How Can We Help Farmers When They Are Already Clever? Adaptation and Neighbor Networks

by

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Abstract

The ability of farmers to adapt to changing rural environments in developing countries is an important determinant of welfare. However, farmers' adaptation may be constrained by their adaptive capacity because economic resources, information, and institutions are often weak or missing in these areas. Networks of relationships can potentially ease these constraints and facilitate adaptation by acting as conduits of information and resources.

The contribution of this thesis is three-fold. First, using the number of farming practices households have changed over the last ten years as our measure of adaptation, we investigate network effects on farmers' adaptation decisions. We use spatial econometric techniques to estimate the effects of adaptive capacity elements and neighbors' adaptation on farmers' adaptation. Second, we propose an approach that analyzes whether or not the adaptation of a subset of neighbors also generates significant network effects. We decompose the total network effect into network effects coming from the most central household, the two most central households, and so on. Third, using the number of food secure days in a year as a measure of households' welfare, we show how the network interactions of households suggest instrumental variables that can be used to address the endogeneity issue in welfare analysis.

We use a rich dataset that contains information from 2,095 households located across 12 countries in Africa and Asia. Our data allows us to examine the importance of network effects, in addition to traditional adaptive capacity elements reported in the literature.

We find that neighbors significantly influence adaptation decisions, and network interactions amplify the marginal effects of adaptive capacity elements by 50 percent. In addition, we find that there are benefits to targeting fewer, but more central, households. Finally, we find that one additional farming practice changed increases welfare by 5.5 food secure days. Our results imply that investing in adaptation programs that relax adaptive capacity constraints could help farmers improve their welfare, and network effects not only catalyze the impacts of policy interventions but also offer a targeting strategy.

To mum and dad,

for praying with me and for me every single night.

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Chapter 1

Introduction

Farmers in rural areas of developing countries make agricultural decisions in the context of innumerous uncertainties, such as changing conditions in climate, prices, and institutions. Economists have noted that these farmers are clever[1] (i.e. rational) and will respond to these challenging circumstances, yet many of these farmers remain poor (e.g Schultz, 1980). While this characteristic of poor but rational appears to create a challenge in the design of development policies because farmers are already doing the best they can to cope with change, the possibility remains that policymakers could help farmers improve their welfare by leveraging on their responsive nature.

Adapting their farming practices is one way farmers respond to challenging situations. For instance, farmers adjust planting dates, switch crop varieties, adopt soil conservation practices, and expand cropped areas to accommodate changing growing conditions and other economic incentives (Burke and Lobell, 2010). Adaptation[2] is especially important in rural areas of developing countries that rely on agriculture as their main source of income. Studies show that variation in environmental characteristics, market risks, policy changes, and the interaction of these factors are expected to have a negative impact on agricultural productivity in these areas (Howden et al., 2007; O'Brien et al., 2004).

[1] We define clever farmers as rational economic agents that make optimal choices often subject to constraints.

[2] This thesis uses Smit and Wandel's (2006, p. 282) definition in which adaptation "refers to an action in a system (household, community, group, sector, region, country) in order for the system to better cope with, manage or adjust to some changing condition, stress, hazard, risk or opportunity."

Adaptation, however, may be constrained by farmers' adaptive capacity.[3] Understanding the factors that constrain farmers' adaptation is important because developing policies that relax these constraints could potentially lead to more adaptation, which in turn could lead to higher welfare. In addition, Hertel and Lobell (2014) argue that the extent to which farmers will be negatively affected by these challenging circumstances depends crucially on their ability to adapt. Access to information, human capital, financial resources, physical assets, demographics, and farming experience have all been suggested as contributors to the adaptive capacity of farmers (Di Falco, 2014; Smit and Pilifosova, 2001; Yohe and Tol, 2002; Feder et al., 1985). Many of these adaptive capacity elements are, however, weak or missing in rural areas of developing countries (Hertel and Lobell, 2014; Dow et al., 2013; Mendelsohn, 2012; Binswanger and Deininger, 1997). These resource and institutional constraints explain why some farmers, who are motivated to adapt and improve their welfare, struggle (Abler and Sukhatme, 2006).

Networks of relationships may be another element of adaptive capacity that can potentially ease some of these constraints (e.g. Smit and Wandel, 2006). Empirical studies in development economics have found that networks play a significant role in risk-sharing, information dissemination, and technology adoption; all features that could facilitate adaptation (see Chuang and Schechter (2015) for a recent review). Despite the potential importance of networks of relationships on adaptation, empirical evidence of network effects on adaptation is scarce.

Neighbor networks are one type of these relationships and may be particularly important in the context of adaptation. For example, neighbors could provide informal loans and gifts to support adaptation investments (Fafchamps and Gubert, 2007). Farmers could also learn about adaptation from their neighbors because they live close and are more likely to experience similar environmental and economic conditions (Krishnan and Patnam, 2014). In addition, neighbors could share more relevant information about adaptation than extension service officers (Ward and Pede, 2014). Indeed, the behavior of neighbors has been found to be more important than extension services in influencing own behavior (e.g. Krishnan

[3]This thesis uses Smit and Wandel's (2006, p.287) definition in which adaptive capacity refers to "the forces that influence the ability of the system to adapt."

and Patnam, 2014; Rogers, 2003). In addition to potentially augmenting adaptive capacity, neighbor networks may also multiply the impacts of policy interventions that faciliate adaptation. In particular, interaction among households in neighbor networks can lead to a network multiplier effect that amplifies elements of adaptive capacity (Anselin, 2003). As a result, neighbor networks can cause the total impact of a policy intervention, such as the provision of information or credit access, to be greater than its first-order impact.

The primary goal of this thesis is to investigate the role of neighbor networks on adaptation and show how policymakers can take advantage of the network multiplier effect to influence the adaptation and welfare of farmers. We pursue this goal through three research objectives, which we discuss in detail below.

To accomplish our goal, we use a rich dataset collected by the Climate Change, Agriculture, and Food Security (CCAFS) research program in late 2010 to early 2011 that contains information of 2,095 households located in 108 villages across 12 different countries in West Africa, East Africa, and South Asia. The dataset offers multiple elements of adaptive capacity reported in the literature, such as access to information (Lemos et al., 2012; Ricker-Gilbert et al., 2008; Atanu et al., 1994), credit (Cai et al., 2014; Dercon and Christiaensen, 2011; Giné and Yang, 2009), and ownership of assets (Aker, 2010; Jensen, 2007; Foster and Rosenzweig, 1995). In addition, the dataset includes multiple stimuli to adaptation, including climate variation, market conditions, and policy changes (Hertel and Lobell, 2014; Ewert, 2012; Gbetibouo, 2009; Westerhoff and Smit, 2009). This wealth of information allows us to estimate the relative importance of different elements of adaptive capacity on adaptation. Whereas existing studies on farmers' adaptation decisions are local case studies (e.g. Di Falco et al., 2011; Deressa et al., 2009; Bryan et al., 2009), our use of a dataset that features households located in multiple and very different settings not only offers a unique opportunity to explore whether adaptation and adaptive capacity elements transcend geographical borders but also provides robust and generalizable findings.

The first objective is to estimate the effects of elements of adaptive capacity, including neighbor networks, on adaptation. We measure adaptation as the number of farming practices that households have changed over the last ten years. We start with a Baseline

Model, which analyzes the impacts of traditional adaptive capacity elements reported in the literature, without neighbor networks, on adaptation. Next, we estimate a Neighbor Network Model, in which we transform the Baseline Model into a spatially autoregressive (SAR) model by adding neighbors' adaptation as an element of adaptive capacity. By using a SAR model, we are able to estimate the network effect (i.e. the impact of neighbors' adaptation) and marginal impacts of traditional elements of adaptive capacity that are disentangled from the network effects. Our estimation strategy follows the approach proposed by Kelejian and Prucha (1998) and refined in Lee (2003) that uses characteristics of neighbors as instruments. This strategy addresses the "reflection problem," which is a common challenge in estimating network effects because the adaptation of farmers may influence the adaptation of their neighbors, and visa versa (Manski, 1993). The estimation results of our Baseline and Neighbor Network Models show that the ability of farmers to adapt is not only affected by traditional elements of adaptive capacity, such as access to information and credit, but also by their neighbors' adaptation decisions. In addition, because farmers are responsive to their neighbors' behavior, the impacts of policy interventions that help farmers adapt could be amplified. These findings suggest the importance of including networks of relationships in adaptation studies.

The second objective is to show how network effects can be used to inform the design of policy interventions. We propose a targeting approach, where we use data on the geographical locations of households in a village to construct weighted network centrality measures as a method to identify potentially influential households in neighbor networks. We decompose the total network effect obtained from the Neighbor Network Model into network effects coming from most central household, the two most central households, the three most central households, and so on. This approach allows us to generate insights about which, and how many, households policymakers should target to exploit network effects. The results of our targeting approach suggest that a subset of central households in a village can positively and significantly influence farmers' adaptation decisions. This finding implies that there are benefits to targeting policy interventions towards fewer, but more central, households. This result is especially important when costs of an intervention are convex in the number of targeted households. With costs increasing at an increasing rate, the net benefit from a policy intervention may be maximized when a fraction of the households in a village are targeted. Our results complement other network-based targeting studies. For instance, Banerjee et al. (2013) find that it matters which people are targeted with information, and the network centrality of households strongly and significantly predicts the uptake of microfinance in a village. Our targeting approach provides policymakers with a framework to help them to compare the benefits of targeting different numbers of households relative to costs associated with various scales of interventions.

The third objective is to analyze the welfare impacts of adaptation. While adaptation is generally thought of as being a desirable process, the literature that provides empirical evidence of welfare benefits arising from adaptation is scarce. One reason for this gap is the issue of reverse causality, in that adaptation may increase welfare, or visa versa (Kristjanson et al., 2012). We use as our welfare measure the number of food secure days that households experience in a year. Our welfare model uses an instrumental variable approach to address endogeneity. The statistically significant network effect on farmers' adaptation decisions suggests a set of instruments that can be used to address endogeneity. Specifically, we use the characteristics of neighbor networks as instruments, and statistical tests provide support for the validity of these instruments. Our proposed set of instruments offers the literature an additional identification strategy to analyze the welfare impacts of adaptation. In addition, our analyses show that adaptation is welfare improving with respect to food security. We find that not correcting for endogeneity underestimates the welfare benefits of adaptation. These results imply that policies aimed at easing adaptive capacity constraints can improve the welfare of farmers, and the presence of a strong neighbor network effect means that policymakers have the opportunity to influence the welfare of more farmers than they initially reach.

The remainder of this thesis is organized as follows. Chapter 2 describes the data and presents our Baseline Adaptation Model. Chapter 3 describes the spatial data and presents our Neighbor Network Adaptation Model. Chapter 4 explains our Household Targeting Model. Chapter 5 discusses our Welfare Model. Chapter 6 summarizes and concludes.

Chapter 2

Baseline Adaptation Model

We assume that the adaptation decisions of farmers are a function of their adaptive capacity. The literature suggests that access to information and human capital, financial resources, physical assets, demographics, and crisis and farming experience all contribute to the ability of farmers to adapt (Di Falco, 2014; Smit and Pilifosova, 2001; Yohe and Tol, 2002; Feder et al., 1985). These elements of adaptive capacity provide farmers with the resources to be aware of ongoing changes as well as the tools to respond to those changes.

A challenge in estimating adaptation decisions is omitted variable bias (e.g. Auffhammer et al., 2013). Our data allows us to account for possible confounding effects by providing us with multiple elements of adaptive capacity that are known to affect adaptation decisions (see Di Falco (2014) for a review). Further, whereas recent farm-level adaptation studies focus on adaptation decisions in response to climate stimuli only (e.g Di Falco et al., 2011; Deressa et al., 2009; Bryan et al., 2009), our data permits us to disentangle the relative importance of other stimuli that farmers adapt to, including market conditions, pests issues, policy changes, land productivity, and labor availability (Hertel and Lobell, 2014; Ewert, 2012; Gbetibouo, 2009; Westerhoff and Smit, 2009; O'Brien et al., 2004; Winters et al., 1998).

In this chapter, we present our baseline econometric model on adaptation, where we estimate the effects of traditional elements of adaptive capacity reported in the literature on adaptation. Our Baseline Model allows us to compare our results with the literature before we add network effects in the next chapter (Chapter 3).

We begin this chapter by first describing the study sites. Next, we present our Baseline Model and discuss the variables we use to capture the adaptive capacity of farmers. Finally, we discuss our regression results.

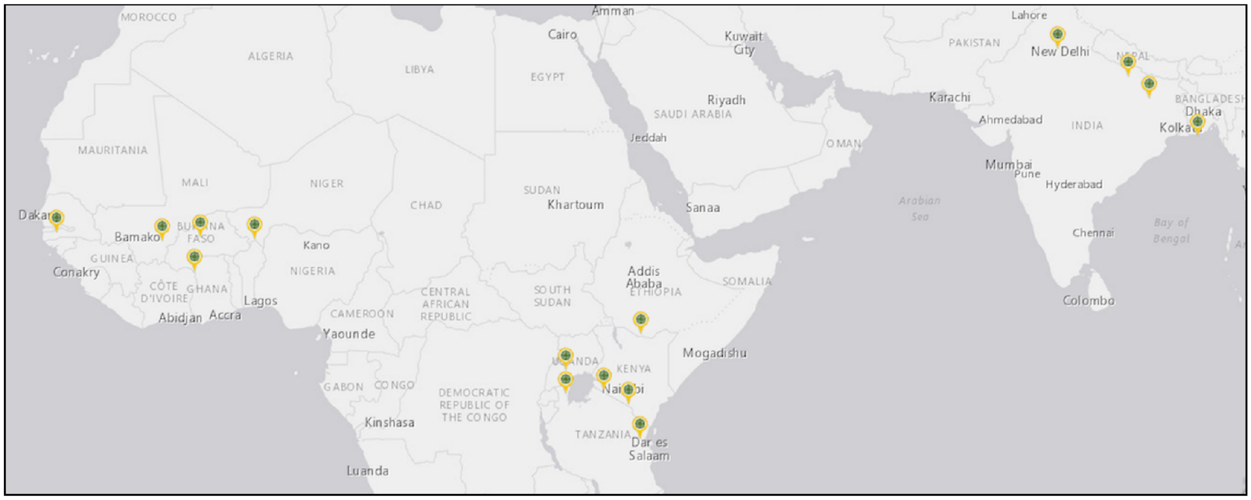
2.1 Study Sites

Our data comes from the household-level survey that CCAFS administered from late 2010 to early 2011 in East Africa, West Africa, and South Asia (CCAFS, 2013). As reported by Wiebke et al. (2013), CCAFS chose these three regions because they represent areas with high levels of poverty and vulnerability, different social and institutional contexts, and climate-related challenges with opportunities for interventions. Using criteria that include biophysical and agro-ecological gradients, socio-economic and demographic characteristics, anticipated climate change, and existing CGIAR research efforts, CCAFS selected 15 sites located in 12 countries (i.e. Ethiopia, Kenya, Tanzania, Uganda, Ghana, Burkina Faso, Mali, Niger, Senegal, Bangladesh, India, and Nepal). Figure 2.1 shows the location of these sites. CCAFS identified each site by designating a 10 by 10 kilometer rectangular block of land, or in areas with low population densities, 30 by 30 kilometer blocks.[4] Within each site, seven villages were randomly chosen, and approximately 20 households within each village were randomly selected for interview.[5] In summary, CCAFS collected information from 2,095 households in 108 villages. However, because of missing data, total observations used in this thesis are 2,043 households. The first three columns of Table 2.1 list the regions, countries, sites, and number of households in each site where the survey was implemented.

[4]Sites where 30 by 30 kilometer blocks were used as the sampling frame are Ethiopia, Mali, Niger, Burkina Faso, Senegal, and Ghana. See Wiebke et al. (2013) for more details about the criteria, sampling selection, and sites.

[5]There are 5 villages where 10 households in each village were interviewed. There is 1 village where 12 households were interviewed. There are 2 villages where 18 households in each village were interviewed. There are 5 villages where 19 households in each village were interviewed. There are 93 villages where 20 households in each village were interviewed. There are 2 villages where 21 households in each village were interviewed.

Figure 2.1: Map of Study Sites



Source: Adaptation and Mitigation Knowledge Framework

2.2 The Baseline Regression Model

The conceptual framework underlying our econometric analysis of adaptation relies on the idea that farmers are rational decision-makers that choose adaptation levels to maximize their household's welfare. Farmers' adaptation decisions may be constrained by their adaptive capacity. In general, we expect adaptive capacity constraints to be binding in developing countries, such as the countries included in this study, because of limited economic resources or weak institutions (Hertel and Lobell, 2014; Dow et al., 2013; Mendelsohn, 2012; Binswanger and Deininger, 1997; Reilly and Hohmann, 1993). Relaxing such constraints may therefore lead to higher levels of adaptation.

Our Baseline Model investigates how elements of adaptive capacity explain variation in farmers' adaptation decisions. Formally, the econometric specification of our Baseline Model can be written as:

$$\mathbf{Y} = \mathbf{X}\beta + \epsilon \tag{2.1}$$

where $\mathbf{Y}$ is a vector of farmers' adaptation, $\mathbf{X}$ is a matrix of elements of adaptive capacity, and ϵ is an error term that captures unobserved determinants of adaptation.

There are two types of adaptation studies that investigate the factors driving farmers' adaptation decisions reported in the literature. The first type looks at the determinants of the extensive margin of adaptation, i.e. the decision to adapt. As a result, these papers capture farm-level decisions with a binary variable (Di Falco, 2014; Di Falco et al., 2011; Deressa et al., 2009; Bryan et al., 2009; Maddison, 2007). The second type examines the determinants of adaptation intensity. These studies are interested in learning about how farmers choose adaptation *levels*, i.e. how much to adapt. Examples include Roco et al. (2014), Below et al. (2012), and Kristjanson et al. (2012). Moreover, the literature that analyzes the adoption of multiple farming practices, such as integrated pest management or soil conservation, widely uses levels to model adoption decisions (e.g. Sharma et al., 2011; Lohr and Park, 2002; Ramírez and Shultz, 2000)

The detailed information provided by the CCAFS survey allows us to examine adaptation levels in depth. We measure adaptation in terms of changes made in farming practices. Specifically, households were asked: "what changes have you made to the crop varieties you have planted and in the way you manage your land over the last 10 years?" Our dataset provides a rich description of adaptation intensity as it records 46 types of changes in farming practices that farmers implemented. In our sample, the three most common changes to farming practices that households have made were introducing new variety of crops, planting a higher yielding variety, and started using manure or compost.[6] We record a count of farming practices that households have changed with respect to any one of their three main crops, which each household has identified as being most important to their livelihood. Approximately 94 percent of the households in our sample have adapted by changing at least one farming practice. The fourth and fifth columns of Table 2.1 report that households in our sample have changed, on average, approximately nine farming practices, with considerable variation across sites.

There are several advantages of using the variation in the number of farming practices changed to capture differences in farmers' adaptation decisions. First, it captures the reality that farmers adapt by changing *multiple* farming practices (e.g. Di Falco and Veronesi, 2013; Seo and Mendelsohn, 2008). Second, it considers farming practices that farmers have

[6] A complete list of these practices is provided in Table A1 in the Appendix.

changed, so it captures an action that farmers have undertaken (i.e. revealed behavior). Third, the CCAFS survey has a follow up question asking for the reason/s why farmers changed their practices; hence, farmers' responses to this question serve as confirmation that they are indeed responding to some changing condition. All these features make our measure of adaptation levels well-suited to the adaptation definition provided by Smit and Wandel (2006).[7]

Table 2.1: Location of Study Sites and Descriptive Statistics of Adaptation

Country	Site	Number of households	Average adaptation	Standard deviation of adaptation	Min	Max
East Africa						
Ethiopia	Borana - Yabero	140	3.750	3.633	0	19
Kenya	Nyando - Katuk Odeyo	139	10.712	4.485	3	24
Kenya	Makueni -Wote	140	17.014	4.519	6	26
Tanzania	Usambara - Lushoto	139	13.439	5.438	0	24
Uganda	Albertine Rift - Hoima	140	6.386	4.842	0	19
Uganda	Kagera Basin - Rakai	140	8.229	4.752	0	28
Region Total		*838*	*9.916*	*6.398*		
West Africa						
Ghana	Lawra - Jirapa	122	11.697	4.697	3	22
Burkina Faso	Yatenga - Tougou	130	10.077	5.718	0	23
Mali	Segou - Cinzana	137	4.095	2.930	0	13
Niger	Kollo - Fakara	140	7.350	3.920	0	19
Senegal	Kaffrine	135	10.000	3.083	2	17
Region Total		*664*	*8.550*	*4.940*		
South Asia						
Bangladesh	Bagerhat - Morrelganj	140	2.607	2.845	0	14
India	Bihar - Vaishali	140	11.300	4.390	0	25
India	Haryana - Karnal	140	12.221	4.700	0	19
Nepal	Midwestern Terrai - Rupendehi	121	8.355	2.179	1	14
Region Total		*541*	*8.630*	*5.329*		
Sample Total		2,043	9.132	5.713	0	28

We measure adaptive capacity in terms of access to information and human capital, finance, physical assets, farm and household characteristics, and farming and crisis experience. The five categories of adaptive capacity are key traditional variables used to analyze farm-level adoption decisions and are known to affect adaptation decisions, as adaptation decisions also include adoption decisions (Di Falco, 2014; Zilberman et al., 2012; Foster and Rosenzweig, 2010; Feder et al., 1985). The categories also capture the resources, capital, and

[7] The adaptation definition of Smit and Wandel (2006) is available in footnote 2.

institutions that are crucial determinants of farmers' ability to adapt (Yohe and Tol, 2002; Fankhauser et al., 1999). We now proceed to explain the variables that comprise each category in more detail. Table 2.2 provides the description, summary statistics, and expected signs of these variables.

The first category of adaptive capacity is access to information and human capital. Empirical evidence shows that information affects the decision making of farmers (Zilberman et al., 2012; Foster and Rosenzweig, 2010; Feder et al., 1985). Farmers need to know about the purpose of adaptation and their options before they can adapt (Aker, 2011; Di Falco et al., 2011; Smit and Wandel, 2006; Fankhauser and Tol, 1997). We use access to weather-related information and participation in farming-related associations as measures of information access. Weather forecasts can help farmers decide which crops to plant and when to plant (Hertel and Rosch, 2010). Also, farming-related associations provide opportunities for farmers to discuss new information, ideas, technologies, and experiences (Matuschke and Qaim, 2009). In our sample, 78 percent of the households have access to some form of weather information, and 45 percent of the households have a member that belongs to at least one farming association. Education may also contribute to adaptive capacity (Yohe and Tol, 2002; Nelson and Phelps, 1966), as education can help farmers better understand, process, and respond to the information they receive (Rosenzweig, 2010; Abdulai and Huffman, 2005; Foster and Rosenzweig, 1996). In addition, Nelson and Phelps (1966) argue that educated farmers are usually better able to distinguish between promising and unpromising adaptation practices. Approximately 87 percent of the households in our sample have a member that received some level of formal education. In general, studies find that increased access to information and higher levels of education are positively associated with increased likelihood of adoption of agricultural technologies (Conley and Udry, 2010; Foster and Rosenzweig, 2010; Bandiera and Rasul, 2006; Feder et al., 1985), so we expect all the variables in this category to have a positive sign.

The second category is finance. Changing farming practices, such as adopting irrigation or introducing mechanized farming, can be costly and risky. Also, farmers often need some form of capital to finance adaptation (Feder et al., 1985). Hence, financial constraints are

Table 2.2: Descriptive Statistics of Right-Hand Side Variables

	Definition	Average	Standard Deviation	Expected Sign
ACCESS TO INFORMATION AND HUMAN CAPITAL				
Access to weather information	=1 if any household (hh) member received information pertaining to one or more of the following: extreme weather events, pest or disease outbreak, start of rains, and general weather forecasts	0.779	0.415	+
Membership in farming association(s)	=1 if any member of a hh belongs to at least one of the following groups: tree nursery, tree planting, forest production collection, water catchment management practices, soil improvement activities, crop introduction, irrigation, productivity enhancement, seed production, and vegetable production	0.447	0.497	+
Highest level of education attained is primary level	=1 if the highest level of education attained by any member of the hh is primary	0.435	0.496	+
Highest level of education attained is secondary	=1 if the highest level of education attained by any member of the hh is secondary	0.310	0.463	+
Highest level of education attained is post-secondary level	=1 if the highest level of education attained by any member of the hh is post-secondary	0.128	0.334	+
FINANCE				
Access to agricultural credit	=1 if the hh received credit for agricultural activites in the last 12 months	0.144	0.352	+
Bank account	=1 if the hh owns a bank account	0.221	0.415	+
Cash from the government	=1 if any member of the hh received cash payments from the government in the last 12 months	0.216	0.412	+
Income from non-farm employment	=1 if any hh member received income from employment on someone else's farm, other paid employment, and business (other than farm products)	0.691	0.462	+
Income from renting out land or machinery	=1 if any hh member received income from renting out land or machinery in the last 12 months	0.136	0.343	+
ASSETS				
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	0.732	1.288	+
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	2.402	1.659	+
Livestock	=1 if the hh owns livestock	0.906	0.293	+
Motorcycle	=1 if the hh owns a motorcycle	0.186	0.390	+
Car or truck	=1 if the hh owns a car or a truck	0.032	0.176	+
Boat	=1 if the hh owns a boat	0.007	0.085	+
FARM AND HOUSEHOLD CHARACTERISTICS				
Running water	=1 if the hh has access to running water	0.095	0.294	+
Storage facility for crops	=1 if the hh owns storage facility for crops	0.217	0.412	+
Planted trees	=1 if the hh has planted at least one tree on their farm	0.452	0.498	+
Farm size	Size of land, in hundreds of hectares, the hh owns and rents	0.192	0.763	+/-
Household size	Number of people living in a hh	10.357	6.111	+
Female-headed	=1 if gender of hh head is female	0.126	0.332	+/-
FARMING AND CRISIS EXPERIENCE				
Farming experience is at least ten years	=1 if any hh member has been farming in that locality for at least 10 years	0.935	0.246	+/-
Experienced climate crisis in the last five years	=1 if a hh has experienced a climate-related crisis in the last 5 years	0.721	0.449	+/-
STATED REASONS				
Market conditions	=1 if the hh made changes because of better yields, better prices, or new opportunities to sell	0.673	0.469	+
Climate variability	=1 if the hh made changes because of rainfall amount and variability, drought and flood frequency, strength of winds, start of rains, cold spell or cyclone frequency, higher salinity, or temperature	0.522	0.500	+
Pests and disease	=1 if the hh made changes because new pests or diseases have come, or the existing farming practice increased resistance to pests/ diseases	0.290	0.454	+
Government/NGO intervention	=1 if the hh made changes because government/project told them to do so or showed them how, or because of policy changes	0.154	0.361	+
Labor availability	=1 if the hh made changes because labor is sufficient or insufficient, or household is able or not able to hire labor	0.439	0.496	+
Land productivity	=1 if the hh made changes because land is less or more productive	0.507	0.500	+

likely to affect farmers' adaptation decisions (Karlan et al., 2012). We capture the financial constraints of households by their access to agricultural credit, whether they have a bank account, and their off-farm income sources in the past 12 months. Studies have emphasized that lack of credit access is a major barrier to adaptation (Di Falco et al., 2011; Bryan et al., 2009; Mertz et al., 2009). In our sample, 14 percent of the households have access to credit in the past year. In addition, a bank account may provide households with a source to save money and build their capital. We find that 22 percent of the households in our sample own a bank account. In many cases, farmers need to fund their investments using their own equity, such as through other income sources (Sunding and Zilberman, 2001; Feder et al., 1985). Other income could also provide a financial buffer towards the households' subsistence income, especially when the change in farming practice they implement may be risky (Feder et al., 1985). Approximately 22 percent of the households in our sample indicated that they received cash from the government in the past year. We find that 70 percent of the households in our sample have received income from non-farm employment, and 14 percent of the households have received income from renting out their land or machinery. Studies suggest that lowering the financial constraints of households would encourage adaptation, so we expect the signs of all variables in this category to be positive.

The third category of adaptive capacity is assets. Ownership of physical assets could provide a household with a greater resource base to implement changes in their farming practices and offer more access to information and markets (Yohe and Tol, 2002). In addition, assets could also be used as collateral (Sunding and Zilberman, 2001) or to smooth consumption in the event of a shock (Dercon and Christiaensen, 2011; Kazianga and Udry, 2006; Croppenstedt et al., 2003). The types of assets we consider are production-related assets, nonproduction-related assets, livestock, and transportation assets. We have measures of counts for the first two types of assets, and dummy variables are used to capture the ownership of livestock and transportation assets. Households in our sample own an average of 0.73 production-related assets and 2.4 nonproduction-related assets. Ninety percent of the households in the sample indicated that they own livestock. The percentage of households owning a motorcycle, a car or truck, and a boat are 19 percent, 3 percent, and 0.7 percent of the sample, respectively. Many studies find ownership of assets to be positively correlated with the adoption of agricultural technologies (Feder et al., 1985), so we expect all these types of assets to have a positive impact on adaptation.

The fourth category is farm and household characteristics. We consider the following farm characteristics: access to running water, storage facility for crops, whether the household has planted trees on their farm, and farm size. Lee (2005) suggests that access to water is imperative to encourage adaptation, such as the use of sustainable agriculture and integrated natural resource management. As an example, Barrett et al. (2004) find that an increase in the number of days of water shortage has a significant and negative effect on the gains of changing rice farming practices. We find that nine percent of the households in our sample have access to running water. In addition, having access to a storage facility provides farmers with greater flexibility about their post-harvest marketing decisions (Park, 2006; Fackler and Livingston, 2002). For instance, in anticipation of higher crop prices in the future, farmers with access to a crop storage facility have the option of delaying sales to take advantage of higher prices in the future. The percentage of households in our sample that owns storage facilities for crops on their farm is 22 percent. Further, Besley (1995) explains that tenure security can provide households with more confidence that they will reap the benefits of implementing changes on their farm, and land could be used as collateral. We use trees planted in one's farm as proxy for tenure security, as suggested in Di Falco and Veronesi (2013). Since trees are visible, it could establish more secure property rights by signalling ongoing use of land (Deininger and Jin, 2006; Place and Otsuka, 2001). In our sample, 45 percent of the households have planted trees. The last farm characteristic we consider is farm size because scale and fixed costs associated with a farming practice may affect farmers' decisions (Feder et al., 1985). On average, households in our sample have access to 19 hectares of land. We expect all farm characteristics to have a positive impact on adaptation with the exception of farm size, where the sign is ambiguous, since its effect depends on other factors, such as scale, fixed costs, and the type of technology considered (Feder et al., 1985). For household characteristics, we consider the household size and the gender of the household head. Since some farming practices may be labor intensive, the availability of labor may affect households' adaptation decisions. We use household size as a proxy to capture households' labor availability, as in Doss (2006) and Croppenstedt et al. (2003). We find that there are approximately ten people living in a household in our sample. The gender of the household head may also affect the ability of households to adapt because access to resources that may affect adaptation decisions may be different between men and women (Doss, 2006). We capture the impact of the gender of the household head using a dummy variable for a female-headed household. In our sample, 13 percent of the households are female-headed. We expect household size to have a positive sign, but we do not have any a priori expectation about the sign of the gender of the household head.

The fifth and final category of adaptive capacity is farming and crisis experience. Farmers who have been farming for a long time in the same area may possess more local knowledge that could enable them to better respond to changes. For instance, more experienced farmers are more likely able to notice changes in their surroundings, such as climate, as compared to farmers with less experience (Bryan et al., 2013; Maddison, 2007). Farmers with more experience are also more likely to be more aware of different sources of information and technologies (Bryan et al., 2013). On the other hand, farmers with more experience may be less likely to change their farming practices because they may be more risk-averse (Adesina and Baidu-Forson, 1995). These farmers may also have a shortened planning horizon over which the benefits of adaptation may be realized (Rahm and Huffman, 1984). In our sample, 94 percent of the households have been living and farming in the locality for at least ten years. With respect to a crisis experience, it is possible that a household might have lost relevant resources to adapt to change as a result of experiencing a climate-related crisis in the last five years, which decreases their ability to adapt (Reardon and Taylor, 1996). But it is also possible that a household has learned about the importance of adaptation from a past crisis experience, which would increase their likelihood of adapting. The percentage of households in our sample that has experienced a climate-related crisis in the past five years is 72 percent. We do not have any expectations on the signs of farming and crisis experience, as the explanations above indicate that the effects of these two variables on adaptation could be either positive or negative.

In addition to elements of adaptive capacity, we also analyze how farmers' stated reasons for adaptation affect their adaptation decisions. Our dataset provides us with six possible reasons: market conditions, climate variability, pests and disease, government/NGO interventions, labor availability, and land productivity. These reasons are not mutually exclusive, as households could provide more than one reason for changing their farming practices. We expect that these six variables will have a positive sign, but it is reasonable to expect that each of these stimuli would lead to different adaptation intensities (Howden et al., 2007). The inclusion of these variables enables our model to capture the impacts of multiple stimuli on adaptation and allows us to compare the relative importance of different stimuli on farmers' adaptation decisions.

We estimate a linear model to investigate the contribution of each element of adaptive capacity on adaptation. This estimation strategy allows for direct comparison of estimates from our Baseline Model and Neighbor Network Model (Chapter 3).[8] Our econometric model also utilizes two types of fixed effects. First, households in our sample are located in villages of different countries, so there may be concerns of spatial correlation in households' adaptation decisions. One common strategy to control for this issue is the use of spatial fixed effects (Kuminoff et al., 2010). In this thesis, we use region, site, and village fixed effects. Second, different types of crops may require different levels of adaptation. A study that aims to explain how adaptive capacity elements affect adaptation decisions must account for variations due to type of crop to ensure that there are no confounding effects. In this thesis, we address this issue using crop fixed effects.

2.3 The Impacts of Adaptive Capacity on Adaptation

Table 2.3 reports the estimation results of our Baseline Model, with different fixed effects. As we move from the left to the right columns, the spatial fixed effects become more localized,

[8]Despite the wide range of adaptation levels (i.e. 0 to 28), some readers might be interested in the results of a negative binomial count model. The results of this estimation is presented in Table A2 in the Appendix. In general, the marginal effect estimates of adaptive capacity elements from ordinary least squares and negative binomial count approaches are similar. For convenience, we discuss the results of the ordinary least squares estimation.

with crops fixed effects added to the most localized spatial fixed effect (i.e. village-level) in the right-most column. We first discuss the impact of different fixed effects on the estimates, and how we used this information to select our preferred specification. Then we explain the impacts of adaptive capacity elements on farmers' adaptation decisions using our preferred specification.

The results show that as the spatial fixed effects become more localized, most coefficients of elements of adaptive capacity decrease in size. This decrease suggests that more localized spatial fixed effects better capture unobserved spatial heterogeneity that might be correlated with our regressors (Heintzelman and Tuttle, 2012). The tradeoff of using a smaller scale of spatial fixed effects, however, is that there is less variation and less power for estimating other coefficients (Heintzelman and Tuttle, 2012). But for our results, the significance of most coefficients is preserved, even at the village level. By adding crop fixed effects to village fixed effects, the model additionally controls for any unobserved crop features. Therefore, our preferred estimation is the last column, where village and crop fixed effects are used.

Estimates of our preferred specification show that all five categories of adaptive capacity influence farmers' adaptation decisions. Of equal importance is that the sign and significance of elements of adaptive capacity are in line with the empirical evidence found in the rich adoption and adaptation literature (Di Falco, 2014; Zilberman et al., 2012; Foster and Rosenzweig, 2010; Yohe and Tol, 2002; Feder et al., 1985). In addition, by considering multiple stimuli to adaptation, our Baseline Model integrates the social, economic, institutional, and ecological contexts that affect farmers' adaptation decisions (Bryan et al., 2009). We now explain in greater detail the results of each adaptive capacity category.

From the first category of adaptive capacity, we find that having access to weather information increases adaptation level by approximately 0.48 practices. The importance of access to weather information in facilitating adaptation has also been found in many adaptation studies, including Di Falco et al. (2012, 2011) and Hassan et al. (2008). Foster and Rosenzweig (1996) also find that the diffusion of an innovation is affected by information access. Other studies also find that participation in farming associations significantly increases the likelihood of adoption (Kabunga et al., 2012; Matuschke and Qaim, 2009). However, in

Table 2.3: Regression Results of the Baseline Model

Fixed Effects	None	Region	Site	Village	Village and Crops
Access to Information and Human capital					
Access to weather information	0.435**	0.329	0.687***	0.473**	0.477**
	(0.202)	(0.205)	(0.194)	(0.194)	(0.191)
Membership in farming association(s)	0.651***	0.626***	0.371**	0.374**	0.298*
	(0.168)	(0.168)	(0.174)	(0.172)	(0.167)
Highest level of education attained is primary	-0.249	-0.186	0.224	0.234	0.177
	(0.238)	(0.242)	(0.217)	(0.220)	(0.215)
Highest level of education attained is secondary	-0.285	-0.097	0.142	0.288	0.146
	(0.261)	(0.276)	(0.252)	(0.253)	(0.250)
Highest level of education attained is post-secondary	-0.927***	-0.673*	-0.340	-0.194	-0.362
	(0.325)	(0.346)	(0.314)	(0.310)	(0.305)
Finance					
Access to agricultural credit	0.231	0.223	1.000***	0.902***	0.719***
	(0.253)	(0.253)	(0.223)	(0.219)	(0.219)
Bank account	0.385	0.609**	-0.226	-0.330	-0.169
	(0.247)	(0.253)	(0.235)	(0.231)	(0.224)
Cash from the government	0.661***	0.894***	0.181	0.190	0.281
	(0.207)	(0.214)	(0.210)	(0.203)	(0.199)
Income from non-farm employment	0.798***	0.809***	0.550***	0.263	0.290*
	(0.173)	(0.174)	(0.169)	(0.166)	(0.163)
Income from renting out land or machinery	0.545**	0.526**	0.200	0.136	0.098
	(0.242)	(0.243)	(0.218)	(0.212)	(0.209)
Assets					
Count of production-related assets	-0.164*	-0.080	0.158	0.209**	0.055
	(0.095)	(0.101)	(0.103)	(0.097)	(0.094)
Count of nonproduction-related assets	0.208***	0.224***	0.123*	0.223***	0.186***
	(0.075)	(0.075)	(0.070)	(0.070)	(0.070)
Livestock	0.859***	0.796***	0.856***	0.663***	0.372
	(0.261)	(0.263)	(0.245)	(0.244)	(0.238)
Motorcycle	-0.346	-0.442	0.466*	0.407*	0.260
	(0.268)	(0.274)	(0.253)	(0.238)	(0.229)
Car or truck	0.628	0.433	0.124	-0.077	0.090
	(0.511)	(0.516)	(0.582)	(0.563)	(0.555)
Boat	-1.788***	-1.521***	0.058	0.047	-0.370
	(0.517)	(0.522)	(0.459)	(0.605)	(0.742)
Farm and Household Characteristics					
Running water	0.101	0.159	0.651**	0.994***	1.013***
	(0.326)	(0.323)	(0.329)	(0.328)	(0.336)
Storage facility for crops	1.631***	1.598***	1.166***	1.305***	1.315***
	(0.225)	(0.226)	(0.201)	(0.212)	(0.210)
Planted trees	0.331**	0.192	0.482***	0.524***	0.565***
	(0.165)	(0.175)	(0.167)	(0.162)	(0.162)
Farm size	-0.243***	-0.149**	0.104	0.047	-0.040
	(0.064)	(0.067)	(0.081)	(0.080)	(0.074)
Household size	-0.027*	-0.037**	-0.020	-0.018	-0.009
	(0.014)	(0.016)	(0.014)	(0.013)	(0.013)
Female-headed	-0.134	-0.286	-0.471*	-0.105	-0.125
	(0.245)	(0.253)	(0.227)	(0.222)	(0.227)
Farming and Crisis Experience					
Farming experience is at least ten years	1.191***	1.148***	1.068***	1.200***	1.064***
	(0.272)	(0.278)	(0.267)	(0.265)	(0.259)
Experienced climate crisis in the last five years	0.066	0.019	-0.221	0.230	0.105
	(0.185)	(0.185)	(0.194)	(0.192)	(0.188)
Stated Reasons					
Market conditions	4.095***	4.148***	3.404***	3.108***	2.659***
	(0.194)	(0.195)	(0.188)	(0.186)	(0.192)
Climate variability	1.831***	1.811***	1.639***	1.828***	1.692***
	(0.206)	(0.206)	(0.191)	(0.190)	(0.189)
Pests and disease	2.070***	2.011***	1.913***	1.905***	1.869***
	(0.215)	(0.217)	(0.201)	(0.205)	(0.207)
Government/NGO intervention	2.507***	2.435***	1.822***	1.531***	1.528***
	(0.253)	(0.256)	(0.254)	(0.249)	(0.244)
Labor availability	1.999***	1.987***	1.419***	1.427***	1.352***
	(0.197)	(0.197)	(0.178)	(0.170)	(0.169)
Land productivity	0.745***	0.675**	0.469**	0.667***	0.549**
	(0.205)	(0.209)	(0.182)	(0.181)	(0.179)
Constant	-0.457	-1.029**	-2.465***	1.627*	-0.880
	(0.416)	(0.454)	(0.487)	(0.915)	(0.830)
R^2	0.627	0.630	0.718	0.758	0.782

Sample Size: N=2,043. Robust standard errors are reported in parentheses.*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

our results, we find that the coefficients on our education variables are not statistically different from zero. A similar result has been found in other studies in the literature (Di Falco et al., 2011; Bryan et al., 2009).

From the second category, we find that credit access increases adaptation by 0.72 practices, and receiving income from non-farm employment increases adaptation by 0.29 practices. This finding corresponds well to many empirical studies that emphasize financial resources are important determinants of farmers' decision making (Dercon and Christiaensen, 2011; Di Falco et al., 2011; Giné and Yang, 2009; Bryan et al., 2009; Deressa et al., 2009; Croppenstedt et al., 2003; Shively, 2001). For example, improved access to credit has also been documented to increase the adoption intensity of farmers, especially among farmers with smaller farms (Sunding and Zilberman, 2001). Di Falco (2014) argue the importance of easing credit constraints because uncertainty, such as long term variability in rainfall, may make farmers more risk-averse and less willing to invest in more profitable and resilient adaptation strategies if they are credit constrained.

From the third category of adaptive capacity, we find that owning one additional non production-related asset increases adaptation by 0.19 practices. This result emphasizes the potential importance of information-related goods, such as cellphone and radio, which are part of nonproduction-related assets. Relevant information, such as weather information and market conditions, may be disseminated through these types of assets (Aker, 2011). For example, both Tack and Aker (2014) and Aker (2010) find that the introduction of mobile phone coverage in Niger reduced grain price dispersion by reducing the search costs of farmers. With respect to transportation assets, ownership of a motorcycle increases adaptation by 0.44 practices. In addition, we find that the marginal effect of owning production-related assets is not statistically different from zero. Kabunga et al. (2012) also find a similar result in the adoption of tissue culture bananas in Kenya and explain that the insignificance of this variable suggests that the technology considered is scale-neutral.

From the fourth category, we find that having running water and storage facility for crops increases adaptation levels by 1.01 and 1.32 practices, respectively. The large impact of these two variables highlights the importance of farm characteristics in influencing farmers' adaptation decisions. Both Kazianga and Udry (2006) and Udry (1995) find that storage significantly affects the ability of farmers in rural areas to cope with climate shocks. In addition, we find that our proxy for tenure security (i.e. *planted trees*) increases adaptation by 0.57 practices. This positive relationship between tenure security and adaptation is in line with the results of other empirical studies (Di Falco, 2014; Di Falco and Veronesi, 2013; Bryan et al., 2009). We also find that the coefficients of farm size and the two household characteristics are not statistically significant, which is a similar result found in Deressa et al. (2009).

From the fifth and final category of adaptive capacity, we find that farming experience leads to an increase in adaptation of 1.06 practices. The importance of farming experience has also been documented in other adaptation studies (Bryan et al., 2009; Deressa et al., 2009; Nhemachena and Hassan, 2007). Likewise, Foster and Rosenzweig (1995) find that farming experience increased the adoption intensity of high-yielding seed varieties among farmers in India. Due to the significant impact of farming experience on farmers' decision making, Nhemachena and Hassan (2007) and Maddison (2007) suggest that policies focusing on farmers with more experience may be successful in promoting adaptation.

With respect to stated reasons for adaptation, we find that the most important reason why farmers changed their farming practices is market conditions. The next most important reason is pests and disease, which is followed by climate variability, government/NGO interventions, labor availability, and land productivity. Our results provide evidence that market conditions are indeed traditional determinants of economic behavior. We also note that all of our reason variables are highly significant. This result suggests that farmers adapt in response to multiple stimuli. An implication is that policymakers should consider the interaction of environmental and non-environmental factors in the design of program interventions that aim to facilitate adaptation among farmers since the interaction of multiple factors may increase the barriers to adaptation (Westerhoff and Smit, 2009; Fankhauser et al., 1999). For instance, O'Brien et al. (2004) explain that there may be a divergence between crops that are more compatible with climate conditions and those with high market demand. Another scenario would be that credit constraints might hinder the adoption of drought or pest resistance crops, even though these varieties could better help farmers adapt to pest and disease incidence and climactic variability.

In sum, our Baseline Model investigates the impacts of multiple elements of adaptive capacity on farmers' adaptation decisions. To the extent that our extensive set of right-hand side variables, together with our fixed effects, are able to capture the relevant heterogeneity in the determinants of adaptation, the estimated coefficients of traditional elements of adaptive capacity represent causal marginal effects. Having causal identification in the Baseline Model as a starting point, we use spatial econometric techniques to identify the causal effect of neighbor networks on adaptation in the next chapter.

Chapter 3

Neighbor Networks Adaptation Model

Networks of relationships have been hypothesized to contribute to the adaptive capacity of farmers (e.g. Smit and Wandel, 2006). These relationships can help farmers by acting as conduits of information and by providing access to resources. Indeed, empirical studies in development economics have found that networks play a significant role in risk-sharing, information dissemination, and technology adoption; all features that could facilitate adaptation (Chuang and Schechter, 2015). Despite the potential importance of these relationships in increasing adaptive capacity, empirical evidence of network effects on adaptation is rare, or to the best of our knowledge does not exist.

In this chapter, we introduce network effects to our Baseline Adaptation Model. We assume that the adaptation levels of farmers are not only influenced by traditional elements of adaptive capacity, but also by the adaptation of other households in their network. We capture networks of relationships using neighbor networks. Previous research has found geographical proximity to be a significant determinant of interpersonal relationships (Ambrus et al., 2014; Karlan et al., 2009; Fafchamps and Gubert, 2007). Key studies that analyze network effects in technology adoption and diffusion in the context of agriculture also capture networks of relationships using neighbor networks and find that neighbors affect farmers' decisions (Munshi, 2004; Foster and Rosenzweig, 1995).

Neighbor networks may be particularly important in the context of adaptation. For example, Fafchamps and Gubert (2007) find that neighbor networks facilitate risk-sharing, such as through gifts and informal loans, because of easier monitoring and enforcement, so neighbor networks could ease financial constraints and lower barriers to adaptation. Furthermore, learning about adaptation may more likely occur in neighbor networks because neighbors experience similar environmental and economic conditions and may share relevant information about adaptation with each other (Krishnan and Patnam, 2014; Ward and Pede, 2014).

We begin this chapter by describing our spatial data and how we construct the neighbor networks of farmers. Next, we explain the empirical strategy we use to identify network effects. Then we discuss the estimation results of our Neighbor Network Model. Finally, we conduct a robustness check that changes the specifications of neighbor networks.

3.1 Spatial Data

The CCAFS data set includes information on the Global Positioning System (GPS) coordinates and the village of residence of all households that participated in the survey. To construct a neighbor network for each household, we use the coordinates to calculate distances between households in each village.[9] This approach assumes that all households residing in the same village are neighbors and will have some degree of influence on farmers' decisions.[10] Munshi (2004) and Foster and Rosenzweig (1995) also make the same assumption.

Our definition of neighbors appears to be a reasonable. Table 3.1 shows that, in our sample, the average distance between two households in a village is approximately 729 meters. On the other hand, in our sample, the average distance between the centroid of two villages in the same site is approximately 9 kilometers. Given the large distance between villages, it is reasonable to expect that households of other villages would have a small (or no) influence on adaptation decisions.

Empirically, we capture the weight of the influence of neighbors' adaptation on adaptation decisions by constructing a weighting matrix. Consider our sample of 2043 farmers indexed by $i = 1, ..., 2043$. These farmers are distributed across 108 villages. Let n_k denote the

[9]We used the Geographic Distance Matrix Generator (Version 1.2.4; Ersts, n.d.) to calculate distances.
[10]We conduct a robustness check at the end of the chapter that changes the specifications of neighbors.

Table 3.1: Descriptive Statistics of Distances

Region, country, and site	Average distance between two households in a village (in meters)	Standard deviation of distance between two households in a village (in meters)	Average distance between two villages in a site (in meters)
East Africa			
Ethiopia (Borana)	980.01	659.31	15,217.11
Kenya (Nyando)	768.77	485.30	5,901.91
Kenya (Makueni)	722.80	398.57	5,362.71
Tanzania (Usambara)	1,303.21	1,030.12	2,842.22
Uganda (Albertine Rift)	853.88	502.64	3,263.99
Uganda (Kagera Basin)	704.54	392.41	1,621.72
West Africa			
Ghana (Lawra)	1,066.81	602.40	18,874.03
Burkina Faso (Yatenga)	617.16	385.11	18,517.12
Mali (Segou)	1,563.77	1,548.47	23,805.93
Niger (Kollo)	770.86	1,149.94	4,497.08
Senegal (Kaffrine)	376.83	297.18	17,707.90
South Asia			
Bangladesh (Khulna)	556.95	354.27	5,424.14
India (Bihar)	407.80	244.59	5,124.48
India (Haryana)	143.06	74.57	5,030.36
Nepal (Midwestern Terrai)	100.50	75.49	4,497.08
Sample Average	729.13	546.69	9,179.19

Note: Average distance of villages in a site is calculated from the centroid of each village.

number of farmers in village k, with $k = 1, ..., 108$.[11] Let $\mathbf{A}$ be a 2043×2043 block diagonal matrix where block k has dimension n_k and corresponds to village k. Each element a_{ij} contains the geographic distance of i to j, for all i and j in the same village, and zero otherwise.[12] The use of a block diagonal matrix assumes that only households in the same village are able to influence one another.

The degree of influence of one household on another may depend on the geographical distances between households. We assume a decline in influence as the distance between two households increase by weighting connections inversely proportional to distance. Specifically, let $\mathbf{W}$ be an inverted row-normalization of $\mathbf{A}$, so the elements $w_{ij} = \frac{1/a_{ij}}{\sum_i 1/a_{ij}}$ if $a_{ij} \neq 0$, and zero otherwise. The row normalization makes every w_{ij} entry lie between 0 and 1. Thus, the $\mathbf{i}^{th}$ row of $\mathbf{W}$ is a distribution of weights that i places on other households in the same village, with households living nearby having more weight than households who live far away.

[11]Notice that $\sum_{k=1}^{108} n_k = 2043$.

[12]This construction makes $a_{ij} = a_{ji}$, i.e. $\mathbf{A}$ is a symmetric matrix.

3.2 The Neighbor Network Model

We hypothesize that farmers' adaptation is a function of traditional elements of adaptive capacity and the adaptation levels of their neighbors. Our empirical Neighbor Network Model builds on our Baseline Model by adding the adaptation of neighbors as an element of adaptive capacity. Specifically, we estimate a spatially autoregressive (SAR) model. Formally, the SAR model can be written in matrix notation as:

$$\mathbf{Y} = \rho\mathbf{W}\mathbf{Y} + \mathbf{X}\beta + \epsilon \tag{3.1}$$

where $\mathbf{Y}$ is a vector of farmers' adaptation, $\mathbf{W}$ is an influence (weights) matrix, and $\mathbf{X}$ is a matrix of elements of adaptive capacity, as in Chapter 2 (Anselin, 1988). $\mathbf{WY}$ is the weighted average of neighbors' adaptation. ρ is the network effect parameter that captures the influence of neighbors' adaptation on adaptation, and β captures the marginal impact of elements of adaptive capacity on adaptation. The error term ϵ captures unobserved determinants of adaptation.

One potential problem with Equation (3.1) is endogeneity. Farmer i's adaptation is affected by his/her neighbors' adaptation, but the reverse is also true. Manski (1993) refers to this issue as the "reflection problem," which makes it difficult to identify the network effect. Our estimation strategy is to use the widely utilized two step general method of moments instrumental variable (GMM/IV) approach proposed by Kelejian and Prucha (1998) and modified by Lee (2003).

To address the endogeneity of $\mathbf{WY}$, our identification strategy requires strict exogeneity of $\mathbf{X}$, i.e. $\mathrm{E}(\epsilon|\mathbf{X}) = 0$ (see Bramoullé et al. (2009)). The wealth of information provided by the CCAFS dataset allows us to investigate in one econometric model multiple elements of adaptive capacity known to influence adaptation decisions (Di Falco, 2014; Zilberman et al., 2012; Foster and Rosenzweig, 2010; Yohe and Tol, 2002; Feder et al., 1985). Moreover, the elements of adaptive capacity in our Baseline Model correspond closely to the well-established determinants of farmers' decision making behavior, including information (Lemos et al., 2012; Ricker-Gilbert et al., 2008; Foster and Rosenzweig, 1996; Atanu et al., 1994;

Birkhaeuser et al., 1991), credit (Cai et al., 2014; Dercon and Christiaensen, 2011; Karlan and Morduch, 2009; Giné and Yang, 2009; Croppenstedt et al., 2003; Shively, 2001), ownership of assets (Tack and Aker, 2014; Aker, 2010; Jensen, 2007; Foster and Rosenzweig, 1995), farm characteristics (Park, 2006; Udry, 1995), and farming experience (Rosenzweig, 1995; Foster and Rosenzweig, 1995). To the extent that we have accounted for all relevant elements of adaptive capacity together with our two fixed effects that capture unobserved village-level determinants and crop characteristics that may affect adaptation decisions, such that there are no significant omitted variables, we believe our assumption of strict exogeneity is reasonable.

As demonstrated by Kelejian and Prucha (1998) and Lee (2003), neighbors' exogenous elements of adaptive capacity may be used to construct instrumental variables for the GMM/IV estimation. We summarize below how to construct valid instruments for our Neighbor Network Model in light of the assumption of strict exogeneity of $\mathbf{X}$. We start with the reduced form of Equation (3.1):

$$\mathbf{Y} = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{X}\beta + (\mathbf{I} - \rho\mathbf{W})^{-1}\epsilon. \tag{3.2}$$

Using a Neumann series (see Meyer, 2001), we can rewrite the reduced form model as

$$\begin{aligned} \mathbf{Y} \quad &= \quad (\mathbf{I} + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + ...)\mathbf{X}\beta + \\ &\quad\quad (\mathbf{I} + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + ...)\epsilon. \end{aligned} \tag{3.3}$$

As Boucher et al. (2014) demonstrate, pre-multiplying both sides of Equation (3.3) with $\mathbf{W}$ and taking the expectation leads to

$$E(\mathbf{WY}|\mathbf{X}) \quad = \quad (\mathbf{W} + \rho\mathbf{W}^2 + \rho^2\mathbf{W}^3 + \rho^3\mathbf{W}^4 + ...)\mathbf{X}\beta. \tag{3.4}$$

From Equation (3.4), we see that the variables $\mathbf{WX}$ and $\mathbf{W}^2\mathbf{X}$ are correlated with $\mathbf{WY}$ and uncorrelated with the error term. Therefore, the variables $\mathbf{WX}$ and $\mathbf{W}^2\mathbf{X}$ can be used as valid instruments for $\mathbf{WY}$.[13] Bramoullé (2001) provides an interesting interpretation of these instruments. $\mathbf{WX}$ is the weighted average adaptive capacity of farmers' neighbors (first-order neighbors), and $\mathbf{W}^2\mathbf{X}$ is the weighted average adaptive capacity of farmers' neighbors' neighbors (second-order neighbors).

As in Chapter 2, we estimate our Neighbor Network Model with different fixed effects specifications. Specifically, we first estimate our model without any fixed effects. Next, we estimate our model with three types of spatial fixed effects beginning with region fixed effects, followed by site fixed effects, and then with village fixed effects. Finally, we estimate our model with village and crop fixed effects.

3.3 The Impacts of Neighbor Networks on Adaptation

Table 3.2 presents the results of the Neighbor Network Model. The results show that the size of most coefficients decrease as more localized fixed effects are used. As discussed in the previous chapter, using village and crop fixed effects better controls for unobserved spatial heterogeneity and crop characteristics that can influence adaptation decisions. Following Section 2.3, we choose the estimation with village and crop fixed effects as our preferred estimation. Since the marginal effects of traditional elements of adaptive capacity of our preferred specification are similar to those discussed in the Baseline Model (Section 2.3), we focus our discussion on network effects.

The statistically significant network effect of $\rho = 0.336$ in our preferred specification means that farmers' adaptation increases by approximately 0.34 practices for each additional increase in neighbors' adaptation. This result is consistent with our hypothesis that neighbors significantly influence adaptation decisions, in addition to traditional elements of adaptive capacity. An implication of the significant network effect is that impacts of a change in adaptive capacity elements will have ripple effects throughout the neighbor network.

[13] Using simulations, Kelejian and Prucha (1998) suggest that instruments up to the second-order term, i.e. $\mathbf{W}^2\mathbf{X}$, are sufficient for most applications.

Table 3.2: Regression Results of the Neighbor Network Model

Fixed Effects	None	Region	Site	Village	Village and Crops
Network effect (ρ)	0.463***	0.457***	0.323***	0.330***	0.336***
	(0.024)	(0.025)	(0.041)	(0.062)	(0.066)
ACCESS TO INFORMATION AND HUMAN CAPITAL					
Access to weather information	0.373**	0.347**	0.542***	0.450**	0.437**
	(0.171)	(0.174)	(0.178)	(0.180)	(0.183)
Membership in farming association(s)	0.412***	0.413***	0.254	0.420***	0.343**
	(0.141)	(0.141)	(0.160)	(0.160)	(0.156)
Highest level of education attained is primary	-0.437**	-0.390*	0.117	0.229	0.212
	(0.195)	(0.201)	(0.199)	(0.203)	(0.207)
Highest level of education attained is secondary	-0.306	-0.204	0.113	0.287	0.254
	(0.218)	(0.239)	(0.234)	(0.236)	(0.254)
Highest level of education attained is post-secondary	-0.768***	-0.636**	-0.327	-0.141	0.026
	(0.275)	(0.300)	(0.292)	(0.288)	(0.340)
FINANCE					
Access to agricultural credit	0.596***	0.586***	0.885***	0.881***	0.577***
	(0.203)	(0.203)	(0.202)	(0.202)	(0.215)
Bank account	-0.110	-0.047	-0.253	-0.381*	-0.262
	(0.214)	(0.222)	(0.220)	(0.218)	(0.266)
Cash from the government	0.529***	0.585***	0.072	0.283	0.396*
	(0.171)	(0.178)	(0.189)	(0.187)	(0.218)
Income from non-farm employment	0.448***	0.458***	0.400***	0.273*	0.238
	(0.149)	(0.150)	(0.154)	(0.155)	(0.188)
Income from renting out land or machinery	0.508**	0.498**	0.179	0.219	0.234
	(0.212)	(0.212)	(0.207)	(0.202)	(0.224)
ASSETS					
Count of production-related assets	-0.079	-0.053	0.216**	0.238***	0.039
	(0.082)	(0.086)	(0.095)	(0.091)	(0.094)
Count of nonproduction-related assets	0.112	0.111	0.149**	0.241***	0.170**
	(0.062)	(0.063)	(0.065)	(0.066)	(0.077)
Livestock	0.981***	0.978***	0.772***	0.620***	0.476**
	(0.234)	(0.235)	(0.227)	(0.229)	(0.242)
Motorcycle	-0.302	-0.367	0.411*	0.341	0.158
	(0.223)	(0.229)	(0.229)	(0.222)	(0.217)
Car or truck	0.221	0.215	-0.166	-0.148	-0.032
	(0.461)	(0.463)	(0.499)	(0.520)	(0.528)
Boat	-0.707	-0.648	-0.228	0.312	-0.854
	(0.463)	(0.466)	(0.440)	(0.561)	(1.011)
FARM AND HOUSEHOLD CHARACTERISTICS					
Running water	0.039	0.067	0.654**	0.887***	0.900**
	(0.284)	(0.282)	(0.298)	(0.305)	(0.381)
Storage facility for crops	1.232***	1.229***	1.125***	1.175***	1.178***
	(0.187)	(0.189)	(0.184)	(0.201)	(0.222)
Planted trees	0.526***	0.506***	0.485**	0.524***	0.646***
	(0.140)	(0.149)	(0.154)	(0.151)	(0.172)
Farm size	-0.006	0.012	0.031	0.022	0.084
	(0.064)	(0.066)	(0.064)	(0.066)	(0.146)
Household size	0.008	0.003	-0.017	-0.018	-0.010
	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)
Female-headed	-0.398	-0.413	-0.357	-0.115	-0.219
	(0.211)	(0.219)	(0.210)	(0.206)	(0.235)
FARMING AND CRISIS EXPERIENCE					
Farming experience is at least ten years	1.239***	1.227***	1.111***	1.304***	1.053***
	(0.251)	(0.255)	(0.254)	(0.254)	(0.381)
Experienced climate crisis in the last five years	0.011	-0.013	-0.038	0.205	0.150
	(0.156)	(0.157)	(0.178)	(0.180)	(0.196)
STATED REASONS					
Market conditions	3.321***	3.356***	3.303***	3.110***	2.641***
	(0.175)	(0.178)	(0.176)	(0.170)	(0.201)
Climate variability	1.168***	1.163***	1.613***	1.650***	1.544***
	(0.170)	(0.170)	(0.174)	(0.176)	(0.206)
Pests and disease	1.553***	1.552***	1.694***	1.858***	1.854***
	(0.184)	(0.187)	(0.187)	(0.193)	(0.215)
Government/NGO intervention	1.796***	1.782***	1.675***	1.613***	1.795***
	(0.223)	(0.223)	(0.232)	(0.234)	(0.282)
Labor availability	1.344***	1.352***	1.303***	1.394***	1.361***
	(0.170)	(0.170)	(0.165)	(0.161)	(0.166)
Land productivity	0.518***	0.491***	0.548***	0.753***	0.718***
	(0.169)	(0.170)	(0.168)	(0.170)	(0.188)
Constant	-2.915***	-3.048***	-3.095***	-2.038	-4.310***
	(0.376)	(0.392)	(0.452)	(1.050)	(1.088)
R^2	0.712	0.712	0.735	0.756	0.740
F-statistic of the first stage regression	217.26	224.61	292.02	444.18	9,380.07

Sample Size: N=2,043. Robust standard errors are reported in parentheses.*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

This spillover occurs because of the interaction among neighbor network members that we captured through the term $(\mathbf{I} - \rho\mathbf{W})^{-1}$ in Equation (3.2). Anselin (2003) refers to this term as the network multiplier and can be approximated by $\frac{1}{1-\rho}$. As a result, the total effect of each element of adaptive capacity on adaptation is $\beta(\frac{1}{1-\rho})$. In contrast, in the Baseline Model without network effects, the total effect of each element of adaptive capacity on adaptation is simply the marginal effect, or β.

Table 3.3 reports the calculated total effect and 95 percent confidence interval of each element of adaptive capacity on adaptation levels of the Baseline and Neighbor Network Models. We use the confidence interval reported in the OLS approach as the 95 percent confidence interval of adaptive capacity elements of the Baseline Model. Meanwhile, we use the delta method to compute the 95 percent confidence interval of adaptive capacity elements of the Neighbor Network Model. We interpret the calculated total effect as significant if the 95 percent confidence interval does not include zero.

Based on the estimated ρ of our preferred specification, we calculate a network multiplier of 1.5. This number implies that interactions among households in neighbor networks amplify the marginal effects of adaptive capacity elements by 50 percent. As a result, the calculated total effects of all adaptive capacity elements in the Neighbor Network Model are greater compared to the Baseline Model. In addition, the total effects of *access to weather information, membership in farming associations, access to agricultural credit, count of production-related assets, count of nonproduction-related assets, access to running water, storage facility for crops, planted trees, farming experience is at least ten years* and the six *stated reasons* are all statistically different from zero in the Neighbor Network Model. But the calculated total effects of *membership in farming associations* and *count of production-related assets* are not statistically different from zero in the Baseline Model. A caveat is that the confidence intervals of all the calculated total effects in the Baseline and Neighbor Network Models overlap.

The large multiplier effect suggests the importance of modeling farmers' adaptation using the Neighbor Network Model. The OLS approach used in estimating the Baseline Model omits neighbor network spillover effects. As a result, when $\rho > 0$, which we find in our

Table 3.3: Total Effects of Adaptive Capacity Elements

Model	Baseline	Neighbor Network
Access to Information and Human capital		
Access to weather information	0.477	0.657
	[0.102,0.852]	[0.1000,1.215]
Membership in farming association(s)	0.298	0.517
	[-0.0295,0.625]	[0.0463,0.987]
Highest level of education attained is primary	0.177	0.319
	[-0.245,0.600]	[-0.289,0.928]
Highest level of education attained is secondary	0.146	0.382
	[-0.343,0.636]	[-0.375,1.139]
Highest level of education attained is post-secondary	-0.362	0.0388
	[-0.961,0.237]	[-0.966,1.043]
Finance		
Access to agricultural credit	0.719	0.868
	[0.289,1.148]	[0.210,1.527]
Bank account	-0.169	-0.394
	[-0.608,0.271]	[-1.181,0.392]
Cash from the government	0.281	0.596
	[-0.109,0.671]	[-0.0498,1.242]
Income from non-farm employment	0.290	0.359
	[-0.0302,0.609]	[-0.202,0.921]
Income from renting out land or machinery	0.0977	0.352
	[-0.312,0.507]	[-0.317,1.022]
Assets		
Count of production-related assets	0.0551	0.256
	[-0.129,0.239]	[0.0285,0.483]
Count of nonproduction-related assets	0.186	0.256
	[0.0496,0.322]	[0.0285,0.483]
Livestock	0.372	0.717
	[-0.0956,0.839]	[-0.0205,1.455]
Motorcycle	0.260	0.237
	[-0.189,0.708]	[-0.404,0.879]
Car	0.0898	-0.0476
	[-0.999,1.178]	[-1.605,1.510]
Boat	-0.370	-1.286
	[-1.826,1.086]	[-4.289,1.717]
Farm and Household Characteristics		
Access to running water	1.013	1.355
	[0.354,1.672]	[0.225,2.485]
Storage facility for crops	1.315	1.773
	[0.904,1.726]	[1.087,2.460]
Planted trees	0.565	0.972
	[0.247,0.883]	[0.433,1.512]
Farm size	-0.0405	0.126
	[-0.185,0.104]	[-0.311,0.563]
Household size	-0.00922	-0.0145
	[-0.0347,0.0163]	[-0.0510,0.0221]
Female-headed	-0.125	-0.330
	[-0.570,0.319]	[-1.025,0.365]
Farming and Crisis Experience		
Farming experience is at least ten years	1.064	1.585
	[0.555,1.572]	[0.477,2.693]
Experienced climate crisis in the last five years	0.105	0.227
	[-0.264,0.475]	[-0.353,0.806]
Stated Reasons		
Market conditions	2.659	3.977
	[2.282,3.035]	[3.012,4.943]
Climate variability	1.692	2.325
	[1.322,2.062]	[1.609,3.041]
Pests and disease	1.869	2.792
	[1.462,2.275]	[1.969,3.615]
Government/NGO intervention	1.528	2.703
	[1.049,2.007]	[1.704,3.702]
Labor availability	1.352	2.050
	[1.022,1.683]	[1.446,2.654]
Land productivity	0.549	1.081
	[0.197,0.900]	[0.468,1.695]

Note: 95 percent confidence interval is reported in brackets. Total effect estimates of adaptive capacity elements for the Baseline Model is β, as reported in the last column of Table 2.3. Total effect estimates of adaptive capacity elements for the Neighbor Network Model is $\beta(\frac{1}{1-\rho})$. The 95 percent confidence interval of adaptive capacity elements for the Baseline Model is the confidence interval of an OLS approach. The 95 percent confidence interval of adaptive capacity elements in the Neighbor Network Model is calculated using the delta method.

results, $E[Y|X] = X\beta_{ols}$ and $|\beta_{ols}| > |\beta|$ for elements of adaptive capacity that are spatially correlated (Mobley et al., 2009). On the other hand, the SAR approach used in estimating the Neighbor Network Model obtains consistent estimates of marginal impacts of elements of adaptive capacity by disentangling the network effect. An implication is that ignoring network effects may potentially lead to incorrect first-order impacts of elements of adaptive capacity on adaptation. Interestingly, the coefficients of most adaptive capacity elements in the Baseline and Neighbor Network Models are similar. Using analytical explanations and Monte Carlo simulations, Anselin and Arribas-Bel (2013) show that this similarity occurs because we define neighbors as all households living in the same village with no inter-village interactions, and we use village-level fixed effects.

3.4 Robustness Check: Changing the Definition of Neighbors

Choosing which households to consider as neighbors has been recognized as a challenge (e.g. Krishnan and Patnam, 2014; Ward and Pede, 2014). This concern arises because a household may be influenced not only by households who live nearby but also by households who live far away, so it is possible that the estimated network effect in the Neighbor Network Model is contingent on our definition of neighbors.

We address this issue by examining how the network effect estimate changes in response to changes in the definition of neighbors. We add five alternative definitions of neighbors to our initial definition that all households living in the same village are neighbors. We investigate situations where neighbors are defined as all households living within 500, 1000, 1500, and 2000 meters of one another. We also define neighbors as all households living in the same site, which is comprised of multiple villages.

Table 3.4 reports the results of the Neighbor Network Model with different definition of neighbors. All these regressions use village and crops fixed effects, as in our preferred specification. The results show that the network effect is statistically significant across all definitions. This finding provides evidence that the adaptation levels of neighbors significantly influence farmers' adaptation decisions, and increasing the adaptive capacity of farmers can lead to significant spillover effects.

The first row of Table 3.4 indicates that the estimated network effect increases continuously as we change the definition of neighbors from all households living within a 500-meter radius of one another to all households living in the same site. We note that the network effect stabilizes when all households living within a 2000-meter radius of one another is used as the definition of neighbors. In particular, we observe a similar network effect when the definition of neighbors are all households living in the same site, which is defined by a 10 by 10 kilometer block for most sites. The results also show similar marginal effect estimates of adaptive capacity elements.

Table 3.4: Regression Results of the Neighbor Network Model with Different Definition of Neighbors

Neighbor definition	500m	1000m	1500m	2000m	Site
Network effect (ρ)	0.124***	0.235***	0.291***	0.336***	0.346***
	(0.032)	(0.047)	(0.053)	(0.057)	(0.071)
ACCESS TO INFORMATION AND HUMAN CAPITAL					
Access to weather information	0.491***	0.485***	0.433**	0.420**	0.373**
	(0.182)	(0.180)	(0.182)	(0.181)	(0.183)
Membership in farming association(s)	0.282*	0.305*	0.281*	0.309**	0.350**
	(0.156)	(0.156)	(0.157)	(0.157)	(0.157)
Highest level of education attained is primary	0.291	0.210	0.198	0.149	0.149
	(0.206)	(0.202)	(0.207)	(0.208)	(0.212)
Highest level of education attained is secondary	0.284	0.224	0.273	0.294	0.314
	(0.249)	(0.252)	(0.257)	(0.255)	(0.265)
Highest level of education attained is post-secondary	-0.159	-0.147	-0.076	-0.078	-0.020
	(0.353)	(0.334)	(0.330)	(0.330)	(0.336)
FINANCE					
Access to agricultural credit	0.497**	0.646***	0.597***	0.605***	0.529**
	(0.218)	(0.222)	(0.219)	(0.219)	(0.224)
Bank account	-0.500*	-0.313	-0.233	-0.178	-0.199
	(0.268)	(0.255)	(0.253)	(0.261)	(0.254)
Cash from the government	0.415*	0.333	0.317	0.331	0.481**
	(0.228)	(0.218)	(0.215)	(0.221)	(0.213)
Income from non-farm employment	0.453**	0.429**	0.402**	0.335*	0.283
	(0.183)	(0.191)	(0.192)	(0.193)	(0.195)
Income from renting out land or machinery	0.099	0.243	0.227	0.239	0.167
	(0.224)	(0.226)	(0.225)	(0.227)	(0.223)
ASSETS					
Count of production-related assets	0.040	0.051	0.038	0.044	0.077
	(0.090)	(0.096)	(0.096)	(0.096)	(0.093)
Count of nonproduction-related assets	0.219***	0.204***	0.192**	0.180**	0.156*
	(0.079)	(0.077)	(0.077)	(0.078)	(0.080)
Livestock	0.379	0.460*	0.502**	0.523**	0.600**
	(0.234)	(0.239)	(0.243)	(0.242)	(0.250)
Motorcycle	0.235	0.151	0.159	0.144	0.139
	(0.218)	(0.215)	(0.216)	(0.215)	(0.217)
Car or truck	0.054	-0.029	-0.000	0.017	0.072
	(0.492)	(0.518)	(0.529)	(0.528)	(0.474)
Boat	-1.528	-0.788	-0.642	-0.461	-0.790
	(1.183)	(1.033)	(0.989)	(1.011)	(0.896)
FARM AND HOUSEHOLD CHARACTERISTICS					
Running water	1.395***	0.998**	0.828**	0.748**	0.926**
	(0.389)	(0.366)	(0.368)	(0.375)	(0.389)
Storage facility for crops	1.226***	1.163***	1.182***	1.132***	1.136***
	(0.205)	(0.215)	(0.217)	(0.217)	(0.223)
Planted trees	0.564***	0.544***	0.558***	0.558***	0.562***
	(0.172)	(0.170)	(0.170)	(0.174)	(0.172)
Farm size	-0.031	0.059	0.049	0.032	0.003
	(0.154)	(0.141)	(0.131)	(0.125)	(0.150)
Household size	-0.009	-0.005	-0.007	-0.007	-0.011
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Female-headed	-0.215	-0.218	-0.230	-0.240	-0.253
	(0.218)	(0.234)	(0.242)	(0.242)	(0.243)
FARMING AND CRISIS EXPERIENCE					
Farming experience is at least ten years	1.203***	1.022***	0.909**	0.761**	0.630
	(0.313)	(0.323)	(0.353)	(0.365)	(0.446)
Experienced climate crisis in the last five years	0.269	0.194	0.238	0.194	0.202
	(0.188)	(0.198)	(0.203)	(0.202)	(0.212)
STATED REASONS					
Market conditions	2.595***	2.683***	2.709***	2.701***	2.698***
	(0.204)	(0.203)	(0.205)	(0.204)	(0.204)
Climate variability	1.482***	1.462***	1.424***	1.449***	1.689***
	(0.203)	(0.206)	(0.204)	(0.204)	(0.213)
Pests and disease	2.001***	1.927***	1.916***	1.913***	1.938***
	(0.208)	(0.215)	(0.219)	(0.218)	(0.235)
Government/NGO intervention	1.568***	1.671***	1.765***	1.776***	1.723***
	(0.250)	(0.275)	(0.293)	(0.292)	(0.289)
Labor Availability	1.431***	1.373***	1.373***	1.350***	1.305***
	(0.169)	(0.166)	(0.166)	(0.165)	(0.166)
Land productivity	0.793***	0.710***	0.719***	0.699***	0.631***
	(0.191)	(0.186)	(0.186)	(0.183)	(0.188)
Constant	-2.611**	-3.523***	-3.843***	-4.048***	-4.329***
	(0.895)	(0.956)	(1.011)	(1.054)	(1.178)
R^2	0.696	0.735	0.731	0.735	0.698
F-statistic of the first stage regression	10,970.91	17,240.82	3,369.64	2,646.33	7,834.26

Sample Size: N=2,043. All regressions control for village and crops fixed effects. Robust standard errors are reported in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Chapter 4

Neighbor Networks and Household Targeting

Results from the Neighbor Network Model show that neighbors significantly influence the ability of farmers to adapt. In each neighbor network, it is possible that some households are more influential than others in contributing to average adaptation levels. Policy interventions targeting these influential households may therefore be an effective approach to relax adaptive capacity constraints in a village. For example, in the case of microfinance, Banerjee et al. (2013) find that the uptake of microfinance in villages of rural India is higher in villages where information was disseminated through households who are influential in their network.

Since network effects are positive and significant when we consider the adaptation levels of all neighbors, we now investigate whether or not the adaptation levels of a subset of neighbors also generate significant network effects. This approach involves choosing which households to select, and the size of the subset. This selection rule allows us to decompose the total network effect obtained in the Neighbor Network Model into network effects coming from different subsets of households.

We begin this chapter by first explaining how we identify potentially influential households. Next, we describe the estimation strategy we use to select which, and how many, households to include in the subsets. Finally, we discuss the results and implications.

4.1 The Household Targeting Model

Consider two households j and k. Household j has 10 neighbors living within 500 meters. Household k, on the other hand, has 3 neighbors living within 500 meters. Because household j has more neighbors who live within 500 meters, it is possible that household j is relatively more central (or geographically well-positioned to influence neighbors) in the village. Central households like household j may therefore exert disproportionate influence in the composition of the overall network effect.

In order to identify central households like household j, network theory allows us to construct a centrality score for every household in a village. For this purpose, we consider a network matrix that is a non-normalized version of the matrix $\mathbf{W}$, that is, a network in which the strength of the connections between households i and j is inversely proportional to the distance between them, i.e. $\frac{1}{a_{ij}}$. We use two centrality measures: weighted degree centrality and weighted eigenvector centrality. A weighted degree centrality of household i reflects how much weight other households in the village places on household i. Formally, weighted degree centrality is defined as:

$$\hat{c}_i = \sum_i \frac{1}{a_{ij}} \tag{4.1}$$

where a_{ij} is the geographic distance of i to j, as in Section 3.1 (Barrat et al., 2004). The intuition of this centrality measure is that a household has a high weighted degree centrality score if the household has a lot of neighbors who live close.

A weighted eigenvector centrality of household i depends on the centrality scores of i's neighbors. Formally, weighted eigenvector centrality is defined as:

$$\lambda \tilde{c}_i = \sum_i \frac{1}{a_{ij}} \tilde{c}_j \tag{4.2}$$

where λ is the largest eigenvalue associated with the network matrix (Jackson, 2010). The intuition of this centrality measure is that a household has a high weighted eigenvector centrality score if the household lives close to neighbors who are, themselves, central.

We compute $\hat{c}_i$ and $\tilde{c}_i$ for all households in all 108 villages. Figures 4.1 and 4.2, respectively, present the distribution of weighted degree and weighted eigenvector centrality scores of all households in our sample. The average weighted degree centrality score is 0.008, and the average weighted eigenvector centrality score is 0.165. The distributions of both weighted degree and weighted eigenvector centrality scores are skewed to the right, so most households have low centrality scores with a few households having high centrality scores. The Spearman's rank correlation coefficient is 0.338, and we reject the null hypothesis that the two centrality scores are independent at the 1 percent level.

For both measures of centrality, we run a series of regressions in which we estimate:

$$\mathbf{Y} = \rho \mathbf{W} \tilde{\mathbf{Y}} + \mathbf{X}\beta + \epsilon \tag{4.3}$$

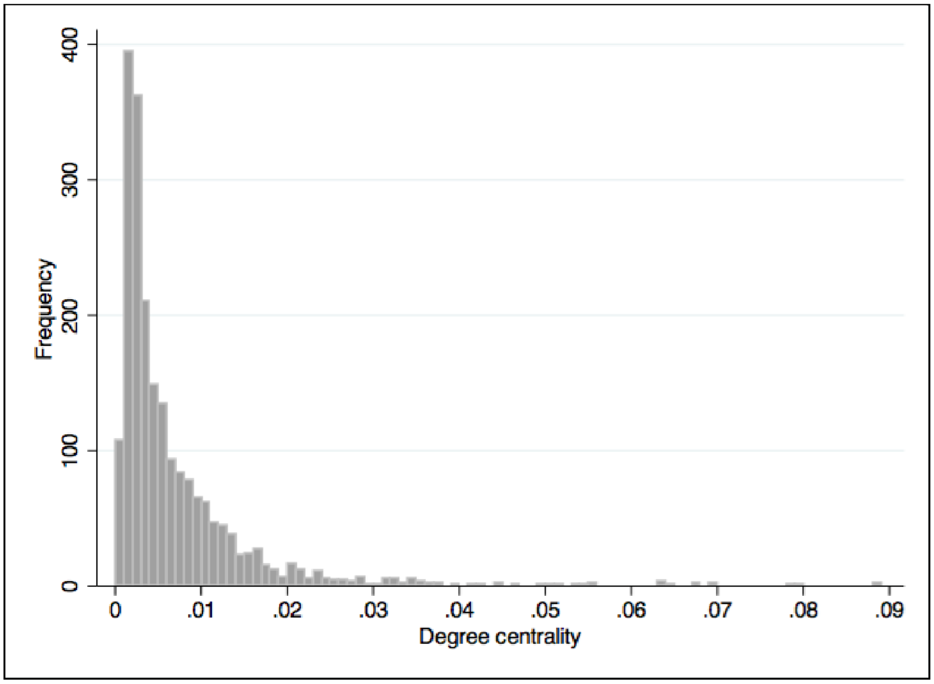
where $\mathbf{Y}$, $\mathbf{W}$, and $\mathbf{X}$, respectively, are the same adaptation vector, weighting matrix, and matrix of adaptive capacity elements, as in the previous chapter. $\tilde{\mathbf{Y}}$ is a vector that collects the adaptation levels of a subset of selected households, and contains zeros for households not selected in the subset. The error term ϵ captures unobserved determinants of adaptation.

We now proceed to explain our selection rule to choose which households to include in the subset of nonzero elements of $\tilde{\mathbf{Y}}$. We estimate Equation (4.3) 21 times. In the first regression, we examine the influence of the most central household in each village on farmers' adaptation levels, so $\tilde{\mathbf{Y}}$ only contains the adaptation level of the most central household in each village, and zero elsewhere. In the second regression, we look at the influence of the two most central households in each village on farmers' adaptation levels, so $\tilde{\mathbf{Y}}$ contains the adaptation levels of the two most central households in each village, and zero elsewhere.[14] We continue to estimate Equation (4.3), where each subsequent regression increases the number of central households that can influence farmers' adaptation levels, until all households in the village are included.

Similar to Equation (3.1), a potential problem with Equation (4.3) is endogeneity because of reverse causality. To address this issue, we use the GMM/IV approach, as in the previous

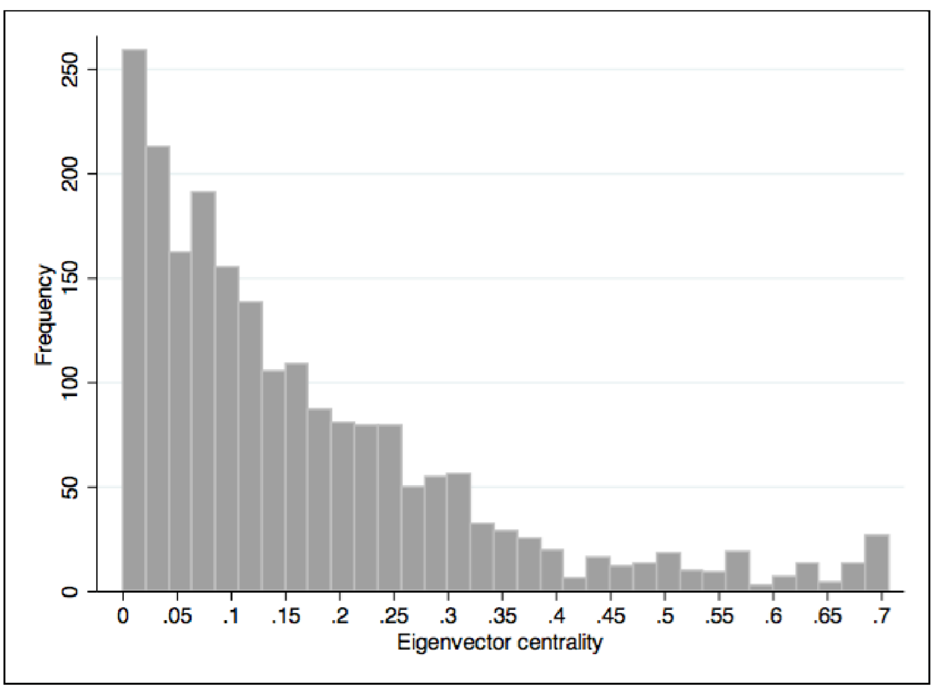
[14] Recall that the 2,043 households in our sample are distributed across 108 villages. Thus, in the first regression, $\tilde{\mathbf{Y}}$ contains 1,935 zeros and the adaptation levels of the most central households in each village (i.e. 108 nonzero elements). In the second regression, $\tilde{\mathbf{Y}}$ contains the 1,827 zeros and the adaptation levels of the two most central households in each village (i.e. 216 nonzero elements).

Figure 4.1: Distribution of Weighted Degree Centrality in our Sample



Note: Because there are only two households with $\hat{c}_i = 0.50$ and another two households with $\hat{c}_i = 0.53$, we only present the distribution of scores when $\hat{c}_i < 0.50$.

Figure 4.2: Distribution of Weighted Eigenvector Centrality in our Sample



chapter. The instruments we use in estimating our Household Targeting Model are $\mathbf{W\tilde{X}}$ and $\mathbf{W^2\tilde{X}}$, where $\mathbf{\tilde{X}}$ is a matrix that collects the adaptive capacity elements of households who are included in the subset, and zero otherwise. The interpretation of these instruments are similar to Bramoullé (2001). $\mathbf{W\tilde{X}}$ is the weighted average adaptive capacity of the first-order neighbors of households selected to be in the subset, i.e. the weighted average adaptive capacity of other households of the subset. $\mathbf{W^2\tilde{X}}$ is the weighted average adaptive capacity of the second-order neighbors of households selected to be in the subset.

For each of these regressions, we control for village and crops fixed effects and estimate a network effect (ρ). Thus, we are able to observe how the size and significance of the network effect changes, as the number of households that can influence farmers' adaptation levels increases. In the final regression, when the adaptation of all households in the village are able to influence adaptation, the estimated network effect (i.e. $\rho = 0.336$) is equivalent to the network effect obtained from the Neighbor Network Model in Chapter 3. We refer to the process that uses weighted degree centrality to rank households as *degree targeting*. When weighted eigenvector centrality measure is used to rank households, we refer to the process as *eigenvector targeting*.

To investigate the potential benefits of our proposed targeting strategy, we establish a baseline by conducting simulations and estimating network effects of choosing random households, as opposed to using the ranking based on centrality scores, to be included in the subsets. In particular, for each possible subset size of $\mathbf{\tilde{Y}}$, we estimate Equation (4.3) 300 times. For example, when the subset size is one, the computer randomly chooses the adaptation of one household in each village to construct $\mathbf{\tilde{Y}}$. Next, we estimate ρ. Then, we repeat this process 300 times. When the subset size is two, the computer randomly chooses the adaptation of two households in each village to construct $\mathbf{\tilde{Y}}$. Next, we estimate ρ. Then, we repeat this process 300 times, and so on. We refer to this simulation as *random selection*. We take the average ρ from the 300 replications of each possible subset size as the simulation estimates of ρ.[15] We also construct the 95 percent confidence interval by taking the average values of the 300 lower and upper bounds of the 95 percent confidence interval for each of

[15]In our sample, the largest number of households in a village is 21, so we have 21 simulation estimates of ρ.

the simulation estimate of ρ. Note that we also control for village and crop fixed effects for all *random selection* regressions.

4.2 The Impacts of Household Targeting on Network Effects

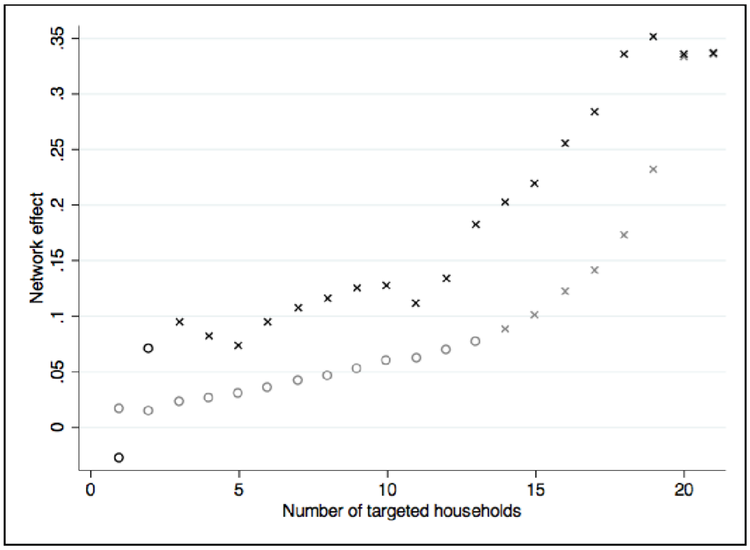
Figure 4.3 graphs the estimated network effects of *degree targeting* and *random selection*, and Figure 4.4 graphs the estimated network effects of *eigenvector targeting* and *random selection*. We interpret the network effect estimates as statistically significant when the 95 percent confidence interval does not include zero. Table A3 in the Appendix displays the coefficients and confidence intervals of the estimated neighbor network effects of *degree targeting*, *eigenvector targeting*, and *random selection*.

The results show that the adaptation levels of subsets of households in a village also lead to positive and significant network effects. Moreover, we find evidence that there are gains to using our selection rule of choosing central households as the initial households to include in the subset, in that all significant estimates of the network effect in *degree* and *eigenvector targeting* are greater than the estimates of the network effect in *random selection*. We also find that ρ is statistically significant when three or more households are included in the subset for *degree targeting*, and when two or more households are included in the subset for *eigenvector targeting*. In contrast, the minimum number of households for ρ to be statistically significant in *random selection* is 14.

A caveat is that the confidence intervals of the estimated network effects of *degree targeting* and *eigenvector targeting* overlap with the confidence interval of the simulated network effects of *random selection*. This result though is not surprising because we expect the confidence intervals of network effects in the *degree* and *eigenvector targeting* to be wide since they are estimated with a GMM approach (Imbens and Spady, 2002). A wide confidence interval is also expected for the estimated network effects in *random selection* because households are randomly chosen to be part of the subset. But despite overlapping confidence intervals, we still find that the confidence intervals of the network effects of *degree* and *eigenvector* targeting, respectively, do not include zero when at least two and three households are targeted, while zero is included in the confidence intervals of the network effects for *random selected* until at least 14 households are targeted. This result suggests that our proposed targeting strategy could still be useful in informing policy design, as it provides policymakers with a method to choose households that are potentially more influential in their network to catalyze the network multiplier.

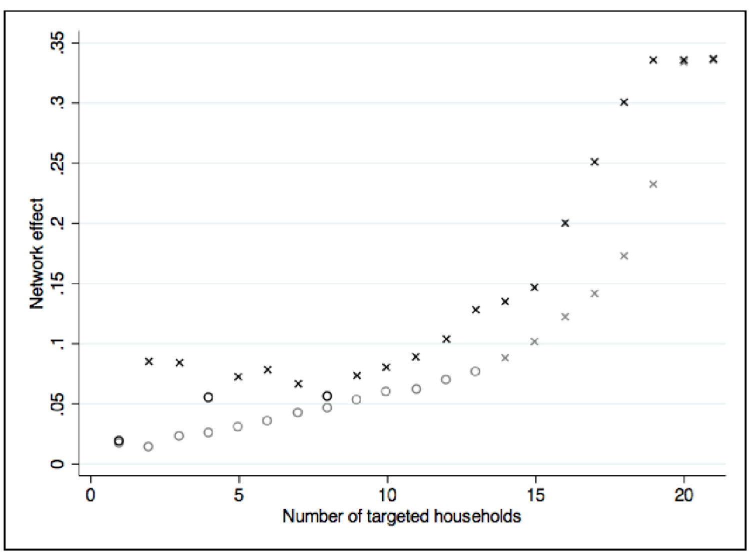
An implication of our results is that targeting policy interventions towards subsets of central households could be beneficial and potentially more cost-effective than targeting all households in a village. The results are especially relevant in deciding the scale of an intervention in which costs increase at an increasing rate as the number of targeted households increases. With convex costs, increasing the reach of an intervention to the entire village to maximize the network effect, and hence the network multiplier, may not be the most cost-effective strategy. Optimal policy design may therefore be at a smaller scale, so choosing which, and how many, households to target may become more important to achieve intervention goals, such as in maximizing the spread of information. For example, participants in a workshop co-organized by CCAFS recognize the importance of providing relevant and timely climate information in order to help farmers adapt (Tall et al., 2013). The participants indicate that reaching a larger number of farmers, especially the "remote farmers at the 'last mile' at scale," is a challenge because of high costs and lack of infrastructure and human resources (Tall et al., 2013, p.17). If costs of providing information to farmers "at the last mile" are high, then the policy intervention providing information that targets fewer but more central farmers, as opposed to the entire village, may be a better use of resources.

Figure 4.3: Network Effects of Targeting an Increasing Number of Households
Degree Targeting and *Random Selection*



Note: Dark markers represent network effect estimates of *degree targeting*. Light markers represent network effect estimates of *random selection*. ○ indicates the network effect estimate is not significant (i.e. the 95 percent confidence interval includes zero). × indicates the network effect estimate is significant.

Figure 4.4: Network Effects of Targeting an Increasing Number of Households
Eigenvector Targeting and *Random Selection*



Note: Dark markers represent network effect estimates of *eigenvector targeting*. Light markers represent network effect estimates of *random selection*. ○ indicates the network effect estimate is not significant (i.e. the 95 percent confidence interval includes zero). × indicates the network effect estimate is significant.

Chapter 5

Welfare Impacts

While adaptation is frequently assumed to be welfare improving, empirical evidence of welfare impacts of adaptation at the farm- or household-level is scarce because of endogeneity issues. For instance, estimates could suffer from reverse causality because adaptation may influence welfare, but welfare may also influence adaptation (Kristjanson et al., 2012). It is therefore important to identify ways to consistently estimate the impacts of adaptation on welfare. This chapter shows that the existence of strong neighbor network effects on adaptation suggests a set of instruments that can be used to address the endogeneity issue. We begin this chapter by first describing our welfare measure. Next, we present our econometric model to analyze the effect of adaptation on welfare and explain our identification strategy in more detail. Finally, we discuss our findings.

5.1 The Welfare Model

We measure welfare in terms of food security. Lobell et al. (2008) identify South Asia, East Africa, and West Africa, the three regions where households in our sample are located, as major food-insecure regions in the world. Households were asked to identify in which months in a typical year they tend to struggle to find sufficient food, or experience shortages to feed their families. We calculate 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.[16] This measure has been used in the literature (e.g. Kristjanson et al., 2012) and follows the definition of 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). On average, households in our sample experience 263 food secure days per year, with a standard deviation of approximately 87 days.

We hypothesize that adaptation positively contributes to food security. To investigate this relationship, we estimate a linear model, which can be written in matrix notation as:

$$\mathbf{FS} = \alpha \mathbf{Y} + \beta \mathbf{X} + \epsilon \tag{5.1}$$

where $\mathbf{FS}$ is a vector of food secure days, and $\mathbf{Y}$ and $\mathbf{X}$, respectively, are the same adaptation vector and matrix of elements of adaptive capacity of households, as in previous chapters. The error term ϵ captures unobserved determinants of food security.

As mentioned earlier, the potential endogneity of adaptation is a challenge for identification. To overcome this identification challenge, we exploit the spatial information of households in our data. Our Neighbor Network Model (Chapter 3) suggests some instrumental variables for identification. Specifically, our proposed set of instruments to identify welfare impacts are $\mathbf{WX}, \mathbf{W}^2\mathbf{X}$, and $\mathbf{W}^3\mathbf{X}$.

The intuition for using this set of instruments can be seen from Equation 3.3. The equation shows that the variables $\mathbf{X}$, $\mathbf{WX}$, and $\mathbf{W^2X}$ are all correlated to the endogenous food security variable. However, $\mathbf{X}$ may not be used as an instrument because elements of adaptive capacity may also directly influence food security. As a result, we use $\mathbf{W^3X}$ as an instrument instead of $\mathbf{X}$. The validity of our instrument relies on the assumption that neighbors' adaptive capacity $\mathbf{WX}$ is not correlated with the unobservable determinants of food security, and does not affect food security directly but only indirectly through adaptation levels $\mathbf{Y}$, as demonstrated by Equation 3.3.

While spatial econometric theory guides the use of spatial lags of X (i.e. $\mathbf{WX}$ and $\mathbf{W}^2\mathbf{X}$) as instruments for identifying SAR models, such as our Neighbor Network Model, there are

[16] We multiplied the number of months that the household indicated that they do not have enough food to eat by 30 days.

no similar theoretical underpinnings that support the use of these instruments in our Welfare Model. To provide support for the use of instruments in our Welfare Model, we conduct two statistical tests. First, we perform a test to determine whether adaptation, which we presume to be endogenous, is in fact exogenous. Our test is based on the C (difference-in-Sargan) statistic (Hayashi, 2000). If the test statistic is significant, the variable is considered to be endogenous. We reject the null hypothesis that adaptation is exogenous with a p-value of 0.013. This result suggests that the use of an instrumental variable estimator is appropriate. Second, we perform a test of overidentifying restrictions in order to investigate the validy of our instruments. Our test is based on Hansen's J test statistic (Hansen, 1982). If the test statistic is significant, the instruments may not be valid. We fail to reject the null hypothesis with a p-value of 0.174. This result provides support that our proposed set of instruments is valid.

5.2 The Impacts of Adaptation on Food Security

Table 5.1 shows the results of estimating Equation (5.1) that controls for village and crops fixed effects. The results in the first column do not instrument for the endogneous adaptation variable and indicates that changing an additional farming practice leads to a 1.4 increase in food secure days. The second column uses neighbors' characteristics as instruments for the endogenous adaptation term and shows that changing an additional farming practice increases food security by 5.5 days. 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 underestimates the welfare contribution of adaptation by 25 percent. With respect to adaptive capacity, we find the following elements to have a positive and significant effect on food security: *bank account, cash from the government, count of nonproduction-related assets,* and *farm size.* On the other hand, *household size* and *experienced climate crisis in the last five years* have a negative and significant effect on food security. In addition, citing *market conditions, pests and disease* and *land productivity* as reasons for adaptation decreases food security days.

Our results that demonstrate the importance of adaptation to food security has been emphasized in many studies (e.g Wheeler and von Braun, 2013; Battisti and Naylor, 2009; Lobell et al., 2008). In addition, our finding that adaptation is welfare improving is in line with a number of empirical studies that addresses the endogeneity issue in analyzing the welfare impacts of adaptation at the farm level. For example, using an endogenous switching regression technique, Di Falco and Veronesi (2013) show that higher levels of adaptation increase net revenues. They find that the joint implementation of water strategies and changing crop varieties increases the net revenues of Ethiopian farmers by 2331 Ethiopian birr per hectare, as compared to no significant increase in net revenues when farmers implement these strategies in isolation. Using the same technique, Di Falco et al. (2011) show 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, and households who did not adapt would have produced 35% more if they had adapted.

Table 5.1: Regression Results of the Welfare Model

Estimation Approach	OLS	GMM/IV
Level of Adaptation	1.401**	5.520***
	(0.509)	(1.672)
ACCESS TO INFORMATION AND HUMAN CAPITAL		
Access to weather information	1.880	-2.787
	(4.511)	(4.256)
Membership in farming association(s)	0.383	-1.613
	(3.442)	(3.130)
Highest level of education attained is primary	9.172	6.708
	(5.280)	(4.823)
Highest level of education attained is secondary	0.973	-0.649
	(5.956)	(5.474)
Highest level of education attained is post-secondary	5.889	9.799
	(7.498)	(7.413)
FINANCE		
Access to agricultural credit	-0.602	-2.201
	(4.500)	(4.462)
Bank account	10.844	11.290*
	(5.558)	(5.617)
Cash from the government	15.633***	10.271*
	(4.187)	(4.538)
Income from non-farm employment	-3.152	-4.105
	(3.587)	(3.784)
Income from renting out land or machinery	0.710	-0.339
	(3.917)	(4.077)
ASSETS		
Count of production-related assets	-1.644	-2.623
	(1.835)	(1.941)
Count of nonproduction-related assets	6.679***	5.312**
	(1.600)	(1.617)
Livestock	9.971	7.881
	(6.410)	(5.940)
Motorcycle	-0.566	-2.308
	(4.839)	(4.378)
Car or truck	-6.170	-9.442
	(8.055)	(7.472)
Boat	25.811	43.812
	(20.628)	(27.437)
FARM AND HOUSEHOLD CHARACTERISTICS		
Running water	7.563	-6.137
	(6.127)	(7.591)
Storage facility for crops	3.756	1.326
	(4.457)	(4.869)
Planted trees	-2.257	-3.822
	(3.618)	(3.669)
Farm size	7.914***	11.161***
	(2.271)	(3.124)
Household size	-0.519*	-0.600*
	(0.250)	(0.236)
Female-headed	-2.507	-4.801
	(5.492)	(5.250)
FARMING AND CRISIS EXPERIENCE		
Farming experience is at least ten years	14.799*	10.176
	(7.390)	(8.331)
Experienced climate crisis in the last five years	-12.868***	-11.438**
	(3.785)	(3.657)
STATED REASONS		
Market conditions	-11.344**	-20.408***
	(4.169)	(5.702)
Climate variability	9.230*	3.304
	(4.242)	(5.029)
Pests and disease	-6.039	-12.798**
	(4.113)	(4.964)
Government/NGO intervention	-4.257	-8.905
	(4.386)	(5.529)
Labor availability	-0.152	-6.807
	(3.632)	(4.152)
Land productivity	-9.618*	-13.536***
	(3.837)	(3.898)
Constant	171.155***	196.077***
	(29.409)	(26.676)
R^2	0.535	0.449
F-statistic of the first-stage regression		160.85

Sample Size: N=2,043. Robust standard errors are reported in parentheses. All regressions control for village and crops fixed effects.*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Chapter 6

Summary and Conclusions

Farmers in rural areas of developing countries may adapt their farming practices in response to a myriad of uncertain circumstances. However, because of weak adaptive capacity, such as lack of access to information and credit, farmers' adaptation decisions may be constrained. Networks of relationships can potentially augment the adaptive capacity of farmers by acting as conduits of information and resources. The primary goal of this thesis is to investigate the role of neighbor networks on adaptation and show how policymakers can take advantage of the network multiplier effect to influence the adaptation and welfare of farmers. We pursue this goal through three research objectives.

The first objective is to estimate the effects of adaptive capacity, including neighbor networks, on adaptation. Our results show that adaptation increases by having access to information and credit, more nonproduction-related assets, owning livestock, having running water and storage facility for crops, tenure security, and farming experience. These significant elements of adaptive capacity highlight possible opportunities that policy interventions can focus on to help farmers adapt. In addition to the traditional elements of adaptive capacity, we find a positive and strongly significant network effect on the adaptation decisions of farmers. Specifically, for every three farming practices that neighbors change, own adaptation increases by one practice. This finding implies a network multiplier of 1.5, which means that the total impact of a marginal change in adaptive capacity is amplified by 50 percent. For policymakers, this result suggests that neighbor network interactions can catalyze the impacts of their policy interventions.

The second objective is to show how network effects could be used to inform the design of policy interventions. Our targeting approach demonstrates that targeting fewer, but more central, households may improve the efficiency of targeting interventions. For instance, a policy can target a minimum of two central households, as opposed to 14 random households, in a village to achieve statistically significant network effects on adaptation of similar magnitudes. This result suggests that achieving positive and significant network effects is not an all or nothing proposition. Policy interventions that target the adaptation of a subset of central households in a village can benefit from network multiplier effects and positively contribute to the adaptation of other households in the village. This implication is especially important in cases where the costs of an intervention are convex as the number of targeted households increase. In these cases, considering trade-off of intervention scale and network multiplier size may increase the net benefits of a policy due to large costs of reaching the farmers at the last mile of scale. For example, our results show that the network multiplier of targeting the two most central households in a village, or a tenth of the village, is equal to 25 percent of the network multiplier size when an entire village is targeted.

The third objective is to analyze the welfare impacts of adaptation. By implementing an instrumental variable approach, where the characteristics of neighbors are used for identification, we find that adaptation increases food security by 5.5 days. This welfare impact is 25 percent greater than the estimated welfare impact when endogeneity is not addressed. Our result not only highlights the positive and significant impact of adaptation on welfare, but it also shows the importance of addressing endogeneity to estimate consistent causal effects of adaptation on welfare. One policy implication of our welfare analysis is that facilitating adaptation can also improve the food security of farmers.

While our study offers generalizable findings about adaptive capacity, adaptation, and welfare, our results also point to several areas of future research. The significance of network effects on adaptation suggests that other studies on adaptation should incorporate network effects into their analysis. In addition, case studies would be able to uncover some context-specific factors that may drive the impacts of networks of relationships on adaptation decisions. For example, Munshi (2004) finds that network effects vary across different types of crops because some farm and farmer characteristics are more difficult to observe.

The results of our targeting strategy, which show that the adaptation of subsets of households also generates significant network effects, suggest that future work should investigate alternative selection rules to identify which, and how many, households to target in a policy to maximize network effects. While our strategy shows that there are benefits to targeting the most central households first, following the ranking of households' centrality scores to choose which households to target first may not be the best approach, as targeting the two most central households may be viewed as a duplication of efforts. If two households are central because they are located in similar positions, there would be a strong connection between these two households. As a result, the reach of a program may be higher if the second target is a household positioned in a different location.

So how can we help farmers? Policymakers should not let the rationality of farmers postpone action to help farmers improve their welfare. Instead, they should leverage the responsive nature of farmers, which they demonstrate by adapting their farming practices and by responding to their neighbors' adaptation decisions. In particular, policymakers should focus on relaxing adaptive capacity constraints. By strategically targeting central farmers in villages, policymakers could amplify the total impacts of their efforts and use their scarce resources more efficiently. These interventions would help farmers be in a better position to face the harsh and uncertain conditions of rural areas of developing countries and ultimately experience higher welfare.

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Appendix

Table A1: Descriptive Statistics of Farming Practices

Type of Practice	Percentage†	Standard Deviation
Introduced any new crop	21.782	0.413
Testing any new crop	3.965	0.195
Stopped growing a crop (totally)	6.559	0.248
Stopped growing a crop (in one season)	17.230	0.378
Introduced new variety of crops	68.527	0.465
Planting higher yielding variety	58.199	0.493
Planting better quality variety	43.661	0.496
Planting pre-treated/improved seed	34.068	0.474
Planting shorter cycle variety46.50024	46.500	0.499
Planting longer cycle variety	13.950	0.347
Planting drought tolerant variety	23.299	0.423
Planting flood tolerant variety	2.643	0.160
Planting salinity-tolerant variety	0.734	0.085
Planting toxicity-tolerant variety	0.196	0.044
Planting disease-resistant variety	21.096	0.408
Planting pest-resistant variety	16.887	0.375
Testing a new variety	13.803	0.345
Stopped using a variety	30.984	0.463
Expanded area	49.290	0.500
Reduced area	27.509	0.447
Started irrigating	5.091	0.220
Stopped irrigating	0.441	0.066
Stopped burning	6.265	0.242
Introduced intercropping	48.605	0.500
Introduced crop cover	2.007	0.140
Introduced micro-catchments	4.699	0.212
Introduced/built ridges or bunds	7.538	0.264
Introduced mulching	7.342	0.261
Introduced terraces	9.643	0.295
Introduced stone lines	4.356	0.204
Introduced hedges	3.671	0.188
Introduced contour ploughing	10.426	0.306
Introduced rotations	29.075	0.454
Introduced improved irrigation	12.041	0.326
Introduced improved drainage	2.986	0.170
Introduced tidal water control management	0.441	0.066
Introduced mechanized farming	20.313	0.402
Earlier land preparation	47.528	0.500
Earlier planting	37.396	0.484
Later planting	21.831	0.413
Started using or using more chemical fertilizers	40.675	0.491
Started using manure/compost	45.277	0.498
Stopped using manure/compost	4.797	0.214
Started using or using more pesticides/herbicide	29.662	0.457
Started using integrated pest management	5.091	0.220
Started using integrated crop management	5.091	0.220

†This column reports the percentage of households in our sample that has adapted by changing the type of farming practice listed in the first column.

Table A2: Marginal Effects of the Baseline Model Estimated Using a Negative Binomial Approach

	Marginal Effect
Access to Information and Human capital	
Access to weather information	0.684***
	(0.235)
Membership in farming association(s)	0.335**
	(0.161)
Highest level of education attained is primary	0.374
	(0.265)
Highest level of education attained is secondary	0.261
	(0.286)
Highest level of education attained is post-secondary	-0.096
	(0.326)
Finance	
Access to agricultural credit	0.638***
	(0.205)
Bank account	-0.324
	(0.206)
Cash from the government	0.346*
	(0.188)
Income from non-farm employment	0.358**
	(0.164)
Income from renting out land or machinery	0.009
	(0.187)
Assets	
Count of production-related assets	0.064
	(0.077)
Count of nonproduction-related assets	0.112*
	(0.068)
Livestock	0.430
	(0.430)
Motorcycle	0.380*
	(0.207)
Car or truck	-0.049
	(0.422)
Boat	-2.006
	(1.509)
Farm and Household Characteristics	
Running water	0.843***
	(0.295)
Storage facility for crops	1.047***
	(0.176)
Planted trees	0.478***
	(0.159)
Farm size	0.285
	(0.182)
Household size	-0.009
	(0.014)
Female-headed	-0.328
	(0.216)
Farming and Crisis Experience	
Farming experience is at least ten years	1.524***
	(0.296)
Experienced climate crisis in the last five years	0.127
	(0.187)
Stated Reasons	
Market conditions	3.762***
	(0.269)
Climate variability	2.143***
	(0.221)
Pests and disease	1.421***
	(0.176)
Government/NGO intervention	0.857***
	(0.184)
Labor availability	1.051***
	(0.156)
Land productivity	0.742***
	(0.190)

Sample Size: N=2,043. The regression controls for village and crops fixed effects. Robust standard errors are reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A3: Neighbor Network Effects from
Degree Targeting, *Eigenvector Targeting*, and *Random Selection*

Number of Targeted Households	Degree Targeting	Eigenvector Targeting	Random Selection
1	-0.028	0.019	0.012
	[-0.125, 0.069]	[-0.083,0.121]	[-0.137 , 0.161]
2	0.070	0.084	0.016
	[-0.004, 0.144]	[0.012 , 0.156]	[-0.104 , 0.135]
3	0.095	0.084	0.016
	[0.022 , 0.167]	[0.022 , 0.146]	[-0.088 , 0.120]
4	0.081	0.055	0.018
	[0.015 , 0.147]	[-0.003 , 0.113]	[-0.077 , 0.113]
5	0.073	0.072	0.022
	[0.002 , 0.145]	[0.016 , 0.128]	[-0.066 , 0.111]
6	0.094	0.078	0.030
	[0.024 , 0.164]	[0.022 , 0.134]	[-0.054 , 0.114]
7	0.107	0.066	0.037
	[0.030 , 0.185]	[0.009 , 0.124]	[-0.044 , 0.118]
8	0.115	0.055	0.036
	[0.041 , 0.190]	[-0.003 , 0.114]	[-0.042 , 0.115]
9	0.125	0.073	0.041
	[0.050 , 0.199]	[0.013 , 0.133]	[-0.036 , 0.118]
10	0.127	0.080	0.048
	[0.053 , 0.202]	[0.020 , 0.140]	[-0.029 , 0.125]
11	0.111	0.089	0.054
	[0.033 , 0.189]	[0.028 , 0.149]	[-0.023 , 0.131]
12	0.133	0.104	0.062
	[0.053 , 0.214]	[0.042 , 0.165]	[-0.015 , 0.139]
13	0.182	0.128	0.069
	[0.096 , 0.268]	[0.064 , 0.192]	[-0.010 , 0.147]
14	0.202	0.134	0.082
	[0.113 , 0.292]	[0.068 , 0.200]	[0.002 , 0.163]
15	0.219	0.146	0.097
	[0.126 , 0.311]	[0.077 , 0.215]	[0.014 , 0.180]
16	0.255	0.200	0.116
	[0.155 , 0.355]	[0.123 , 0.277]	[0.030 , 0.203]
17	0.283	0.250	0.144
	[0.174 , 0.393]	[0.155 , 0.346]	[0.051 , 0.236]
18	0.335	0.301	0.183
	[0.210 , 0.461]	[0.192 , 0.409]	[0.082 , 0.284]
19	0.351	0.335	0.239
	[0.223 , 0.479]	[0.215 , 0.456]	[0.128 , 0.351]
20	0.336	0.336	0.335
	[0.208 , 0.464]	[0.208 , 0.464]	[0.206 , 0.463]
21	0.336	0.336	0.336
	[0.207 , 0.464]	[0.207 , 0.464]	[0.207 , 0.464]

Note: 95 percent confidence interval is reported in brackets.