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# Connecting the unconnected? Social ties and ICT adoption among smallholder farmers in developing countries<sup>☆</sup>

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## ABSTRACT

Information and Communication Technologies (ICTs) can reduce information asymmetries and thereby promote rural development for smallholder farmers in developing countries. Despite rising adoption rates of ICTs, many smallholders remain information constraint. Using panel data from 12,456 smallholder households across 12 developing countries, we analyze the role of social ties in determining ICT adoption and access to agricultural extension services. We find that weak social ties significantly reduce ICT adoption and access to agricultural advice, increasing information inequality. Moreover, ICT adoption, strong social ties and extension services positively correlate with agricultural productivity. Our findings highlight that ICTs, while transformative, may reinforce existing inequalities by marginalizing already disadvantaged smallholders.

## 1. Introduction

In recent decades, mobile phone coverage and access to the internet have increased massively in rural areas of developing countries.<sup>1</sup> According to the International Telecommunications Union (ITU), between 2010 and 2022, mobile phone subscriptions in developing countries surged from 33% to 79%, and internet use grew from 3% to 33%.<sup>2</sup> However, this progress masks persistent inequalities: many smallholder farmers in rural areas remain disconnected, limiting their access to critical agricultural information and support. Historically, there has been unequal access to Information and Communication Technologies (ICTs) between developing and developed countries, referred to as the digital divide (e.g., Engås et al., 2023). Within developing countries, this divide is further pronounced between urban and rural populations. Based on surveys carried out between 2016 and 2020, the ITU finds that 90% of households in urban areas had at least one member with a mobile phone, while this only applies to 70% of households in rural areas (International Telecommunication Union, 2021). The rate of internet use in rural areas is considerably lower, even though it

increased from 16% to 28% between 2019 and 2022.<sup>3</sup>

The benefits of ICTs for smallholder farmers are multifaceted and offer potentials to increase rural development. The rise of mobile phones and the internet could accelerate agricultural development for those previously unconnected through better and faster information access. Access to ICTs, such as mobile phones and internet access, facilitate knowledge transfer, increases household prosperity and boosts smallholder productivity (e.g., Beuermann et al., 2012; Cole and Fernando, 2012; Sekabira and Qaim, 2017). Connected smallholders can benefit from financial services via mobile money, reduced information asymmetries and better and more up-to-date agricultural information, including information on pest and disease control, seeds, prices and weather forecasts (e.g., Jensen, 2007; Aker, 2008; Svensson and Yanagizawa, 2009; Aker, 2010; Jack and Suri, 2014; Aker et al., 2016; Krell et al., 2021; Abdul-Rahaman and Abdulai, 2022). In addition, smallholders are responsive to external advice via mobile-based services that are tailored to their specific context (Gandhi et al., 2009; Deichmann et al., 2016).

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<sup>1</sup> We refer to developing as low-income and lower-middle-income economies using the classification provided by the World Bank.

<sup>2</sup> Regional ICT data is used from <https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx>, accessed on Dec 10, 2023.

<sup>3</sup> Regional ICT data is used from <https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx>, accessed on Dec 10, 2023.

In this paper, we shed light on the determinants of ICT adoption, while considering the interface with other sources of information and their agricultural and economic relevance. In more detail, we analyze the interconnectedness of ICT adoption, social ties, access to agricultural extension services and the agricultural productivity of smallholder farmers in rural areas of developing countries. Our analysis encompasses various dimensions of social ties, such as social interaction with peers through getting contacted for agricultural advice or membership in organizations, connection to local decision takers or remoteness to information sources such as markets. We contribute to the literature in three key ways. First, we analyze whether social ties determine the likelihood of ICT use for smallholders. Second, we analyze whether agricultural extension services exhibit a bias towards socially well-connected smallholders and those with ICT access. Third, we analyze the agricultural economic relevance of ICT access, social ties and extension services for smallholders by analyzing their respective relationships with agricultural productivity.

Our research is centered around three hypotheses. Our first hypothesis is that strong social offline ties are associated with a higher likelihood of adopting ICTs. Second, we hypothesize that social ties also determine access to agricultural extension services. As a consequence of the first two hypotheses, socially unconnected smallholders are exposed to a threefold agricultural information constraint. First, because of their weak social ties. Second, because of not being connected through digital means. And third, because they are less likely to be reached by agricultural extension services. The third hypothesis focuses on the agricultural economic importance of the information constraint. Thereby, we expect that ICT access, social ties and access to agricultural extension services are positively correlated with agricultural productivity.

We empirically test our hypotheses by using a unique cross-country dataset of smallholder households collected in two waves (the first in 2016 and the second in 2018) covering Benin, Burkina Faso, Cameroon, Ethiopia, Ghana, India, Kenya, Nigeria, Malawi, Mozambique, Togo and Zambia. The data used include 12,456 observations across both waves and all countries. These observations include 1,682 households that have been interviewed twice. The data were provided by the Gesellschaft für Internationale Zusammenarbeit (GIZ), the German government's implementing agency in development cooperation. The dataset covers smallholders active in diverse agricultural value chains, including mostly crops and some livestock. It is limited to rural areas for which the respective value chain is of economic relevance. The data collection followed a detailed sampling strategy, targeting representative data for the respective region/value chain combination.<sup>4</sup>

To test hypotheses 1 and 2, we apply a logit estimation to the full sample and the balanced panel with mobile phone, internet and being accessed by agricultural extension services, respectively. In all specifications, smallholder farmer's social offline ties are the main characteristic of interest. To do so, we measure social offline ties in different dimensions individually and compositely. Finally, we test our third hypothesis on the agricultural economic relevance of access to the information sources. To this end, we normalize the agricultural productivity of the main value chain of the smallholders within their peer group operating in the same value chain in a given region and apply an OLS estimation.

The empirical results strongly back hypothesis 1 by revealing that social ties are significantly associated with access to ICTs including mobile phone and internet access. The results hold for both, the full sample and the balanced panel. Further, the results support hypothesis 2 by showing that smallholders with weak social offline ties are

significantly less likely to receive training or advice from public or private extension services. In combination the findings strongly suggest a threefold information constraint — weak social ties and no access to ICTs and extension services. The economic relevance for smallholders is revealed by significant relationships of social ties, extension services and ICTs with productivity, respectively.

The structure of the remaining sections of this paper is as follows. Section 2 includes the conceptual framework by discussing the value added to the literature and deriving the hypotheses. It is followed by a section describing the data collection, including its methodology, survey design, sampling strategy and data quality checks during the data collection. Moreover, Section 3 presents the measurement and descriptive insights on our main measures of interest: ICT adoption, social ties and productivity. Section 4 presents the empirical strategy. Next, Section 5 discusses the main results of the analysis. Finally, we conclude the paper in Section 6.

## 2. Background literature and hypotheses

Our paper complements a rapidly growing literature on the determinants of ICT access and its importance for rural development particularly in developing countries (e.g., [Aparo et al., 2022](#)). Most studies focus on the opportunities of ICTs for smallholders. A meta-analysis of [Fabregas et al. \(2019\)](#) suggests that transmission of agricultural information through mobile technologies in sub-Saharan Africa and India increased yields by 4% and the odds of adoption of recommended agro-chemical inputs by 22%. However, heterogeneity in the dynamics of access and effects of different kinds of ICT adoption and the interaction with other channels of information access are still poorly understood. For instance, [Voss et al. \(2021\)](#) emphasize that simple mobile phones, a commonly used tool to access ICT services, are being rapidly replaced by smartphones. Accordingly, we believe that a split of internet-capable and non-internet-capable mobile phones will enable insights on their adoption at different levels of diffusion. Moreover, in Africa's rural areas, internet access is often available through mobile devices but the share of the population accessing it is still low.<sup>5</sup> A main reason for this is the cost of connectivity ([Milek et al., 2011](#); [Bahia and Suardi, 2019](#)). But beyond costs, other socio-economic characteristics explain different adoption rates ([Aparo et al., 2022](#)), such as alphabetization, education and cultural norms. Some researchers have started to dig deeper into the role of socio-economic characteristics explaining the digital divide. For instance, [Abdul-Rahaman and Abdulai \(2022\)](#) investigate the effect of access to mobile money on agricultural technology use for smallholder rice farmers. In their empirical setting they control for a selection bias in the adoption of mobile money. In so doing, they find that education, farm size, access to credit, farmer-based organization membership and location specific factors influence the adoption of mobile money. Similarly, [Milek et al. \(2011\)](#), [Cole and Fernando \(2012\)](#), [Penard et al. \(2015\)](#) and [Cole and Sharma \(2017\)](#) analyze the determinants of ICT adoption in developing countries and show that adoption rates differ with gender, age, education and wealth. [Aparo et al. \(2022\)](#) discuss in a systematic review the determinants of mobile phone technology adoption. They find that age, gender, perceived ease of use, perceived usefulness, perceived cost, performance and effort expectancy, attitude, skills and knowledge are relevant driving factors. However, they emphasize that studies so far are often geographically narrow and restricted to one specific sub-sector of agriculture. We overcome this constraint by empirically analyzing data from smallholder farmers from different developing countries active in a wide range of agricultural value chains, including crops and livestock, and add to the literature on unequal access to ICTs by focusing on different social offline ties as a widely neglected socio-economic determinant of

<sup>4</sup> Accordingly, it is not representative at the country level. Nonetheless, we argue that the wide coverage of different value chains, countries and regions allows for deep insights into smallholder farmer related aspects in rural areas of developing countries.

<sup>5</sup> An overview is provided by GSMA here: <https://www.gsma.com/coverage/>, accessed on 21st of October, 2020.

adoption.

We are aware of only two studies that also research possible interactions between offline social ties and ICT use (Penard et al. (2012) and Krell et al. (2021)). Penard et al. (2012) analyze household data from Gabun and find a positive correlation between voluntary membership in organizations and internet adoption, but no significant relationship for mobile phone adoption. Conversely to our study, they do not focus on smallholders. Krell et al. (2021) use a sample of smallholders in Kenya. They find that membership in farming organizations increases the likelihood of using mobile phone services. In contrast to Penard et al. (2012) and Krell et al. (2021), we analyze a diverse set of social ties when analyzing the determinants of mobile phone and internet adoption. Moreover, we use a dataset covering developing countries with substantially lower adoption rates of mobile phones than Kenya. In addition, and going beyond a pure focus on the determinants of ICT adoption, we analyze the interconnectedness between ICT adoption, social ties and agricultural extension services. Finally, we go further and test the economic relevance of the respective information sources. Next, we turn to a discussion of the hypotheses we empirically analyze in this study.

The analysis centers around three key predictions regarding social offline ties, agricultural extension services and productivity. First, we expect that smallholder's access to ICTs is determined by their social offline ties. This is based on the premise that socially disconnected smallholders have fewer incentives to interact with others via ICTs and are therefore less aware of the benefits that they offer, an aspect that was also highlighted in focus group discussions that accompanied the questionnaire based data collection we use in this paper. Moreover, we draw inspiration from the literature on social learning and technology diffusion, which shows that smallholders in developing countries tend to socialize with and learn from peers. For example, past research has demonstrated this phenomenon in the adoption of irrigation technology, input use and agricultural innovations (Ellison and Fudenberg, 1993; Bandiera and Rasul, 2006; Conley and Udry, 2010; Hunecke et al., 2017; Mekonnen et al., 2018). Drawing on the work of Penard et al. (2012, 2015), we argue that the use of digital tools spreads with knowledge sharing along social groups and that the motivation for adoption is higher for smallholders with strong social ties. This relationship has been shown to hold true in the context of a developed country as well. For instance, Goldfarb (2006) demonstrated how e-mail use first diffused across groups in universities before spreading to the social networks of those connected to universities in the United States. Accordingly, we formulate the first hypothesis as follows:

**H1:** *Smallholder farmer's access to ICTs is determined by their social offline ties.*

In our second hypothesis, we refer to the relationship of social offline ties and agricultural extension services, an alternative important source of information. Interestingly, Voss et al. (2021) find for rural smallholder farmers in Senegal that extension services using ICT failed to significantly encourage the use of certified seeds and fertilizers. In line with this, they highlight reasons for caution for an ICT-based approach of agricultural extension services, e.g., because of low adoption rates of smartphones or gender-based disparities in engagement with ICTs. We add to this study, by analyzing socio-economic determinants of ICT adoption. Analyzing Mozambican data, Cunguara and Moder (2011) find that agricultural extension services improve productivity but target more likely wealthier households, ultimately increasing income inequality. Besides wealth, women are shown to be less likely to receive agricultural extension services (Kondylis et al., 2016). Beyond the bias depending on socio-characteristics. In some contexts, smallholders tend to distrust the recommendations of extension services (Cole and Sharma, 2017). Benyishay and Mobarak (2019) show that social networks are a channel smallholders are likely to trust. Smallholders are most convinced to adopt new technologies when the extensions are provided by communicators sharing a group identity with them and more importantly for our analysis: using similar means

of communication. Although powerful for a large share of smallholders, such an approach risks neglecting smallholders with weak social ties. In line with this, Bandiera et al. (2018) reveal for a sample of Ugandan smallholders that extension workers favor their own social networks. Conversely to Bandiera et al. (2018), we analyze the relationship in a multi-country context, regard other domains of social ties and go beyond the focus on development programs.<sup>6</sup> Following these insights analyzed for Ugandan smallholders, we expect that smallholders with weak social ties are less likely to receive agricultural extensions, leaving them in a trap of low personal and digital access to information.

**H2:** *Smallholder farmers with strong social offline ties are more likely reached by agricultural extension services.*

Third, we analyze the economic relevance of social offline ties, ICTs and agricultural extensions for the unique sample we use. Concluding from the first two hypotheses, we expect that smallholders with weak social ties are exposed to a threefold agricultural information constraint: having weak social ties, and low ICT access rates as well as being less likely reached by agricultural extension services. Based on the literature discussed above, we expect that all our analyzed information sources are of high relevance for rural development because the information sources themselves manifest in higher agricultural productivity (e.g., Bandiera and Rasul, 2006; Kondylis et al., 2016; Mekonnen et al., 2018; Fabregas et al., 2019).

**H3:** *Smallholder farmers with strong social offline ties, access to ICTs and being reached by agricultural extension services show higher agricultural productivity.*

The next section presents the data we use to empirically test the three hypotheses.

### 3. Data collection and description

#### 3.1. Country, region and value chain coverage

We use data from 12 countries, namely: Benin, Burkina Faso, Cameroon, Ethiopia, Ghana, India, Kenya, Nigeria, Malawi, Mozambique, Togo and Zambia. The data were collected as part of a baseline and midline study of the program "Green Innovation Centres for the Agriculture and Food Sector (GIAE)" implemented by GIZ.<sup>7</sup> The baseline data were collected between January and March 2016 in parallel in all the countries, except Kenya and Mozambique. In Kenya, the data collection was slightly delayed to May and June 2016. In Mozambique, the data collection was in September 2017. The midline data were collected between April and June 2018 in parallel in all the countries, except in Mozambique where only baseline data were available at the time of this study.

The countries participating in the GIAE program were selected in political negotiations between governments. In each country, two to four crops or livestock products in several regions of each country were selected for treatment by the political parties. Relevant selection criteria for crops and livestock were (a) relevance to smallholder farming, (b) at minimum one staple food and one cash crop per country. The targeted regions had to be relevant to the chosen value chains and not in the focus of another big development program. Existing GIZ presence in the region may also have played a role in the selection. Overall, the selection of countries, regions and value chains was not in control of the researchers, but entirely independent of social ties and ICT usage or connectivity patterns. Table 1 provides an overview of the regional and value chain coverage of the data used.

<sup>6</sup> A similar caveat might be observable for the lead farming approach that also favors socially and digitally well connected households. See Holden et al. (2018) for a discussion of the lead farmer approach.

<sup>7</sup> For more information on the project visit (GIZ, 2023), accessed on 13 April 2023.

<sup>8</sup> Notably, the program extended its scope to more countries in the later years. We use all data available to us with complete coverage of information needed for this study.



**Table 1**

Country, region and value chain coverage.

Country	Regions	Value chains
Benin	Borgou-Alibori, Zou-Collines	Rice, soy, chicken
Burkina Faso	Sud-Ouest, Haut-Bassins, Cascades, Boucle de Mouhoun	Rice, sesame, onion, tomato
Cameroon	Nord-Ouest, Adamaoua, Sud-Ouest, Ouest	Chicken, potato, cocoa
Ethiopia	Arsi Robe, Lode Hitosa, Hitosa, Tiyo, Digalu Tijo, Limuna Bilbillo, Enkolo Wabe, Munesa	Wheat, faba bean
Ghana	Brong-Ahafo, Ashanti, Eastern, Volta, Central Region, Greater Accra	Rice, maize, pineapple
India	Maharashtra, Karnataka	Tomato, potato
Kenya	Siaya, Bungoma, Kakamega, Nyandarua	Sweet-potato, dairy
Malawi	Mzimba, Rumphi, Kasungu, Mchinji, Ntchisi, Ndowa, Lilongwe, Salima, Machinga Zomba, Mulanje	Peanuts, soy, sunflower, cassava
Mozambique	Sofala, Manica	Baobab, pigeon pea, rice
Nigeria	Kano, Kaduna, Benue, Nassarawa, Plateau, Oyo, Ogun	Rice, maize, cassava, potato
Togo	Maritime, Plateaux, Centrale, Kara, Savanes	Peanut, cashew, soy
Zambia	Eastern province	Soy, groundnuts, dairy

The table provides an overview about the countries, regions and value chains covered in this study. However, the aggregated-level of the regions differs between countries. This depends on the respective country project. Notably, also in bigger regions the sampling was conducted at a less aggregated region/ value-level.

The data collection within the chosen regions was coordinated by a headquarter, including researchers in cooperation with GIZ and its partners.<sup>9</sup> One uniform sampling strategy was implemented in all the countries. This sampling strategy aimed at representativeness of the small-scale agricultural sector in the chosen value chains in the chosen regions, which we discuss in more detail next.

### 3.2. Sampling strategy

The broad coverage of countries, regions and value chains in our study allows us to capture many sources of heterogeneity between agricultural smallholders in rural areas of these countries, such as those who cultivate crops versus those who raise livestock. However, it is important to note that the data is not representative of all rural areas in the covered countries, as the survey regions were selected by program decision makers. Nevertheless, we believe that our study provides a unique perspective on agricultural smallholders in developing countries, as the broad cross-country and cross-value coverage is uncommon in the literature. Moreover, the data collection process included a carefully conducted sampling design to ensure representativeness:

The survey was designed to obtain statistically representative data for small-scale farming households that are commercially active in one or more of the chosen target value chains in the target regions in each of the program countries. The regions were divided into sub-regions, based on the next lower administrative unit in each country. Since not all of the target value chains were targeted in each sub-region, the sub-region-target value chain combinations were defined as universes for sampling. To ensure the transparency and scientific rigor of the survey design, a unified approach was taken to ensure comparability across all countries where the survey was conducted. The sampling strategy involved several layers:

The first layer is the allocation of the planned interviews within a country across universes. The number of smallholders in the universe was used as a basis for proportional allocation across universes. This is the most suited allocation of interviews of different universes considering the need for precise estimates within universes, potentially very large, but unobserved, heterogeneity across universes. Using this

allocation method the number  $n$  of interviews done in each universe  $h$  is

$$n_h = \frac{N_h n}{N} \quad (1)$$

, where  $n$  is the number of interviews in each country,  $N$  is the total underlying population per country across all universes,  $N_h$  the estimated size of the underlying population of universe  $h$  and  $n_h$  is the resulting number of interviews for that universe. The formula shows that the sample size per universe relative to the size of the underlying population in the universe is equal to the total sample size compared to the total underlying population in that country. In order to avoid very small samples in cases where, within a country, the underlying populations per universe are very unequal, we imposed a floor sample size per universe of 50. Proportional allocation was chosen whenever information about underlying population sizes was known, because (1) statistically correct averages of features across universes can also be calculated by users of the data with no knowledge of statistical weighting (“self-weighting property” under homogeneous response rates), (2) the precision of the estimates derived from the survey is highest in the universes comprising the largest number of relevant smallholder households. For proportional sampling, the only information required is the approximate number of farmers in each sampled sub-group  $N_h$ . When no lists of farmers were available, we used a combination of official statistics and estimates from extension services and local agricultural ministry staff to estimate the number of farmers.

In the second layer, clustered random sampling was used with clustering being at the primary sampling unit (PSU), the village, to account for incomplete information about the distribution/ location of the target population and partly very large areas under consideration. Randomization was documented using tables with pre-generated random numbers. The correlation in clustered samples can decrease the effective sample size. This so-called design effect is the lowest (i.e. data precision is the highest) when many different interviewers go to many different villages conducting one interview per village only. For logistical reasons (i.e. especially the administered time to conduct the survey) this was not possible. This is typically the same in other surveys, mostly for cost reasons. When drawing samples, we minimized the so-called design effect by aiming at low clustering with a target number of four interviews per village and ensuring that interviewers

<sup>9</sup> We have been in leading role of the headquarter activities, including methodology design and data quality-related activities.

are shuffled across value chains when possible.

Finally, within each selected village, random route techniques were used to interview a random selection of four households per village. The crucial point for this technique was defining the starting points of the random routes of each enumerator. In particular, if villages are large or dispersed, starting in the center of the village will mean that more remote parts of the village will be systematically missed. Therefore, starting points were determined with the help of village heads or local organizations helping to point out areas, in which farm households of the respective value chains were most likely to live. From starting points defined in this way, each interviewer walked from the respective starting point along a route, flipping a coin to choose whether to walk left or right and approached every third household with a screening question on whether the household is commercially active in the respective target value chains. If yes, the enumerators asked for consent to interview the main farmer. The main farmer was defined as the person in the household who is most knowledgeable about agricultural production and sales decisions in the targeted value chains. In some cases, it was not possible to interview this person. If there has been another knowledgeable person, this person was interviewed. However, in 93.4% of the cases, the respondent stated to be the main farmer.

In the second wave of the survey, the midline, the lists of interviewed households from the first wave constituted the preferred sample. During the preparation of the survey, we realized several obstacles for re-interviewing the entire sample, mostly and in a list of decreasing frequency: households not engaged in the target value chain as part of regular crop rotation, households changing their phone number or place of living, households having changed to different value chains or occupations, households being unavailable for reasons like sickness, households having dropped out of the program (only treatment group) and households being strongly engaged in a similar program (only control group). For such circumstances, we returned to the same procedure as in the first wave of the survey. In this study, we use panel data from 1,682 households in nine countries. For Burkina Faso and Togo, the dataset includes cross-sectional baseline and midline observations. For Mozambique, only baseline data was available.

### 3.3. Cross-country questionnaire, quality control and focus group discussions

This strategy ensured that the survey captured the diversity of smallholder agricultural households in the target regions. In addition, the headquarter-centered-approach allows for meaningful cross-country and cross-value chain comparisons.

In all countries, a similar questionnaire has been used. Also, the changes between baseline and midline were kept to a minimum. For this study, we only refer to data which is comparable over both waves. Country-specific adaptations were only built for responses that require adaptation to local definitions, e.g., country-specific education system classifications or units applicable for value chains or regions. A headquarter team coordinated the study design, ensuring comparability across value chains and countries. The respective surveys were conducted in each country by a national team consisting of team leaders, supervisors and enumerators. The extensive tablet-based questionnaire was designed at the headquarters level and used the World Bank Survey Software Survey Solutions. This software has a strong data quality feature that allows for different layers of quality checks. Firstly, after an enumerator finished an interview, the national team verified the quality. If an interview was rejected, the enumerator could directly correct it or write a comment to verify its validity. This correction process occurred shortly after the interview, making it less error-prone than doing quality checks after the complete data collection. Secondly, once the national team accepted an interview, the headquarter verified its quality. Similarly, the headquarter could reject an interview to allow the national team to comment or correct. Finally, the data cleaning and analysis were conducted using Stata.

In addition to the questionnaire-based data collection, between eight and twenty focus group discussions were held in each country and wave. The topics touched upon in the focus group discussions were not aimed at supporting this research, but rather the program implementation. As such, they focused on e.g., adoption of agricultural practices and general agricultural challenges. However, they nevertheless revealed interesting aspects of farmers' access to information and social ties, which we used to inform the explanation of our hypotheses. The next sub-sections present insights on how we measure the key variables of interest and provide descriptive insights.

### 3.4. ICT adoption among smallholder farmers

We measure two domains of ICT adoption. First, mobile phone access states whether the respondent owns a mobile phone. Second, internet defines whether the respondent has a mobile phone and internet access.<sup>10</sup> Table 2, Figs. 1 and 2 summarize the respective adoption rates of internet and mobile phones split by countries.<sup>11</sup>

With 82.9%, most households in our sample of smallholder farmers have access to mobile phones. Between baseline and midline, the share increased from 79.3% to 86.8%. Six out of 12 countries have phone possession rates higher than 90%, namely Benin, Burkina Faso, Cameroon, Ghana, India and Kenya. Although adoption is relatively high, there is still a share without access in these countries (except India which nearly shows full coverage). In addition, some countries show significantly lower adoption rates. The lowest rates are observable in Mozambique, Zambia and Malawi with only 17.8%, 69.7% and 61.9%.

Smallholders without a mobile phone, might also be laggards in the use of other new technologies. Such a technology is the internet. Here adoption rates are much lower, with only 14.7% having access to the internet.<sup>12</sup> Focusing on country heterogeneity shows that India has the highest internet use rate with 46.0%, followed by Kenya and Cameroon with 25.0% and 23.1%, respectively. At the lower end are Mozambique, Burkina Faso and Togo with only 0.9%, 2.4% and 3.2%, respectively.

From the statistics above, we infer that the ICT adoption rates are highly heterogeneous across the regions covered in the data. The overall adoption rates and particularly the heterogeneity is broadly in line with general trends of ICT adoption.<sup>13</sup>

According to our first hypothesis, we expect that ICT adoption rates increase with the level of a household's social ties. Next, we present how we measure social ties and descriptively analyze whether ICT adoption rates differ with different levels of social ties.

<sup>10</sup> Table 9 in the Appendix included the respective survey questions and response options for ICT adoption, social offline ties and agricultural extension services. In addition, Tables 14–16 report summary statistics of all variables covered in the regression analysis. Finally, Table 17 reports the correlations between all variables.

<sup>11</sup> For all descriptive statistics, the sample is reduced to the coverage of the empirical analysis.

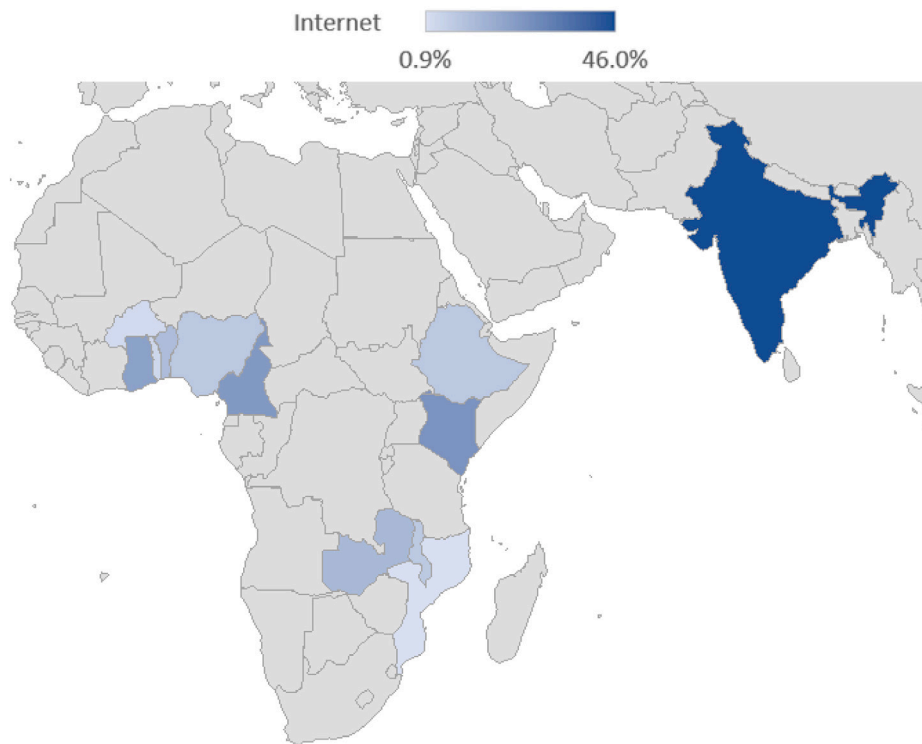
<sup>12</sup> We acknowledge that with the ongoing speed in the adoption of ICTs, some households might have adopted mobile phones and/or the internet since the survey has been conducted. However, as stated above, we still argue for limitations in internet access and that there is also in light of high adoption rates much to learn from the analysis of how social ties relate to the adoption of new technologies in rural areas of developing countries.

<sup>13</sup> The GSMA illustrates on <https://www.mobileconnectivityindex.com/connectivityIndex.html#year=2021&dataSet=dimension> (accessed on July 4, 2023) includes a relatively detailed list of different dimensions of connectivity per country, it is important to remember that the respective values are not representative for neither, the countries nor the countrywide rural areas. Conversely, the data is representative for target regions and agricultural value chains of the analyzed countries.

**Table 2**  
Internet and mobile phone adoption split by country and survey round.

Survey	Baseline			Midline			Both surveys		
Country	Int.	Mobile	Freq.	Int.	Mobile	Freq.	Int.	Mobile	Freq.
Benin	NA	91.9%	876	11.8%	92.7%	536	11.8%	92.2%	1,412
Burkina Faso	2.7%	91.8%	476	2.1%	94.8%	612	2.4%	93.5%	1,088
Cameroon	15.6%	94.6%	482	30.5%	96.9%	489	23.1%	95.8%	971
Ethiopia	5.7%	88.3%	494	10.4%	82.7%	566	8.2%	85.3%	1,060
Ghana	22.9%	96.8%	528	18.5%	95.0%	583	20.6%	95.9%	1,111
India	39.5%	99.8%	494	51.5%	99.8%	590	46.0%	99.8%	1,084
Kenya	26.4%	95.6%	432	23.7%	92.1%	456	25.0%	93.8%	888
Malawi	9.0%	64.2%	525	6.9%	57.7%	520	7.9%	61.0%	1,045
Mozambique	0.9%	17.8%	583			NA	0.9%	17.8%	583
Nigeria	5.3%	77.9%	638	11.2%	92.5%	590	8.1%	84.9%	1,228
Togo	2.8%	71.2%	472	3.6%	73.2%	526	3.2%	72.2%	998
Zambia	15.8%	66.2%	506	10.0%	73.4%	482	13.0%	69.7%	988
All	12.9%	79.3%	6,506	16.4%	86.8%	5,950	14.7%	82.9%	12,456

NA = Not available. In Mozambique only data for the baseline is available. For Benin, data on internet adoption in the baseline is incomplete and hence not considered.



**Fig. 1.** Internet adoption in survey region (both surveys).

### 3.5. Social offline ties

We measure four dimensions of social offline ties. Table 9 includes the survey questions which we use to derive the measures of social ties. First, *organization member* is a dummy and states whether a household member is a member of a local group related to saving, farming or religion. The variable proxies the degree of social organization around farming, business-related topics and also include religious groups which are an important place to foster social ties and for information sharing in many communities. By capturing organization membership, we link to Penard et al. (2012) and Krell et al. (2021) as discussed in Section 2. Going beyond these studies, we also capture additional domains of social ties. Our second measure is a dummy variable *agricultural knowledgeable* that captures if the respondent got contacted by other farmers for agricultural advice during the last two weeks. The variable proxies if a respondent is a focal point within the social network. Third, *connected with decision taker* is a dummy capturing whether the respondent states strong ties to the local government. The latter

links to a higher social rank which may correlate to better information access or other kinds of privileges. Fourth, *market information* covers the relevance of community markets as a place for social interactions and a source for agricultural information. The dummy variable equals one if a respondent states local markets as a usual source to access market information.

Among the smallholders, 46.6% are *agricultural knowledgeable*, 74.1% are an *organization member*, 9.1% are strongly *connected with decision taker* and 60.8% state local markets as a usual source of *market information*.<sup>14</sup> To analyze how each domain of social ties correlates with our variables of interest, we include the proxies of social ties separately in the empirical analysis. However, we are particularly interested in the relative direction of the respondent's social ties, e.g., weak social ties vs. strong social ties and not in a specific domain of social ties. To this

<sup>14</sup> Tables 10 and 11 in the Appendix include the share of smallholders with a respective domain of social ties split by countries and surveys.

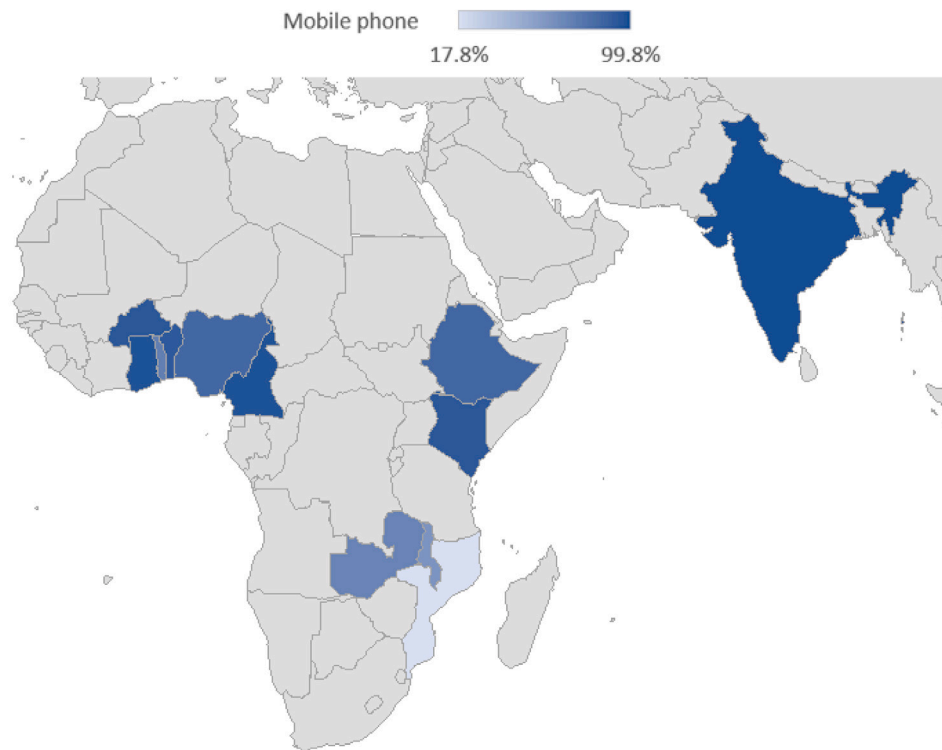


Fig. 2. Mobile phone adoption in survey region (both surveys).

**Table 3**  
Principal component (eigenvector)

	PCA	Unexplained
Agr. knowledgeable	.6600748	.4912653
Organization member	.507979	.6987018
Connected with decision taker	.4681984	.7440443
Market information	.2950405	.8983592

end, we reduce the four different dimensions of social ties by applying a principal component analysis (PCA).

The main principal component measures the social ties of the respondent in a single variable by maximizing the loaded variance with constructed linear combinations of the four social domains we cover. Table 3 include the eigenvectors of the main principal component we include in our regression analysis. In addition, Fig. 3 shows the screeplot for a different number of principal components.

The eigenvalue of the main principal component is 1.17, which corresponds to an explained variance of 29.19%.<sup>15</sup> We infer from the explained variance that the model fails to load up the majority of the variance of the different proxies for offline ties in a single variable. However, the limited overlapping of the four proxies shows that they all cover different forms of social ties. By considering all domains in a single variable, we can capture whether a respondent has strong social ties, allowing us for a direct interpretation in the regression analysis.

### 3.6. External agricultural extension services

In addition to the importance of offline social ties for the adoption of ICTs, we expect that they also relate to the likelihood of receiving external advice (H2). To this end, we the variable *external advice*

measures the whether households have received advice or training by extension services, donor programs, government, NGOs and others over the last 12 months.<sup>16</sup> Table 4 includes the share of smallholders reached by external agricultural extension services split by country and survey.

Overall, 74.7% have been reached by agricultural extension services. However, there is much heterogeneity between countries observable. The lowest rate is observable in Mozambique with only 17.3% and the highest share in Ethiopia with 96.4%. Next, we turn to a descriptive analysis on how ICT adoption and access to agricultural extension surveys correlate with social ties.

### 3.7. Social ties by ICT adoption and access to agricultural advice

Following hypotheses 1 and 2, we expect that households with strong social ties have better access to information via ICT and are more likely to receive external advice, for instance by extension services and training courses. Before turning to the empirical analysis, we descriptively analyze whether ICT adoption rates and received agricultural advice vary with the different domains of social ties. To this end, we perform a one-sided mean-comparison t-test controlling for differences in adoption rates depending on the respective social domain. Table 5 summarizes the respective adoption rates for the households with a respective social tie and reports the results of the respective t-tests, e.g., stating whether smallholders with strong connection to decision takers are more likely having access to the internet.

For all social domains higher ICT adoption rates as well as more likely access to agricultural advice is observable. The one-sided t-test points to a significant different mean between households with and without a respective social tie in all specifications. Smallholders who got contacted by others because of their agricultural knowledge show the highest internet adoption rate with 18.9%. For mobile phone

<sup>15</sup> The share of the variance explained by a main principal component is the eigenvalue of the main principal component divided by the sum of all eigenvalues.

<sup>16</sup> Notably, this goes beyond the GIZ program beneficiaries. Accordingly, no inference on the targeting of the GIZ program can be made based on our analysis.



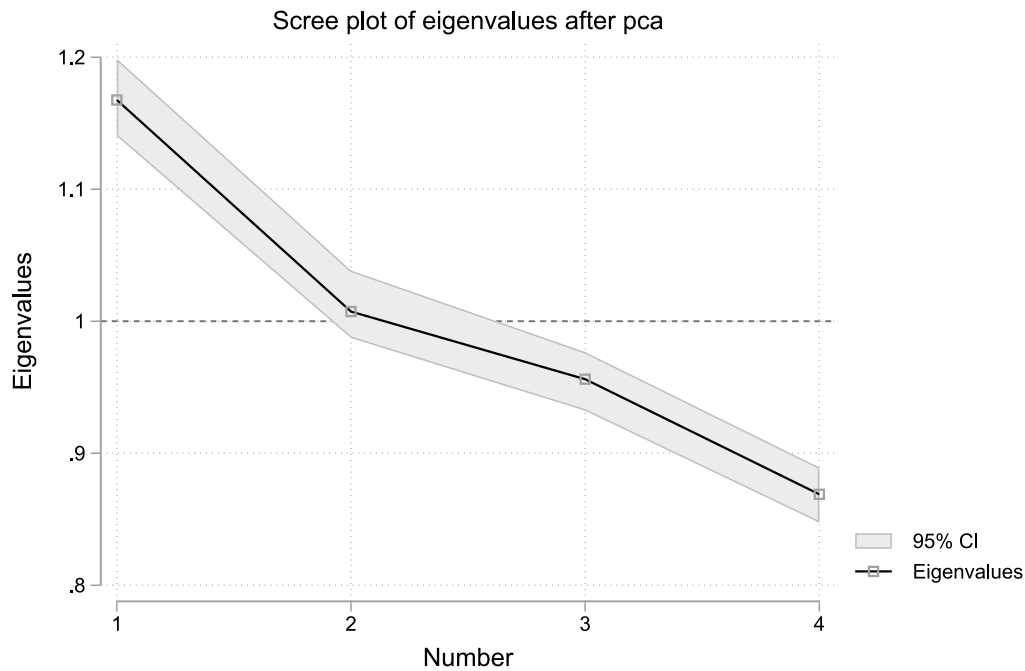


Fig. 3. Different eigenvalues for each number principal components and the respective 95% confidence interval.

Table 4

Share of smallholders reached by external agricultural extension services split by country and survey.

Survey	Baseline		Midline		Both surveys	
	Advice	Freq.	Advice	Freq.	Advice	Freq.
Benin	61.8%	876	76.1%	536	67.2%	1,412
Burkina Faso	69.1%	476	75.7%	612	72.8%	1,088
Cameroon	84.2%	482	85.1%	489	84.7%	971
Ethiopia	96.8%	494	96.1%	566	96.4%	1,060
Ghana	83.3%	528	91.8%	583	87.8%	1,111
India	93.9%	494	91.4%	590	92.5%	1,084
Kenya	81.7%	432	57.2%	456	69.1%	888
Malawi	79.2%	525	82.7%	520	81.0%	1,045
Mozambique	17.3%	583	NA	NA	17.3%	583
Nigeria	22.6%	638	96.3%	590	58.0%	1,228
Togo	59.3%	472	63.3%	526	61.4%	998
Zambia	81.2%	506	92.5%	482	86.7%	988
All	67.1%	6,506	83.1%	5,950	74.7%	12,456

NA = Not available; Advice refers to our variable of interest *external advice*.

Table 5

Dependent variables by different domains of social ties.

Dependent variable	Internet	Mobile phone	Agr. advice	Frequency
Agr. knowledgeable	18.9%***	85.6%***	81.3%***	5,808
Organization member	16.1%***	87.3%***	84.6%***	9,233
Connected with decision taker	18.0%**	88.4%***	81.4%***	1,133
Market information	16.7%***	86.7%***	76.6%***	7,571
All	14.7%	82.9%	74.7%	12,456

The *p*-value is stated in parenthesis and refers to the respective results of a one-sided t-test on the equality of means depending on the respective domain of social ties. To this end, we used the *ttest* command in Stata which refers to the mean-comparison t-test. In total, we performed 12 t-tests. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

adoption, the highest rate is observable for smallholders with strong connections with decision taker. These smallholders have an adoption rate of 88.4%. This points to the privileged position within a community of smallholders. In terms of access to external agricultural advice, the highest rate is observable for organizational members with 84.6%. These members might be more aware of activities of extension services or service providers directly use organizations to find beneficiaries. Notably, so far, we do not control for any other socio-economic characteristics. To this end, we refer to our empirical analysis. However, before presenting the empirical strategy, we introduce our measure for the economic performance of smallholders.

### 3.8. Agricultural productivity

The third hypothesis focuses on the economic relevance of social ties access to ICTs and being reached by agricultural extension services. To this end, we use agricultural productivity as a measure of smallholder farmers' agricultural performance.

The questionnaire includes a module to calculate the agricultural productivity of the value chains a household is active in and the GIAE project target on. The respective information is a key part of the questionnaire because the information is also used in the Monitoring and Evaluation activities of the GIAE. Given the wide range of different crops and livestock, each value chain requires its own approach. For crops, the productivity was measured in kg of harvest per hectare. To this end, the harvest volume of the last 12 months and the size of the cultivated fields have been collected. Such an approach does not make much sense for baobab (Mozambique) because baobab is typically collected in community areas and the respondents do not possess the trees. Hence, baobab is excluded from the calculation of productivity. For livestock, the approach varies with the value chain but we only use data for dairy. For dairy, productivity is measured as liters of milk per female cattle (Kenya and Zambia). To this end, the household stated how many liters they milk per day. The information was collected for the wet and dry season separately and transformed to an annual average. For chicken (Benin and Cameroon), no meaningful productivity is available for this study. Hence, these value chains are excluded from the analysis regarding hypothesis 3.

During the training of the enumerators, a focus has been on measuring productivity. Such a measurement is not an easy task because it requires for instance to verify field sizes and volumes of harvest. The data quality monitoring process had a strong focus on the validation of the collected data required to calculate smallholders' productivity, e.g., quality control of relevant entries and general plausibility checks with secondary data accessible for the respective value chain/country combination.<sup>17</sup>

To make the productivity of households comparable across value chains and regions, we have normalized the respective values, e.g., you cannot compare the kg of harvest per hectare of pigeon pea (Mozambique) with tomatoes (Burkina Faso and India) since the latter have a much higher potential in volume. Even within a similar value chain, differences between countries can be substantial, e.g., due to agricultural conditions such as the climate or soil quality. Accordingly, we have normalized the productivity within countries and value chains by solving:

$$\text{normalized productivity}_{i,t} = \frac{\text{productivity}_{i,t} - \text{mean}(\text{productivity}_{i,t})}{\text{standard deviation}_{i,t}} \quad (2)$$

, with  $\text{normalized productivity}_{i,t}$  is the normalized productivity of household  $i$  active in value chain  $v$  at time  $t$ . In the case a household is

active in several value chains covered in the survey in a respective year, we take the average normalized productivity of this household to derive  $\text{normalized productivity}_{i,t}$ . This measure of productivity enters the respective specification as dependent variable.

## 4. Empirical strategy

For the empirical analysis, we pool the cross-country data to a single dataset and run several different specifications to test our three hypotheses. The first set-up of estimations focuses on hypotheses 1 and 2. Following H1, we expect a positive relationship between ICT adoption and social ties. Following H2, we expect a positive relationship between external agricultural advice and social ties. To test the hypotheses, we apply cross-sectional and panel logit estimations, respectively. The cross-sectional specifications are specified for a household  $i$  at time  $t$  living in region  $j$  as -

$$\text{ICT}/\text{Advice}_{i,t} = \alpha + \sum_{n=1}^4 \beta_n \text{social ties}_{i,t} + \sum_{m=1}^{11} \beta_m \text{controls}_{i,t} + \gamma \text{region}_j + \delta \text{year}_t + \epsilon_{i,t} \quad (3)$$

The (balanced) panel specifications are limited to households interviewed in both survey rounds.<sup>18</sup> It is specified for a household  $i$  at time  $t$  living in region  $j$  as -

$$\text{ICT}/\text{Advice}_{i,t} = \alpha + \sum_{n=1}^4 \beta_n \text{social ties}_{i,t} + \sum_{m=1}^4 \beta_m \text{controls}_{i,t} + \zeta \text{household}_i + \delta \text{year}_t + \epsilon_{i,t} \quad (4)$$

The dependent variables are similar in the cross-sectional and panel estimation.  $\text{ICT}_{i,t}$  captures two forms of digital adoption as presented in 3.4. First, we include a dummy *mobile phone* capturing if a household possesses a mobile phone, which continues to be the most widespread tool for internet access. In an alternative specification, we measure *internet* as a dummy if a household possesses a mobile phone and has internet access. Further, in a similar set of specifications, we take *advice<sub>i,t</sub>* as dependent variable which measures whether a household got reached by external agricultural advice (see Section 3.6).

The variable *social ties<sub>i,t</sub>* is our main independent variable of interest. It covers the four domains of social offline ties presented in Section 3.5. In an additional specification, we replace the four domains of social ties by the main principle component.

The main difference between the cross-sectional and panel approaches is the choice of fixed effects. By adding regional fixed effects with the variable *region<sub>j</sub>*, we capture regional-specific characteristics such as level of development. Hence, we exploit within regional variation and go beyond adding country-fixed effects as often done in cross-country studies. In the panel estimation, we replace the country fixed effects by *household* fixed effects. The latter considers time-invariant factors and unobservable household characteristics, which are time-invariant. Unobservable factors are for instance a respondent's openness to new technologies and motivation to participate in agricultural training courses.<sup>19</sup> Hence, the panel approach goes beyond the

<sup>18</sup> In so doing, observations from Burkina Faso, Togo and Mozambique drop out of the sample because there is no panel data available (Burkina Faso and Togo) or only baseline data is available (Mozambique).

<sup>19</sup> These unobservable factors might correlate with our dependent variable and justify that we complement the cross-sectional approach with the panel approach. In addition, we use household fixed effects rather than random fixed effects for two main reasons. First, random fixed effects need the assumption that unobserved household characteristics are uncorrelated with the explanatory variables. We argue that this assumption does not hold in our case. Second, in non-linear models such as logit, the random effects estimator needs a pre-specified assumption about the distribution of the random effects which we want to avoid because the validity of it is questionable.

<sup>17</sup> We describe the feedback loop to ensure data quality in more detail in Section 3.3. Unfortunately, we cannot report on the descriptive statistics of productivity at the country/value chain level because of data handling requirements. However, we once again refer to the extensive activities on improving the data quality.

**Table 6**  
Description control variables.

Variable	Survey questions, question type and relevant response options
Mobility asset (dummy)	“Which of the following assets, household appliances and means of transportation are in your possession?” [multi select] “Car” or “Moped” was selected
Level of education	“What is the highest level of education the respondent has completed?” [single select] 1. Did not attend school; 2. “Pre-school” or “Primary” was selected; 3. “Secondary” was selected school; 4. “College”, “Higher religious school (e.g., Koran school)” or “University” was selected
Ethnic majority (dummy)	“To which social group/community membership/ ethnic group does the respondent belong?” [single select] The respondent selected the most frequent ethnicity within a region in a country
Fem. main farmer (dummy)	“What is the respondents’ status in respect to the agricultural activities the household?” [multi select] “Main farmer” was selected and the respondent is female
Village settled (dummy)	“How many years has the respondent lived in this village?” [numerical question] More than 10 years are stated
(ln) farm size	Natural logarithm of the total farm size a household possesses in hectare [calculated based on numerical questions]
(ln) age	“How old is the respondent?” [numerical question]

cross-sectional approach. However, derived results exploit variation of the dependent variable over time. Hence, only a subset of the sample enters the final estimation. In line with this, we see a value in both approaches. In both approaches, we add with *year<sub>*i*</sub>* time fixed effects. By doing so, we capture year-specific effects, such as shocks related to climate risks such as cyclones, droughts or other weather events.

Guided by the literature review presented in Section 2, we add a set of control variables in our empirical analysis (e.g., Aparo et al., 2022). The choice of control variables differs between Eqs. (3) and (4). In the cross-sectional approach, we add all available control variables which cover a wide set of socio-economic characteristics. In the panel approach, we limit the number of controls to time-varying factors. Table 6 provides an overview of all control variables.

*Mobility asset* is a dummy variable if the household possesses a car or motorcycle. First, this captures the mobility of the household, which makes for instance the market access easier. On the other hand, both are valuable assets and hence relate to the household’s wealth. Controlling for wealth is important since ICT adoption rates are shown to increase with income (e.g., Penard et al., 2012; Aparo et al., 2022). Next, we include a variable capturing the *level of education*. The variable have four different levels: First, the respondent did not attend school. Second, the respondent finished pre-school or primary school. Third, the respondent finished secondary school. Fourth, the respondent finished college, a higher religious school or university. In our empirical specifications, we take not attending school as the reference value. We expect that with higher education, households might be more aware of the opportunities of digital tools (e.g., Cole and Fernando, 2012; Penard et al., 2012; Abdul-Rahaman and Abdulai, 2022). In addition, higher education also points to higher wealth. *Ethnic majority* captures whether the respondent belongs to the most widespread ethnic group in the region. This might also relate to social ties, e.g., if minorities have less access to community activities. Conversely, minorities might also be more organized to establish internal networks within a community. *Village settled* is a dummy indicating whether the respondent lives in a village at least 10 years. Living in a city for a longer time, makes it easier for households to establish social ties. *Fem. main farmer* equals one if the main farmer of the household is female and hence controls for gender differences in the ICT adoption. We expect that on average male respondents are more likely adopt ICTs, although such a gender gap might not hold for all countries (e.g., Milek et al., 2011).

Next, *(ln) age* is the natural logarithm of age of the respondent. For instance, Penard et al. (2012) show that ICT usage decreases with age.

Finally, *(ln) farm size* is the natural logarithm of the total farm size in hectare. By taking the natural logarithm, we reduce the impact of the extremes, e.g., the value for smallholders who possess larger farms gets closer to the mean. Following, Abdul-Rahaman and Abdulai (2022), we expect that smallholders with larger land possession show higher ICT adoption rates. The panel approach reduces the set of controls to time-varying factors. Namely these are: *mobility asset*, *female main farmer* and *farm size*.

The error terms  $\epsilon$  are clustered at the regional level in the cross-sectional specifications and at the household level in the panel estimation.<sup>20</sup>

Hypothesis 3 focuses on the economic relevance of ICT adoption, social ties and external agricultural advice. We limit the estimation to the cross-sectional approach because of the noisiness of the variable, e.g., given seasonal changes in productivity. The respective specifications mirror Eq. (3) with *normalized productivity* as the dependent variable. Since the dependent variable is continuous, we apply an OLS estimation. In addition, the specification also includes *internet*, *mobile phone access* and *external advice* as additional independent variables.

## 5. Results

Table 7 depicts the results of an logit-estimation to analyze the determinants of ICT adoption. Columns (1) to (4) use the full sample, while columns (5) to (8) limit the sample to the balanced panel.<sup>21</sup>

All specifications reveal a significant relationship between social ties and access to ICTs, including mobile phone and internet access. These findings are consistent across both the full sample and the balanced panel. There is heterogeneity in the relationship between ICTs and the different dimensions of social offline ties. While all four dimensions are significantly correlated with the use of mobile phones in the full sample, the relationships of agricultural knowledge and market information diminish in the panel estimation. When examining the various social offline ties and their relationship with the internet, the results indicate that being a focal point for agricultural knowledge and being a member of an organization are associated with a higher probability of internet access. These relationships hold in the cross-sectional and panel approach. In addition, having strong connections

<sup>20</sup> Regions in each country are the universe of the sampling in each value chain.

<sup>21</sup> See Table 12 in the Appendix for the marginal effects.

**Table 7**  
Determinants of ICT adoption.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cross-section				Balanced panel			
	Mobile phone		Internet		Mobile phone		Internet	
Social ties (1st PC)	0.237*** (0.035)		0.173*** (0.040)		0.174* (0.090)		0.320*** (0.093)	
Agr. knowledgeable		0.186** (0.075)		0.219*** (0.085)		−0.152 (0.187)		0.574*** (0.180)
Organization membership		0.416*** (0.077)		0.274** (0.125)		0.397* (0.236)		0.669** (0.274)
Connected with decision taker		0.326* (0.171)		0.374** (0.158)		0.876** (0.400)		0.402 (0.280)
Market information		0.263* (0.155)		−0.080 (0.089)		0.256 (0.181)		−0.285 (0.203)
Mobility asset	0.997*** (0.183)	0.992*** (0.175)	0.847*** (0.083)	0.854*** (0.082)	0.487 (0.379)	0.440 (0.395)	0.831*** (0.256)	0.871*** (0.262)
Max. primary school	0.606*** (0.081)	0.607*** (0.082)	0.527*** (0.138)	0.524*** (0.138)				
Max. secondary school	1.237*** (0.133)	1.235*** (0.129)	1.055*** (0.162)	1.048*** (0.162)				
Higher education	1.132*** (0.164)	1.141*** (0.153)	2.132*** (0.198)	2.121*** (0.197)				
Ethnic majority	−0.004 (0.112)	−0.011 (0.115)	−0.321*** (0.118)	−0.316*** (0.117)				
Fem. main farmer	−0.173*** (0.062)	−0.189*** (0.062)	−0.024 (0.118)	−0.029 (0.115)	0.268 (0.397)	0.370 (0.415)	−0.014 (0.552)	0.181 (0.576)
Village settled	0.123 (0.093)	0.124 (0.092)	−0.026 (0.096)	−0.025 (0.097)				
(ln) farm size	0.187*** (0.057)	0.184*** (0.057)	0.114 (0.072)	0.108 (0.072)	0.319** (0.138)	0.340** (0.141)	0.251** (0.109)	0.237** (0.113)
(ln) age	−0.301** (0.120)	−0.306*** (0.118)	−0.901*** (0.138)	−0.905*** (0.139)				
Observations	11,361	11,361	11,350	11,350	572	572	676	676
Survey dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummy	Yes	Yes	Yes	Yes	No	No	No	No
Household dummy	No	No	No	No	Yes	Yes	Yes	Yes
Pseudo R <sup>2</sup>	0.310	0.311	0.267	0.268	0.0454	0.0720	0.0663	0.0820
Log Pseudol.	−3,781	−3,775	−3,511	−3,507	−189.2	−184	−218.8	−215.1

Notes: Robust standard errors in parentheses (clustered at the regional-level in the first four columns and the household level in last four columns).

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

Estimated using a logit-estimator.

to local decision-makers is significant in the cross-section but not in the panel. Despite some heterogeneity in the relationship between ICTs and individual social offline ties, the results strongly confirm our main prediction summarized in hypothesis 1 that weak offline ties reduce the likelihood of participating in opportunities related to ICTs. Since the control variables are not in the focus of our theory and analysis, we do not discuss them in detail. However, patterns are widely in line with our expectations, e.g., education and wealth positively associate with ICT adoption rates, while younger respondents more likely adopt ICTs.

Next, we turn to the relationship of social ties and access to extension services as well as to the economic relevance of the analyzed information sources. Columns (1) to (4) of Table 8 include the results on the relationship between social ties and external advice.<sup>22</sup> The first two columns use the full sample, while columns (3) and (4) use the balanced panel. The last two columns report the results of an OLS-estimation to explain the normalized productivity of the smallholders.

The results back hypothesis 2 by revealing that smallholders with weak social offline ties are less likely to receive training or advice from

public or private extension services. The main principal component capturing social ties is significant at the one-percent level in the cross-sectional and panel approach. Moreover, all four dimensions of social ties are significant in both approaches. Overall, the empirical finding on testing hypotheses 1 and 2 strongly suggest that smallholders with weak social ties face a triple-faced information constraint of having weak social ties and less access to ICTs and extension services.

Columns (5) and (6) include the results on testing hypothesis 3. The empirical results show that social ties, extension services and ICT adoption positively correlate with productivity. However, and similar as before, there is some heterogeneity observable once social ties are split into its different dimensions. Focusing on the different domains of social ties reveal that only being a focal point for agricultural knowledge and market information positively correlate with productivity. Connection with decision takers does not relate to increased productivity. The latter indicates that having a strong position within the community does not result in better agricultural economic outcomes. Similarly, organization membership does not relate to increased productivity. However, the measure does include many form of organization which are not necessarily linked to agricultural activities, e.g., being a member of a religious group. The last chapter discusses the main results and derives respective policy conclusions.

<sup>22</sup> See Appendix Table 13 for the marginal effects.



**Table 8**  
Determinants of getting external advice and agricultural productivity.

VARIABLES	(1) Cross-section	(2)	(3) Balanced panel	(4)	(5) Cross-section	(6)
	External advice				Productivity	
Social ties (1st PC)	0.519*** (0.043)		0.581*** (0.079)		0.059*** (0.014)	
Agr. knowledgeable		0.537*** (0.081)		0.550*** (0.157)		0.116*** (0.028)
Organization membership		1.130*** (0.083)		1.199*** (0.199)		0.047 (0.041)
Connected with decision taker		0.314** (0.138)		0.782** (0.381)		−0.014 (0.041)
Market information		0.135* (0.070)		0.267* (0.162)		0.086** (0.034)
Mobility asset	0.121 (0.076)	0.124* (0.074)	−0.047 (0.219)	−0.057 (0.221)	0.090*** (0.033)	0.089*** (0.032)
Max. primary school	0.238*** (0.066)	0.215*** (0.069)			0.040* (0.024)	0.042* (0.024)
Max. secondary school	0.396*** (0.072)	0.360*** (0.070)			0.023 (0.035)	0.025 (0.036)
Higher education	0.461*** (0.132)	0.432*** (0.136)			0.056 (0.040)	0.061 (0.039)
Ethnic majority	0.266** (0.122)	0.252** (0.122)			−0.069** (0.034)	−0.067** (0.033)
Fem. main farmer	0.096 (0.082)	0.039 (0.087)	0.279 (0.324)	0.212 (0.323)	−0.078*** (0.028)	−0.074** (0.028)
Village settled	0.086 (0.075)	0.089 (0.074)			0.059 (0.038)	0.059 (0.038)
(ln) farm size	0.108*** (0.041)	0.085** (0.041)	0.342*** (0.119)	0.329*** (0.119)	−0.042* (0.022)	−0.041* (0.022)
(ln) age	0.011 (0.107)	−0.005 (0.108)			−0.068 (0.042)	−0.064 (0.043)
Mobile phone					0.140*** (0.031)	0.142*** (0.031)
Internet					0.093*** (0.031)	0.094*** (0.030)
External advice					0.080** (0.037)	0.080** (0.037)
Observations	11,838	11,838	988	988	9,348	9,348
R-squared					0.107	0.109
Survey dummy	Yes	Yes	Yes	Yes	Yes	Yes
Region dummy	Yes	Yes	No	No	Yes	Yes
Household dummy	No	No	Yes	Yes	No	No
Pseudo R <sup>2</sup>	0.240	0.250	0.171	0.187		
Log Pseudol.	−5,169	−5,101	−283.8	−278.5		

Notes: Robust standard errors in parentheses (clustered at the regional-level in columns 1, 2, 5 and 6 and at the household-level in columns 3 and 4).

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

Notes: Estimated using a logit-estimator in the first four columns and an OLS-estimator in the last two columns.

## 6. Conclusions and policy implications

This paper investigates whether (offline) social connections and use of digital technologies reinforce or complement each other, using the case of smallholder farmers in several African countries over two waves of surveys between 2016 and 2018. We find that socially less connected smallholders are also less likely connected to digital technologies (ICTs) in developing countries. Our conclusion is that, while the potential of ICTs for access to information and advice is significant, current usage patterns suggest that the winners are those farmers who already benefit from strong information channels via personal networks.

Our findings reveal that having stronger personal social ties increases the likelihood of using ICTs (defined as having a mobile phone and/or internet access). Based on qualitative information from accompanying focus group discussion, we conclude that the benefits of using ICTs are clearer, when having closer social ties — because of the options of staying in touch with the own social network. In

addition, we empirically reveal that smallholders with weak social ties are less likely targeted by external agricultural advice or training from extension services because they are harder to reach and less likely aware of such support schemes. As a result, households with strong social ties become information insiders through offline social ties, ICT access and being more likely reached by agricultural extension services. Conversely, smallholders with weak social ties remain information outsiders. We show empirically that these information sources positively relate with agricultural productivity, showing the economic relevance for smallholders of getting information insiders.

Our analysis also indicates that other aspects, such as wealth and age determine ICT use. In addition, a positive relationship between education and ICT use adds to the existing evidence about the importance of fostering education in rural areas of developing countries.

We conclude that, even though ICTs create opportunities to reach previously excluded individuals and spread valuable agricultural information more widely, the realization of these opportunities depends

on more people getting access to information. Currently, ICTs fail to reach information outsiders, who face a mutually reinforcing triangle of missing access to valuable information: weak social ties, less access to agricultural extension services and lower adoption of ICTs. This exclusion results in lower agricultural productivity and thus has significant disadvantages.

Our results have relevant implications for practitioners aiming for inclusive agricultural development, leaving no one behind. Governments and development programs must recognize the linkages between social ties, access to ICTs and agricultural training and strengthen their efforts to better target information outsiders. While digital technology still has an impressive potential to improve the diffusion of information to outsiders, it requires additional effort and specific targeting to be inclusive in reducing digital divides.

Future research should explore innovative strategies to promote the adoption of ICTs by information outsiders, such as community-based interventions that leverage existing social ties to facilitate access to digital technologies and extension services. Furthermore, research should investigate how digital technologies can be integrated with traditional extension services to improve the effectiveness of agricultural advice and training for smallholders. Notably, although the analyzed data contains panel data, we interpret the results as correlations rather than claiming for causality. Future longitudinal studies might help researchers to consider possible reverse causality. Finally, longitudinal might help researchers to assess the impact of ICT adoption on agricultural productivity over time and explore potential pathways through which these effects are realized.

## CRediT authorship contribution statement

**Linda Kleemann:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Finn Ole Semrau:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix

See [Tables 9–17](#).

**Table 9**  
Description of ICT adoption, social offline ties and agricultural extension services.

Variable	Survey questions, question type and relevant response options
Mobile phone (dummy)	“Which of the following assets, household appliances and means of transportation are in your possession?” [multi select] “Mobile phone” was selected
Internet access (dummy)	“Do you have a private internet access in your accommodation and/or using your phone?” [single select] “Yes” was selected and mobile phone access
External advice (dummy)	“How long ago was your last contact with any technical adviser or training course related to ....” [single select] Question asked for: 1. crops; 2. livestock; 3. home economics; 4. micro credit; 5. conservation; 6. processing or post harvest handling of focus crop or livestock [only in midline] and agribusiness/farm business including marketing [only in midline]
(Normalized) productivity	“A week ago”, “A month”, “Three months”, “Six months” or “A year” was selected Agricultural productivity of the smallholder farmers main value chain normalized within years, countries and value chains For crops: kg of harvest per hectare [calculated based on numerical questions about harvest and field sizes] For dairy: liters of milk per female cattle per day, weighted by wet and dry season [calculated based on numerical questions about daily volume milked per female cattle in wet and dry season, respectively]
Organization member (dummy)	1. “And/Or is anyone in the household a member of a local savings group or micro-credit project/scheme?” [single select]; 2. “Is anyone in the household a member of a local farmers’ organization or association, a cooperative, a common interest group, a committee, or any other local group that has to do with farming or marketing of farm produce?” [single select] 3. “And/Or is anyone in the household a member of a women, youth or religious group?” [single select] “Yes” was selected in at least one of three questions
Agr. knowledgeable (dummy)	“Were you approached for advice about farming in the last two weeks?” [single select] “Yes” was selected
Connected with decision taker (dummy)	“What is the household head’s relationship to the local government?” [single select] “Strong relation or household head him/herself politically active” was selected which is out of for options the closest option
Market information (dummy)	“How do you usually access market information?” [multi select] “Through local markets” was selected

**Table 10**  
Share of smallholders who are agricultural knowledgeable and/or organization members split by country and survey.

Survey	Baseline			Midline			Both surveys		
	Agr.	Org.	Freq.	Agr.	Org.	Freq.	Agr.	Org.	Freq.
Benin	47.1%	67.7%	876	38.4%	81.2%	536	43.8%	72.8%	1,412
Burkina Faso	33.2%	76.9%	476	24.3%	77.5%	612	28.2%	77.2%	1,088
Cameroon	61.6%	81.3%	482	68.9%	84.3%	489	65.3%	82.8%	971
Ethiopia	55.1%	89.3%	494	31.3%	95.4%	566	42.4%	92.5%	1,060
Ghana	46.4%	77.8%	528	64.0%	97.9%	583	55.6%	88.4%	1,111
India	88.1%	73.1%	494	59.3%	88.5%	590	72.4%	81.5%	1,084
Kenya	32.6%	74.5%	432	29.2%	65.8%	456	30.9%	70.0%	888
Malawi	49.3%	74.1%	525	32.9%	77.5%	520	41.1%	75.8%	1,045
Mozambique	51.3%	14.4%	583			NA	51.3%	14.4%	583
Nigeria	44.0%	31.0%	638	57.5%	72.0%	590	50.5%	50.7%	1,228
Togo	36.2%	66.9%	472	28.9%	68.8%	526	32.4%	67.9%	998
Zambia	45.7%	90.7%	506	45.4%	94.8%	482	45.5%	92.7%	988
All	49.2%	66.6%	6,506	43.8%	82.4%	5,950	46.6%	74.1%	12,456

Agr.= Agricultural knowledgeable; Org. = Organization member; NA = Not available.

**Table 11**

Share of smallholders who are strongly connected with decision takers and/or have local markets as a usual source for information split by country and survey.

Survey Country	Baseline			Midline			Both surveys		
	Con.	Mark.	Freq.	Con.	Mark.	Freq.	Con.	Mark.	Freq.
Benin	21.8%	61.4%	876	16.2%	56.7%	536	19.7%	59.6%	1,412
Burkina Faso	12.6%	50.0%	476	8.3%	49.2%	612	10.2%	49.5%	1,088
Cameroon	13.7%	61.4%	482	5.3%	57.3%	489	9.5%	59.3%	971
Ethiopia	22.9%	68.2%	494	15.2%	71.7%	566	18.8%	70.1%	1,060
Ghana	2.8%	49.4%	528	7.5%	66.4%	583	5.3%	58.3%	1111
India	21.3%	94.9%	494	2.7%	94.6%	590	11.2%	94.7%	1,084
Kenya	1.6%	87.0%	432	5.0%	63.2%	456	3.4%	74.8%	888
Malawi	4.4%	30.7%	525	3.8%	49.8%	520	4.1%	40.2%	1,045
Mozambique	10.1%	43.4%	583			NA	10.1%	43.4%	583
Nigeria	5.5%	67.4%	638	5.6%	73.7%	590	5.5%	70.4%	1,228
Togo	2.8%	68.4%	472	5.7%	62.7%	526	4.3%	65.4%	998
Zambia	4.7%	41.1%	506	1.2%	27.6%	482	3.0%	34.5%	988
All	10.9%	59.8%	6,506	7.1%	61.9%	5,950	9.1%	60.8%	12,456

Con. = Connected with decision taker; Mark. = Markets as usual source of information; NA = Not available.

**Table 12**

Determinants of ICT adoption (marginal effects).

VARIABLES	(1) Mobile	(2) Mobile	(3) ICT	(4) ICT	(5) Mobile	(6) Mobile	(7) ICT	(8) ICT
Social ties (1st PC)	0.0243*** (0.00348)		0.0162*** (0.00364)		0.0407* (0.0212)		0.0678*** (0.0189)	
Agr. knowledgeable		0.0189** (0.00756)		0.0206*** (0.00790)		−0.0119 (0.0164)		0.0955*** (0.0304)
Organization membership		0.0447*** (0.00854)		0.0246** (0.0108)		0.0326 (0.0286)		0.120*** (0.0440)
Connected with decision taker		0.0316** (0.0157)		0.0376** (0.0169)		0.0523 (0.0407)		0.0598 (0.0390)
Market information		0.0272* (0.0161)		−0.00751 (0.00842)		0.0198 (0.0178)		−0.0453 (0.0344)
Mobility asset	0.0971*** (0.0162)	0.0964*** (0.0155)	0.0875*** (0.00932)	0.0882*** (0.00931)	0.111 (0.0818)	0.0306 (0.0318)	0.174*** (0.0458)	0.133*** (0.0364)
Max. primary school	0.0700*** (0.00952)	0.0700*** (0.00946)	0.0389*** (0.00927)	0.0387*** (0.00929)				
EMax. secondary school	0.127*** (0.0130)	0.127*** (0.0125)	0.0913*** (0.0125)	0.0906*** (0.0125)				
Higher education	0.119*** (0.0152)	0.119*** (0.0141)	0.243*** (0.0238)	0.241*** (0.0236)				
Ethnic majority	−0.000443 (0.0115)	−0.00114 (0.0117)	−0.0309*** (0.0114)	−0.0303*** (0.0114)				
Fem. main farmer	−0.0180*** (0.00650)	−0.0197*** (0.00649)	−0.00225 (0.0110)	−0.00273 (0.0107)	0.0620 (0.0897)	0.0275 (0.0296)	−0.00292 (0.117)	0.0286 (0.0871)
Village settled	0.0129 (0.00986)	0.0129 (0.00978)	−0.00244 (0.00911)	−0.00235 (0.00919)				
(ln) farm size	0.0192*** (0.00578)	0.0188*** (0.00578)	0.0107 (0.00675)	0.0101 (0.00668)	0.0747** (0.0299)	0.0265 (0.0200)	0.0533** (0.0213)	0.0383** (0.0175)
(ln) age	−0.0308** (0.0122)	−0.0313*** (0.0120)	−0.0845*** (0.0127)	−0.0849*** (0.0129)				
Observations	11,361	11,361	11,350	11,350	572	572	676	676
Survey dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummy	Yes	Yes	Yes	Yes	No	No	No	No
Household dummy	No	No	No	No	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses (clustered at the regional-level in the first four columns and the household level in last four columns).

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

Estimated using a logit-estimator.



**Table 13**  
Determinants of getting external advice (marginal effects).

VARIABLES	(1) Ext. advice	(2) Ext. advice	(3) Ext. advice	(4) Ext. advice
Social ties (1st PC)	0.0732*** (0.00524)		0.126*** (0.0143)	
Agr. knowledgeable		0.0742*** (0.0108)		0.0931*** (0.0255)
Organization membership		0.182*** (0.0143)		0.219*** (0.0328)
Connected with decision taker		0.0417** (0.0173)		0.114** (0.0466)
Market information		0.0187* (0.00970)		0.0455* (0.0270)
Mobility asset	0.0170 (0.0107)	0.0172* (0.0102)	−0.0103 (0.0476)	−0.00959 (0.0378)
Max. primary school	0.0349*** (0.00963)	0.0308*** (0.00985)		
Max. secondary school	0.0566*** (0.00990)	0.0505*** (0.00964)		
Higher education	0.0651*** (0.0174)	0.0599*** (0.0176)		
Ethnic majority	0.0380** (0.0177)	0.0352** (0.0174)		
Fem. main farmer	0.0135 (0.0114)	0.00534 (0.0119)	0.0607 (0.0706)	0.0352 (0.0514)
Village settled	0.0123 (0.0108)	0.0125 (0.0105)		
(ln) farm size	0.0152*** (0.00587)	0.0117** (0.00561)	0.0744*** (0.0250)	0.0556*** (0.0179)
(ln) age	0.00155 (0.0151)	−0.000673 (0.0150)		
Observations	11,838	11,838	988	988
Survey dummy	Yes	Yes	Yes	Yes
Region dummy	Yes	Yes	No	No
Household dummy	No	No	Yes	Yes

Notes: Robust standard errors in parentheses (clustered at the regional-level in columns 1, 2 and at the household-level in columns 3 and 4).

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

Notes: Estimated using a logit-estimator.

**Table 14**  
Summary statistics of dependent and independent variables: baseline and midline.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Mobile phone	12,527	0.828	0.377	0	1
Internet access	11,648	0.147	0.354	0	1
External advice	12,527	0.747	0.435	0	1
Productivity	9,992	−0.00797	0.966	−6.885	5.782
Agr. knowledgeable	12,527	0.466	0.499	0	1
Organization member	12,527	0.669	0.471	0	1
Connected with decision taker	12,527	0.0911	0.288	0	1
Market information	12,527	0.608	0.488	0	1
Village settled	12,527	0.903	0.297	0	1
Fem. main farmer	12,527	0.238	0.426	0	1
(ln) farm size	12,527	0.924	1.085	−8.805	3.689
Mobility asset	12,527	0.387	0.487	0	1
(ln) age	12,527	3.777	0.286	2.708	4.595
Ethnic majority	12,527	0.648	0.478	0	1
Max. primary school	12,527	0.345	0.475	0	1
Max. secondary school	12,527	0.260	0.439	0	1
Higher education	12,527	0.0710	0.257	0	1

**Table 15**  
Summary statistics of dependent and independent variables: baseline.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Mobile phone	6,506	0.793	0.405	0	1
Internet	5,630	0.129	0.335	0	1
External advice	6,506	0.671	0.470	0	1
Productivity	4,837	−0.0199	0.977	−6.126	5.782
Agr. knowledgeable	6,506	0.492	0.500	0	1
Organization membership	6,506	0.666	0.472	0	1
Connected with decision taker	6,506	0.109	0.312	0	1
Market information	6,506	0.598	0.490	0	1
Mobility asset	6,506	0.359	0.480	0	1
Ethnic majority	6,506	0.691	0.462	0	1
Max. primary school	6,506	0.343	0.475	0	1
Max. secondary school	6,506	0.258	0.438	0	1
Higher education	6,506	0.0630	0.243	0	1
Fem. main farmer	6,506	0.229	0.420	0	1
Village settled	6,506	0.899	0.302	0	1
(ln) farm size	6,506	0.847	1.095	−7.601	3.689
(ln) age	6,506	3.771	0.288	2.708	4.554

**Table 16**  
Summary statistics of dependent and independent variables: midline.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Mobile phone	5,950	0.868	0.338	0	1
Internet	5,950	0.164	0.370	0	1
External advice	5,950	0.831	0.375	0	1
Productivity	5,108	−0.000943	0.957	−6.885	3.673
Agr. knowledgeable	5,950	0.438	0.496	0	1
Organization membership	5,950	0.824	0.381	0	1
Connected with decision taker	5,950	0.0709	0.257	0	1
Market information	5,950	0.619	0.486	0	1
Mobility asset	5,950	0.419	0.493	0	1
Max. primary school	5,950	0.347	0.476	0	1
Max. secondary school	5,950	0.263	0.440	0	1
Higher education	5,950	0.0798	0.271	0	1
Ethnic majority	5,950	0.600	0.490	0	1
Fem. main farmer	5,950	0.248	0.432	0	1
Village settled	5,950	0.907	0.291	0	1
(ln) farm size	5,950	1.012	1.065	−8.805	3.689
(ln) age	5,950	3.783	0.285	2.773	4.595

**Table 17**  
Correlation of dependent and independent variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	1.00															
(2)	0.20	1.00														
(3)	0.21	0.07	1.00													
(4)	0.05	0.06	0.03	1.00												
(5)	0.20	0.13	0.28	0.04	1.00											
(6)	0.07	0.12	0.13	0.05	0.72	1.00										
(7)	0.24	0.04	0.36	0.00	0.53	0.08	1.00									
(8)	0.06	0.02	0.04	0.00	0.51	0.10	0.04	1.00								
(9)	0.11	0.09	0.07	0.03	0.33	0.06	0.02	0.01	1.00							
(10)	0.24	0.20	0.05	0.05	0.09	0.05	0.04	0.04	0.09	1.00						
(11)	0.25	0.30	0.16	0.05	0.18	0.14	0.13	0.03	0.07	0.06	1.00					
(12)	−0.09	0.03	0.02	0.00	−0.03	−0.02	−0.03	−0.01	0.01	−0.20	0.06	1.00				
(13)	−0.14	−0.07	−0.07	−0.05	−0.12	−0.12	−0.02	−0.08	−0.03	−0.21	−0.14	0.05	1.00			
(14)	0.08	0.01	0.06	0.01	0.08	0.03	0.04	0.06	0.05	0.09	−0.04	−0.03	−0.09	1.00		
(15)	0.18	−0.04	0.09	0.00	0.08	0.01	0.17	0.06	−0.10	0.31	−0.02	−0.25	−0.25	0.09	1.00	
(16)	0.00	−0.04	0.04	−0.03	0.05	0.03	0.05	0.02	0.01	−0.04	−0.11	0.02	0.00	0.18	0.05	1.00

Notes: (1) mobile phone; (2) Internet (3) External advice; (4) Productivity; (5) Offline ties (1st PC); (6) Agricultural knowledge; (7) Organization member; (8) Connected to decision taker; (9) Market information; (10) Mobility asset; (11) Highest education; (12) Ethnic majority; (13) Female main farmer; (14) Village settled; (15) (ln) farm size; (16) (ln) age

## Data availability

The authors do not have permission to share data.

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