Impacts of Smallholder Agricultural Adaptation on Food Security: Evidence from Africa, Asia, and Central America

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Abstract:

Understanding the efficacy of smallholder adaptation to changing environments is crucial to policy design. Past efforts in understanding whether, and to what extent, adaptation improves household welfare have faced some key challenges including: 1) endogeneity of adaptation; 2) localized results that are difficult to generalize; and 3) understanding whether the efficacy of adaptation depends on the reasons for adaptation (e.g. market conditions vs climate change). In this study we estimate effects of smallholder agricultural adaptation on food security, while addressing each of these three challenges. First, we identify and test instrumental variables based on neighbor networks. Second, we use a dataset that contains information from 5159 households located across 15 countries in Africa, Asia, and Central America. Third, we investigate whether adaptation that is motivated by changes in market conditions influences the efficacy of adaptation differently than adaptation motivated by climate change. Across our global sample, an average household made almost 10 adaptive changes, which are responsible for approximately 47 days of food security yearly; an amount nearly 4 times larger than is indicated if endogeneity is not addressed. But these effects vary depending on what is motivating adaptation. Adaptation in response to climate change alone is not found to significantly affect food security. When climate adaptation is paired with adaptation in response to changing market conditions, the resulting impact is 96 food secure days. These results suggest the need for further work on the careful design of climate change interventions to complement adaptive activities.

Key Words: Adaptation, Smallholder Agriculture, Food Security, Global Dataset, Instrumental Variables.

Running Page Title: Adaptation and Food Security in Smallholder Agriculture

1. Introduction

Changing market and climatic conditions can be a threat to food security (Lobel *et al.* 2008, IPCC 2007, Peri 2017, Usman and Haile 2017), which are likely to be disproportionately felt among smallholder farming households in areas that already suffer high levels of hunger (Muller *et al.* 2011, Wheeler and von Braun 2013). The adaptive activities[1] that households undertake are thought to be an important means of coping with changing circumstances (e.g. Biggs *et al*. 2013). Accordingly, several studies have analyzed the determinants of these adaptation decisions in order for policymakers to facilitate adaptation and mitigate the losses arising, for instance, from climate impacts (e.g. Deressa *et al.* 2009, Bryan *et al*. 2009, Di Falco 2014, Chen *et al.* 2018). Typically, these papers attempt to identify elements of adaptive capacity, and find that household characteristics such as level of education, farm and non-farm income, wealth, access to information and credit, farming experience, as well as participation in government programs, are significant factors that influence farmers' ability to undertake adaptive activities.

As smallholder farmers are already undertaking adaptive farm-level changes, it is important to understand how these types of adaptive behavior affect their welfare. Policymakers and development practitioners can use this information to target interventions to given contexts, and to assess whether policies aimed at incentivizing farmers to undertake adaptive activities are able to mitigate the anticipated losses arising from changing climatic and economic conditions.

Despite the importance of understanding the welfare impacts of adaptation, due to a number of difficulties, empirical evidence of how smallholder adaptation impacts welfare is scarce.[2] The objective

[1] Smallholder farming adaptation is typically defined along the lines of actions undertaken by households in order to better cope with or adjust to some changing condition, stress, hazard, risk or opportunity (e.g. Smit and Wandel 2006). Note that this concept of adaptation is similar to technology adoption, but different in at least two ways. First, while adaptation refers to a suite of potential actions that household can undertake, technology adoption is focussed on a particular activity. Second, while technology adoption focuses on a new activity that a household may try, adaptation can include ceasing activities, or reverting to old approaches that were temporarily abandoned

[2] We describe these difficulties briefly below, with a literature review supporting this statement in the next section.

of this paper is to investigate impacts of agricultural adaptation at the household level on food security, while addressing three types of difficulties.

First, estimates of how adaptation affects household welfare are plagued by empirical identification issues. In a typical (yet naïve) approach, the researcher would estimate a regression model using a welfare measure as a dependent variable, with an adaptation measure and a set of co-variates as independent variables. The challenge of such a regression is that adaptation is likely an endogenous variable. For instance, estimates could suffer from reverse causality because adaptation may influence welfare, but welfare may also influence adaptation. Therefore, there is a need to identify ways to consistently estimate the impacts of adaptation on welfare.

Our empirical strategy is to use an instrumental variable (IV) approach to address endogeneity of adaptation in welfare regressions. While numerous technology adoption papers have used IVs (e.g., Adekambi et al. 2009, Arellanes, and Lee 2003, Dibba et al. 2017 Ogada et al. 2010), we are not aware of any IVs that have been developed for studying welfare effects of adaptation. Our method relies on the concept that information relevant to agricultural adaptation flows within a neighbor network. In order to identify an IV approach, we turn to a group of papers that find that neighbors in developing countries learn from each other and these interactions influence household behavior (Keil et al. 2017, Foster and Rosenzweig 1995, Ward and Pede 2014, Krishnan and Patnam 2014). The neighbor networks effects on farmers' decisions suggest a set of instruments to address the endogeneity of adaptation in welfare regressions. Specifically, our instrumental variables are weighted averages of adaptation and human capital characteristics of neighbors, with weights inversely proportional to the physical distance between farms. Under-identification and over-identification statistical tests provide support for the validity of these instruments.

Second, most studies attempting to link adaptation to welfare are limited by data collected from local case studies, which provide little information regarding the generalizability of results. Our dataset contains socio-economic and agricultural practices information collected by Climate Change, Agriculture and Food Security (CCAFS) from more than five thousand households located in 15 developing countries in Africa, Asia, and Central America. We use as our welfare measure the number of food secure days that households experience in a year, and we use the number of adaptive activities that households undertake as our measure of agricultural adaptation.[3] Moreover, the CCAFS dataset contains farm-level Global Positioning System coordinates that allow us to build the neighbor networks required in our IV approach. The dataset also allows us to estimate adaptation effects controlling for various co-variates, including levels of education, farm characteristics, financial factors, productive and non-productive assets, demographics, farming experience, and participation in government programs. Our estimations also control for varying crop mix and site-specific effects.

Third, though adaptation to climate change is currently a widespread concern, there are numerous types of changes that could be spurring adaptation. Within this context, there is the potential that the impact of adaptation on food security could vary depending on the type of change to which smallholders are responding. In our study, we employ data that indicate whether adaptive activities are undertaken in response to climate change, changes in market conditions, or both. This data allow us to investigate whether smallholders are able to use adaptation to better cope with some types of changes, rather than others.

Overall, we find that smallholder adaptation is welfare improving with respect to food security. Our estimates indicate that, on average, undertaking one additional adaptive activity leads to approximately 5 additional days of food security in a year, or put differently, adaptive activities are responsible for 16% of the food security of smallholders. The effect is robust to the specification of crop mix, varying models of network effects (i.e. varying approaches to calculate the spatial weights of

[3] We also consider two measures of adaptation that assign weights to different adaptive activities. Specifically, first we follow Shikuku et al. (2017) and estimate models where adaptation is measured using a food security-based index that assigns weights to activities based on their contributions to food security. Next, we used a principal component analysis and assign weights to different activities based on the first principal component.

our instrumental variables), and using weighted measurements of adaptation. We also show that spatially weighted network transformations of adaptation and human capital are well suited to estimate IV food security regressions, and that not correcting for the endogeneity of adaptation significantly underestimates impacts on food security benefits. Finally, we report empirical evidence suggesting that the food security impacts of adaptation are generally more effective in responding to changing market conditions than in responding to climate change.

This paper is organized as follows. Section 2 discusses the literature related to approaches for using observational data to estimate the impact of adaptation on welfare measures. Section 3 describes the sampling framework, the data, and the empirical model. Section 4 presents diagnostics tests for our IV approach, along with the model estimates. We offer some concluding remarks in section 5.

2. Related Literature

A number of studies have examined the link between smallholder farmers' adaptation activities and their welfare (e.g. Di Falco *et al*. 2011, Di Falco and Veronesi 2013). This section presents a discussion of this literature with a focus on the three challenges discussed above.

The first challenge is the endogeneity of adaptation in the estimation of welfare benefits. Scholars have adopted a number of approaches to address this difficulty. One group of papers employ switching regression approaches. For example, Di Falco and Veronesi (2013) use a multinomial endogenous switching regression model to estimate the effect of adaptation strategies on crop net revenues of farmers. These authors argue that both the decision to adapt and what strategy to use are endogenous as these factors may be influenced by unobservable characteristics and might, for example, lead to self-selection bias. Their approach consists of two stages. First, they use a multinomial selection to model farmers' strategy choices from a (relatively small) set of possible strategies. Second, they estimate a net revenue model for each strategy in the choice set. They find that a combination of adaptation strategies is more effective than a single strategy in increasing crop revenues.

Several papers assume that farmers face a binary strategy set: to adapt or not to adapt. Di Falco *et al.* (2011) estimate a two-stage endogenous switching model and find that adaptation leads to significant increases in food productivity. In particular, they find that households who adapted would have produced 20% less if they did not adapt. Moreover, households who did not adapt would have produced 35% more if they had adapted. Huang *et al.* (2015) use a similar approach and show that households that implement farm-level changes in response to extreme weather events experience significant increases in yield. Using the same approach, Asfaw *et al*. (2012) find that adaptation in terms of adopting improved varieties generates a significant positive impact on consumption expenditures.

Other papers complement endogenous switching models with propensity score approaches. Khonje *et al*. (2015) examine welfare impacts of smallholder farmer adaptation using both a regression and propensity score matching (PSM). First they estimate a binary endogenous switching model. Second, they implement a PSM strategy as a robustness check. Their methods suggest that the adoption of improved maize varieties increases crop income, consumption expenditures, and food security. Shiferaw *et al*. (2014) use a similar approach, and in addition to endogenous switching regressions and PSM, they also use a two-step generalized propensity score (GPS) approach. The GPS approach differs from PSM in that it allows for varying intensities of treatment (e.g. varying adaptation levels as opposed to binary adaptation). Their GPS approach consists of two steps. They first estimate a GPS model to balance covariates, and follow this step with a regression model of the outcome (i.e. food consumption expenditures and a food security binary indicator) where treatment (adaptation) level is a right hand side variable. They find a positive relationship between intensity of adaptation (area devoted to improved wheat) and food security and consumption.

Most studies focus on a small set of farming changes. Di Falco and Veronesi (2013) focus on three types of changes (water strategies, changing crop varieties, and soil conservation) and their combinations, while Di Falco *et al*. (2011), Asfaw *et al*. (2012), and Huang *et al.* (2015) examine binary adaptation choice. In contrast, our approach allows us to explore the rich nature of our data to use information on 46 possible changes in farming practices (refer to section 3). Such a variety of adaptation strategies rules out the possibility of estimating multinomial choice models like in Di Falco and Veronesi (2013). In addition, as most households adopted at least one of the 46 possible strategies, the binary (to adapt or not) identification strategy used by Di Falco *et al*. (2011), Asfaw *et al*. (2012), and Huang *et al.* (2015) would be problematic with our data. For example, in our sample, all households from Ghana, Kenya, Niger, and Senegal adopted at least one new farming practice.

Also, note that the validity of PSM depends on the assumption that, controlling for the probability of adaptation, the outcome of interest (e.g. food security) and the adaptation status (adapted or not) are independent. The probability of adaptation is estimated using observable determinants, and therefore the matching approach controls for endogenous adaptation using observable heterogeneity, and is sensitive to selection based on unobservables. The literature refers to this assumption as the conditional independence assumption (CIA). As Angrist and Pischke (2009) explain, assuming consistency of matching estimators under the CIA is equivalent to assuming consistency of estimates from a regression of food security on adaptation and controls. Nevertheless, above we refer to this approach as the *naïve regression* because it is very likely that there are unobservable factors that are correlated to adaptation decisions, even after controlling for available co-variates. In fact, the attractiveness of the IV approach lies on offering a solution when the CIA is not reasonable. When a valid instrument is available, the IV approach is able to address multiple sources of endogeneity of adaptation.[4]

While PSM uses binary adaptation status, the GPS method (Shiferaw *et al*., 2014) allows for varying adaptation levels. Nevertheless, the method relies on the same independency assumptions as the standard PSM methods. Moreover, Hirano and Imbens (2004) argue that the estimated coefficients from the second stage regression do not have a causal interpretation. This weakness would be problematic for us, as estimating the effect of adaptation intensity on food security is the primary goal of our paper. As a result, we develop an instrumental variable approach to address the endogeneity of adaptation and establish a causal relationship between farming practices changed and food security.

The second challenge is the limited spatial context of most studies. The findings reported by the papers above are based on case studies with localized data, and as a result, they often reflect a focus on a specific crop. Huang *et al.* (2015) focus on rice production of 1,653 households in five rice producing provinces of China. The analysis of Khonje *et al.* (2015) is based on a sample of 810 households located in major maize growing areas of eastern Zambia. Shiferaw *et al*. (2014) examine 2,017 smallholder wheat producers in the eight main wheat-growing agro-ecological zones of Ethiopia. Di Falco and Veronesi (2013) and Di Falco *et al*. (2011) study adaptation of 941 smallholder farmers in the Nile Basin of Ethiopia. The sampling of Asfaw *et al*. (2012) focus on chickpea and pigeonpea production among 700 households in the Shewa region in the central highlands of Ethiopia, and 613 households in four districts of Northern Tanzania. Finally, Shikuku et al. (2017) offer a wider investigation by focusing on East Africa; however, the work is limited to a sample of 500 households from the CCAFS dataset (a subset of the data that we employ here). In contrast, our large dataset with more than five thousand households allows us to investigate a broader link between smallholder farmer adaptation and food security in developing countries, while controlling for crop and site effects. To this

[4] We also note that matching approaches are often motivated by the fact that IVs are hardly available. Interestingly, PSM estimates would not benefit from having an IV available. Recent research shows that the inclusion of IVs in matching approaches actually *maximizes* inconsistency (Wooldridge 2016).

end, our estimates use data on more than five thousand households located in 15 countries (see Table 1), which increases the external validity of our results.

The third challenge in the empirical estimation of impacts of adaptation is the possible dependence of welfare results to the *reasons* for adaptation. For example, welfare effects could depend on whether adaptation is spurred by changes in market conditions, or motivated by climate change. These differential effects could imply alternative policy approaches; say for example, if adaptation were effective in responding to changing market conditions, but not climate change. But, to our knowledge, there has been very little work on adaptation and welfare impacts in the context of market changes and climate change stimuli. Eakin et al. (2014) and Gandure et al. (2013) look at relative risk perceptions of market vs. climate change, and find that market changes were generally perceived as higher risks than climate change. But the focus of both of these studies was on risk perceptions, with little, if any, information on resulting adaptive behaviour. To our knowledge, only one study has considered both market and climate changes as reasons for change (Chen et al. 2018), and such information was used to explain adaptation rather than welfare impacts on households.

In summary, the literature review above discloses three primary contributions of our paper regarding estimating impacts of adaptation on household welfare. First, though a number of alternative approaches have been employed to address the potential endogeneity of adaptation, we are unaware of any studies that have used an IV approach. Our identification of an effective IV strategy provides an alternative approach for future studies. Second, our review discloses that studies that have addressed endogeneity concerns have been limited to localized sites or regions. To our knowledge, ours is the first study to investigate whether impacts of adaptation on welfare are generalizable over multiple countries, while addressing the endogeneity issue. Finally, we are unaware of any studies that have investigated whether the reason for changing farming practices has variable effects on household welfare. We investigate this by using a split sample approach to estimate reason dependent food security gains from adaptation.

3. Methods

3.1. Data

We use a rich dataset from the CCAFS research program collected in West Africa, East Africa, South Asia, and Central America.[5] Data were collected from late 2010 to late 2013 for the Africa and Asia sites, and in 2014 for the Central America sites[6]. Households were sampled from randomly located 10x10 km sampling blocks; 30x30km sites were selected in West Africa and Ethiopia due to low population densities. Within each block, 20 households in each of seven villages were randomly selected. The dataset contains information from 5,314 households from 39 sites in 15 countries. Incomplete data for some of these households leave us with 5,159 observations. Table 1 contains a more detailed description of our sample and its distribution across regions, countries, and sites. Kristjanson *et al.* (2010) contains more details on the sampling framework.

⇨ **Table 1. Distribution of the CCAFS data set sample across Regions, Country and Sites.**

3.2. Empirical Approach

We hypothesize that adaptation positively contributes to food security. To empirically investigate this relationship, we estimate the following regression model:

$$FS_{is} = \alpha A_{is} + X_{is}'\beta + Z_{is}'\gamma + \lambda_s + \varepsilon_{is} \qquad (1)$$

[5] Lobell *et al*. (2008) identify South Asia, East Africa, and West Africa, three regions where households in our sample are located, as major food-insecure regions in the world.
[6] The data are available online at Harvard Dataverse (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/IUJQZV)

where FS_{is} is the number of food secure days (in a year) of household i in site s, A represents adaptation (number of farming practices changed), X are control variables, Z are crop dummies (used to control for variation in food security as a function of the household's crop mix), λ is a site fixed effect, and ε is an idiosyncratic error term.[7] Our statistical tests allow for within site correlations by clustering standard errors at the site level.

The potential endogeneity of adaptation is a challenge for econometric identification. To address this challenge, we exploit the spatial information of households in our data. Literature shows that the spatial position of neighbors may influence the formation of networks, which in turn could affect adaptation decisions (e.g. Foster and Rosenzweig 1995). This observation suggests an IV approach for the identification of model (1). Our proposed set of instruments to identify welfare impacts are adaptation and human capital measures of a farmer's neighbor, weighted by their spatial proximity. Let W represent a spatial weighting matrix. An element (i,j) of W captures the strength of the spatial correlation between households i and j. As a result, W can be thought of as a neighbor network where the strength of the link between two households is inversely proportional to their spatial distance. Specifically, W is a row normalized inverse distance matrix, with truncation at 10km such that the influence of households beyond the truncation point is set to zero. This truncation allows for a simple specification of spatial effects, and the threshold of 10km matches the dimensions of the sites for the vast majority of our sample.[8] Let X^* denote the portion of X that captures education levels. Our set of instruments is WA and WX^*, where WA is the spatially weighted average adaptation of farmers' neighbors, and WX^* is the spatially weighted average education of farmers' neighbors.

Our instrumental variable identification strategy is inspired by the spatial econometrics literature where instruments are spatial lags of the right-hand side variables based on normalized

[7] We discuss these variables in detail in the next section.
[8] In the results that follow, we also do robustness checks for shorter and longer distances and show that results are not sensitive to the truncation point.

weighting matrices (Kelejian and Prucha 1998, Lee 2003). The strength of these instruments depends on the strength of their correlation with adaptation. There are several reasons for a strong correlation between our spatial and human capital spillover instruments and adaptation. First, as mentioned above, empirical research suggests that adaptation of new technologies (e.g., high-yielding seed varieties) is influenced by the adaptation behavior of neighbors (Foster and Rosenzweig 1995). This result suggests that neighbor adaptation WA is correlated with own adaptation A. Second, adaptation-related learning happens primarily in local networks because neighbors and close farmers experience similar economic and climactic conditions and are likely to have relevant information about adaptation. Indeed, farmers' networks have been shown to be more effective in influencing behavior than specialized extension services (Foster and Rosenzweig 1995, Conley and Udry 2010, Krishnan and Patnam 2014, Ward and Pede 2014). As a result, we expect the level of human capital of farmers' networks WX^* to be correlated with own adaptation A. Finally, the existence of human capital and adaptation spillovers is also in line with the fact that major adaptation programs (for example, the United Nations Climate Change program in Uganda)[9] focus on developing tools and enabling farmers to adapt, as opposed to other strategies with less spillover effects such as direct cash or food transfers. In addition to the economic arguments above, we use an F-test to statistically examine the correlation between our instruments and adaptation.

The validity of our instruments also relies on the assumption that neighbors' adaptation and adaptive capacity (WA and WX*) are not correlated with the unobservable determinants of food security, and does not affect food security directly but only indirectly through adaptation levels A. Therefore, this assumption may not hold if, for example, adaptation generated higher wealth, enhanced welfare, and allowed individuals to systematically share this higher wealth with neighbors. This would create a link between own adaptation and neighbors food security, weakening our instruments. Note,

[9] Source: United Nations Climate Change. Available online at https://unfccc.int/climate-action/momentum-for-change/ict-solutions/enabling-farmers-to-adapt-to-climate-change (Accessed on July 10, 2018).

however, that this triangulation is unlikely to be effective in poor rural regions of developing countries. The significant negative effect of household size on food security and other important adaptive constraints faced by poor households (e.g., Babatundea and Qaimb, 2010) make it unlikely that direct transfers between neighbors are an effective means of providing food security, especially in the most vulnerable and food insecure regions of the world, represented in our sample. In addition to F-tests, we also use under-identification and over-identification tests to check the validity of our instruments.[10]

Note that our approach is based on a linear model as opposed to a nonlinear count model. Our choice is motivated by difficulties in implementing instrumental variable strategies to nonlinear models. Instrumental variable approaches when directly applied to nonlinear models typically deliver inconsistent estimates. Wooldridge (2010) refers to this method as the 'forbidden regression'. One estimation approach for nonlinear endogenous variable models is the control function approach. However, this approach is less reliable when the endogenous variable is not continuous, which is the case with our measure of adaptation. Deeper discussions of these issues are available in Lewbel et al. (2013), Lloyd-Smith et al. (2018), and Lloyd-Smith et al. (2019). In addition, maximum likelihood estimation of count models is inconsistent under heteroskedasticity of unknown form. These issues are mitigated by the specification of a linear regression model. Our GMM estimator is consistent and inference is based on robust standard errors clustered at the site level.

3.3. Variables

We measure welfare in terms of food security (i.e. *FS* from equation 1). Households were asked to identify, for a typical year, periods when they tend to struggle to find sufficient food, or experience shortages to feed their families. We measure the number of days in a year the household does not experience shortage to feed the family and use this number to capture the food security of households. This measure has been used in the literature (e.g. Kristjanson *et al*. 2012) and follows the definition of

[10] The findings of all statistical tests are discussed in the results section.

Pinstrup-Andersen (2009) in which a household is food secure "if it has the ability to acquire the food needed by its members to be food secure" (p.6).[11] A summary of our variables, and their descriptive statistics, in Table 2 shows that on average, households in our sample experience 293 food secure days per year, with a standard deviation of approximately 84 days.

⇨ ***Table 2. Variable Descriptions and Descriptive statistics (n=5159)***

Our measure of adaptation (i.e. *A* from equation 1) is based on responses of households regarding changes that were made in households' farming activities within the past 10 years. Households were instructed to select all alternatives that would apply from a list of 46 farming practices (Table 3). To measure adaptation, we count the total number of changes to farming practices made by each household. Households responses for the questions about changes in farming practices were captured with binary indicators (e.g. response =1 for yes, "stopped using manure/compost"). Therefore, the mean values in the Table represent the proportion of the households in the sample that implemented the change.

⇨ ***Table 3. Activities and descriptive statistics associated with changes in farming practices (n=5159)***

In order to identify effects of adaptation on household welfare, it is also necessary to control for elements of adaptive capacity. Poor households in rural areas of developing countries face numerous economic constraints that help identify the adaptive capacity of households (e.g. Mendelsohn 2012). These determinants include variables that capture various socio-economic characteristics of households (see for example, Smit 2001, Yohe and Tol 2002, Feder *et al*. 1985). Our model includes controls for

[11] Our measure for food security primarily captures food access and is expected to be correlated with caloric availability. However, the concept of food security is thought to have a number of dimensions that are difficult to capture with any one measure (FAO et al. 2018). Nevertheless, for our study, we are limited to the data collected as described above. .

these socio-economic factors, as they may influence smallholder farmers' welfare (i.e. *X* from equation 1). The CCAFS survey provides us with a number of variables that capture human capital, access to information, financial and physical assets, farm and household characteristics, and farming and climate crises experience. The variables that we employ for each of these categories are described in Table 2.

We also include in our model controls for the types of crops that each household grows. Dummy variables for 10 crops (see Table 4) are included to control for possible differential effects of crop mix on food security (i.e. *Z* from equation 1). These crops represent the most important crops of our sample as they are grown by at least 5% of our households. Our estimation also controls for local characteristics (e.g. weather) of each of the 39 sites shown in Table 1 (i.e. site fixed effects).

⇨ Table 4. Crop Summary Statistics (n=5159)

Finally, we investigate differential effects of alternative stimuli for adaptation by segmenting our sample. In addition to asking households about their changing farming practices, farmers were also asked whether the changes were caused by climate variability and/or market conditions. We split our sample into four groups to estimate models targeting different motivators for changing farming practices. The first group contains 1,036 households (20% of the sample) that did not adapt in response to climate or market; this is our baseline group whose adaptation was not in response to either of these two factors. The second group contains 483 households (9% of the sample) that adapted due to climate variability only. The third group has 1,286 households (25% of the sample) that adapted due to market conditions only. Finally, the fourth group contains 2,354 households (46% of the sample) whose agricultural adaptation was in response to both climate variability and market conditions. For each of these segments, we run separate models and compare the impacts of adaptation on food security.

4. Results

Table 5 shows the results of four estimated models, which explore potential differences in results of using instrumental variables and fixed effects. OLS1 is an ordinary least squares model that does not include instrumental variables or crop fixed effects. The OLS2 model adds crop fixed effects. The next two models employ the widely utilized two step generalized method of moments instrumental variable approach. IV/GMM1 includes instrumental variables, but not crop fixed effects, while IV/GMM2 adds crop fixed effects.

We begin with results of statistical tests regarding the validity of the instruments we employ in our IV/GMM models, presented in the bottom of Table 5. First, we test whether the instruments are correlated with the endogenous variable. The F statistic of the auxiliary regression of A on WA and WX^* is equal to 979.18 ($p<0.001$), which indicates that the correlation between the instruments and adaptation is statistically significant. Next, we use the Kleibergen-Paap test of under-identification to examine whether the excluded instruments (neighbors' adaptation and education) are correlated with the endogenous variable (own adaptation) under the assumption of site-level clustering (Kleibergen and Paap 2006). Table 5 shows that we reject the null, that the equation is under-identified, with $p<0.05$ in both instrumental variable models. Finally, we perform a test of over-identifying restrictions. The test uses Hansen's J test statistic (Hansen 1982). It is based on the joint null hypothesis that the excluded instruments are uncorrelated with the error term of the food security regression, and that they are correctly excluded from the food security equation. If the test statistic is significant, the instruments may not be valid. We fail to reject the null hypothesis with p-values of 0.16 and 0.17 for, respectively, the IV/GMM1 and IVGMM2 models. These results provide support that our proposed set of instruments is valid.

We now turn to the estimates of equation 1. Our central concern is to quantify the impact of agricultural adaptation on food security, which is captured by our estimate of α in equation 1. Our preferred (IV/GMM) estimates indicate a positive and statistically significant relationship between adaptation and food security. We find that one additional farming practice changed increases food security of smallholder farmers by 4.8 days. Interestingly, this effect does not depend on crop effects (i.e. the estimates of α in IV/GMM1 and IV/GMM2 are very similar). The IV/GMM estimates that account for the endogeneity of adaptation are approximately 4 times larger than estimates obtained through a standard OLS regression. This result underscores the importance of correcting for endogeneity when estimating the impacts of adaptation on welfare.

The magnitudes and significance of the control coefficients in Table 5 indicate that the results are generally robust across the four models. In particular, variables that increase food secure days, which are consistent across all specifications of the model, include having a bank account (approx. 11 more food secure days), having rental income (approx. 10 more food secure days), and having more non-productive assets (approx. 5 more food secure days for each asset). Conversely, variables that decrease food secure days include having more people in a household (approx. 1 less food secure day per additional person) and having faced a climate related crisis (approx. 14 less food secure days).

There are, however, two control variables whose coefficients are substantially different when the model is estimated with instrumental variables. First, whether a family has been farming in the same locality for 10 years is highly significant and large in the OLS models, while it is insignificant and much smaller in the IV/GMM models. Second, whether the farm has access to running water is also highly significant and large in the OLS models, but smaller and marginally significant when crop effects and instruments are used.

⇨ **Table 5: Model Results**

We further investigate the robustness of our IV/GMM models by running additional IV specifications. We are interesting in the sensitivity of results to two key aspects of the weighting matrix

W; distance truncation and normalization. In Table 5, we defined neighbor networks as having potential impacts to a distance of 10 km. In addition to the 10 km truncation, the spatial weights of our IVs were based on row normalization of inverse distances. Both row and spectral normalizations are common in spatial analysis. While row normalization makes the row sum of the weights in *W* equal to 1, with spectral normalization the weighting matrix is normalized so that the largest eigenvalue of *W* is equal to 1. Table 6 shows results where we modify our instruments. Estimates reported in the first two columns keep row normalization but vary the spatial designations of neighbor networks (i.e. a 5 km truncation for IV/GMM3 and a 50 km truncation for IV/GMM4). Estimates of the last column use our standard 10 km truncation but the IVs are based on spectral weights.

Estimates of models IV/GMM3 and IV/GMM4 are similar to those IV/GMM estimates in Table 5. Moreover, across all of the distance truncations, the instrumental variables tests again provide evidence in favor of our spatial identification strategy. This suggests that our instrumental variable approach based on row normalized weights is not sensitive to the specification of spatial truncation. The final model, IV/GMM5, investigates whether spectral normalization of the weighting matrix influences the results. The IV/GMM5 model is estimated with 10km truncation, so is comparable to the models IV/GMM1 and IV/GMM2. The estimate of the effect of adaptation on food security is larger in model IV/GMM5. In this model, the instrumental variables statistical tests offer mixed empirical support for the identification strategy (contrary to the case of row normalized instruments). Specifically, while we are not able to reject the null in the Hansen over-identification test (which is evidence in favor of the strategy as a rejection generates uncertainty on the validity of the instrumental variables), the Kleibergen-Paap under-identification test indicates that we cannot reject the null of no correlation between the instruments and the endogenous variable. We conclude that spatial effects based on row normalized spatial weights generate better instrumental variables for use in estimating welfare regressions.

⇨ **Table 6: Robustness Checks Regarding Distance and Spatial Matrix Properties**

Note that our approach is based on an adaptation measure that counts adaptive activities and implicitly assumes equal weights to each activity. Previous works warrant caution regarding this assumption (e.g. Below et al 2012; Shikuku et al 2017). As another robustness check, we estimate model IV/GMM2 using two different methods to incorporate activity weights. The first is to use principal component analysis to determine weights. Specifically, we implement a weighting scheme based on the first principal component (which explains 16% of the total variance) and measure adaptation as the weighted sum of adaptive activities. The second method computes a food security-based index where weights are given by the marginal contribution of each adaptive activity to food security. Specifically, we follow Shikuku et al (2017) and regress our outcome variable, food secure days, on the set of activity indicators. The predicted level of food security is used as a weighted adaptation index. While regressions using these adaptation indices make the magnitudes of the effects not comparable to the estimates in Table 5, both methods confirm previous results; adaptation significantly increases food security.

Our estimates with IVs indicate that changing an additional farming practice increases food security, on average, by 4.8 days (see Table 5). For the mean household, that made approximately 9.8 farming practices changes (see Table 2), the effect of adaptation is approximately 47 additional days of food security in a year. These results imply that policies aimed at fostering smallholder farm agricultural adaptation can significantly improve the welfare of farmers.

We further explore our data by examining the effects of adaptation that is motivated by market conditions and climate change. Table 7 shows the average number of farming practices changed by each of the four segments of the sample; changes due to: i) neither reason (n=1036), ii) both reasons (n=2354), iii) climate reason only (n=483), or iv) market reason only (n=1286). Households in the baseline group (i.e. neither reason) changed approximately 2 farming practices while households that respond to climate and market conditions changed 13.5 practices. Interestingly, households that respond to climate (but not to market conditions) only adapt with approximately half as many activities as those that respond to the market (but not to climate variability).

⇨ **Table 7: Average number of farming practices changed, by reason for adaptation**

For each subsample, we estimate equation 1 using instrumental variables based on row-normalized weighting matrices with 10km truncation, and with site and crop fixed effects (i.e. the specification followed in model IV/GMM2). Table 8 shows, for each group, the estimate of the marginal effect of adaptation of food security ($\hat{\alpha}$) and its 95% confidence interval.[12] We estimate that an increase in one adaptive activity from the baseline group increases food security by 5.6 days; however this estimate is not statistically significant. The marginal effect estimate for the climate variability group is 4.4; however, again we cannot reject the null of no effect. Households that adapt due to market conditions increase their food security, on average, by 7.5 days per farming practice changed ($p<0.01$). Similarly, those who adapt to both market conditions and climate variability increase their food security by 7.1 days per practice changed.[13] For the households that adapt with double motivation, the average contribution of adaptation to food security is an impressive 95.6 days (i.e., 7.09 per practice changed times 13.48 changes, on average). These households have, on average, 295.6 days of food security in a year; hence, agricultural adaptation provides 32% of their yearly food security.

[12] Full model estimates are available upon request.
[13] The confidence intervals of these two estimates (i.e. 7.51 and 7.09) significantly overlap indicating that they are not statistically different from one another.

⇨ **Table 8: Marginal effect of adaptation on the number of food secure days, by reason for adaptation**

5. Summary of Contributions, Limitations, and Concluding Remarks

This paper offers several contributions to the literature on the welfare impacts of adaptation. Overall, we find that adaptation, in terms of an additional farming practice changed, increases food security by approximately 5 days. For an average household that makes almost 10 adaptive changes, adaptation is responsible for approximately 47 more days of food security. Put differently, our results indicate that approximately 16% of the food security of smallholder farmers in our sample comes from their adaptive activities. Other factors that increase food security include having: a bank account, income from renting land or machinery, larger numbers of non-productive assets, running water, and 10 or more years of farming experience. Factors that decrease food security include larger household sizes, and having experienced a climate-related crisis in the last 5 years. Our finding, that adaptation is welfare improving, is in line with a number of empirical studies that address the endogeneity issue in analyzing the welfare impacts of adaptation at the household level (e.g. Di Falco *et al*. 2011; Di Falco and Veronesi 2013).

These results also reflect a number of more specific contributions of this study. First, our study employs spatial or neighbour network effects to construct instrumental variables to address endogeneity of adaptation in food security models. Our proposed set of instruments (that are validated by under-identification and over-identification tests) offers researchers an additional identification strategy to analyze the welfare impacts of adaptation. We also show the importance of correcting for endogeneity in adaptation, in that our IV/GMM estimates of impacts of adaptation on food security are up to 4 times larger than estimates derived from models that do not correct for endogenous adaptation. The larger impact of adaptation on number of food secure days, after instrumenting for adaptation, demonstrates the importance of addressing endogeneity. Our results show that ignoring this identification challenge can underestimate the welfare contribution of adaptation.

Second, while earlier work has focused on case studies or farmers living in localized geographical regions, this paper uses a dataset that contains information on more than five thousand households located across 3 continents (Africa, Asia, and Central America) and 15 countries (Bangladesh, Burkina Faso, Costa Rica, Ethiopia, Ghana, India, Kenya, Mali, Mozambique, Nepal, Nicaragua, Niger, Senegal, Tanzania, and Uganda). This dataset substantially enhances the external validity of our findings and allows us to provide robust and generalizable estimates of welfare impacts of household-level adaptation.

Third, we investigate whether the impact of adaptation on household welfare differs depending on whether adaptation is motivated by changes in market conditions or climate change. Results indicate that adaptation motivated by climate change alone does not significantly impact food security, while adaptation done in response to market conditions is welfare enhancing. When adaptation is done in response to both climate variability and market conditions, our results indicate that an additional farming practice changed increases food security by approximately 7 days, which, when extrapolated over an average of approximately 13 activities, leads to an average effect of 96 food secure days (or 32% of their food security). These results suggest that households have been more successful at adapting to changing market conditions than in responding to climate change. Therefore, as impacts of climate change increase, in addition to policy approaches designed to increase adaptive capacity, it may be necessary to design targeted interventions (e.g. irrigation schemes, information dissemination) that complement the adaptive capacities of households.

Despite the robustness of our results, some cautionary notes are in order. First and foremost, our study (like most adaptation studies) relies on data derived from recall regarding behavioral changes over long periods. An alternative approach could be to design a randomized control trial, or a natural (quasi) experiment, that would measure more immediate changes in behavior (e.g. Duflo *et al*. 2011). However, the implementation of such methods in 15 countries would be challenging, and a smaller sample would limit the external validity of these approaches. Though we believe that the breadth of our sample is a strength, this contribution comes at a cost of lower resolution. For example, understanding heterogeneity in results across geographic regions and types of farming systems would provide useful information for policy development. Though initial inquiries into regional differences in adaptive behaviour have been investigated (Chen et al. 2018) much more work is needed.

In assessing food security effects on adaptation, it is challenging to develop econometric approaches for identifying causal impacts, such as finding valid instrumental variables to control for endogeneity. Several studies have used detailed data on social networks, and used social learning variables as instruments in identifying causal impacts of agricultural innovations. Unfortunately, our dataset has no social networks information. Instead, our approach is to construct instruments based on neighbor networks as defined by GPS coordinates. The outcome of such an approach is a general network variable - one that includes social learning and other types of networks. In our developing country settings, networks can play several roles, from information exchange to borrowing and risk sharing. Our use of this general network variable as an IV is only valid to the extent that memberships in such networks do not directly influence food security. Otherwise, our results represent correlations rather than causations.

Our approach requires spatial information. We use Global Positioning System coordinates to calculate distances between households, which is needed to build the weighting matrices and hence the instrumental variables. This requirement limits the application of this approach to existing datasets that contain spatial markers. Given Global Positioning System technology, which makes it increasingly cheaper and easier to collect such information, we suggest that collecting these coordinates could become standard practice when applying survey instruments, not only for network analysis, but for other uses such as maintaining options of relocating households to collect panel data. We also have little information about how changing market conditions and adaptation affect food security. Changing market conditions could include new market opportunities for smallholders that may require adaptation. But changing market conditions could also imply more volatility and price risks that could cause smallholders to adapt by moving away from activities involved with volatile prices. Both of these circumstances might encourage adaptive activities, but could result in different impacts on the food security of households. Future research could unpack more specific scenarios regarding changing market conditions, and investigate how different types of responses lead to differences in food security. Understanding these behaviours in the context of climate change risks would provide valuable information for understanding local behaviour and policy design.

Overall, our findings support economic concepts of rational households, who can be effective in adapting to changing circumstances in ways that attempt to ameliorate negative changes, thereby improving welfare. But for some types of newly emerging threats, such as climate change, these abilities to adapt may need to be complemented with carefully designed interventions, as data indicate that historic adaptation has not been clearly welfare improving. With further research in this area, we are hopeful that governments will be in a better position to design policies that not only promote better adaptive capacity, but also complement such capacity with developments that better enable the effectiveness of adaptation.

Conflict of Interest

The authors declared that they have no conflict of interest.

References

Adekambi, S.A., Diagne, A., Simtowe, F., and Biaou, G. 2009. The Impact of Agricultural Technology Adoption on Poverty: The case of NERICA rice varieties in Benin. Conference paper presentation. International Association of Agricultural Economists (IAAE) 2009 Conference, August 16-22, 2009, Beijing, China.

Angrist, J. D., and Pischke, J.-S. (2009). Mostly harmless econometrics: An empiricist's companion. Princeton: Princeton University Press.

Arellanes, P. and Lee, D.R., 2003. The Determinants Of Adoption Of Sustainable Agriculture Technologies: Evidence From The Hillsides Of Honduras. 2003 International Association of Agricultural Economists Annual Meeting, August 16-22, 2003, Durban, South Africa.

Asfaw, S., B. Shiferaw, F. Simtowe, and L. Lipper. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy* 37(3): 283-295.

Babatundea, Raphael O.and Matin Qaimb. (2010). Impact of off-farm income on food security and nutrition in Nigeria. *Food Policy*, 35(4) 303-311.

Below, T.B., Mutabazi, K.D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., Tscherning, K., 2012. Can farmers' adaptation to climate change be explained by socioeconomic household-level variables? *Global Environmental Change* 22, 223–235.

Biggs, E. M., E. L. Tompkins , J. Allen , C. Moon and R. Allen (2013) Agricultural adaptation to climate change: observations from the Mid-Hills of Nepal, *Climate and Development*, 5:2, 165-173.

Chen M., B. Wichmann, M. Luckert, L. Winowiecki, W. Foerch, and P. Laderach (2018). Diversification and Intensification of Agricultural Adaptation from Global to Local Scales, PLoS ONE 13(5): e0196392. https://doi.org/10.1371/journal.pone.0196392.

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). CCAFS Baseline Household Level Survey. Copenhagen, Denmark: Available from: www.ccafs.cgiar.org.

Conley, T. G. and Udry, C. R. (2010). Learning About a New Technology: Pineapple in Ghana. *American Economic Review*, 100(1):35-69.

Deressa T., Hassan, R., Ringler, C., Alemu, T., and Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change* 19(2):248-255.

Dibba, L., Zeller, M., and Diagne, A. 2017. The impact of new Rice for Africa (NERICA) adoption on household food security and health in the Gambia. *Food Security* 9(5): 929–944.

Di Falco, S. (2014). Adaptation to Climate Change in Sub-Saharan Agriculture: Assessing the Evidence and Rethinking the Drivers. *European Review of Agricultural Economics*, 41(3):405-430.

Di Falco, S. and Veronesi, M. (2013). How Can African Agriculture Adapt to Climate Change? A Counterfactual Analysis from Ethiopia. *Land Economics*, 89(4):743–766.

Di Falco, S., Veronesi, M., and Yesuf, M. (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3):829–846.

Duflo E, M Kremer, J Robinson. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review* 101(6): 2350–2390.

Eakin, H., Tucker, C.M., Castellanos, E., Diaz-Porras, R., Barrera, J.F., Morales, H. 2014. Adaptation in a multi-stressor environment: perceptions and responses to climatic and economic risks by coffee growers in Mesoamerica. *Environment, Development and Sustainability*. (16)1: 123-139.

FAO, IFAD, UNICEF, WFP and WHO. (2018). *The State of Food Security and Nutrition in the World 2018.* Rome, FAO.

Feder G, Just RE, Zilberman D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Econ Devel Cult Change*. 33(2):255–298.

Foster, A. D. and Rosenzweig, M. R. (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy*, 103(6):1176–1209.

Gandure, S. Walker, S., and Botha, J.J. 2013, Farmers' perceptions of adaptation to climate change and water stress in a South African rural community. *Environmental Development* (5): 39-53.

Hansen, L. P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*, 50(4):1029–1054.

Hayashi, F. (2000). Econometrics. Princeton, New Jersey: Princeton University Press.

Hirano, K. and G.W. Imbens. (2004). The Propensity Score with Continuous Treatments. X. Meng, A. Gelman (Eds.), Applied Bayesian Modelling and Causal Inference from Incomplete-Data Perspectives, Wiley.

Huang, J., Wang, Y., and Wang, J. (2015) Farmers' Adaptation to Extreme Weather Events through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China. *American Journal of Agricultural Economics*. 2(1): 602–617.

Keil, A., D'souza, A., McDonald, A. 2017. Zero-tillage is a proven technology for sustainable wheat intensification in the Eastern Indo-Gangetic Plains: what determines farmer awareness and adoption? *Food Security* 9(4): 723–743

Kelejian, H. H. and Prucha, I. R. (1998). A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances. *The Journal of Real Estate Finance and Economics*, 17(1):99–121.

Khonje, M., J. Manda, A.D. Alene, M. Kassie. (2015). Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development* 66: 695-706.

Kleibergen, F. and Paap, R. 2006. Generalized Reduced Rank Tests Using the Singular Value Decomposition. *Journal of Econometrics*, Vol. 133, pp. 97–126.

Krishnan, P. and Patnam, M. (2014). Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption? *American Journal of Agricultural Economics*, 96(1):308–327.

Kristjanson, P., Förch, W., Barahona, C., Garlick, C., Thornton, P.K. 2010. CCAFS Baseline Household Level Survey – Manual for Survey Sites. Copenhagen, Denmark: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Available from: www.ccafs.cgiar.org.

Kristjanson, P., Neufeldt, H., Gassner, A., Mango, J., Kyazze, F. B., Desta, S., Sayula, G., Thiede, B., F¨orch, W., Thornton, P. K., and Coe, R. (2012). Are Food Insecure Smallholder Households Making Changes in Their Farming practices? Evidence from East Africa. *Food Security*, 4(3):381–397.

Lee, L. F. (2003). Best Spatial Two-Stage Least Squares Estimators for a Spatial Autoregressive Model with Autoregressive Disturbances. *Econometric Reviews*, 22(4):307–335.

Lewbel A, Dong Y, Yang TT (2013) Comparing features of convenient estimators for binary choice models with endogenous regressors. Canadian Journal of Economics 45(3): 809–829.

Lloyd-Smith, P., Schram, C., Adamowicz, W. et al. (2018). Environmental and Resource Economics 69: 217.

Lloyd-Smith, P. W. Adamowicz, and D. Dupont. (2019). Incorporating Stated Consequentiality Questions in Stated Preference Research, Land Economics, Volume 95, Number 3, August 2019, pp. 293-306.

Lobell, D. B. and Burke, M.B (2010). Chapter 8: Adaptation - What Do We Know? In Lobell, D.B. and Burke, M.B (eds.) Climate Change and Food Security. Springer.

Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., Falcon, W. P., and Naylor, R. L. (2008). Prioritizing Climate Change Adaptation Needs for Food Security in 2030. *Science*, 319(5863):607–610.

Lobell, D.B., Banziger, M., Magorokosho, C., and Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature Climate Change* 1, 42-45.

Mendelsohn, R. (2012). The Economics of Adaptation to Climate Change in Developing Countries. *Climate Change Economics*, 3(02).

Muller, C., Cramer, W., Hare, W., and Lotze-Campen, H. (2011). Climate change risks for African Agriculture. *PNAS*. 108(11): 4313:4315.

Ogada, M.J., Nyangena, W., and Yesuf, M. 2010. Production risk and farm technology adoption in the rain-fed semi-aridshi lands of Kenya. *African Journal of Agricultural and Resource Economics* 6: 159-174.

Paul, C.J., Weinthal, E.S., Bellemare, M.F., and Jeuland, M.A. (2016). Social capital, trust, and adaptation to climate change: Evidence from rural Ethiopia. *Global Environmental Change*. 36:124-138.

Peri, M. (2017). Climate variability and the volatility of global maize and soybean prices. *Food Security*, 9(4): 673-683.

Pinstrup-Andersen, P. (2009). Food Security: Definition and Measurement. *Food security*, 1(1):5–7.

Schlenker, W. and Lobell, D. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters* 5(1): 1-8.

Shiferaw, B., M. Kassie, M. Jaleta, C. Yirga. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy* 44: 272-284.

Shikuku, K.M., Winowiecki, L., Twyman, J., Eitzinger, A., Perez J.G., Mwongera, C. and Läderach, P. 2017. Smallholder farmers' attitudes and determinants of adaptation to climate risks in East Africa. *Climate Risk Management* 16:234-245.

Smit, B. and Pilifosova, O. (2001). Adaptation to Climate Change in the Context of Sustainable Development and Equity. In McCarthy, J., Canziani, O., Leary, N., Dokken, D., and White, K., editors, Climate Change 2001: Impacts, Adaptation, and Vulnerability, Climate Change 2001: Impacts, Adaptation and Vulnerability, chapter 18, pages 877–912. Cambridge University Press, Cambridge.

Smit, B. and Wandel, J. (2006). Adaptation, Adaptive Capacity and Vulnerability. *Global Environmental Change*, 16(3):282-292.

Stock, J.H. and Yogo, M. 2002. Testing for Weak Instruments in Linear IV Regression. NBER Technical Working Paper 284.

Usman, M.A. & Haile, M.G. (2017). Producer to retailer price transmission in cereal markets of Ethiopia. *Food Security,* 9: 815.

Ward, P. S. and Pede, V. O. (2014). Capturing Social Network Effects in Technology Adoption: The Spatial Diffusion of Hybrid Rice in Bangladesh. *Australian Journal of Agricultural and Resource Economics,* 58.

Wheeler, T. and von Braun, J. (2013). Climate Change Impacts on Global Food Security. *Science* 341(508).

Wooldridge JM (2010) Econometric analysis of cross section and panel data, 2nd edn. MIT Press, Cambridge.

Wooldridge, J. (2016). Should instrumental variables be used as matching variables? *Research in Economics*, 70(2): 232-237.

Wuepper, D., Ayenew, H.Y., Sauer, J. (2017). Social Capital, Income Diversification and Climate Change Adaptation: Panel Data Evidence from Rural Ethiopia. *Journal of Agricultural Economics*. *Forthcoming.*

Yohe, G. and Tol, R. S. (2002). Indicators for Social and Economic Coping Capacity Moving Toward a Working Definition of Adaptive Capacity. *Global Environmental Change*, 12(1):25–40.

Intergovernmental Panel on Climate Change, 2007. Climate change 2001: impacts, adaptation and vulnerability – contribution of working group II to the third assessment report of IPCC.

Table 1. Distribution of the CCAFS data set sample across Regions, Country and Sites.

Region	**Country**	**Number of Sites**	**Number of Households**
West Africa	Ghana	1	140
	Burkina Faso	1	139
	Mali	1	141
	Niger	1	140
	Senegal	1	138
East Africa	Mozambique	2	266
	Ethiopia	1	140
	Kenya	2	279
	Tanzania	1	134
	Uganda	2	280
South Asia	Bangladesh	7	783
	India	10	1362
	Nepal	5	668
Central America	Costa Rica	1	132
	Nicaragua	3	417
Total	15	39	5,159

Table 2. Variable Descriptions and Descriptive statistics (n=5159)

Variable	Description	Mean	Standard Deviation
DEPENDENT VARIABLE *(FS IN EQUATION 1)*			
Food Security	number of days in a year that the household does not experience a shortage of food to feed the family	292.7	84.121
MEASURE OF ADAPTATION *(A IN EQUATION 1)*			
Count of Adaptive Activities	Number of adaptive activities undertaken by a household in the past 10 years (see Table 3)	9.790	6.479
HUMAN CAPITAL *(X^* – PART OF X IN EQUATION 1)*			
Education – primary	1 if the highest level of education attained by any household member is primary	0.373	0.484
Education – secondary	1 if the highest level of education attained by any household member is secondary	0.333	0.471
Education – post-secondary	1 if the highest level of education attained by any household member is post-secondary	0.192	0.394
ACCESS TO INFORMATION & FINANCE *(PART OF X IN EQUATION 1)*			
Access to weather information	1 if any "Yes" to question "Did you receive any information?"	0.731	0.443
Bank account	1 if household has a bank account	0.329	0.470
Cash from the government	1 if "Yes" to question "Any cash income during the last 12 months?" with source from projects/government	0.325	0.469
Income from renting out land or machinery	1 if "Yes" to question "Any cash income during the last 12 months?" with source from renting out machinery/land	0.143	0.350
ASSETS *(PART OF X IN EQUATION 1)*			
Count of production-related assets	Count of ownership of the following items: mechanical plough, mill, generator, battery, water pump, biogas digester, thresher, LPG, fishing nets, and solar panel	0.756	1.172
Count of nonproduction-related assets	Count of ownership of the following items: radio, television, cell phone, bicycle, computer, improved stove, refrigerator, air conditioning, electric fan, and internet access	2.639	1.837
Livestock	1 if household owns large or small livestock	0.865	0.342
Motorcycle	1 if household owns a motorcycle	0.160	0.367
Boat	1 if household owns a boat	0.008	0.091
FARM & HOUSEHOLD CHARACTERISTICS *(PART OF X IN EQUATION 1)*			
Running water	1 if household has running/tap water	0.170	0.375
Storage facility for crops	1 if household has improved storage facility for crops	0.227	0.419
Planted trees	1 if household has planted at least one tree on his farm	0.369	0.483
Household size	Number of people living in a household	6.058	3.042
Household is female-headed	1 if the gender of household head is female	0.101	0.301
FARMING & CRISIS EXPERIENCE *(PART OF X IN EQUATION 1)*			

Variable	Description	Mean	Standard Deviation
Farming experience is at least 10 years	1 if "Yes" to question "Have you or your family been farming or keeping animals or fish in this locality for 10 years or more?"	0.923	0.267
Experienced climate crisis in the last 5 years	1 if "Yes" to question "Have you faced a climate related crisis in the last 5 years?"	0.701	0.458

Note: Detailed descriptions for each variable are available from CCAFS Baseline Household Level Questionnaire

(Available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/IUJQZV)

Table 3. Activities and descriptive statistics associated with changes in farming practices (n=5159)

Changes in Activities undertaken within the past 10 years	Mean	Standard Deviation
Crop management Activities		
1. Introduced any new crop	0.338	0.473
2. Are you testing any new crop	0.093	0.290
3. Stopped growing a crop (totally)	0.457	0.498
4. Stopped growing a crop (in one season)	0.231	0.421
5. Introduced intercropping	0.439	0.496
6. Introduced rotations	0.228	0.420
7. Earlier planting	0.271	0.445
8. Later planting	0.172	0.378
9. Started using or using more pesticides/herbicides	0.384	0.486
10. Stared using integrated pest management	0.043	0.202
11. Started using integrated crop management	0.036	0.185
Changing Crop Variety Activities		
12. Introduced new variety of crops	0.714	0.452
13. Planting higher yielding variety	0.619	0.486
14. Planting better quality variety	0.449	0.497
15. Planting pre-treated/improved seed	0.346	0.476
16. Planting shorter cycle variety	0.388	0.487
17. Planting longer cycle variety	0.159	0.366
18. Planting drought tolerant variety	0.193	0.395
19. Planting flood tolerant variety	0.059	0.235
20. Planting salinity-tolerant variety	0.016	0.127
21. Planting toxicity-tolerant variety	0.004	0.065
22. Planting disease-resistant variety	0.206	0.405
23. Planting pest-resistant variety	0.162	0.369
24. Testing a new variety	0.123	0.329
25. Stopped using a variety	0.475	0.499
Soil, Water and Land Management Activities		

Changes in Activities undertaken within the past 10 years	Mean	Standard Deviation
26. Expanded area	0.474	0.499
27. Reduced area	0.404	0.491
28. Started irrigating	0.109	0.312
29. Stopped irrigating	0.010	0.098
30. Stopped burning	0.090	0.286
31. Introduced crop cover	0.051	0.220
32. Introduced micro-catchments	0.034	0.182
33. Introduced/built ridges or bunds	0.082	0.274
34. Introduced mulching	0.065	0.246
35. Introduced terraces	0.050	0.217
36. Introduced stone lines	0.020	0.140
37. Introduced hedges	0.045	0.207
38. Introduced contour ploughing	0.049	0.217
39. Introduced improved irrigation (water efficiency)	0.104	0.305
40. Introduced improved drainage	0.023	0.150
41. Introduced tidal water control management	0.014	0.116
42. Introduced mechanized farming	0.258	0.437
43. Earlier land preparation	0.390	0.488
44. Started using or using more mineral/chemical fertilizers	0.515	0.500
45. Started using manure/compost	0.337	0.473
46. Stopped using manure/compost	0.063	0.242

Table 4. Crop Summary Statistics (n=5159)

Crop*	Mean	Standard Deviation
Rice	0.405	0.491
Maize	0.388	0.487
Wheat	0.333	0.471
Beans	0.200	0.400
Millet	0.116	0.320
Sorghum	0.102	0.303
Cowpeas	0.082	0.274
Banana	0.069	0.254
Cassava	0.066	0.249
Peanuts	0.066	0.249

* Dummy variable that equals one if the crop is cultivated by the household, zero otherwise.

Table 5: Model Results

	OLS1	OLS2	IV/GMM1	IV/GMM2
Count of adaptive activities	1.709***	1.243***	4.766***	4.759***
	(0.400)	(0.410)	(1.369)	(1.343)
Education – primary	4.052	3.162	-0.689	-0.668
	(4.360)	(4.218)	(4.135)	(3.980)
Education – secondary	5.048	3.576	-3.565	-3.190
	(5.276)	(5.008)	(5.831)	(5.394)
Education – post-secondary	8.417	6.584	-2.214	-1.752
	(5.262)	(5.032)	(6.246)	(5.487)
Access to weather information	-1.995	-2.489	-3.139	-2.963
	(4.292)	(4.304)	(4.447)	(4.158)
Bank account	12.691***	12.222***	10.678***	10.980***
	(3.015)	(2.867)	(2.752)	(2.649)
Cash from the government	4.874	5.592	4.575	4.205
	(3.447)	(3.370)	(2.951)	(2.895)
Income from renting out land or machinery	10.333***	9.877***	9.739**	9.642**
	(3.428)	(3.305)	(3.707)	(3.607)
Count of production-related assets	2.184	2.181	0.502	0.608
	(1.735)	(1.816)	(1.840)	(1.867)
Count of nonproduction-related assets	5.616***	5.701***	5.289***	5.397***
	(1.292)	(1.313)	(1.205)	(1.220)
Livestock	5.464	4.844	1.552	1.572
	(4.369)	(4.285)	(4.033)	(3.939)
Motorcycle	-0.600	-0.653	0.005	-0.142
	(2.873)	(2.851)	(2.736)	(2.608)
Boat	1.636	0.247	1.152	1.869
	(9.394)	(9.408)	(7.597)	(7.517)
Running water	10.924**	11.181**	7.131	7.534*
	(4.630)	(4.316)	(4.350)	(4.056)
Storage facility for crops	-0.862	-1.746	-6.235	-6.543
	(3.467)	(3.540)	(4.490)	(4.236)
Planted trees	0.458	0.903	-2.810	-2.455
	(2.604)	(2.641)	(3.062)	(3.117)
Household size	-0.788*	-0.897*	-1.186***	-1.163***
	(0.453)	(0.444)	(0.426)	(0.428)
Household is female-headed	-2.916	-3.199	-1.004	-1.061
	(3.715)	(3.625)	(3.955)	(3.997)
Farming experience is at least 10 years	14.269***	9.983**	3.483	4.151
	(4.689)	(4.503)	(5.538)	(4.571)
Experienced climate crisis in the last 5 years	-14.040***	-13.905**	-14.533***	-14.244***
	(5.155)	(5.299)	(4.669)	(4.738)
Site Effects	Yes	Yes	Yes	Yes
Crop Effects	No	Yes	No	Yes
Kleibergen-Paap Under identification test (p-value)	-	-	0.0342	0.0295

Hansen Over identification test (p-value)	-	-	0.1559	0.1674
R^2	0.41	0.41	0.38	0.38
N	5,159	5,159	5,159	5,159

Notes: Cluster-robust standard errors are reported in parentheses. Standard errors are clustered at the site level.
For the IV/GMM models, the instrumental variables are the spatial lags of adaptation and education levels. The weighting matrix uses a 10km spatial truncation and is row normalized. * p<0.1; ** p<0.05; *** p<0.01

Table 6: Robustness Checks Regarding Distance and Spatial Matrix Properties

	IV/GMM3	IV/GMM4	IV/GMM5
Spatial Matrix Specification:			
Truncation	5 km	50 km	10 km
Normalization	Row	Row	Spectral
Count of Adaptive Activities	4.655***	4.991***	6.364*
	(1.309)	(1.390)	(3.448)
Access to weather information	-3.236	-3.083	-9.609
	(4.126)	(4.278)	(6.750)
Education – primary	-0.509	-1.211	0.855
	(3.999)	(3.963)	(4.585)
Education – secondary	-2.742	-4.215	0.793
	(5.411)	(5.314)	(6.463)
Education - post-secondary	-1.279	-2.790	1.840
	(5.504)	(5.402)	(6.953)
Bank account	11.015***	10.839***	13.255***
	(2.650)	(2.636)	(3.167)
Cash from the government	4.279	4.146	0.181
	(2.922)	(2.895)	(3.542)
Income from renting out land	9.675**	9.235**	8.518*
or machinery	(3.589)	(3.651)	(4.255)
Count of production-related	0.672	0.405	1.336
assets	(1.855)	(1.866)	(2.104)
Count of nonproduction-	5.436***	5.443***	5.121***
related assets	(1.196)	(1.227)	(1.337)
Livestock	1.997	1.633	-1.266
	(3.970)	(3.931)	(4.377)
Motorcycle	-0.184	0.033	-2.236
	(2.614)	(2.599)	(2.593)
Boat	1.539	2.739	-4.289
	(7.625)	(7.451)	(8.402)
Running water	7.789*	7.197*	6.755
	(4.069)	(4.040)	(4.177)
Storage facility for crops	-6.363	-6.968	-8.754
	(4.143)	(4.316)	(7.162)
Planted trees	-2.321	-2.524	-3.256
	(3.094)	(3.134)	(3.989)
Household size	-1.158**	-1.192***	-0.907*
	(0.429)	(0.425)	(0.459)
Household is female-headed	-1.365	-0.870	-2.115
	(3.982)	(4.004)	(4.818)
Farming experience is at least	4.262	4.027	6.090
10 years	(4.537)	(4.587)	(5.949)
Experienced climate crisis in	-14.206***	-14.365***	-15.904***
the last 5 years	(4.730)	(4.738)	(4.943)
Site Effects	Yes	Yes	Yes
Crop Effects	Yes	Yes	Yes

Kleibergen-Paap Under identification test (p-value)	0.0174	0.0331	0.4007
Hansen Over identification test (p-value)	0.2039	0.1288	0.5170
R^2	0.38	0.38	0.35
N	5,159	5,159	5,159

Notes: Cluster-robust standard errors are reported in parentheses. Standard errors are clustered at the site level.
* p<0.1; ** p<0.05; *** p<0.01

Table 7: Average number of farming practices changed, by reason for adaptation

	Climate Variability (No)	Climate Variability (Yes)
Market Conditions (No)	2.28 (3.59)	5.93 (4.32)
Market Conditions (Yes)	10.47 (4.07)	13.48 (5.61)

Note: Standard deviations are in parenthesis.

Table 8: Marginal effect of adaptation on the number of food secure days, by reason for adaptation

	Climate Variability (No)	Climate Variability (Yes)
Market Conditions (No)	5.64 [-9.63 , 20.91]	4.43 [-7.70 , 16.56]
Market Conditions (Yes)	7.51*** [1.91 , 13.12]	7.09*** [2.12 , 12.06]

Note: Squared brackets show 95 % confidence interval. ** p<0.05, *** p<0.01.