



**AgEcon** SEARCH  
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

*The World's Largest Open Access Agricultural & Applied Economics Digital Library*

**This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.**

**Help ensure our sustainability.**

Give to AgEcon Search

AgEcon Search  
<http://ageconsearch.umn.edu>  
[aesearch@umn.edu](mailto:aesearch@umn.edu)

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

# Mobile Internet Use and Climate Adaptation: Empirical Evidence from Vietnamese Coffee Farmers

Goytom Abraha Kahsay, Nerea Turreira Garcia, and Aske Skovmand Bosselmann

This paper investigates the association between mobile internet use (MIU) and climate adaptation among Vietnamese coffee farmers. We find that farmers with access to mobile internet are more likely to take adaptation measures and obtain higher coffee yields using both simple regression and instrumental variable models. Our data suggest that the adaptation results are driven by changes in water and crop management practices and mediated by farmers' access to weather forecasts and farm price information. Policy support for MIU may enhance farmers' climate resilience in developing countries.

*Key words:* information and communication technology, price information, smallholder farmers, weather information

## Introduction

Climate change affects smallholder farmers in many parts of the world, but those with access to information on climate and technologies are in a better position to take adaptation measures (Adger, Arnell, and Tompkins, 2005; Hassan and Nhemachena, 2008; Deressa et al., 2009; Di Falco, Veronesi, and Yesuf, 2011; Frank, Eakin, and López-Carr, 2011; Bryan et al., 2013). While much of the climate adaptation literature focuses on traditional information sources (e.g., as social networks and interactions with input dealers and extension services), there is an increasing emphasis on the role of information and communication technology (ICT)<sup>1</sup> on climate adaptation and mitigation (Aubert, Schroeder, and Grimaudo, 2012; Kroschel et al., 2013; Westermann et al., 2018). In contrast to traditional information sources and communication strategies, ICT offers a great leap forward in (i) improving access to a variety of information and knowledge on, for example, market prices, climate change, and climate smart-technologies; (ii) expanding outreach as well as increasing rapidity and flexibility of information delivery; and (iii) facilitating a platform for governments, nongovernmental organizations (NGOs), and private companies to share context relevant and timely information and advice to farmers through text messaging, audio and video, or agri-advisory smartphone applications (Pretty, Toulmin, and Williams, 2011; Westermann et al., 2018).

While ICT may contribute to the adaptation process in various ways, one of the most direct impacts of ICT is when it is in the hands of smallholder farmers themselves. Following expanded mobile phone availability and mobile internet coverage, farmers have unprecedented access to information, for example, on weather, finance mechanisms, best farming practices and improved yields, through

---

Goytom Abraha Kahsay (corresponding author, goytom@fro.ku.dk) is an assistant professor, Nerea Turreira Garcia is an assistant professor, and Aske Skovmand Bosselmann is an associate professor in the Department of Food and Resource Economics at the University of Copenhagen.

The authors acknowledge support from the Nordic Climate Facility (no. NCF-C7-047) and collaborating partners Real-Time Analytics, the International Center for Tropical Agriculture Asia hub, and Sustainable Management Services Vietnam.

This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License. 

Review coordinated by Christian A. Langpap.

<sup>1</sup> ICT is a broad term that “consists of hardware, software, networks, and media for collection, storage, processing, transmission, and presentation of information (voice, data, text, images)” (Mundial, 2003).

simple text-based messages or smartphone applications (Baumüller, 2017; Krell et al., 2021).<sup>2</sup> However, empirical studies on why and how mobile internet use (MIU) affects climate adaptation among smallholder farmers in developing countries remain scant. In this paper, we investigated the association between MIU and climate adaptation among Vietnamese smallholder coffee farmers.

The literature on the role of ICT on smallholder farmers' production and welfare in developing countries mostly focuses on ownership of mobile phone or SMS services and generally finds a positive effect on technology adoption and agricultural productivity (see Aker, 2011; Aker, Ghosh, and Burrell, 2016, for surveys on ICT and agriculture).<sup>3</sup> A small number of recent empirical studies investigate the role of internet access on smallholder farmers in developing countries. Internet is found to affect prices (Goyal, 2010), use and efficiency of fertilizer applications (Kaila and Tarp, 2019; Yuan, Tang, and Shi, 2021), technical efficiency (Zhu et al., 2021), and agricultural output (Chavula, 2014; Kaila and Tarp, 2019), rural cropland abandonment (Deng et al., 2019), market participation (Fan and Salas Garcia, 2018), and rural income (Ma et al., 2020). Empirical studies on the impact of MIU on smallholder farmers' climate adaptation practices in developing countries, however, appear to be missing.

The main objective of this paper is to investigate the association between MIU and climate change adaptation. Additionally, we analyze the link between adaptation and coffee yield. We use a unique cross-sectional dataset collected in Spring 2019 from 400 Vietnamese robusta coffee farmers, that includes details of climate change perceptions and exposure, adaptation practices, and ICT use. We first investigate the association between MIU and climate adaptation using simple ordinary least squares (OLS) and probit models. The results suggest a positive correlation between the two. However, identifying causal relationship between MIU and adaptation is challenging as MIU is likely to be affected by unobserved farmer characteristics, (e.g., innate preference or openness for mobile internet). We therefore employ an instrumental variable (IV) approach, in which farmer-level MIU is instrumented by commune-level MIU (CMIU, the share of people in the commune who use mobile internet) to circumvent omitted variable bias. Theories of technology diffusion, peer effects, and social learning (e.g., Foster and Rosenzweig, 2010) suggest that commune-level MIU is a relevant instrument and thus explains household-level MIU in the first-stage regression. All communes in our data have easy access to mobile phone and internet technologies. Moreover, CMIU is unlikely to correlate with farmer-level unobserved characteristics. As a result, we argue that CMIU could be assumed to be exogenous in our context. Finally, for a valid causal inference, our IV should not affect farmer-level climate adaptation directly or through other channels. To mitigate such concerns, we control for proxies of wealth, risk and trust preferences, and other sources of information and advice related to coffee production and climate adaptation in addition to key sociodemographic characteristics. However, care should be taken when interpreting our IV results since we cannot completely rule out potential household and commune-level unobservable factors that may drive both MIU and climate adaptation.

The IV regression results confirm the OLS findings that MIU is associated with an increase in the likelihood of coffee farmers taking adaptation measures. These results remain robust irrespective of how we construct the adaptation variable: (i) a binary indicator of whether the farmers take any adaptation measure; (ii) a binary indicator of whether farmers implemented at least one of the adaptation measures listed in the questionnaire; and (iii) number of adaptation measure implemented by farmers. We also categorize the list of adaptation measures into pest management, changes in

<sup>2</sup> Open networks, such as Wefarm, and coffee and cocoa buying companies—such as Olam, Nestlé Vietnam, and Neumann Kaffee Group—increasingly promote smartphone applications emphasizing finance mechanisms, best farming practices, and improved yields.

<sup>3</sup> Some studies find that farmers' use of ICT increases technology adoption and agricultural productivity (Lio and Liu, 2006), land and labor productivity (Ogutu, Okello, and Otieno, 2014), market efficiency (Jensen, 2007), market participation (Muto and Yamano, 2009; Fan and Salas Garcia, 2018), and household welfare (Sekabira and Qaim, 2017) and decreases price dispersion (Jensen, 2007). However, other studies find no effect of ICT on market participation (Fafchamps and Minten, 2012), prices (Fafchamps and Minten, 2012; Tadesse and Bahiigwa, 2015), adaptation measures (Asfaw et al., 2019), or production practices and technology adoption (Fafchamps and Minten, 2012). Furthermore, Aker and Fafchamps (2015) do not find any effect of ICT on producer prices or market participation, although it decreases price dispersion.

planting and harvesting time, water management, shade tree management, and crop management. The OLS and IV results suggest that the association between MIU and climate adaptation is driven by changes in water and crop management practices. An additional analysis using propensity score matching confirms these results. To investigate the association between farmers' climate adaptation and coffee yield, we estimate a Cobb–Douglas production function and three-stage least squares (3SLS) models and find that adaptation is associated with higher coffee yield. Finally, looking into potential mechanisms through which MIU influences adaptation, we find that farmers with mobile internet access are more likely to get timely weather and price information, which are crucial to farmers' climate adaptation. Price information affects farmers' decision on, for example, what farm input and when to buy as well as which crop to plant or mix while weather information affects the timing of fertilizer and pesticide applications, irrigation use, harvest planning, and other on-farm activities such as pruning and planting shade trees. Changes in fertilizers and pesticide applications may involve an increase/decrease in their quantities or efficiency in their use. For example, using panel data, Kaila and Tarp (2019) find that commune-level internet access increased efficient use of fertilizers among Vietnamese farmers.

### **Coffee Production and Climate Change in Vietnam**

Vietnam is the world's second largest coffee producer, and robusta coffee brings billions of dollars to the Vietnamese economy yearly (Ho et al., 2018). Vietnam's coffee production is mainly concentrated in the Central Highlands and plays an important role in rural livelihoods. For example, in Dak Lak Province, coffee accounts for 96% of local income (Marsh, 2007). Coffee production is highly intensified; smallholder farms are usually 1–2 ha and produce 2.2 t/ha of dry green beans on average. Coffee is often planted together with black pepper at a tree density of 850–1,200 coffee trees/ha together with 1,000–2,500 black pepper plants (Tiemann et al., 2018).

The Central Highlands enjoy a tropical monsoon climate characterized by distinct rainy and dry seasons. Temperatures oscillate between 18°C and 25°C all year, and annual precipitation ranges from 1,750 mm to 3,150 mm, depending on altitude and geography. By the year 2100, Vietnam is expected to experience a 1–3.4°C rise in temperature and extreme rainfall events (World Bank and Asian Development Bank, 2020); an exponential increase in the number of hot days in a year and long duration of droughts (Haggard and Schepp, 2012); and unpredictable rainy seasons (Pham-Thanh et al., 2020). These predictions are expected to substantially affect coffee production by reducing the area suitable for coffee production, intensifying soil erosion, reducing soil fertility, and increasing pests and diseases (Bunn et al., 2015). From 2008 to 2017, 4 drought years were observed in the majority of coffee districts across the Central Highlands, with the 2015 drought being most severe, negatively affecting yields and income margins and lowering water reservoirs in the following season by up to 50% (Byrareddy et al., 2021). Unless farmers adapt their management practices to changing weather and climate, their livelihoods are at great risk.

Current adaptation practices among coffee farmers in Vietnam mainly include water management techniques (e.g., using sprinklers, irrigating rotationally, building water reservoirs), crop diversification, and intercropping with pepper and/or avocados (Thi and Chaovanapoonphol, 2014; Nguyen and Nguyen, 2019; Byrareddy et al., 2021). Nguyen and Drakou (2021) find that adaptation practices are influenced by coffee farmers' perception of climate change and social pressure as well as their past behavior, while Byrareddy et al. (2021) find mulching as an adaptation strategy to be influenced positively by farm ownership compared with tenancy. With faster penetration of mobile phone technology (World Bank, 2016) and higher numbers of internet users (about 70% of the population in 2018) (World Bank, 2019), MIU has the potential to enhance Vietnamese smallholder coffee farmers' adaptation capacity and resilience. Recent studies on the use of ICT among Vietnamese smallholders suggest that most surveyed farmers deemed mobile phones to be an effective tool for accessing agricultural information; younger, more educated, and relatively richer farmers are more likely to effectively use them (Hoang, 2020a,b, 2021). Moreover, there is an

increasing focus by the Ministry of Agriculture and Rural Development to promote the use of ICT for agricultural information distribution and extension services (Ministry of Agriculture and Rural Development, 2018).

### Data

In Spring 2019, we conducted a survey of 400 randomly selected Vietnamese smallholder coffee farmers from two provinces and four districts (Cu M'gar and Krong Buk in Dak Lak and Lam Ha and Bao Lam in Lam Dong). The survey data include sociodemographic characteristics, economic indicators, coffee farming, agronomic practices, use of ICT, access to information (e.g., weather, price, farming practices), exposure to extreme weather events, adaptation practices, and personal attitudes toward trust and risks.

We asked the sampled farmers about their access to different ICTs, including whether they owned a mobile phone, the type of the phone (smartphone or basic phone), and whether they had access to mobile internet, television (TV), radio, personal computers (PC), and tablets. They were asked specifically to indicate the purpose of their internet use: weather information, prices, social media, internet-based calling and messaging apps, and news. Farmers were also asked to indicate whether they had access to other sources of information and advice on coffee production and climate adaptation, including from farmer organizations (farmer associations, unions, and co-operatives and women's organizations); coffee companies (buyers, dryers, exporters, certifiers, and input suppliers); friends, relatives, and neighbors; and extension agents and NGOs.

The sampled farmers were asked whether they had experienced climate shocks over the past 5 and 10 years and number of these shocks over the past 5 years. In addition, respondents were asked to indicate the changes in climate they perceived from a list of 23 items, which included, among others, higher and lower temperatures, more and less rain, and longer and shorter dry and rainy seasons. We also asked respondents to indicate whether they had faced any of 12 listed consequences of climate change, which included, among others, changes in yield, pest occurrences and severity, erosion, and coffee flowering. Finally, they were asked whether they too had taken any adaptation measures and specifically to indicate which measures they had implemented from a list of 16 items, which included changes in spraying and water management practices, changing planting date, intercropping, and use of improved varieties.

We collected sociodemographic and economic variables (e.g., age, gender, years of schooling, and income) and agronomic variables (e.g., coffee plot sizes, coffee yield per ha, and labor use in person days, quantity of fertilizer, and spraying cost); and proxies for preferences such as risk taking and trust. Risk taking was measured on an 11-point Likert-type scale following Dohmen et al. (2011), in which participants were asked to indicate their risk-taking preferences on a scale from 0 (risk averse) to 10 (very prepared to take risks). Generalized trust was measured on a 5-point Likert-type scale following Kosse et al. (2020), in which participants were asked to indicate how much they agreed with three statements on a scale from 1 (totally disagree) to 5 (totally agree): (i) "One can trust other people," (ii) "Other people have good intentions toward me," and (iii) "One can rely on other people, even if one does not know them well." Generalized trust was then measured as an average of responses for the three statements. Detailed descriptive results are presented in the results section.

### Econometric Method and Identification Strategy

To explain variations in adaptation among smallholder coffee farmers by MIU while controlling for other farmer-level characteristics, we first specify simple probit and OLS models in which we regress adaptation on MIU and other controls:

$$(1) \quad \text{Adaptation}_i = \beta_0 + \beta_1 \text{MIU}_i + \beta_2 \mathbf{X}_i + \varepsilon_i,$$

where  $Adaptation_i$  is a binary indicator that equals 1 if the farmer takes any adaptation measure and 0 otherwise and  $MIU_i$  is a binary indicator that equals 1 if the farmer has mobile internet access and 0 otherwise. Our main interest is  $\beta_1$  which captures the association between MIU and adaptation.  $X_i$  is a vector of sociodemographic and economic control variables that includes age, gender, household size, education, income, total land holding, TV and radio ownership;  $\varepsilon_i$  is the error term. We also include an indicator variable on whether farmers receive information and advice on coffee production and climate adaptation from other sources (e.g., friends, relatives and neighbors) as well as whether farmers have experienced climate shocks. We control for farmers' risk preferences and trust, which have been found to affect climate adaptation of farmers. Previous studies show that risk preferences are important determinants of farm management decisions in general (Chavas, Chambers, and Pope, 2010) and climate adaptation in particular (Jianjun et al., 2015). The literature on the link between social capital (often proxied by trust) and climate adaptation also finds both negative and positive correlations (e.g., Wossen, Berger, and Di Falco, 2015; Paul et al., 2016; Wuepper, Yesigat Ayenew, and Sauer, 2018; Cologna and Siegrist, 2020). We hypothesize that farmers with a higher trust are more likely to adopt new adaptation practices. Collinearity does not appear to be a problem in our data, as can be seen from the correlation matrix in Table S1 in the online supplement (see [www.jareonline.org](http://www.jareonline.org)).

With cross-sectional data, identifying the causal effect of internet access on adaptation is difficult since MIU is most likely affected by unobserved farmer-level characteristics (e.g., innate preference or openness for new technologies in general and mobile internet in particular). This makes MIU endogenous and thus prone to omitted variable bias. To circumvent omitted variable bias, we estimate the following instrumental variable (IV) approach for the OLS model, in which we instrument MIU by sample commune-level MIU ( $CMIU$ ), which is the share of sampled farmers in each commune who use mobile internet. We believe that this variable is a good proxy for the population  $CMIU$  given that our sampling is random and proportional to each member of the commune's population:

$$(2) \quad MIU_i = \rho_0 + \rho_1 CMIU_i + \beta_2 X_i + \varepsilon_i,$$

$$(3) \quad Adaptation_i = \beta_0 + \beta_1 MIU_i^* + \beta_2 X_i + \varepsilon_i,$$

where  $CMIU_i$  is commune-level MIU and  $MIU_i^*$  is the predicted farmer-level MIU.  $X_i$  refers to a vector of sociodemographic and economic control variables, as in equation (1), and  $\varepsilon_i$  is the error term.

For a valid causal inference, our IV must be relevant, exogenous, and fulfill the exclusion restriction criteria. We argue that  $CMIU$  is a relevant instrument as it shows the diffusion of mobile internet use among farmers and is expected to explain household-level MIU in line with theories of technology diffusion, peer effects, and social learning (e.g., Foster and Rosenzweig, 2010). Given that there is no difference among communes in our sample in terms of mobile phone and internet technology availability and farmer-level unobserved characteristics are unlikely to correlate with  $CMIU$ , we argue that  $CMIU$  could be assumed to be exogenous. Finally, we assume that  $CMIU$  does not affect farmer-level adaptation directly or through other channels. While this assumption cannot be directly tested using econometric techniques, it can be argued based on theoretical or local contextual factors. We argue that the fact that other people in the commune use mobile internet is not likely to directly affect farmers' climate adaptation. There could, however, be an indirect effect: Noninternet users might get information or advice about weather, prices, and new technologies and farm management practices, which are important for climate adaptation, from internet users in the commune, who can be neighbors, friends and relatives, farmer organizations, extension workers, coffee companies (e.g., suppliers, exporters, certifiers), or NGOs. This can be ruled out in our context for two reasons. First, implementing concrete adaptation measures require frequent, timely, flexible, and detailed access to information, which is more likely to happen when a farmer can directly access the information (Kaila and Tarp, 2019). Second and more important, we have data on these sources of information and advice and control for them in our regressions.

Previous studies have used aggregated variables at the village or district level as an IV for individual farmer decisions to examine technology adoption in general (Mathenge, Smale, and Olwande, 2014; Smale and Mason, 2014; Arslan, Belotti, and Lipper, 2017) and internet use in particular (Hübler and Hartje, 2016; Hartje and Hübler, 2017; Deng et al., 2019; Zhu et al., 2021). However, they have also been criticized. For example, Betz, Cook, and Hollenbach (2018) argue that there are two main challenges that limit the use of spatial IVs (constructed by using the values of neighboring units) to establish causal associations. First, they argue that “spatial instruments require supporting the presence of one type of spatial relationship while concurrently denying other spatial relationships in the form of spillovers in predictors and interdependence in the outcomes” (Betz, Cook, and Hollenbach, 2018, p. 474), and these assumptions may not be fulfilled. In our context, the exclusion restriction assumes that there is no direct spillover effect (CMIU  $\rightarrow$  household-level adaptation) and indirect effects through interdependence of outcomes (CMIU  $\rightarrow$  commune-level adaptation  $\rightarrow$  household-level adaptation), as argued above. Second, Betz, Cook, and Hollenbach (2018, p. 474) also argue that “spatial instruments produce simultaneity in the first stage and therefore are not exogenous—put simply, spatial instruments imply a first stage where left-hand side outcomes are included as right-hand side predictors.” In our context, this implies that CMIU affects household-level MIU while at the same time CMIU is in part determined by household-level MIU.

Despite these identification challenges, Sundquist (2021) argues that spatial instruments can still provide valid causal inference if both commune- and household-level MIU are determined by an unobserved variable, which could have been a valid instrument had it been observed. CMIU is then used as a proxy for the unobservable variable, after controlling for any observable confounders. In our context, such an unobservable factor that may explain cross-commune variation in MIU could, for example, be the local norm of openness to mobile internet, which may evolve as a result of historical and cultural factors. However, if the local norm of openness to mobile internet is correlated with the local norm of openness to adaptation strategies, the exclusion restriction is less likely to hold. Sundquist (2021) further argues that while spatial instruments limit the ability to use commune-level fixed effects (because of perfect collinearity with the unobservable variable and CMIU), researchers should use as many groups as possible to narrow the scope of threats to inference and demonstrate that the instrument is sufficiently strong by reporting the first-stage  $F$ -statistic. We have 18 communes in our data and the reported  $F$ -statistic is much higher than 10, the threshold partial  $F$ -statistic recommended by Stock, Wright, and Yogo (2002).

As an additional analysis, we confirmed the results we got from the simple models and IV regressions by using propensity score matching. By increasing comparability between internet users and nonusers based on observable characteristics, the decision to use mobile internet is assumed to be almost random for coffee farmers, who have similar values of the observable characteristics.

Finally, we used the following log-linearized Cobb–Douglas production function to investigate the association between climate adaptation and coffee yield:

$$(4) \quad \ln Yield_i = \beta_0 + \beta_1 Adaptation_i + \beta_2 \ln Y_i + \varepsilon_i,$$

where  $\ln Yield_i$  is the natural logarithm of coffee yield per ha in 2018,  $\ln Y_i$  is a vector of natural logarithm of inputs, which include labor (in person days), quantity of fertilizer, and spraying cost (in USD); and  $\varepsilon_i$  is the error term. Given that many farmers do not use fertilizers and sprays, the natural logarithm transformation substantially reduces the number of observations. We use two approaches to address this problem. First, we follow Lin and Green (2016) and reestimate our model by replacing the missing values with the mean of the corresponding variables and including dummy variables that indicate these replacements. Second, we follow Bellemare (2018) and use inverse hyperbolic sine (IHS) transformation of these variables. The IHS transformation retains observations with negative or 0 values through log-like transformation,  $\ln(Y + \sqrt{Y^2 + 1})$ . To circumvent potential endogeneity problems related to adaptation, we estimated a 3SLS model in which (i) yield is explained by

adaptation, (ii) adaptation is instrumented by MIU, and (iii) MIU is instrumented by CMIU as follows:

$$(5) \quad MIU = \rho_0 + \rho_1 CMIU_i + \beta_2 X_i + \epsilon_i,$$

$$(6) \quad Adaptation_i = \beta_0 + \beta_1 MIU_i^* + \beta_2 X_i + \epsilon_i,$$

$$(7) \quad \ln Yield_i = \beta_0 + \beta_1 Adaptation_i^* + \beta_2 \ln Y_i + \epsilon_i,$$

where  $X_i$  is a vector of sociodemographic and economic control variables and  $\ln Y_i$  is a vector of natural logarithm of agricultural inputs. Our 3SLS model assumes that there are no direct or indirect (other than adaptation) channels through which MIU affects yield.

## Results

### Descriptive Results

#### Climate Shock and Adaptation

As can be seen from Table 1, about 93% and 37% of farmers report that they have faced climate shocks over the past 10 and 5 years, respectively. The most common changes in climate that farmers perceived are related to changes in the amount and duration of rainfall, higher temperature, and longer and warmer dry seasons (48.4%) (Table S2). As a consequence of these changes, farmers report lower yields (29.2%), fall of cherries (15.5%), reduced flowering (12%), and more pests (10.2%) (Table S3). When farmers were asked whether they implemented measures in their farm management as a result of changes in climate, about 58% of them reported implementing adaptation measures (Table 1).<sup>4</sup> Of those who took adaptation measures, the most common measures include irrigation (65%), crop mix (32%), spraying (20%), and use of improved varieties (13%). In the overall sample, also considering nonadapters, the corresponding figures for irrigation, crop mix, spraying and improve varieties are about 38%, 18%, 12% and 8%, respectively (Table S4).

#### Source of Information and Advice on Coffee Production and Climate Adaptation

The coffee farmers in our sample report that they get information and advice about coffee production and adaptation measures from different sources, including farmer organizations, coffee companies, extension agents, NGOs, and friends, relatives, and neighbors. Table 1 show that the most common sources of information and advice are friends, relatives, and neighbors (62%), followed by coffee companies (45%). Only 6.5% of farmers report extension agents as a source of information and advice.

#### Information and Communication Technologies (ICTs)

Farmers report that they have access to different ICTs, including TV, radio, mobile phones, PCs, and tablets (Table 1): 89% of the coffee farmers report having access to TV, followed by mobile phones (81%). The majority of mobile phone owners have smartphones (79.6%), or 65% of the total sample. Almost half of the sampled farmers have mobile internet access. Of those who use mobile internet, about 62% said they use internet daily and 70% said internet is not expensive. About 31% and 41% of the sampled farmers use internet to access information on weather forecasts and farm prices/coffee market, respectively (Table S4).

Table S6 shows the distribution of the main covariates by MIU, suggesting that mobile internet users are, on average, younger and more educated and have higher income and household size.

<sup>4</sup> The question on measures farmers took in response to changes in climate was asked immediately after farmers responded to the question on perceived changes in climate over the past 5 years, so the adaptation practices may reflect any measures undertaken in the past 5 years.

**Table 1. Descriptive Statistics**

	<i>N</i>	Mean	Std. Dev.	Min.	Max.
Adaptation					
Implemented adaptation measure	400	0.575	0.495	0	1
Implemented at least one of the listed adaptation measures	400	0.542	0.499	0	1
No. of adaptation measures implemented	400	0.902	0.985	0	4
ICT					
Smartphone	400	0.645	0.479	0	1
Feature phone	400	0.575	0.495	0	1
TV	400	0.890	0.313	0	1
Radio	400	0.048	0.213	0	1
PC	400	0.075	0.264	0	1
Tablet	400	0.010	0.100	0	1
Mobile internet use (MIU)	400	0.485	0.500	0	
Commune-level MIU (CMIU)	399	0.484	0.132	0.211	0.68
MIU purpose					
Weather	400	0.313	0.464	0	1
Agri-advisory app	398	0.048	0.213	0	1
Farm input and output prices	400	0.407	0.492	0	1
Source of information/advice on coffee production and climate adaptation					
Friends, neighbors, and relatives	400	0.620	0.486	0	1
Extension agent	400	0.065	0.247	0	1
Farmer organizations	400	0.210	0.408	0	1
Coffee companies	400	0.453	0.498	0	1
Non-governmental organizations	400	0.005	0.071	0	1
Sociodemographic characteristics					
Income (USD)	400	223.025	182.947	18	1,500
Land holding	400	1.788	1.444	.2	10
Household size	400	3.828	1.573	1	10
Female	398	0.083	0.276	0	1
Age	398	49.389	11.444	20	78
Years of schooling	396	7.417	5.145	0	61
Risk taking	400	6.242	2.388	1	10
Trust	400	2.779	0.656	1	4.333
Climate shock	400	0.367	0.483	0	1
Coffee production					
Yield/ha in 2018	388	3,074.651	1,325.083	0	8,000
Fertilizer (quantity)	400	748.987	1,234.976	0	10,000
Labor (person-days)	400	14.838	26.470	0	250
Spraying cost (USD)	388	77.400	110.997	0	869.565

*Notes:* Risk taking refers to a person's willingness to take risks generally, measured on 11-point Likert-type scale from 0 ("risk-averse") to 10 ("very prepared to take risks").

**Table 2. Mobile Internet Use (MIU) and Adaptation**

Variables	Implemented Adaptation Measure				Implemented at Least One of the Listed Adaptation Measures		Number of Adaptation Measures Implemented	
	OLS 1	Probit 2	Matching 3	IV 4	OLS 5	IV 6	OLS 7	IV 8
MIU	0.146*** (0.050)	0.134*** (0.048)	0.181*** (0.049)	0.385* (0.214)	0.119** (0.051)	0.420* (0.216)	0.331*** (0.096)	1.412*** (0.457)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.467* (0.248)	−2.855*** (0.740)	0.485*** (0.034)	−0.393 (0.253)	−0.473* (0.248)	−0.382 (0.257)	−1.313*** (0.497)	−1.039* (0.544)
$R^2$	0.112		0.034	0.062	0.111	0.032	0.155	0.156
Pseudo- $R^2$		0.095						
No. of obs.	396	396	396	395	396	395	396	395

*Notes:* Values in parentheses are robust standard errors. Single, double, and triple asterisks (\*, \*\*, \*\*\*) indicate significance at the 10%, 5%, and 1% level, respectively. Coefficients under the probit model are marginal effects. Control variables include income, household size, gender (1 if female, 0 if male), age, years of schooling, access to radio (1 if yes, 0 otherwise), access to TV (1 if yes, 0 otherwise), experience of climate shocks over the past 5 years (1 if yes, 0 otherwise), risk taking, generalized trust, and other sources of information and advice (1 if yes, 0 otherwise).

However, there is no significance difference between mobile internet users and nonusers in terms of total land holding, gender, and risk-taking and trust preferences. The share of farmers who implemented adaptation measures is significantly higher among mobile internet users. Similarly, farmers who use mobile internet, on average, implemented significantly more adaptation measures than nonusers. Though mobile internet users have significantly higher access to smartphones than nonusers, there is no significant difference between the two groups in terms of access to TV. Access to information and advice from friends, relatives, and neighbors and extension agents appears to be significantly higher among mobile internet users. Finally, mobile internet users, on average, use more fertilizers and labor and obtain higher coffee yields, albeit the latter difference is statistically insignificant.

### Regression Results

Table 2 presents the main estimation results on the association between MIU and adaptation across alternative model specifications and construction of the adaptation variable. Columns 1–4 present results from the OLS, probit, matching, and IV models, respectively, for a binary indicator on whether farmers took any adaptation measure. Columns 5–6 and 7–8 present OLS and IV results for binary indicators on whether farmers implemented a listed adaptation measure and number of implemented measures, respectively. Full estimation results are reported in Appendix Table A1.

The results indicate that farmers who use mobile internet are 14.6 percentage points (OLS model) more likely to implement adaptation measures. Considering the mean of climate adaptation (0.574), the estimated coefficient is economically meaningful. The magnitude of the estimated coefficients for the probit (13.4 percentage points) and matching (18.1 percentage points) models are comparable to the OLS estimate, while the magnitude is much higher in the IV model (38.5 percentage points). Similarly, mobile internet users are 12 (OLS model) to 42 (IV model) percentage points more likely to implement at least one of the adaptation measures listed in Table S4. Finally, farmers' use of mobile internet is associated with the implementation of 0.33 (OLS model) to 1.4 (IV model) more adaptation measures. The larger coefficients in the IV models, which are not uncommon in these kinds of analyses, may reflect the fact that our IV approach addresses potential measurement errors or reverse

**Table 3. Mobile Internet Use (MIU) and Adaptation, First Stage Results ( $N = 395$ )**

Mobile Internet Use	
Commune-level MIU (CMIU)	0.938*** (0.192)
Controls	Yes
Constant	-0.502** (0.248)
F(1,383)	23.830***
$R^2$	0.155

*Notes:* Values in parentheses are robust standard errors. Single, double, and triple asterisks (\*, \*\*, \*\*\*) indicate significance at the 10%, 5%, and 1% level, respectively. Control variables include income, household size, gender (1 if female, 0 if male), age, years of schooling, access to radio (1 if yes, 0 otherwise), access to TV (1 if yes, 0 otherwise), experience of climate shocks over the past 5 years (1 if yes, 0 otherwise), risk taking, generalized trust, and other sources of information and advice (1 if yes, 0 otherwise).

positive effects of adaptation on MIU, in which case OLS would underestimate the true effect. Looking at the estimated coefficients of the control variables reported in the appendix, years of schooling, risk taking and trust are positively and significantly associated with climate adaptation. The first-stage results are reported in Table 3 (see Appendix Table A2 for full estimation results) and confirms the positive and significant association between commune-level internet access and individual farmer's mobile use: A 10% increase in the share of commune-level mobile internet users is associated with a 9-percentage-point increase in farmer-level mobile internet use. The partial  $F$ -statistic in column 3 is much greater than the threshold partial  $F$ -statistic recommended by Stock, Wright, and Yogo (2002), which is 10.

Based on the individual adaptation practices of coffee farmers, we reestimate our models by also categorizing these practices in five adaptation measures (Table S4): pest management, changes in crop calendar, water management, shade tree management, and crop management. Both the OLS and IV results suggest that the association between MIU and climate adaptation is driven by changes in water and crop management practices (Table S7).

Table 4 presents the main estimation results for the association between adaptation and coffee yield. Columns 1 and 2 present estimated results from a log-linearized Cobb–Douglas production function without and with control variables, respectively.<sup>5</sup> Column 3 presents estimated results with control variables, replacing missing values with the mean of the corresponding variables and including indicator dummies for these replacements. Column 4 presents the third-stage results of our 3SLS model, while columns 5 and 6 present the second- and first-stage results, respectively. Table S8 reports full estimation results.<sup>6</sup>

These results suggest that climate adaptation is significantly associated with higher coffee yield. That is, implementing an adaptation measure is associated with a 15-percentage-point increase in coffee yield (column 1). Reestimation of the yield model with the five adaptation categories suggest that water, crop and pest management practices are significantly correlated with coffee yield (Table S10).

<sup>5</sup> The substantial reduction in the number of observations in column 2 of Table 4 is due to many farmers who do not use fertilizers and pesticides; thus, logarithmic transformation implies that these are dropped out of the estimation.

<sup>6</sup> Results with inverse hyperbolic sine transformation of variables are reported in Table S9 of the online supplement.

**Table 4. Adaptation and Coffee Yield**

Variables	OLS				3SLS	
	Yield/Ha 1	Yield/Ha 2	Yield/Ha 3	Yield/Ha 4	Adaptation 5	Mobile Internet Use 6
Adaptation	0.278*** (0.097)	0.144* (0.082)	0.277*** (0.093)	1.041*** (0.299)		
Mobile internet use (MIU)					0.451*** (0.165)	
Commune-level MIU (CMIU)						0.964*** (0.201)
Controls	No	Yes	Yes	Yes	Yes	Yes
Constant	7.716*** (0.092)	6.605*** (0.389)	6.748*** (0.332)	6.449*** (0.574)	−0.636** (0.268)	−0.405 (0.277)
$R^2$	0.027	0.171	0.046	−0.154	0.012	0.165
No. of obs.	375	112	375	370	370	370

*Notes:* Values in parentheses are robust standard errors. Single, double, and triple asterisks (\*, \*\*, \*\*\*) indicate significance at the 10%, 5%, and 1% level, respectively. Control variables for models 2 and 3 include labor, fertilizer quantity and spraying cost. Control variables for models 4 and 5 include income, household size, gender (1 if female, 0 if male), age, years of schooling, access to radio (1 if yes, 0 otherwise), access to TV (1 if yes, 0 otherwise), experience of climate shocks over the past 5 years (1 if yes, 0 otherwise), risk taking, generalized trust, and other sources of information and advice (1 if yes, 0 otherwise).

## Discussion

Our findings of a positive association between mobile internet use and climate change adaptation practices follow other recent empirical studies on the positive role of internet access among agricultural communities. In an early study of village internet kiosks providing information on prices, weather, and agricultural practices, Goyal (2010) found that internet access led to higher prices and net profits among small-scale soy producers in India. Using a large panel dataset from Vietnam, Kaila and Tarp (2019) found that individual households' internet access led to a higher volume of agricultural output for a range of crops. The increased volume was a result of more efficient use of chemical fertilizers among internet users. Their results are interesting, as more traditional information sources (e.g., extension services, radio, and television) did not have significant influences on agricultural productivity. Similar findings were made by Yuan, Tang, and Shi (2021) on fertilizer use, while Zhu et al. (2021) find that internet use improved the technical efficiency of Chinese apple-producing farm households through the acquisition of technological information.

Our results suggest that coffee farmers were able to improve their yield when taking climate adaptive measures, which we found to be mediated by farmers' access to mobile internet use. Our findings specifically contribute to the role of MIU for informing farmers' decisions concerning adaptive measures, adding a source of more flexible as well as constantly and timely available information on top of traditional information sources. However, having a mobile phone and the means to receive information does not necessarily mean that agricultural information services are used. A number of factors including digital literacy, affordability and relevant information sources play a role in farmers' use of and benefits from mobile information services (Tadesse and Bahiigwa, 2015; Wyche and Steinfield, 2016).<sup>7</sup> In Vietnam, mobile phones are among the preferred ICT tools to access agricultural information and the Ministry of Agriculture and Rural Development has put efforts into disseminating agricultural information to farmers, not only through traditional ICT outlets such as

<sup>7</sup> In our data, although MIU and years of schooling are positively and significantly correlated (see Table S1), the estimated interaction term (between MIU and years of schooling) is insignificant after controlling for sociodemographic and economic control variables (see Table S11).

**Table 5. Mobile Internet Use and Information, Ordinary Least Squares (OLS) Model**

	Weather Information	Price Information	Agri-Advice App
Mobile internet use (MIU)	0.230*** (0.048)	0.349*** (0.048)	0.020 (0.022)
Controls	Yes	Yes	Yes
Constant	-0.092 (0.217)	-0.489** (0.218)	0.006 (0.116)
$R^2$	0.180	0.294	0.055
No. of obs.	396	396	394

*Notes:* Values in parentheses are robust standard errors. Single, double, and triple asterisks (\*, \*\*, \*\*\*) indicate significance at the 10%, 5%, and 1% level, respectively. Control variables include income, household size, gender (1 if female, 0 if male), age, years of schooling, access to radio (1 if yes, 0 otherwise), access to TV (1 if yes, 0 otherwise), experience of climate shocks over the past 5 years (1 if yes, 0 otherwise), risk taking, generalized trust, and other sources of information and advice (1 if yes, 0 otherwise).

radio and TV but also through mobile phones (Kaila and Tarp, 2019; Hoang, 2020a). This helps to explain the positive association between MIU and climate adaptation among the Vietnamese farmers in this study. In contrast, Asfaw et al. (2019) found no effect of mobile phones on adaptation measures in a context where farmers received training on the studied adaptation measures indicating that, in their case, information was not the limiting factor.

MIU is expected to affect farmers' climate adaptation through several channels. First, MIU can affect adaptation by providing timely weather information to farmers, which is important for deciding when and which adaptation measures to implement. The value of real-time weather information has long been recognized in terms of improving production decisions, efficient use of inputs and irrigation as well as reducing weather-related losses (Kenkel and Norris, 1995). The timing of many farm management activities—such as fertilizer and pesticides applications, harvesting, pruning and shade tree management—depends on the weather; for example, heavy rains may wash away leaf pesticides, leaving the leaf vulnerable to mealybugs. Thus, if rains are delayed, spraying is an alternative. Seasonal forecasts can help farmers to plan for irrigation as well as practices that maintain soil and air humidity, such as mulch and shade tree management. Even shorter-term weather forecasts may help to decide when to begin pruning coffee trees and shade trees, as well as to carefully plan for fertilizer applications, avoiding heavy rains. This is also in line with previous evidence, which found that improved management of weather-related risks is one of the most often-cited benefits of mobile phone information services to farmers (see Baumüller, 2018, for a literature review). Second, it may help farmers get timely output price information, which could be used as an input, for example, in mixing crops or price inputs such as fertilizer, improved varieties, and other inputs that are important for implementing climate adaptation. Timely information on prices of inputs and outputs is also key in enhancing competitiveness of farmers (Smith et al., 2004). Finally, MIU may provide access directly to advisory on climate-related adaptation measures and enables farmers to download agri-advisory apps that provide important advice to farmers in managing their farm. Table 5 presents the main estimation results for weather information (column 1), price information (column 2) and agri-app use (column 3). Table S12 reports full estimation results.

The results suggest that MIU is associated with a higher likelihood of acquiring weather information, price information, and agri-app use. Although the latter is insignificant, it may be seen as an indication of the development of ICT tools for agricultural information. While mobile information services have so far been dominated by voice recordings and short text messages, there is a need and a potential to develop smarter information solutions for smartphone owners (Baumüller, 2017). Currently, many smartphone applications focus on increasing productivity and keeping track of farm diaries and are most often used by technical field staff as an extended arm

of the extension services offered by, for example, buying companies, such as Olam's OFIS platform. With time, more applications are also expected to include information and features focusing on climate adaption advisory, just as we have seen in simpler text-based mobile information services. As farmers' experiences of climatic changes and access to adaptation measures vary across regions, crop types, and social status of farmers, it is particularly important that applications be developed and designed in collaboration with farming communities (World Bank, 2011; Gbangou et al., 2020)

## Conclusion

Among smallholder farmers in developing countries, ICT is increasingly being recognized as a key ingredient in agriculture production decisions in general and climate change adaptation in particular. In this paper, we used survey data to examine the association between Vietnamese coffee farmers' mobile internet use and their adaptation decisions and production outcomes. We found that (i) mobile internet access is positively associated with farmers' climate adaptation; (ii) these adaptation practices are mainly driven by changes in water and crop management; (iii) these results are manifested through an increase in weather and farm price information access; and (iv) climate adaptation is associated with higher coffee yield. These results offer interesting and important insights into the potential of ICT in enhancing resilience of smallholder farmers against climate change.

Our results remain robust across the alternative models and climate adaptation proxies, and we control for important sociodemographic variables, proxies of wealth, risk-taking and trust preferences, and other sources of information and advice on coffee production and climate adaptation (e.g., friends, relatives, and neighbors and extension agents). While these measures narrow the scope of threats to a valid causal inference, care should be taken when interpreting our IV results as there may be unobserved household-level and commune-level characteristics that are correlated with commune-level MIU. We hope that future research, using more rigorous methods such as field experiments, will shed light on the impact and mechanisms through which MIU affects farmers' adaptation and productivity.

[First submitted June 2021; accepted for publication June 2022.]

## References

- Adger, W. N., N. W. Arnell, and E. L. Tompkins. 2005. "Adapting to Climate Change: Perspectives across Scales." *Global Environmental Change* 15(2):75–76. doi: 10.1016/j.gloenvcha.2005.03.001.
- Aker, J. C. 2011. "Dial 'A' for Agriculture: A Review of Information and Communication Technologies for Agricultural Extension in Developing Countries." *Agricultural Economics* 42(6):631–647. doi: 10.1111/j.1574-0862.2011.00545.x.
- Aker, J. C., and M. Fafchamps. 2015. "Mobile Phone Coverage and Producer Markets: Evidence from West Africa." *World Bank Economic Review* 29(2):262–292. doi: 10.1093/wber/lhu006.
- Aker, J. C., I. Ghosh, and J. Burrell. 2016. "The Promise (and Pitfalls) of ICT for Agriculture Initiatives." *Agricultural Economics* 47(S1):35–48. doi: 10.1111/agec.12301.
- Arslan, A., F. Belotti, and L. Lipper. 2017. "Smallholder Productivity and Weather Shocks: Adoption and Impact of Widely Promoted Agricultural Practices in Tanzania." *Food Policy* 69: 68–81. doi: 10.1016/j.foodpol.2017.03.005.
- Asfaw, A., B. Simane, A. Bantider, and A. Hassen. 2019. "Determinants in the Adoption of Climate Change Adaptation Strategies: Evidence from Rainfed-Dependent Smallholder Farmers in North-Central Ethiopia (Woleka Sub-Basin)." *Environment, Development and Sustainability* 21(5):2535–2565. doi: 10.1007/s10668-018-0150-y.

- Aubert, B. A., A. Schroeder, and J. Grimaudo. 2012. "IT as Enabler of Sustainable Farming: An Empirical Analysis of Farmers' Adoption Decision of Precision Agriculture Technology." *Decision Support Systems* 54(1):510–520. doi: 10.1016/j.dss.2012.07.002.
- Baumüller, H. 2017. "Towards Smart Farming? Mobile Technology Trends and their Potential for Developing Country Agriculture." In K. E. Skouby and I. Williams, eds., *Handbook for ICT in Developing Countries: 5G Perspectives*, Delft, Netherlands: River Publishers, 191–201.
- . 2018. "The Little We Know: An Exploratory Literature Review on the Utility of Mobile Phone-Enabled Services for Smallholder Farmers." *Journal of International Development* 30(1):134–154. doi: 10.1002/jid.3314.
- Bellemare, M. F. 2018. "Contract Farming: Opportunity Cost and Trade-Offs." *Agricultural Economics* 49(3):279–288. doi: 10.1111/agec.12415.
- Betz, T., S. J. Cook, and F. M. Hollenbach. 2018. "On the Use and Abuse of Spatial Instruments." *Political Analysis* 26(4):474–479. doi: 10.1017/pan.2018.10.
- Bryan, E., C. Ringler, B. Okoba, C. Roncoli, S. Silvestri, and M. Herrero. 2013. "Adapting Agriculture to Climate Change in Kenya: Household Strategies and Determinants." *Journal of Environmental Management* 114:26–35. doi: 10.1016/j.jenvman.2012.10.036.
- Bunn, C., P. Läderach, O. Ovalle Rivera, and D. Kirschke. 2015. "A Bitter Cup: Climate Change Profile of Global Production of Arabica and Robusta Coffee." *Climatic Change* 129(1-2): 89–101. doi: 10.1007/s10584-014-1306-x.
- Byraredy, V., L. Kouadio, S. Mushtaq, J. Kath, and R. Stone. 2021. "Coping with Drought: Lessons Learned from Robusta Coffee Growers in Vietnam." *Climate Services* 22:100229. doi: 10.1016/j.cliser.2021.100229.
- Chavas, J.-P., R. G. Chambers, and R. D. Pope. 2010. "Production Economics and Farm Management: A Century of Contributions." *American Journal of Agricultural Economics* 92(2): 356–375. doi: 10.1093/ajae/aaq004.
- Chavula, H. K. 2014. "The Role of ICTs in Agricultural Production in Africa." *Journal of Development and Agricultural Economics* 6(7):279–289. doi: 10.5897/JDAE2013.0517.
- Cologna, V., and M. Siegrist. 2020. "The Role of Trust for Climate Change Mitigation and Adaptation Behaviour: A Meta-Analysis." *Journal of Environmental Psychology* 69:101428. doi: 10.1016/j.jenvp.2020.101428.
- Deng, X., D. Xu, M. Zeng, and Y. Qi. 2019. "Does Internet Use Help Reduce Rural Cropland Abandonment? Evidence from China." *Land Use Policy* 89:104243. doi: 10.1016/j.landusepol.2019.104243.
- Deressa, T. T., R. M. Hassan, C. Ringler, T. Alemu, and M. Yesuf. 2009. "Determinants of Farmers' Choice of Adaptation Methods to Climate Change in the Nile Basin of Ethiopia." *Global Environmental Change* 19(2):248–255. doi: 10.1016/j.gloenvcha.2009.01.002.
- Di Falco, S., M. Veronesi, and M. Yesuf. 2011. "Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia." *American Journal of Agricultural Economics* 93(3):829–846. doi: 10.1093/ajae/aar006.
- Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner. 2011. "Individual Risk Attitudes: Measurement, Determinants and Behavioral Consequences." *Journal of the European Economic Association* 9(3):522–550. doi: 10.1111/j.1542-4774.2011.01015.x.
- Fafchamps, M., and B. Minten. 2012. "Impact of SMS-Based Agricultural Information on Indian Farmers." *World Bank Economic Review* 26(3):383–414. doi: 10.1093/wber/lhr056.
- Fan, Q., and V. B. Salas Garcia. 2018. "Information Access and Smallholder Farmers' Market Participation in Peru." *Journal of Agricultural Economics* 69(2):476–494. doi: 10.1111/1477-9552.12243.
- Foster, A. D., and M. R. Rosenzweig. 2010. "Microeconomics of Technology Adoption." *Annual Review of Economics* 2(1):395–424. doi: 10.1146/annurev.economics.102308.124433.

- Frank, E., H. Eakin, and D. López-Carr. 2011. "Social Identity, Perception and Motivation in Adaptation to Climate Risk in the Coffee Sector of Chiapas, Mexico." *Global Environmental Change* 21(1):66–76. doi: 10.1016/j.gloenvcha.2010.11.001.
- Gbangou, T., R. Sarku, E. V. Slobbe, F. Ludwig, G. Kranjac-Berisavljevic, and S. Paparrizos. 2020. "Coproducing Weather Forecast Information with and for Smallholder Farmers in Ghana: Evaluation and Design Principles." *Atmosphere* 11(9):902. doi: 10.3390/atmos11090902.
- Goyal, A. 2010. "Information, Direct Access to Farmers, and Rural Market Performance in Central India." *American Economic Journal: Applied Economics* 2(3):22–45. doi: 10.1257/app.2.3.22.
- Haggar, J. P., and K. Schepp. 2012. "Coffee and Climate Change: Impacts and Options for Adaptation in Brazil, Guatemala, Tanzania and Vietnam." NRI Working Paper 4. Gillingham, UK: University of Greenwich Natural Resources Institute.
- Hartje, R., and M. Hübler. 2017. "Smartphones Support Smart Labour." *Applied Economics Letters* 24(7):467–471. doi: 10.1080/13504851.2016.1203054.
- Hassan, R. M., and C. Nhemachena. 2008. "Determinants of African Farmers' Strategies for Adapting to Climate Change: Multinomial Choice Analysis." *African Journal of Agricultural and Resource Economics* 2(1):83–104. doi: 10.22004/ag.econ.56969.
- Ho, T. Q., V.-N. Hoang, C. Wilson, and T.-T. Nguyen. 2018. "Eco-Efficiency Analysis of Sustainability-Certified Coffee Production in Vietnam." *Journal of Cleaner Production* 183: 251–260. doi: 10.1016/j.jclepro.2018.02.147.
- Hoang, G. H. 2020a. "Adoption of Mobile Phone for Marketing of Cereals by Smallholder Farmers in Quang Dien District of Vietnam." *Journal of Agricultural Extension* 24(1):106–117. doi: 10.4314/jae.v24i1.11.
- . 2020b. "Determinants of the Adoption of Mobile Phones for Fruit Marketing by Vietnamese Farmers." *World Development Perspectives* 17:100178. doi: 10.1016/j.wdp.2020.100178.
- Hoang, H. G. 2021. "Use of Information and Communication Technologies by Vietnamese Smallholders: Implications for Extension Strategies." *Information Development* 37(2):221–230. doi: 10.1177/0266666920906603.
- Hübner, M., and R. Hartje. 2016. "Are Smartphones Smart for Economic Development?" *Economics Letters* 141:130–133. doi: 10.1016/j.econlet.2016.02.001.
- Jensen, R. 2007. "The Digital Divide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector." *Quarterly Journal of Economics* 122(3):879–924. doi: 10.1162/qjec.122.3.879.
- Jianjun, J., G. Yiwei, W. Xiaomin, and P. K. Nam. 2015. "Farmers' Risk Preferences and Their Climate Change Adaptation Strategies in the Yongqiao District, China." *Land Use Policy* 47: 365–372. doi: 10.1016/j.landusepol.2015.04.028.
- Kaila, H., and F. Tarp. 2019. "Can the Internet Improve Agricultural Production? Evidence from Viet Nam." *Agricultural Economics* 50(6):675–691. doi: 10.1111/agec.12517.
- Kenkel, P. L., and P. E. Norris. 1995. "Agricultural Producers' Willingness to Pay for Real-Time Mesoscale Weather Information." *Journal of Agricultural and Resource Economics* 20(2): 356–372. doi: 10.22004/ag.econ.30767.
- Kosse, F., T. Deckers, P. Pinger, H. Schildberg-Hörisch, and A. Falk. 2020. "The Formation of Prosociality: Causal Evidence on the Role of Social Environment." *Journal of Political Economy* 128(2):434–467. doi: 10.1086/704386.
- Krell, N. T., S. A. Giroux, Z. Guido, C. Hannah, S. E. Lopus, K. K. Caylor, and T. P. Evans. 2021. "Smallholder Farmers' Use of Mobile Phone Services in Central Kenya." *Climate and Development* 13(3):215–227. doi: 10.1080/17565529.2020.1748847.
- Kroschel, J., M. Sporleder, H. Tonnang, H. Juarez, P. Carhuapoma, J. Gonzales, and R. Simon. 2013. "Predicting Climate-Change-Caused Changes in Global Temperature on Potato Tuber Moth *Phthorimaea operculella* (Zeller) Distribution and Abundance Using Phenology Modeling and GIS Mapping." *Agricultural and Forest Meteorology* 170:228–241. doi: 10.1016/j.agrformet.2012.06.017.

- Lin, W., and D. P. Green. 2016. "Standard Operating Procedures: A Safety Net for Pre-Analysis Plans." *PS: Political Science & Politics* 49(03):495–500. doi: 10.1017/S1049096516000810.
- Lio, M., and M.-C. Liu. 2006. "ICT and Agricultural Productivity: Evidence from Cross-Country Data." *Agricultural Economics* 34(3):221–228. doi: 10.1111/j.1574-0864.2006.00120.x.
- Ma, W., P. Nie, P. Zhang, and A. Renwick. 2020. "Impact of Internet Use on Economic Well-Being of Rural Households: Evidence from China." *Review of Development Economics* 24(2):503–523. doi: 10.1111/rode.12645.
- Marsh, A. 2007. *Diversification by Smallholder Farmers: Viet Nam Robusta Coffee*. Agricultural Management, Marketing and Finance Working Document 19. Rome, Italy: Food and Agriculture Organization of the United Nations. Available online at <https://www.fao.org/sustainable-food-value-chains/library/details/ar/c/262875/>.
- Mathenge, M. K., M. Smale, and J. Olwande. 2014. "The Impacts of Hybrid Maize Seed on the Welfare of Farming Households in Kenya." *Food Policy* 44:262–271. doi: 10.1016/j.foodpol.2013.09.013.
- Ministry of Agriculture and Rural Development. 2018. *Agricultural Extension Activities in 2018 and Plan for 2019*. Hanoi, Vietnam: Ministry of Agriculture and Rural Development. Available online at <https://www.mard.gov.vn/Pages/cong-tac-khuyen-nong-nam-2018-va-dinh-huong-hoat-dong-nam-2019.aspx>.
- Mundial, B. 2003. *ICT and MDGs: A World Bank Group Perspective*. Washington, DC: World Bank Group Global ICT Department.
- Muto, M., and T. Yamano. 2009. "The Impact of Mobile Phone Coverage Expansion on Market Participation: Panel Data Evidence from Uganda." *World Development* 37(12):1887–1896. doi: 10.1016/j.worlddev.2009.05.004.
- Nguyen, N., and E. G. Drakou. 2021. "Farmers Intention to Adopt Sustainable Agriculture Hinges on Climate Awareness: The Case of Vietnamese Coffee." *Journal of Cleaner Production* 303: 126828. doi: 10.1016/j.jclepro.2021.126828.
- Nguyen, P. L., and M. D. Nguyen. 2019. "Drought Adaptation and Coping Strategies among Coffee Farmers in the Central Highlands of Vietnam." *Journal of Agriculture and Environmental Sciences* 8(1):52–66. doi: 10.15640/jaes.v8n1a6.
- Ogutu, S. O., J. J. Okello, and D. J. Otieno. 2014. "Impact of Information and Communication Technology-Based Market Information Services on Smallholder Farm Input Use and Productivity: The Case of Kenya." *World Development* 64:311–321. doi: 10.1016/j.worlddev.2014.06.011.
- Paul, C. J., E. S. Weinthal, M. F. Bellemare, and M. A. Jeuland. 2016. "Social Capital, Trust, and Adaptation to Climate Change: Evidence from Rural Ethiopia." *Global Environmental Change* 36:124–138. doi: 10.1016/j.gloenvcha.2015.12.003.
- Pham-Thanh, H., R. Linden, T. Ngo-Duc, Q. Nguyen-Dang, A. H. Fink, and T. Phan-Van. 2020. "Predictability of the Rainy Season Onset Date in Central Highlands of Vietnam." *International Journal of Climatology* 40(6):3072–3086. doi: 10.1002/joc.6383.
- Pretty, J., C. Toulmin, and S. Williams. 2011. "Sustainable Intensification in African Agriculture." *International Journal of Agricultural Sustainability* 9(1):5–24. doi: 10.3763/ijas.2010.0583.
- Sekabira, H., and M. Qaim. 2017. "Can Mobile Phones Improve Gender Equality and Nutrition? Panel Data Evidence from Farm Households in Uganda." *Food Policy* 73:95–103. doi: 10.1016/j.foodpol.2017.10.004.
- Smale, M., and N. Mason. 2014. "Hybrid Seed and the Economic Well-Being of Smallholder Maize Farmers in Zambia." *Journal of Development Studies* 50(5):680–695. doi: 10.1080/00220388.2014.887690.
- Smith, A. D., C. J. Morrison Paul, W. R. Goe, and M. Kenney. 2004. *Computer and Internet Use by Great Plains Farmers*. Working Paper 04-010. Davis, CA: UC Davis Department of Agriculture and Resource Economics. doi: 10.2139/ssrn.711262.

- Stock, J. H., J. H. Wright, and M. Yogo. 2002. "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments." *Journal of Business & Economic Statistics* 20(4):518–529. doi: 10.1198/073500102288618658.
- Sundquist, J. 2021. "How to Use Spatial Instruments." Working Paper. Available online at [https://jamessundquist.github.io/website/docs/How\\_to\\_Use\\_Spatial\\_Instruments.pdf](https://jamessundquist.github.io/website/docs/How_to_Use_Spatial_Instruments.pdf).
- Tadesse, G., and G. Bahiigwa. 2015. "Mobile Phones and Farmers' Marketing Decisions in Ethiopia." *World Development* 68:296–307. doi: 10.1016/j.worlddev.2014.12.010.
- Thi, T. P., and Y. Chaovanapoonphol. 2014. "An Evaluation of Adaptation Options to Climate Pressure on Highland Robusta Coffee Production, Daklak Province, Vietnam." *World Journal of Agricultural Research* 2(5):205–215. doi: 10.12691/wjar-2-5-2.
- Tiemann, T., T. Maung Aye, N. Duc Dung, T. Minh Tien, M. Fisher, E. Nalin de Paulo, and T. Oberthür. 2018. "Crop Nutrition for Vietnamese Robusta Coffee." *Better Crops with Plant Food* 102(3):20–23. doi: 10.24047/BC102320.
- Westermann, O., W. Förch, P. Thornton, J. Körner, L. Cramer, and B. Campbell. 2018. "Scaling Up Agricultural Interventions: Case Studies of Climate-Smart Agriculture." *Agricultural Systems* 165:283–293. doi: 10.1016/j.agsy.2018.07.007.
- World Bank. 2011. *ICT in Agriculture: Connecting Smallholders to Knowledge, Networks, and Institutions*. Washington, DC: World Bank. doi: 10.1596/978-1-4648-1002-2.
- . 2016. *World Development Report 2016: Digital Dividends*. World Bank.
- . 2019. "Individuals Using the Internet (% of Population) - Vietnam." International Telecommunication Union (ITU) World Telecommunication/ICT Indicators Database. Available online at <https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=VN>.
- World Bank and Asian Development Bank. 2020. "Climate Risk Country Profile – Vietnam." Washington, DC: World Bank and Asian Development Bank.
- Wossen, T., T. Berger, and S. Di Falco. 2015. "Social Capital, Risk Preference and Adoption of Improved Farm Land Management Practices in Ethiopia." *Agricultural Economics* 46(1):81–97. doi: 10.1111/agec.12142.
- Wuepper, D., H. Yesigat Ayenew, and J. Sauer. 2018. "Social Capital, Income Diversification and Climate Change Adaptation: Panel Data Evidence from Rural Ethiopia." *Journal of Agricultural Economics* 69(2):458–475. doi: 10.1111/1477-9552.12237.
- Wyche, S., and C. Steinfeld. 2016. "Why Don't Farmers Use Cell Phones to Access Market Prices? Technology Affordances and Barriers to Market Information Services Adoption in Rural Kenya." *Information Technology for Development* 22(2):320–333. doi: 10.1080/02681102.2015.1048184.
- Yuan, F., K. Tang, and Q. Shi. 2021. "Does Internet Use Reduce Chemical Fertilizer Use? Evidence from Rural Households in China." *Environmental Science and Pollution Research* 28(5):6005–6017. doi: 10.1007/s11356-020-10944-4.
- Zhu, X., R. Hu, C. Zhang, and G. Shi. 2021. "Does Internet Use Improve Technical Efficiency? Evidence from Apple Production in China." *Technological Forecasting and Social Change* 166: 120662. doi: 10.1016/j.techfore.2021.120662.

## Appendix

Table A1. Mobile Internet Use (MIU) and Adaptation

	Implemented Adaptation Measure				Implemented at Least One of the Listed Adaptation Measures		Number of Adaptation Measures Implemented	
	OLS	Probit	Matching	IV	OLS	IV	OLS	IV
	1	2	3	4	5	6	7	8
MIU	0.146*** (0.050)	0.134*** (0.048)	0.181*** (0.049)	0.385* (0.214)	0.119** (0.051)	0.420* (0.216)	0.331*** (0.096)	1.412*** (0.457)
Income	0.035 (0.042)	0.026 (0.042)		−0.004 (0.050)	0.032 (0.042)	−0.016 (0.050)	0.033 (0.082)	−0.131 (0.103)
Land holding	0.002 (0.020)	0.002 (0.020)		0.006 (0.020)	0.009 (0.021)	0.014 (0.020)	0.044 (0.046)	0.065 (0.045)
Household size	0.010 (0.015)	0.013 (0.015)		0.005 (0.016)	0.007 (0.015)	0.001 (0.017)	0.022 (0.030)	−0.000 (0.035)
Female	0.087 (0.098)	0.071 (0.093)		0.059 (0.102)	0.091 (0.097)	0.055 (0.101)	0.025 (0.176)	−0.099 (0.212)
Age	0.001 (0.002)	0.002 (0.002)		0.003 (0.003)	0.000 (0.002)	0.002 (0.003)	0.003 (0.004)	0.009* (0.006)
Years of schooling	0.017*** (0.005)	0.028*** (0.007)		0.015*** (0.005)	0.018*** (0.005)	0.016*** (0.005)	0.030*** (0.007)	0.023** (0.010)
Radio	0.064 (0.092)	0.087 (0.110)		0.015 (0.097)	0.101 (0.094)	0.041 (0.098)	0.483** (0.227)	0.262 (0.251)
TV	0.106 (0.080)	0.079 (0.079)		0.116 (0.078)	0.065 (0.081)	0.077 (0.078)	−0.034 (0.187)	0.016 (0.185)
Climate shock	−0.011 (0.051)	−0.015 (0.049)		−0.042 (0.057)	−0.002 (0.051)	−0.041 (0.059)	−0.047 (0.101)	−0.192 (0.127)
Risk taking	0.024** (0.010)	0.022** (0.010)		0.022** (0.010)	0.025** (0.010)	0.023** (0.011)	0.057*** (0.019)	0.046** (0.023)
Trust	0.102*** (0.036)	0.101*** (0.035)		0.105*** (0.037)	0.104*** (0.037)	0.109*** (0.037)	0.286*** (0.076)	0.315*** (0.083)
Other information and advice sources	0.034 (0.104)	0.023 (0.098)		−0.004 (0.110)	0.090 (0.097)	0.042 (0.102)	0.243 (0.166)	0.078 (0.198)
Constant	−0.467* (0.248)	−2.855*** (0.740)	0.485*** (0.034)	−0.393 (0.253)	−0.473* (0.248)	−0.382 (0.257)	−1.313*** (0.497)	−1.039* (0.544)
$R^2$	0.112		0.034	0.062	0.111	0.032	0.155	0.156
Pseudo- $R^2$		0.095						
No. of obs.	396	396	396	395	396	395	396	395

Notes: Values in parentheses are robust standard errors. Single, double, and triple asterisks (\*, \*\*, \*\*\*) indicate significance at the 10%, 5%, and 1% level, respectively. Coefficients under probit model are marginal effects.

**Table A2. Mobile Internet Use and Adaptation, First-Stage Results ( $N = 395$ )**

	Mobile Internet Use
CMIU	0.938*** (0.192)
Income	0.148*** (0.039)
Land holding	-0.008 (0.019)
Household size	0.009 (0.015)
Female	0.033 (0.090)
Age	-0.006*** (0.002)
Years of schooling	0.003 (0.007)
Radio	0.201* (0.104)
TV	-0.124* (0.071)
Climate shock	0.113** (0.050)
Risk taking	0.001 (0.010)
Trust	-0.009 (0.037)
Other information and advice sources	0.096 (0.085)
Constant	-0.502** (0.248)
F(1,383)	23.830***
$R^2$	0.155

Notes: Values in parentheses are robust standard errors. Single, double, and triple asterisks (\*, \*\*, \*\*\*) indicate significance at the 10%, 5%, and 1% level, respectively.

Online Supplement:

Mobile Internet Use and Climate Adaptation:

Empirical Evidence from

Vietnamese Coffee Farmers

Goytom Abraha Kahsay, Nerea Turreira Garcia,  
and Aske Skovmand Bosselmann

Table S1. Correlation Matrix of Covariates

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
(1) MIU	1.000												
(2) Income (in USD)	0.092	1.000											
(3) Land holding	0.063	0.662	1.000										
(4) Household size	0.087	0.034	0.118	1.000									
(5) Female	0.018	-0.140	-0.125	-0.123	1.000								
(6) Age	-0.116	0.119	0.111	-0.189	0.070	1.000							
(7) Years of schooling	0.118	0.076	-0.008	-0.088	-0.023	-0.057	1.000						
(8) Radio	0.090	-0.009	-0.016	-0.005	0.018	0.070	0.143	1.000					
(9) TV	-0.002	0.015	0.031	0.054	-0.159	0.065	0.152	0.002	1.000				
(10) Climate shock	0.154	0.037	0.071	0.053	0.071	0.007	0.002	-0.026	-0.017	1.000			
(11) Risk taking	0.070	0.136	0.159	-0.070	0.007	0.081	0.090	0.001	0.030	0.046	1.000		
(12) Trust	-0.036	0.050	-0.009	0.006	-0.024	-0.117	-0.100	0.034	-0.056	-0.124	-0.007	1.000	
(13) Other information/ advice sources	0.114	-0.037	-0.056	0.022	-0.105	-0.069	0.101	0.060	0.137	0.098	0.006	0.015	1.000

**Table S2. Farmers' Perceived Changes in Climate ( $N = 400$ )**

	Mean	Std. Dev.	Min.	Max.
More rain rainy season	0.155	0.362	0	1
Less rain rainy season	0.077	0.268	0	1
Shorter rainy season	0.072	0.26	0	1
Longer rainy season	0.077	0.268	0	1
More rain dry season	0.01	0.1	0	1
Less rain dry season	0.04	0.196	0	1
Longer dry season	0.627	0.484	0	1
Shorter dry season	0.007	0.086	0	1
More intense rain	0.015	0.122	0	1
Less intense rain	0.007	0.086	0	1
Flood	0	0	0	0
Temp increase dry season	0.2	0.401	0	1
Temp decrease dry season	0	0	0	0
Early rain begin	0.063	0.242	0	1
Late rain begin	0.05	0.218	0	1
Early rain end	0.022	0.148	0	1
Late rain end	0.005	0.071	0	1
Increase winds rainy season	0	0	0	0
Increase winds dry season	0.005	0.071	0	1
Higher temp	0.355	0.479	0	1
Lower temp	0.02	0.14	0	1
More rain	0.135	0.342	0	1
Less rain	0.07	0.255	0	1

**Table S3. Farmers' Perceived Climate Impacts ( $N = 400$ )**

	Mean	Std. Dev.	Min.	Max.
Lower yield	0.292	0.455	0	1
Higher yield	0.005	0.071	0	1
More pest	0.102	0.304	0	1
Less pest	0	0	0	0
More fungi	0.028	0.164	0	1
Less fungi	0	0	0	0
More erosion	0.015	0.122	0	1
Reduced flowering	0.12	0.325	0	1
Fall of flowers	0.09	0.287	0	1
Fall of cherries	0.155	0.362	0	1
Disrupt drying	0.022	0.148	0	1
More insect	0.013	0.111	0	1
Less insect	0	0	0	0

Table S4. Farmers’ Adaptation Practices

	Overall Sample		Non-Users		Users		Diff.	p-Value
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.		
	1	2	3	4	5	6	7	8
<b>Pest management</b>								
Spray more	0.115	0.319	0.097	0.297	0.134	0.342	-0.037	0.248
Spray less	0.003	0.05	0	0	0.005	0.072	-0.005	0.303
Remove pest	0	0	0	0	0	0	0	.
<b>Changes in crop calendar</b>								
Change planting time	0	0	0	0	0	0	0	.
Change harvesting time	0.005	0.071	0.005	0.07	0.005	0.072	-0.001	0.966
<b>Water management</b>								
Dig drainage	0.005	0.071	0.005	0.07	0.005	0.072	-0.001	0.966
Drill hole	0.052	0.223	0.034	0.182	0.072	0.259	-0.038	0.088
Irrigate more	0.375	0.485	0.311	0.464	0.443	0.498	-0.133	0.006
Irrigate less	0.033	0.178	0.024	0.154	0.041	0.199	-0.017	0.34
Rainwater harvesting	0	0	0	0	0	0	0	.
Dig more	0.035	0.184	0.039	0.194	0.031	0.174	0.008	0.668
<b>Shade tree management</b>								
Plant more shade tree	0.02	0.14	0.024	0.154	0.015	0.124	0.009	0.53
Remove shade tree	0	0	0	0	0	0	0	.
<b>Crop management</b>								
Use improved variety	0.077	0.268	0.068	0.252	0.088	0.283	-0.019	0.464
Intercropping	0.182	0.387	0.092	0.29	0.278	0.449	-0.186	0

Table S5. Farmers’ Use of Mobile Internet (N = 400)

	Mean	Std. Dev.	Min.	Max.
Farm prices/coffee market	0.407	0.492	0	1
Weather forecasts	0.313	0.464	0	1
Facebook	0.380	0.486	0	1
Email	0.015	0.122	0	1
Internet based calling and message apps	0.325	0.469	0	1
News	0.427	0.495	0	1

**Table S6. Descriptive Statistics by Mobile Internet Users**

	Non-Users		Users		Mean	
	N	Mean	N	Mean	Difference	p-Value
<b>Adaptation</b>						
Implemented adaptation measure	206	0.485	194	0.67	-0.184	0
Implemented at least one of the listed adaptation measures	206	0.461	194	0.629	-0.168	0.001
No. of adaptation measures implemented	206	0.699	194	1.119	-0.419	0
<b>ICT</b>						
Smartphone	206	0.481	194	0.82	-0.339	0
Feature Phone	206	0.544	194	0.608	-0.065	0.193
TV	206	0.888	194	0.892	-0.004	0.913
Radio	206	0.029	194	0.067	-0.038	0.075
PC	206	0.029	194	0.124	-0.095	0.001
Tablet	206	0.005	194	0.015	-0.011	0.288
Commune-level MIU (CMIU)	205	0.45	194	0.519	-0.069	0
<b>Source of information/advice on coffee production and climate adaptation</b>						
Friends, neighbors and relatives	206	0.524	194	0.722	-0.198	0
Extension agent	206	0.044	194	0.088	-0.044	0.075
Farmer organizations	206	0.18	194	0.242	-0.063	0.125
Coffee companies	206	0.442	194	0.464	-0.022	0.657
NGOs	206	0.005	194	0.005	-0.001	0.966
<b>Socio-demographic characteristics</b>						
Income (in USD)	206	206.122	194	240.975	-34.853	0.057
Land holding	206	1.696	194	1.887	-0.192	0.185
Household size	206	3.689	194	3.974	-0.285	0.07
Female	205	0.078	193	0.088	-0.01	0.718
Age	205	50.693	193	48.005	2.688	0.019
Years of schooling	204	6.828	192	8.042	-1.213	0.019
Risk taking	206	6.078	194	6.418	-0.34	0.155
Trust	206	2.804	194	2.753	0.052	0.432
Climate shock	206	0.296	194	0.443	-0.147	0.002
<b>Coffee production</b>						
Yield per ha in 2018	200	3,036.867	188	31,14.846	-77.978	0.563
Fertilizer (quantity)	206	595.971	194	911.469	-315.498	0.011
Labor (person days)	206	10.184	194	19.778	-9.594	0.001
Spraying cost (in USD)	200	81.933	188	72.579	9.354	0.408

Table S7. Mobile Internet Use and Different Types of Climate Adaptation

	Pest Management		Changes in Crop Calendar		Water Management		Shade Tree Management		Crop Management	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	1	2	3	4	5	6	7	8	9	10
MIU	0.030 (0.034)	0.114 (0.134)	-0.001 (0.009)	-0.036 (0.028)	0.120** (0.052)	0.608*** (0.220)	-0.019 (0.016)	0.003 (0.052)	0.136*** (0.041)	0.384** (0.174)
Income	0.048* (0.025)	0.036 (0.030)	0.006 (0.005)	0.011 (0.008)	0.021 (0.040)	-0.050 (0.050)	0.010 (0.010)	0.007 (0.012)	-0.044 (0.032)	-0.085** (0.040)
Land holding	-0.006 (0.014)	-0.004 (0.014)	-0.002 (0.002)	-0.003 (0.003)	-0.012 (0.021)	-0.002 (0.020)	-0.009* (0.005)	-0.009* (0.005)	0.048** (0.019)	0.052*** (0.018)
Household size	0.007 (0.010)	0.005 (0.010)	0.000 (0.002)	0.001 (0.003)	0.006 (0.016)	-0.004 (0.018)	0.002 (0.005)	0.001 (0.005)	-0.018 (0.012)	-0.022* (0.013)
Female	-0.010 (0.058)	-0.017 (0.057)	-0.003 (0.002)	0.001 (0.004)	0.105 (0.095)	0.059 (0.110)	-0.020* (0.010)	-0.022* (0.012)	-0.112* (0.068)	-0.138* (0.077)
Age	0.001 (0.002)	0.001 (0.002)	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.002)	0.002 (0.003)	-0.000 (0.001)	-0.000 (0.001)	0.003* (0.002)	0.005** (0.002)
Years of schooling	0.007 (0.004)	0.006 (0.005)	-0.000 (0.000)	0.000 (0.000)	0.009 (0.005)	0.005 (0.004)	-0.000 (0.001)	-0.000 (0.001)	0.013*** (0.002)	0.011*** (0.003)
Radio	0.048 (0.078)	0.031 (0.081)	-0.005 (0.005)	0.002 (0.005)	0.036 (0.110)	-0.064 (0.114)	0.095 (0.073)	0.091 (0.077)	0.329*** (0.102)	0.279*** (0.103)
TV	-0.085 (0.057)	-0.080 (0.055)	0.004 (0.003)	0.002 (0.004)	0.079 (0.079)	0.103 (0.083)	0.017** (0.008)	0.018** (0.008)	-0.011 (0.064)	-0.002 (0.063)
Climate shock	-0.095*** (0.031)	-0.107*** (0.037)	0.003 (0.010)	0.008 (0.009)	0.057 (0.052)	-0.011 (0.061)	0.015 (0.016)	0.012 (0.016)	-0.098** (0.042)	-0.129*** (0.049)
Risk taking	0.010 (0.007)	0.009 (0.007)	-0.001 (0.002)	-0.000 (0.002)	0.022** (0.010)	0.017 (0.012)	0.003 (0.003)	0.003 (0.003)	0.020** (0.008)	0.018** (0.009)
Trust	0.090*** (0.027)	0.094*** (0.027)	-0.001 (0.001)	-0.002 (0.002)	0.078** (0.038)	0.094** (0.040)	-0.006 (0.008)	-0.006 (0.008)	0.106*** (0.032)	0.108*** (0.033)
Other info. and advice sources	0.039 (0.051)	0.027 (0.056)	0.003 (0.002)	0.008 (0.007)	0.096 (0.093)	0.023 (0.107)	0.007 (0.008)	0.004 (0.009)	0.080 (0.064)	0.040 (0.070)
Constant	-0.499*** (0.177)	-0.486*** (0.175)	-0.020 (0.016)	-0.029 (0.026)	-0.297 (0.256)	-0.188 (0.275)	-0.028 (0.088)	-0.023 (0.087)	-0.330* (0.200)	-0.244 (0.206)
R <sup>2</sup>	0.098	0.083	0.005	0.008	0.069	0.076	0.037	0.032	0.184	0.108
Observations	396	395	396	395	396	395	396	395	396	395

Notes: Robust standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

**Table S8. Adaptation and Coffee Yield, Imputation Method**

	OLS				3SLS	Mobile
	Yield/Ha 1	Yield/Ha 2	Yield/Ha 3	Yield/Ha 4	Adaptation 5	Internet Use 6
Adaptation	0.278*** (0.097)	0.144* (0.082)	0.277*** (0.093)	1.041*** (0.299)		
Ln (fertilizer)		0.147** (0.060)	0.099* (0.055)	0.085 (0.079)		
Ln (labor)		-0.085*** (0.032)	-0.039 (0.053)	-0.050 (0.044)		
Ln (Spraying)		0.091* (0.049)	0.087** (0.039)	0.076 (0.058)		
Ln (fertilizer) dummy			0.049 (0.103)	0.060 (0.096)		
Ln (labor) dummy			-0.029 (0.092)	0.049 (0.096)		
Ln (Spraying) dummy			-0.064 (0.110)	-0.054 (0.103)		
MIU					0.451*** (0.165)	
Income					0.068 (0.049)	0.157*** (0.043)
Land holding					-0.027 (0.021)	-0.011 (0.022)
Household size					0.001 (0.015)	0.000 (0.016)
Female					0.066 (0.086)	0.027 (0.089)
Age					0.003 (0.002)	-0.007*** (0.002)
Years of schooling					0.015*** (0.005)	0.003 (0.005)
Radio					-0.045 (0.111)	0.210* (0.110)
TV					0.131* (0.076)	-0.116 (0.080)
Climate shock					-0.072 (0.054)	0.132*** (0.051)
Risk taking					0.016 (0.010)	-0.002 (0.010)
Trust					0.094** (0.037)	-0.016 (0.038)
Other information and advice sources					-0.014 (0.096)	0.061 (0.099)
CMIU						0.964*** (0.201)
Constant	7.716*** (0.092)	6.605*** (0.389)	6.748*** (0.332)	6.449*** (0.574)	-0.636** (0.268)	-0.405 (0.277)
R <sup>2</sup>	0.027	0.171	0.046	-0.154	0.012	0.165
Observations	375	112	375	370	370	370

Notes: Robust standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

**Table S9. Adaptation and Coffee Yield, Inverse Hyperbolic Sine Transformation Method**

	OLS		3SLS	
	Yield/Ha	Yield/Ha	Adaptation	Mobile Internet Use
	1	2	3	4
Adaptation	0.264*** (0.094)	1.103*** (0.322)		
Ln (fertilizer)	-0.008 (0.011)	-0.010 (0.012)		
Ln (labor)	-0.000 (0.022)	-0.024 (0.028)		
Ln (Spraying)	0.023 (0.018)	0.020 (0.020)		
MIU			0.446** (0.186)	
Income			0.079 (0.050)	0.158*** (0.043)
Land holding			-0.027 (0.021)	-0.011 (0.022)
Household size			0.001 (0.015)	0.000 (0.016)
Female			0.066 (0.084)	0.027 (0.089)
Age			0.003 (0.002)	-0.007*** (0.002)
Years of schooling			0.014*** (0.005)	0.003 (0.005)
Radio			-0.050 (0.110)	0.210* (0.110)
TV			0.129* (0.075)	-0.116 (0.080)
Climate shock			-0.072 (0.055)	0.131*** (0.051)
Risk taking			0.016 (0.010)	-0.002 (0.010)
Trust			0.094*** (0.036)	-0.016 (0.038)
Other information and advice sources			-0.011 (0.094)	0.061 (0.099)
CMIU				0.966*** (0.202)
Constant	7.676*** (0.123)	7.258*** (0.168)	-0.697*** (0.262)	-0.410 (0.277)
R <sup>2</sup>	0.032	-0.207	0.014	0.165
Observations	375	370	370	370

Notes: Robust standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

**Table S10. Adaptation Categories and Coffee Yield (OLS model)**

	1	2	3	4	5
Water management	0.175** (0.075)				
Crop management		0.161** (0.064)			
Pest management			0.185** (0.091)		
Shade tree management				0.033 (0.118)	
Changes in crop calendar					-0.179 (0.137)
Ln (fertilizer)	0.085 (0.057)	0.086 (0.056)	0.094 (0.057)	0.087 (0.057)	0.086 (0.057)
Ln (labor)	-0.037 (0.053)	-0.035 (0.054)	-0.025 (0.054)	-0.028 (0.054)	-0.027 (0.054)
Ln (Spraying)	0.094** (0.039)	0.090** (0.040)	0.087** (0.039)	0.093** (0.040)	0.093** (0.040)
Ln (fertilizer) dummy	0.055 (0.104)	0.051 (0.105)	0.035 (0.108)	0.052 (0.105)	0.052 (0.105)
Ln (labor) dummy	-0.036 (0.094)	-0.041 (0.096)	-0.048 (0.097)	-0.044 (0.098)	-0.044 (0.098)
Ln (Spraying) dummy	-0.093 (0.109)	-0.093 (0.110)	-0.078 (0.114)	-0.103 (0.109)	-0.104 (0.110)
Constant	6,907*** (0.327)	6,955*** (0.320)	6,914*** (0.332)	6,958*** (0.334)	6,964*** (0.328)
$R^2$	0.031	0.027	0.025	0.020	0.021
Observations	375	375	375	375	375

Notes: Robust standard errors in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table S11. Mobile Internet Use and Adaptation, Interaction Effect with Education (OLS model)**

	<b>Implemented Adaptation Measure 1</b>	<b>Implemented at Least One of the Listed Adaptation Measures 2</b>	<b>Number of Adaptation Measures Implemented 3</b>
MIU	0.165* (0.087)	0.114 (0.089)	0.369** (0.146)
Years of schooling	0.018*** (0.006)	0.017*** (0.006)	0.033*** (0.011)
MIUXYears of schooling	-0.002 (0.009)	0.001 (0.009)	-0.005 (0.014)
Income	0.033 (0.042)	0.032 (0.043)	0.030 (0.083)
Land holding	0.002 (0.020)	0.009 (0.021)	0.045 (0.046)
Household size	0.010 (0.015)	0.007 (0.015)	0.022 (0.030)
Female	0.085 (0.098)	0.092 (0.097)	0.020 (0.176)
Age	0.001 (0.002)	0.000 (0.002)	0.003 (0.004)
Radio	0.060 (0.093)	0.102 (0.094)	0.476** (0.230)
Tv	0.106 (0.080)	0.065 (0.081)	-0.035 (0.187)
Climate shock	-0.011 (0.051)	-0.002 (0.051)	-0.046 (0.101)
Risk taking	0.024** (0.010)	0.025** (0.010)	0.058*** (0.019)
Trust	0.102*** (0.036)	0.104*** (0.037)	0.286*** (0.076)
Other information and advice sources	0.034 (0.105)	0.090 (0.097)	0.242 (0.167)
Constant	-0.467* (0.248)	-0.473* (0.249)	-1.313*** (0.497)
$R^2$	0.112	0.111	0.155
Observations	396	396	396

Notes: Robust standard errors in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table S12. Mobile Internet Use and Information, Full Estimation Results (OLS model)**

	<b>Weather Information</b>	<b>Price Information</b>	<b>Agri-Advice APP</b>
MIU	0.230*** (0.048)	0.349*** (0.048)	0.020 (0.022)
Income	0.022 (0.036)	0.157*** (0.036)	-0.011 (0.015)
Land holding	0.013 (0.018)	0.004 (0.017)	0.001 (0.010)
Household size	-0.024* (0.013)	-0.032** (0.014)	0.014 (0.009)
Female	0.027 (0.084)	0.009 (0.079)	-0.036** (0.017)
Age	-0.007*** (0.002)	-0.008*** (0.002)	-0.001 (0.001)
Years of schooling	0.010** (0.005)	0.007 (0.005)	0.004 (0.002)
Radio	0.103 (0.121)	0.047 (0.118)	-0.058*** (0.022)
TV	0.167*** (0.064)	0.014 (0.068)	0.033** (0.013)
Climate shock	-0.101** (0.045)	0.046 (0.046)	0.016 (0.025)
Risk taking	0.012 (0.009)	-0.008 (0.009)	0.008* (0.004)
Trust	0.117*** (0.034)	0.110*** (0.031)	-0.012 (0.015)
Other information and advice sources	-0.026 (0.082)	0.069 (0.083)	0.024 (0.015)
Constant	-0.092 (0.217)	-0.489** (0.218)	0.006 (0.116)
$R^2$	0.180	0.294	0.055
Observations	396	396	394

Notes: Robust standard errors in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .