.155 (84.935)	79.896 (38.365)	27.260***
Number of cultivated crops	1.140 (0.375)	1.187 (0.533)	-0.047	2.231 (0.574)	2.144 (0.475)	0.087
Farmer's opinion about own decisions on crop cultivation (categorical: 1=not free at all ... 5= completely free)	4.692 (0.895)	4.712 (0.662)	-0.021	3.170 (1.559)	2.475 (1.656)	0.695***
Farm has own knowledge on agronomy (1/0)	0.925 (0.264)	0.935 (0.247)	-0.010	0.435 (0.498)	0.381 (0.487)	0.054
Farmer is open to new things (1/0)	0.645 (0.481)	0.439 (0.498)	0.206***	0.755 (0.432)	0.489 (0.502)	0.266***
Farmer cares about opinion of other farmers (1/0)	0.794 (0.406)	0.748 (0.436)	0.046	0.497 (0.502)	0.705 (0.458)	-0.208***
Farmer participated in at least one training during the last 3 years (1/0)	0.364 (0.483)	0.101 (0.302)	0.264***	0.823 (0.383)	0.820	0.003
Share of good soils in farmland (0-1)	0.488 (0.498)	0.672 (0.459)	-0.184***	0.668 (0.361)	0.649 (0.417)	0.019
Distance from farm fields to dwellings (km)	7.740 (8.375)	5.926 (5.238)	1.815*	4.086 (4.781)	3.663 (5.099)	0.423
Distance from farm fields to a district center (km)	46.262 (27.226)	37.460 (26.908)	8.801**	15.255 (6.512)	15.683 (6.656)	-0.428
Farms with near irrigation canal and satisfying irrigation & drainage (1/0)	0.131 (0.339)	0.266 (0.444)	-0.135***	0.145 (0.353)	0.199 (0.400)	-0.054
Farmer receives information on agronomy from newspaper, radio, TV, internet (1/0)	0.645 (0.481)	0.604 (0.491)	0.040	0.571 (0.497)	0.554 (0.499)	0.017
Number of people farmer talks daily on telephone about farm business (1/0, 1=more than 4 people)	0.654 (0.478)	0.496 (0.502)	0.158**	0.939 (0.241)	0.942 (0.233)	-0.004
Farmer's perception about quality of local mobile internet connection (1/0, 1=very good)	0.299 (0.460)	0.223 (0.418)	0.076	0.429 (0.497)	0.245 (0.431)	0.184***
Using mobile internet does not fit farm business (categorical, 5=does not fit)	3.196 (0.829)	3.043 (0.806)	0.153	1.891 (0.922)	2.273 (0.841)	-0.382***
Size of cotton area (ha)	11.615 (11.194)	9.604 (13.091)	2.011	45.624 (33.858)	35.925 (16.834)	9.699***
Labor cost per ha (US\$/ha)	145.439 (161.751)	157.481 (179.984)	-12.040	280.551 (294.196)	303.257 (225.310)	-22.710
Fertilizer costs for cotton (US\$/ha)	99.779 (43.537)	112.840 (55.526)	-13.060**	232.532 (63.819)	220.853 (50.048)	11.680*
Cotton seed costs (US\$/ha)	34.495 (16.354)	29.578 (18.813)	4.917**	64.213 (23.217)	59.899 (20.737)	4.315*
Cotton yield (t/ha)	2.312 (0.715)	2.286 (0.685)	0.025	2.804 (0.596)	2.780 (0.560)	0.025
Cotton net returns (US\$/ha)	1401.917 (570.866)	1372.575 (622.476)	29.340	1132.638 (509.803)	1060.319 (458.746)	72.320

Note: Standard deviation in parenthesis. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01.

## 6. Analytical framework and estimation technique

The assessment of the participation in social media groups based on non-experimental cross-sectional data requires the correction of self-selection bias, identification of proper counterfactuals, and controlling for non-observable farm characteristics (Asfaw et al. 2012; Jaleta et al. 2016). We explain the empirical models in the following subsections and motivate the selection of our methodology.

### 6.1 Decision to participate in social media group and farm outcomes

We assume that a farmer's decision to participate in a social media groups is based on farm profitability and indicators of yield increase. To estimate the effect of group participation on farm outcomes, we employed a two-stage estimation approach following existing standard protocols in the literature (Jaleta et al. 2016; Läpple et al. 2013). Although the perceived benefits from participation, are unknown to the researcher, the characteristics of the farmer are observed during the survey period. We can therefore represent the farm outcome derived from participation by a latent variable  $SG_i^*$  (Abdulai and Huffman 2014). We assume that farmers will participate in social media group if they expect to achieve higher yields and net returns from participation ( $SG_1^*$ ) compared to a decision of non-participation ( $SG_0^*$ ). Here, expected yields and net returns were not recorded, but participation decisions were observed. With this as the basis, participation decision ( $SG_i$ ) is treated as a dichotomous choice, namely  $SG_i = 1$  if  $SG_1^* > SG_0^*$  and  $SG_i = 0$  if  $SG_1^* < SG_0^*$ . Thus, farmers' participation decision is related with their perception whether social media groups increase net returns or not. Based on given latent variable model, in the first stage, determinants of participation in social media group are analyzed by the following probit model of the form:

$$SG_i^* = \delta K_i + \varepsilon_i \text{ with } SG_i = \begin{cases} 1 & \text{if } SG_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad [1]$$

here,  $SG_i$  is a dummy variable indicating whether farmer  $i$  participates in agricultural information-sharing group or not.  $K_i$  is a vector of determinants of decision to participate ( $n \times m$ ).  $\delta$  is a vector of parameters to be estimated  $m \times 1$ ,  $\varepsilon_i$  is a vector of error term ( $n \times 1$ ) that is normally and independently distributed with a mean of 0 and a variance of  $\sigma^2$ .

In order to empirically explore the relationship between participation in the social media groups and farm outcomes, we assume that farmers maximize expected net returns from cotton production, and the function is expressed following Dubbert (2019):

$$\max \pi_i = P_i Q_i(R_i, Z_i) - I_i R_i \quad [2]$$

where  $\pi$  is the net returns of farmer  $i$  gained from cotton production,  $P$  is cotton price per kg, and  $Q$  is cotton yield in kg.  $R$  represents input quantities such as fertilizer, seeds, and labor.  $Z$  represents the vector of explanatory variables, i.e. farm/farmer characteristics.  $I$  is a vector of input prices. We express net returns ( $\pi_i$ ) as a function of input and output prices, farm/farmer characteristics and participation in social media groups as follows:

$$\pi_i = \pi(P_i, I_i, Z_i, SG_i) \quad [3]$$

Applying Hotelling's lemma to Equation (2) yields a reduced form of the cotton output supply function as follows:

$$Q_i = Q(P_i, I_i, Z_i, SG_i) \quad [4]$$

Based on the arguments made by Foster and Rosenzweig (2010) that production costs can be difficult to measure and incomplete, we assume that farmers maximize cotton yields and net returns. In our study, the net returns from cotton production are calculated by excluding fertilizer costs (nitrogen, phosphorous and potassium costs), cottonseed costs, and labor costs (total payment to permanent workers and hired workers for cotton production) from cotton revenue (yield multiplied cotton price). From Equations (3) and (4), net returns and cotton yield are determined by the input and output prices, farm/farmer characteristics and participation in social media groups.

In the second stage, to better understand the impact of group participation, we begin with a simple model of farmers' outcomes. Cotton yield and net returns were determined by several factors including land, labor, and fertilizer. We used the Cobb-Douglas production function (e.g. Amadu et al. 2020) that connects farm outputs with inputs and other factors:

$$Y_i = F(A, L, N, S) \quad [5]$$

where  $Y_i$  is a vector of outcome variables of farmer  $i$ ,  $A$  stands for cotton area (ha),  $L$  stands for labor use (US\$ per ha),  $S$  stands for seed use (US\$ per ha) and  $N$  stands for fertilizer use (US\$ per ha).

Taking the logarithm of outcome variables and production inputs, we derive cotton yield (or cotton net returns) function as linearly separable. Additionally, we account for other dummy or non-logarithmic variables. Thus, the effect of participation in social media groups on cotton yield and net returns is modelled through a  $\ln(Y)$  functional form related with production inputs and other factors such as farm/farmer characteristics and institutional settings as follows:

$$\ln Y_i = \alpha_0 + \beta \ln A + \mu \ln L + \kappa \ln N + \tau \ln S + \psi Z_i + \zeta SG_i + u_i \quad [6]$$

We assume that the outcome variable ( $Y_i$ ) is associated with production inputs ( $A$ ,  $L$ ,  $S$  and  $N$ ), a vector of other explanatory variables ( $Z_i$ ), and social media group participation  $SG_i$  take a value of 1 if a farmer participates and 0 otherwise.  $\alpha_0$  is a constant,  $\beta$ ,  $\mu$ ,  $\kappa$ ,  $\tau$ ,  $\psi$  and  $\zeta$  are vectors of estimated parameters, and  $u_i$  is an error term. The impact of participation in social media groups on cotton yield and net returns is computed by the estimation of the parameter  $\zeta$ . This approach might create biased estimates because it assumes that group participation is exogenously determined while it is potentially endogenous (Di Falco et al. 2011). Farmers' decision to participate or not to participate may be based on individual self-selection and other factors (e.g. lack of technological affinity as seen in senior citizens). Farmers who participate in social media groups can have different characteristics compared to non-participants. Furthermore, farmers can decide to participate based on expected benefits but they structurally differ in their individual expectations (Di Falco et al. 2011). Considering that the interviewed farmers might have self-selected into participating in social media groups, selection bias can occur because of observable and unobservable attributes affecting group participation and outcome variables at the same time. Hence, to overcome this bias, an Ordinary Least Squares (OLS) estimator might generate biased and inconsistent estimates (Di Falco et al. 2011; Dubbert 2019; Jaleta et al. 2016). Following these arguments, we employ endogenous switching regression (ESR) model that accounts for both endogeneity and sample selection.

## 6.2 Endogenous switching regression

To examine the influence of participation in social media groups on the farm outcomes, we apply the Average Treatment Effect on the Treated (ATT) (Amadu et al. 2020; Jaleta et al. 2016). The ATT estimates average differences in outcome variables between participants who actually participated in social media group (observed) and who would not have participated in it (counterfactual). Although the Propensity Score Matching (PSM) method can also calculate ATT, it does not account for unobservable factors that simultaneously influence farmers' participation decision and outcome variables (Jaleta et al. 2016). In the second stage, the relationship between outcome variables and group participation decision including other explanatory variables can be formulated in two regimes with an OLS regression model. Consequently, we express Equation 6 as follows:

$$\text{Regime 1 (Social media group participants): } y_{1i} = X_{i1}\beta_1 + \omega_{1i} \text{ if } SG_i = 1 \quad [7a]$$

$$\text{Regime 2 (Social media group non-participants): } y_{2i} = X_{i2}\beta_2 + \omega_{2i} \text{ if } SG_i = 0 \quad [7b]$$

where  $y_{1i}$  and  $y_{2i}$  are outcome variables for participants and non-participants.  $X_{i1}$  and  $X_{i2}$  are vectors of determinants of the outcome variables (including production inputs).  $\beta_1$  and  $\beta_2$  are vectors of parameters to be estimated.  $\omega_{1i}$  and  $\omega_{2i}$  are error terms.

The probit model in Equation 1 supplies essential information to examine and correct the potentially resulting bias (Maddala 1983: 223). To test selection bias, according to Heckman (1979) the Inverse Mills Ratio (IMR) can be calculated from the results of a probit estimation as follows:

$$\lambda_{1i} = \frac{\varphi(\delta K_i)}{\Phi(\delta K_i)} \quad \lambda_{2i} = \frac{-\varphi(\delta K_i)}{1-\Phi(\delta K_i)} \quad [8]$$

where  $\varphi(\cdot)$  and  $\Phi(\cdot)$  indicate probability density function and cumulative density function of the standard normal distribution respectively.  $\lambda_{1i}$  and  $\lambda_{2i}$  represent IMR. Equations 7a and 7b are used to correct selection bias. Thus, in our model the outcome equations in two regimes stand for:

$$\text{Regime 1 (participants in social groups): } y_{1i} = X_{i1}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i} + \eta_{1i} \text{ if } SG_i = 1 \quad [9a]$$

$$\text{Regime 2 (non-participants in social groups): } y_{2i} = X_{i2}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i} + \eta_{2i} \text{ if } SG_i = 0 \quad [9b]$$

where  $\sigma_{1\varepsilon}$  and  $\sigma_{2\varepsilon}$  are parameters to be estimated,  $\eta_{1i}$  and  $\eta_{2i}$  are normally distributed error terms with mean zero and constant variance.

Existing studies explain that for a more robust identification it is important to select instrumental variables (IV) that affect  $SG_i$  in Equation 1 and do not appear in explanatory variables of outcome equation. Technology adoption studies employ physical distances to markets as valid IVs (e.g., Di Falco et al. 2011). Based on these arguments we use variables 'Distance from farm fields to the district center and dwellings' as IVs for measuring the impact of participants in social groups in both regions. For Kazakhstan, we also use 'Quality of mobile internet connection'. Thus, we exclude these variables from Equations 9a and 9b. Several empirical studies about impact evaluation (e.g., Jaleta et al. 2016; Khonje et al. 2015; Khonje et al. 2018) used similar variables as IVs.

We explore acceptability of instruments through a simple falsification test whether the selected variables are reasonable and thus affect farmer's participation decision, but not outcome variables (Di Falco et al. 2011; Jaleta et al. 2016). The results of the falsification test show that selected instruments are jointly statistically significant in the participation decision (for participation decision  $\chi^2=6.43$ , p-value=0.04 for Kazakhstan;  $\chi^2=3.49$ , p-value=0.06 for Uzbekistan), but statistically insignificant in the outcome equation (F-stat=1.01, p-value=0.36 for Kazakhstan; F-stat=0.17, p-value=0.68 for Uzbekistan). Table A1 in Appendix provides information about the falsification tests for IVs. Consequently, we can consider that selected instruments are plausible.

### 6.3 Average treatment effect

The impact of social media group participation on farmer's outcome can be tested through the comparison of expected outcomes of participants and non-participants in actual and counterfactual situations. We compute the Average Treatment Effect on the Treated (ATT) and the Treatment Effect on the Untreated (ATU) in the framework of ESR model. To do this, we calculate the expected outcome for participants and non-participants in actual and counterfactual scenarios based on Equations 9a and 9b as follows:

$$E(y_{1i}|X, SG_i = 1) = X_{1i}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i} \quad [10a]$$

$$E(y_{2i}|X, SG_i = 0) = X_{2i}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i} \quad [10b]$$

$$E(y_{2i}|X, SG_i = 1) = X_{1i}\beta_2 + \sigma_{2\varepsilon}\lambda_{1i} \quad [10c]$$

$$E(y_{1i}|X, SG_i = 0) = X_{2i}\beta_1 + \sigma_{1\varepsilon}\lambda_{2i} \quad [10d]$$

Here, Equation 10a is for participants ( $SG_i = 1$ ), and Equation 10b is for non-participants ( $SG_i = 0$ ), both observed in the sample. In contrast, two other equations consider counterfactuals, such as Equation 10c is for participants who would have decided not to participate, and Equation 10d is for non-participants who would have decided to participate. The differences between Equations 10a and 10c can be formulated as Equation 11 which explains the comparisons of the expected outcomes (net returns in US\$/ha, and cotton yield in t/ha), and allows us to calculate the average treatment effect on the treated (ATT) as follows:

$$\begin{aligned} ATT &= (10a) - (10c) = E(y_{1i} | X, SG_i = 1) \\ &\quad - E(y_{2i}|X, SG_i = 1) = X_{1i} (\beta_1 - \beta_2) \\ &\quad + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \end{aligned} \quad [11]$$

The differences between Equations 10b and 10d can be formulated as Equation 12 which is the average treatment effect on the untreated (ATU):

$$\begin{aligned} ATU &= (10b) - (10d) = E(y_{2i}|X, SG_i = 0) \\ &\quad - E(y_{1i}|X, SG_i = 0) = X_{2i} (\beta_1 - \beta_2) \\ &\quad + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \end{aligned} \quad [12]$$

Thus, we measure the heterogeneity effect by utilizing Equations 11 and 12. According to Di Falco et al. (2011) and Jaleta et al. (2016), the effect of base heterogeneity (BH) for participants can be calculated as the difference between Equations 10a and 10d, and for non-participants as the difference between Equations 10c and 10b (see Table 3).

**Table 3** Expected conditional, average treatment and heterogeneity effects

Subsamples	Decision stage		Treatment effects
	To participate	Not to participate	
Participants	a) $E(y_{1i} X, SG_i = 1)$	c) $E(y_{2i} X, SG_i = 1)$	ATT
Non-participants	d) $E(y_{1i} X, SG_i = 0)$	b) $E(y_{2i} X, SG_i = 0)$	ATU
Heterogeneity effects	BH <sub>1</sub>	BH <sub>2</sub>	TH

Notes: (a) and (b) represent observed expected farm outcome (cotton net returns (US\$/ha); crop yield (t/ha)); (c) and (d) represent counterfactual expected farm outcome (cotton net returns (US\$/ha); crop yield (t/ha)).

$SG_i = 1$  if farm  $i$  participated in social media group;  $SG_i = 0$  if farm  $i$  did not participate in social media group.

$y_{1i}$  = farm outcome if farms treated with group participation;  $y_{2i}$  = farm outcome if farms treated with non-participation.

ATT = average treatment effect on treated; ATU = average treatment effect on untreated; BH<sub>1</sub> = the effect of base heterogeneity for group participants; BH<sub>2</sub> = the effect of base heterogeneity for group non-participants; TH = transitional heterogeneity (ATT-ATU).

Source: Authors based on Jaleta et al. (2016).

## 7. Model results

### 7.1 Determinants of farmers' participation in social media groups

Table 4 presents the probit model estimation results for the determinants of participation in social media groups among sampled cotton-growing farmers in two countries. We begin with presenting the estimated coefficients for ICT characteristics. Perceptions of mobile internet matter for farmers decisions to participate in online social media groups. Particularly, the likelihood of participation in social media groups drops if farmers do not see the relevance of mobile internet to farm business. This finding especially relates to farmers in Uzbekistan whose production decisions are closely tied to top-down procurement policy. Perceptions of mobile internet connection is positively related to likelihood of participation in social media among farmers in Kazakhstan. Both these findings reflect the description presented earlier that in Kazakhstan ICT infrastructure and connection quality and in Uzbekistan the profitability and relevance of mobile internet use are bottlenecks for scaling up ICTs use and enabling farmers to benefit from instant messaging apps and exchange and communication through online social groups (Caffaro et al. 2020).

Next, personal characteristics are important factors that shape farmers' decisions to participate in social media groups. As farmers get older the likelihood of participation in social media groups drops in both countries. The relationship is statistically significant in Kazakhstan. The negative relationship between age and motivation to use ICTs has been documented by many empirical studies (Hoang 2020; Michels et al. 2020; Poushter 2016; Smith et al 2004). Older farmers often are not only less acquainted with new technologies as the studies mention as the main barrier for adoption but also have lower drive to expand farm business than their younger counterparts (Gale 1994). Younger farmers engage more actively in information-sharing networks and are more acquainted with smartphones and associated applications (Michels et al. 2020).

Having an agricultural education increases the likelihood of participation in social media by 22.7% among Kazakhstan farmers; the relationship is statistically significant at 5% level. The coefficient of specialized agricultural education had positive and statistically significant effects on the likelihood of farmers' participation in AISG in Kazakhstan. Farmers with formally obtained agricultural education are likely to participate social media groups. Furthermore, in Kazakhstan, likelihood of participation in social media groups is higher among farmers who attended agronomy-related training courses. These results emphasize the importance of farmers' knowledge in promoting ICT tools in agriculture. For Uzbekistan the relationship is negative and statistically insignificant. However, among Uzbekistan farmers having own knowledge on agronomy seems to be important for their participation decisions. Although having own knowledge may require less need to seek information from external sources such



as online groups, in the Uzbek setting it appears own knowledge and external knowledge obtained from social media groups are complementary.

Farmer's openness to new things is positively related to participation decisions in social media in both countries but only among Uzbekistan farmers, this relationship is statistically significant. The findings for these four variables are in line with the findings of a recent study by Michels et al. (2020) who estimated the determinants of mobile device and mobile internet adoption among a sample of German farmers. Last but not least, among farmers in Uzbekistan the likelihood of participation in social media groups decreases if they care about the opinion of other farmers. Specifically, the likelihood of participation drops by almost 25% among farmers who care very much about peer farmers' opinion. This suggests that seeking information from external sources such as peers acts as (more reliable) substitute to information obtainable from social media groups. The economic magnitude of this variable is in the range of education variable just described, implying farmers learn from each other about the information, new technologies.

Farmers' participation decisions in social media groups are also driven by how production is organized. Further, we present how farm business characteristics in two settings are related to participation decisions of cotton farmers. Larger farm size is positively associated with the decision to participate in social media in both countries, but the estimated coefficients are statistically insignificant. There is scarce empirical research on farm size and social media group participation in particular. Michels et al. (2021) shows statistically weak positive relationship between farm size and mobile internet adoption. Larger farms and farms with more diverse production portfolio tend to have more complex organization of production that might increase the use of social media groups. However, in the Kazakhstan setting, higher number of cultivated crops reduces the likelihood of farmer's participation in social media groups. This can imply that social media groups in Kazakhstan seem to offer solutions to less complex issues that attract farmers with simple production portfolio. From another side, participation in AISG does not require large initial investment and does not imply economies of scale that may prevent smaller farms from using smartphone-based instant messaging apps.

Communication circle is positively related to participation decisions of Kazakhstan farmers. Particularly, if farmers communicate on the phone with more than four people on daily basis, the likelihood of participation in social media increases by 10.2%. It appears larger communication circle related to farm business encourages Kazakhstan farmers to organize exchange more efficiently by creating and attending social media platforms. Further, activity diversification, particularly crop diversification is negatively related to participation decisions only in Kazakhstan. Michels et al (2020) also documents (statistically insignificant) negative relationship between farm diversification and adoption of mobile device and mobile internet. Other studies looking at decisions to adopt computers, internet, information technology document mixed evidence (Hitt 1999; Mishra and Park 2005; Briggeman and Whitacre 2010).

Land tenure security is important for technology adoption in general (Feder and Nishio 1998), and particularly for social media group participation. One-standard deviation in perceived freedom to allocate crops is associated with 3.6% increase in the likelihood of participation in social media groups among Uzbekistan farmers. More secure tenure environment in neighboring Kazakhstan appears less important for their decisions to participate.

Finally, the more time farmers spend off-farm work the more likely they participate in social media groups. Although the relationship is positive in both countries, it is statistically significant only in Uzbekistan at 10% level. The view in the current literature on the role of off-farm work on farm productivity is mixed. Proponents argue nonfarm work creates extra internal funds to finance farm production, while others argue off-farm work lowers farm productivity. However, it is also the case that off-farm work can be the opportunity for farmers to create political connections (Markussen and Tarp 2014) which they can use to obtain recent information<sup>4</sup> on subsidies, farm technologies. Smith et al. (2004) found among US farmers off-farm employment has a strong positive effect on Internet connection, but insignificant effect on computer ownership and business-related internet use.

Finally, among farm infrastructure variables soil fertility and access to irrigation water are negatively related to the participation decisions in social media in both countries. Favorable bio-physical environment such as fertile soil is vital for land productivity. Although soil fertility is complementary with alternative-productivity-enhancing investments (Feder and Nishio 1998), it seems it may also substitute such investments or efforts for example crop diversification (Di Falco and Zoupanidou 2017). Similar substitution effect may be occurring in relation to farmers' efforts to obtain useful information through social media. Distance from farm field to district center and house of farmers are positively associated with the likelihood of participation in social media among farmers in Kazakhstan and Uzbekistan, respectively. Hoang et al. (2020) also finds positive relationship between distance to nearest markets and adoption of mobile phones for marketing among fruits farmers in Vietnam. Larger geographic area as in Kazakhstan increases transaction cost associated with transportation of inputs and outputs. By participating in social media farmers may seek ways to reduce these costs.

Overall, the results in Table 4 show that no same variables have similar relationship with participation decisions in social media in two settings. In Kazakhstan, participation decisions are driven by the quality of mobile internet connection, age, agriculture-related education, communication circle on telephone, crop diversification and bio-physical factors such as soil fertility, access to irrigation water and distance from farm field to district center. In Uzbekistan farmers participation in social media is influenced by relevance of mobile internet for their

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<sup>4</sup> During our interview with farmers in southern city in Kazakhstan (Jettisai), we noticed some farmers held a position in the local administration (i.e., akimiat) as accountants, analyst. Working in administration may be beneficial to "stay tuned" to information flow especially in top-down settings where important information about cheap credits and lease arrangements trickle down from national to local levels.

farm business, farmers own knowledge, openness to new things, caring about the opinion of other farmers, land tenure as well as access to irrigation water, and distance from farm field to farmers' house.

**Table 4** Probit model estimation of ICT use determinants in Kazakhstan and Uzbekistan

Dependent variable: Decision to participate in social media group	<b>Kazakhstan</b>	<b>Uzbekistan</b>
	<i>Marginal effect</i>	<i>Marginal effect</i>
<b>ICT characteristics</b>		
Using mobile internet does not fit farm business, categorical (5=yes, does not fit)	0.008 (0.034)	-0.101*** (0.030)
Quality of mobile internet connection, dummy (1=very good)	0.064* (0.035)	-0.031 (0.035)
<b>Farmer characteristics</b>		
Farmer's age	-0.005*** (0.002)	-0.004 (0.003)
Special education in agriculture of farm manager, dummy (1=yes)	0.185** (0.091)	-0.014 (0.051)
Farm has own knowledge on agronomy, dummy (1=Yes)	-0.042 (0.129)	0.103* (0.057)
Openness to new things, dummy (1=yes)	0.081 (0.060)	0.213*** (0.070)
Caring opinion of farmers-colleagues, dummy (1=very much)	0.077 (0.066)	-0.254*** (0.053)
Farms with near irrigation canal and have satisfying irrigation and drainage, dummy (1=yes)	-0.168** (0.075)	-0.144** (0.073)
<b>Farm business characteristics</b>		
Total currently available land of farm (ha) (ln)	0.049 (0.041)	0.060 (0.060)
Number of peoples that talk on telephone about farm business, dummy (1=more than 4 people daily)	0.077 (0.055)	-0.106 (0.120)
Number of cultivated crops	-0.138** (0.062)	0.020 (0.051)
Free to decide crop cultivation, categorical (1 to 5, 5=free)	-0.017 (0.034)	0.035* (0.020)
Amount of time that farmer spends for off-farm work	0.0004 (0.002)	0.008 (0.005)
Information on agronomy from newspaper/radio/TV/internet, dummy (1=yes)	0.046 (0.061)	-0.057 (0.059)

<b>Farm infrastructure</b>		
Good soil fertility index	-0.146** (0.058)	0.060 (0.072)
Farms with near irrigation canal and have satisfying irrigation and drainage, dummy (1=yes)	-0.168** (0.075)	-0.144** (0.073)
Distance to the district center from farm field (km)	0.001** (0.001)	-0.004 (0.004)
Distance to the house from farm field (km)	0.006 (0.005)	0.012* (0.006)
<b>Model diagnosis</b>		
<i>No. of observations</i>	<b>246</b>	<b>281</b>
<i>Wald <math>\chi^2</math> (18)</i>	<b>71.710***</b>	<b>60.060***</b>
<i>Pseudo R2</i>	<b>0.215</b>	<b>0.194</b>
<i>Log likelihood</i>	<b>-132.300</b>	<b>-156.884</b>

Note: Standard errors in parentheses, \* p<0.1, \*\* p<0.05, \*\*\* p<0.01

## 7.2 Cotton yield and net returns impacts of farmers' participation in social media groups

As described earlier, the impact of participation in social media groups on farmers' expected outcome under actual and counterfactual conditions is measured by average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATU) estimated by the ESR model. Table 5 presents the results from the ESR treatment effect model for Kazakhstan and Uzbekistan. The last column of Table 5 provides the treatment effects of participation in social media groups. The obtained results reveal that the impact of participation in social media groups on net returns and cotton yields differs between farmers in Kazakhstan and Uzbekistan. The second-stage regression estimates (Equation 5) are not discussed due to space limitation, but presented in Table A2 in Appendix.

It was found that group participation has significant positive impact on both outcome variables of cotton-growing farmers in Kazakhstan. The statistical analysis reveal that participation in social media groups indeed increase cotton yields and net revenues by almost 12% and 5% respectively. In other words, interviewed farmers in Kazakhstan who actually participate in AISG would have obtained 12% less net returns or 5% lower cotton yields had they remained with the conventional methods and not engaged in social media groups. These findings are congruent with the studies of Mendes et al. (2023) who found that in Brazil AISG had a positive impact on farm income per hectare by approximately 20%.

**Table 5** Average expected net returns and cotton yield for participants and non-participants in social media groups in Kazakhstan and Uzbekistan

Outcome variables	Category	Decision to participate in social media group	Decision not to participate in social media group	Treatment effect	
Cotton net returns (US\$/ha) (ln)	Farmer decisions in Kazakhstan				
	ATT	(a) 7.455 (0.014)	(c) 7.342 (0.037)	0.113** (0.040)	
	ATU	(d) 7.429 (0.015)	(b) 7.373 (0.030)	0.055 (0.036)	
	HE	BH <sub>1</sub> = 0.026	BH <sub>2</sub> = - 0.031	TH = 0.058	
	Farmer decisions in Uzbekistan				
	ATT	(a) 7.380 (0.022)	(c) 7.307 (0.059)	0.073 (0.063)	
	ATU	(d) 7.375 (0.017)	(b) 7.306 (0.040)	0.068 (0.042)	
	HE	BH <sub>1</sub> =-0.005	BH <sub>2</sub> =0.001	TH = 0.005	
	Cotton yield (ton/ha) (ln)	Farmer decisions in Kazakhstan			
		ATT	(a) 0.778 (0.017)	(c) 0.725 (0.016)	0.053** (0.024)
ATU		(d) 0.732 (0.019)	(b) 0.773 (0.012)	- 0.041* (0.022)	
HE		BH <sub>1</sub> =0.046	BH <sub>2</sub> =-0.048	TH =0.094	
Farmer decisions in Uzbekistan					
ATT		(a) 1.010 (0.007)	(c) 0.986 (0.012)	0.024* (0.013)	
ATU		(d) 0.978 (0.008)	(b) 1.002 (0.007)	-0.024** (0.011)	
HE		BH <sub>1</sub> =0.032	BH <sub>2</sub> =-0.016	TH =0.048	

Note: Standard errors are in parenthesis, \* p<0.1, \*\* p<0.05, \*\*\* p<0.01

In Uzbekistan, on the other hand, the farmers' participation in agricultural knowledge-sharing groups brings only a smaller increase in cotton yields of approximately 2.5%. However, similar impact of social media group participation does not hold for net revenues. This can be explained by the institutional context of cotton production in Uzbekistan where farmers are restrained in deciding what crop and how to cultivate. Thus, the regulation imposed on cotton

producers does not allow to convert the social media group participation into increased farm net revenues. Although farmers can increase their cotton yields from participating in AISG, they do not face proper input and output prices that would translate this gains in physical output into monetary gains. This suggests that to promote ICT tools among cotton growers in Uzbekistan, economic incentives should be considered, not only cotton yields.

For both countries, the model results show that cotton growers who actually did not participate in social media groups would have higher net returns if they had participated in social media groups. However, opposite sign is observed in case of cotton yields. Although, the ATU on cotton yield is negative, the result presents positive TH effects for cotton yields for both countries indicating that cotton yields as well as net returns are higher among participants in AISG (Table 5). From this result, we can conclude that there are several important sources of heterogeneity that make participants in social media groups better cotton producers than not-participants.

## 8. Conclusions and policy implications

Instant messaging apps is an ICT-based tool with great potential to be used for knowledge sharing and extension and advisory services in agriculture. The relative easiness and zero costs for joining the social media groups in these messaging apps will increase their popularity among farmers further. The application can help public extension agents overcome barriers and thus scale up information flow about new agricultural practices and technologies. The importance of social media group participation can be relevant for solving daily farm issues particularly in Central Asia where extension and advisory services are lacking or difficult to access. To the best of our knowledge, this is the first empirical and cross-country study of the determinants and effects of farmers' participation in AISG in smartphone-based messaging apps in Central Asia. Our study contributes to an emerging research area that relates farmers' participation in social groups to enhanced farm performance through knowledge sharing, problem solving and broader forms of distant (online) collaboration. First, we examined the determinants of participation in social messaging groups such as WhatsApp and Telegram apps using farm survey data collected among farmers in the context of two Central Asian economies—Kazakhstan and Uzbekistan. Following this, we looked at the impact of participation in social media groups on farm performance measured in terms of cotton yields and net revenues. Since farmer's decision whether or not to participate in smartphone-based agricultural knowledge-sharing group is voluntary, we used an endogenous switching regression model to correct for possible sample selection bias stemming from both observed and unobserved factors.

## 8.1 Conclusions

Our study reveals a pattern of the increased use of digital communication technologies in farm business and exchange among farmers through social media groups. Majority of respondents perceived mobile- and smartphones, mobile internet and messenger apps to be an essential everyday tool for their farm business operations. Majority of respondents reported about using instant messaging apps as well as participating in such platforms in groups for addressing issues related to farm business.

We find that in the two countries considered in this study, the underlying reasons for participation in social groups differ. In Kazakhstan, participants are those who have better access to mobile internet connection, are younger, have agriculture-related education, have wider communication circle on telephone with more than four individuals, cultivate fewer crops, have lower quality of soil fertility and irrigation water access as well as located in remote areas. In Uzbekistan, however, the participation decisions are made by those who see the relevance of mobile internet for their farm business, have own knowledge, are open to new things, care less about the opinion of other farmers, free to allocate crops, have off-farm work, as well as face with poor access to irrigation water. These findings suggest that farmers use and adoption of information and communication technologies are influenced less by the type of crops but by the environment, they operate such as socio-economic, institutional and regulatory environment.

With respect to the treatment effects of farmers' participation in AISG on net returns and cotton yields differs between farmers in Kazakhstan and Uzbekistan. Our findings indicate that participation in social media groups has a positive and statistically significant effect on both outcome variables of cotton-growing farmers in Kazakhstan. The estimation results reveal that participation in social media groups increases cotton yields and net revenues by almost 12% and 5% respectively. In Uzbekistan, the participation in agricultural knowledge-sharing groups brings smaller increase in cotton yields, namely by approximately 2.5%. However, similar positive impact of social media group participation does not hold for net revenues of cotton growers in Uzbekistan. This can be explained by the institutional context of cotton production in Uzbekistan where farmers' decisions over crop choice and marketing are restrained. Thus, the regulation imposed on cotton farmers in Uzbekistan does not allow to convert the participation in AISG into higher net revenues. Although farmers can increase their cotton yields from participating in AISG, they do not face proper input and output prices that would translate the physical output gains into monetary gains. This suggests that to promote ICT tools among cotton growers in Uzbekistan, economic outcomes should be considered, not pure physical harvest.

## 8.2 Policy implications

Our findings provide empirical evidence that are useful to design ICT-enabled agricultural extension services in Central Asia. Both Kazakhstan and Uzbekistan made commitments to increase farm productivity and transform agricultural sector into major food-exporting engine. For example, by 2050 the Kazakhstan government aims to increase the contribution of agricultural sector in GDP by 5 times (Anderson et al. 2018). Similarly, Uzbekistan's ambitions are not far apart from Kazakhstan. Reforms related to digital transformation in agriculture is expected to increase farm productivity and propel the sectoral growth. This discussion paper provides relevant policy and marketing advice to highlight important barriers for adoption on ICT technologies particularly social media.

In Kazakhstan where farmers produce under more liberal and secure tenure conditions, the focus could be given to improve internet connection to stimulate adoption of personal computers and mobile internet connection. Also, when introducing mobile-based technologies scaling up should be started with younger and more educated farmers. Where cotton and wheat farmers' production decisions are closely tied to top-down production arrangement, the focus should be first on showing the economic usefulness of participating in social media groups in combination of promoting more decision-making freedom among farmers. Explaining how farm business benefits from online social groups is a vital step to encourage further participation. In such context, it should be considered to scale up such digital extension and advisory services first among educated, entrepreneurial farmers who rely on their own knowledge and are more open to embracing new technologies and ways of farming. Making farmers self-reliant entrepreneurs will reduce their tendencies to follow top-down recommendation but make more nuanced decisions that relate to their needs and capacities. Higher decision-making autonomy will be crucial for converting digitalization processes in agricultural sector into economic benefits for farmers. To fully realize the potential of ICT tools, public extension services will need to minimize centralized top-down decision-making in favor of greater decentralization and diversity of advisory services.

## 8.3 Limitation and future research direction

The study has some limitations. First, from the data we cannot tell how long farmers have been using or how long they intend to participate in social groups using WhatsApp and Telegram apps. It is possible that some of the farmers using these messaging apps as of survey time may opt out in the following year or those who did not participate may opt in. Thus, the determinants we estimated should be interpreted as underlying factors for current or short-term participation in social media groups rather than continuous use. Second, technology adoption may be sequential. It is possible that farmers first need to be acquainted with personal computers, smartphones before they could see the benefits of using instant messaging apps and joining AISG there. These two limitations are promising directions for



future research. Finally, our sample comes from three districts in each of two irrigated areas. A broader understanding about potential digitalization of extension and advisory services in Central Asia will require replicating the study, not just in Kazakhstan and Uzbekistan, but also in other regions.

In terms of future research directions, our study points at the need of more in-depth insights on thematic content analysis of information and the nature of participants representing various social groups addressing the social equity topics related to digital transformation. A network analysis will allow for understanding of the types of content exchanged within social groups as well as the socio-economic fabric of online exchange particularly in terms of stakeholders and actors characteristics in terms of the involvement of farmers and other actors such as agricultural experts, extension agents or public administration in sending and receiving information. For instance, data collected through social group surveys can establish how such exchange patterns are influenced by social relations, trust to external experts, self-representational interests and institutional settings that influence farmers' decisions.

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## APPENDIX

**Table A1** Falsification test for instrumental variables (IV) that affect  $SG_i$  in Equation 1

	Kazakhstan		Uzbekistan	
	Joint significance test	p-value	Joint significance test	p-value
Participation in social media group (probit model regression)	$\chi^2 (2)=6.43$	0.04	$\chi^2 (1)=3.49$	0.06
Net returns from cotton (US\$/ha) (ln)	$F(3, 223) = 1.01$	0.36	$F(3, 223) = 0.17$	0.68
Cotton yield (ton/ha) (ln)	$F(3, 223) = 1.21$	0.3	$F(3, 223) = 0.00$	0.98

Note: IVs are Quality of mobile internet connection, and the Distance to the district center from farm field (for Kazakhstan model), and Distance to the house from farm field (for Uzbekistan model).

**Table A2** Second stage endogenous switching regression estimates for the outcome variables

	Net benefit, US\$/ha (ln)				Cotton yield, ton/ha (ln)			
	Kazakhstan		Uzbekistan		Kazakhstan		Uzbekistan	
	Participants (N=107)	Non- participants (N=139)	Participants (N=145)	Non- participants (N=136)	Participants (N=107)	Non- participants (N=139)	Participants (N=145)	Non- participants (N=136)
Cotton land area (ha) (ln)	-0.283	-0.162	0.033	0.856	-0.348	-0.151	-0.150**	0.026
st err	0.271	0.133	0.247	0.549	0.333	0.106	0.067	0.064
Fertilizer costs for cotton (US\$/ha) (ln)	-0.032	-0.162	-0.321**	0.169	0.080	-0.033	-0.027	-0.042
st err	0.087	0.134	0.141	0.395	0.085	0.059	0.084	0.112
Labor cost per ha (US\$/ha) (ln)	-0.010	-0.072**	-0.113***	-0.235*	0.032	0.001	-0.009	0.067**
st err	0.017	0.034	0.022	0.122	0.022	0.019	0.015	0.026
Cotton seed costs (US\$/ha) (ln)	-0.074	-0.146	-0.036	-0.184	-0.112	-0.041	-0.026	0.129*
st err	0.087	0.146	0.077	0.230	0.112	0.073	0.069	0.073
Farmer's age (years)	-0.003	-0.006	0.003	-0.002	-0.002	-0.003	0.001	-0.002
st err	0.003	0.005	0.004	0.006	0.004	0.003	0.002	0.002
Farmer's has a special education in agriculture (1/0)	0.021	-0.157	-0.028	0.089	-0.023	-0.100	-0.028	0.029
st err	0.122	0.227	0.051	0.101	0.144	0.183	0.035	0.039
Amount of time that farmer spends for off-farm work (hours/week)	-0.001	-0.001	0.004	0.036	0.000	0.000	0.002	0.003
st err	0.002	0.002	0.004	0.024	0.002	0.003	0.002	0.006
Total currently available land (ha) (ln)	0.262	0.400*	0.012	-0.894	0.286	0.215*	0.125	0.056
st err	0.264	0.234	0.197	0.647	0.325	0.121	0.079	0.076
Number of cultivated crops	-0.040	0.040	0.084	-0.329	-0.067	0.052	0.058	0.080**
st err	0.148	0.119	0.064	0.384	0.179	0.097	0.051	0.034
Farmer's opinion about own decisions on crop cultivation (1=not free at all ... 5= completely free)	0.020	-0.120	0.011	0.014	0.031	-0.047	0.003	0.025

st err	0.035	0.101	0.029	0.046	0.040	0.041	0.018	0.023
Farm has own knowledge on agronomy (1/0)	0.058	-0.228	-0.008	-0.216	0.059	-0.197	-0.038	-0.009
st err	0.187	0.167	0.091	0.209	0.234	0.159	0.065	0.058
Farmer is open to new things (1/0)	-0.136	-0.117	0.114	0.084	-0.139	0.047	0.1382*	0.035
st err	0.091	0.188	0.105	0.194	0.114	0.077	0.074	0.083
Farmer cares about opinion of other farmers (1/0)	0.018	-0.147	-0.226	-0.136	0.087	-0.059	-0.091	-0.126
st err	0.113	0.142	0.163	0.232	0.141	0.065	0.099	0.092
Farmer participated in at least one training during the last 3 years (1/0)	-0.113	0.285	-0.233***	-0.439**	-0.142	0.086	-0.140**	-0.175***
st err	0.133	0.247	0.085	0.177	0.174	0.162	0.059	0.062
Share of good soils in farmland (0-1)	0.189**	0.275	0.051	0.049	0.198*	0.145	0.090	-0.002
st err	0.084	0.230	0.085	0.126	0.106	0.095	0.067	0.055
Farms with near irrigation canal and satisfying irrigation & drainage (1/0)	0.223	0.177	-0.012	-0.169	0.269	0.086	0.007	-0.053
st err	0.139	0.175	0.088	0.180	0.176	0.097	0.061	0.062
Number of people farmer talks daily on telephone about farm business (1/0, 1=more than 4 people)	-0.097	-0.006	-0.130	-0.571	-0.109	-0.004	-0.019	-0.1399*
st err	0.080	0.109	0.128	0.365	0.086	0.064	0.072	0.073
Using mobile internet does not fit farm business (categorical, 5=does not fit)	-0.009	0.021	0.019	-0.030	-0.016	-0.001	0.015	-0.070*
st err	0.049	0.048	0.055	0.098	0.056	0.032	0.035	0.039
Farmer receives information on agronomy from newspaper, radio, TV, internet (1/0)	-0.001	0.303**	0.116	0.102	0.016	0.090	0.058	-0.025
st err	0.082	0.143	0.095	0.164	0.099	0.076	0.052	0.051
Distance from farm fields to dwellings (km)	0.000	0.003			-0.005	0.003		
st err	0.006	0.010			0.007	0.006		
Farmer's perception about quality of local mobile internet connection (1/0: 1=very good)			0.007	0.076			-0.002	-0.001

	st err			0.029	0.108			0.024	0.027
Distance from farm fields to a district center (km)				-0.007	-0.001			-0.002	0.000
	st err			0.006	0.008			0.005	0.003
mills1	-0.330			0.309		-0.518		0.078	
	st err	0.303		0.300		0.407		0.156	
mills2		0.178			0.384		0.111		0.223
	st err	0.338			0.401		0.227		0.190
Constant	8.302***	9.197***	9.371***	11.029***	1.204	1.305**	1.077**	0.538	
	st err	0.741	1.246	0.588	1.932	0.899	0.546	0.424	0.572
	R-squared	0.199	0.193	0.402	0.303	0.202	0.163	0.169	0.211
N		107	139	145	136	107	139	145	136

Note: \* p<0.1, \*\* p<0.05, \*\*\* p<0.01

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