Agricultural Extension, Technology Adoption and Household Food Security:

Evidence from DRC

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Agricultural Extension, Technology Adoption and Household Food Security: Evidence from DRC

Jozimo Santos Rocha

Thesis

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I dedicate this thesis to my loving daughter Isabella, sons Iker and Ian, and wife Cecilia, and to the bright memory of my father Temistocles Rocha

Table of Contents

1
General introduction

1.1. Overview

The haggard face and battered hands of a small-scale farmer in a little rural village in eastern Democratic Republic of Congo (DRC) portray lurid evidence of the harsh reality of millions of heads of households in DRC who, year after year, use agriculture as their single most important resort to provide for their families, yet with very limited reward. Globally, more than 75 percent of the poor live in rural areas and depend on agriculture as their main livelihood (World Bank, 2007). Given the important contribution of small-scale farmers to the sector, growth in agriculture has the potential to benefit the poorest (Christiaensen, Demery *et al.*, 2010). Agriculture is the economic sector with unrivaled potential to foster growth, empowerment and inclusiveness (AGRA, 2015; Blein, Bwalya *et al.*, 2013; FAO, 2015b) and to reduce poverty (Christiaensen, Demery *et al.*, 2010; de Janvry & Sadoulet, 2010; World Bank, 2007), however the reality is that, in SSA and certainly in DRC, agriculture holds millions of small-scale farmers and their families hostage in a cycle of unproductiveness, privation, poverty, and food insecurity.

Food insecurity affects many households in Sub-Saharan Africa (SSA). According to FAO (2015a), 23 percent of the SSA population is undernourished and the total number of people continue to increase in the region. Food insecurity impacts an important share of the population in DRC as well, where the prevalence of food insecurity is at 73 percent (Nord, Cafiero *et al.*, 2016), and stunting affects about 50 percent of children (Akakpo, Randriamamonjy *et al.*, 2014; Ortega, Melgar-Quiñonez *et al.*, 2016).

Like the rest of SSA, household food insecurity in DRC has its roots in widespread poverty, largely caused by the low productivity of its ill-equipped small-scale agriculture. The agriculture sector accounts for 42 percent of the gross domestic product (GDP), and 62 and 84 percent of employment for women and men, respectively (D'Haese, Banea-Mayambu *et al.*, 2013), however the level of productivity is one of the lowest in the region. During the last four decades of the 20th century, SSA experienced the least agricultural growth (Evenson & Gollin, 2003b), and the yields of its major crops, namely cereals, roots and tubers, pulses, sugar crops, oil crops and vegetables registered major gaps compared to other regions (FAO, 2014). Decades of conflict, a weak and under-resourced central and provincial-level government, and poor infrastructure have inhibited research and development activities in the country (Lambrecht, Vanlauwe *et al.*, 2016a; Rossi, Hoerz *et al.*, 2006), leading to a highly fragile agricultural system.

The low and stagnant agricultural productivity in DRC (Lambrecht, Vanlauwe *et al.*, 2016a) is primarily caused by severe crop diseases, deteriorating farming infrastructure, over fragmented plot sizes, depleted soil fertility, and the limited adoption of improved farming technologies (Ortega, Melgar-Quiñonez *et al.*, 2016). As a reflection of the situation in DRC, as of 1998, SSA had adopted less than one-third of the newly created green revolution varieties that Asia has (Evenson & Gollin, 2003a). Similarly, the use of fertilizers in SSA is just 8 kilograms per hectare which is also substantially lower than other developing regions (Morris, Kelly *et al.*, 2007). Agricultural intensification and productivity growth is greatly needed in DRC as an important pre-condition to enhanced food security, however farmers have had little exposure to information on improved agricultural technologies, and very limited economic and physical access to inputs such as fertilizers and improved germplasm (Pypers, Sanginga *et al.*, 2011).

The adoption of new technologies can increase crop productivity, reduce production costs, and ultimately alleviate poverty (De Janvry & Sadoulet, 2002). As pointed out by Minten and Barrett (2008) in Lambrecht, Vanlauwe *et al.* (2016a), the adoption of improved agricultural technologies is paramount to expanding agricultural productivity, and reducing poverty and food insecurity. Agricultural extension can play an important role overcoming knowledge gaps of improved technologies, providing more context specific information about cultivation practices, and familiarizing farmers with the precise benefits of new technologies (Lambrecht, Vanlauwe *et al.*, 2014). Yet, large investments to foster agricultural transformation through different extension methods in SSA have not resulted in the expected levels of adoption and productivity increase (Byerlee, 2011). The centralized extension methods have not only been ineffective in boosting adoption, but also expensive to implement in a way that benefits the individuals that need it the most: the small-scale farmers.

According to Anandajayasekeram, Davis *et al.* (2007) what is required is a shift towards the use of a more decentralized method which is more cost effective and promotes farmers' empowerment, pays more attention to farmers' priorities, and incentivizes peer learning. In a significant number of countries in Asia and SSA this has resulted in the adoption of the Farmer Field School (FFS) approach, which is an important tool to introduce farmers to improved technologies and to induce them to adopt these technologies. FFS have largely been found to have positive results in adoption, agricultural productivity and incomes (Van den Berg & Jiggins, 2007; Waddington, Snilstveit *et al.*, 2014). However, while the cost to train farmers through FFS is lower than that of other traditional methods, cost is still an important obstacle to its introduction, and the limited dissemination of knowledge from FFS participants to other farmers has been largely criticized (Quizon, Feder *et al.*, 2001; Rola, Jamias *et al.*, 2002). Feder, Murgai *et al.* (2004a) suggests that the costs of FFS training and its viability largely depend on the effectiveness of information and knowledge transmission within the FFS area of influence. Thus, there is a need to find ways to improve the cost-effectiveness of FFS, which according to Anderson and Feder (2004), can be achieved by improving farmer-to-farmer informal communications. In this thesis, I argue that the introduction of farmer-to-farmer (F2F) training is a plausible option to increase knowledge dissemination from FFS participants to other neighboring farmers, thus leading to lower costs per beneficiary.

The high initial costs needed to invest in improved agricultural technologies such as improved germplasm, and to implement practices like row planting and mulching is also an important factor which may prevent small-scale farmers from adopting these technologies. The need to use disease-resistant germplasm for example, contrasts with the limited capacity of small-scale farmers to afford their higher costs. Temporary subsidies could help farmers to gain exposure and experiment with improved inputs while addressing the issue of limited finance (Morris, Kelly *et al.*, 2007). While there has been a recent revival of government subsidy programs to stimulate the use of fertilizers and other improved inputs in many developing countries (Carter, Laajaj *et al.*, 2014), and many NGOs have implemented their own versions of subsidy programs, the impact of these subsidies to increase take up of new agricultural technologies is still unclear. In fact, the literature has been divided on the question if subsidies should be granted. On one side, some studies show evidence of positive impact of subsidies on, for example, technology take up and yields (Carter, Laajaj *et al.*, 2013, 2014; Chibwana, Fisher *et al.*, 2012). On the other side, critics of subsidies argue that it could lead to the creation of continued subsidization, which may affect long-term take up of the technology at market prices (Glennerster & Suri, 2012).

Different studies showcase evidence of the impact of FFSs, through technology adoption, on agricultural productivity (Blein, Bwalya *et al.*, 2013; Davis, Nkonya *et al.*, 2012; Gonzales, Ibarrarán *et al.*, 2009; Van den Berg & Jiggins, 2007; Waddington, Snilstveit *et al.*, 2014; World Bank, 2007). However this is not always the case. Davis, Nkonya *et al.* (2012) for example did not find a significant impact of FFS on crop productivity in Uganda. Godtland, Sadoulet *et al.* (2004) argue that the findings of FFS impact evaluations are often not consistent due to differences in the settings, the evaluation method used, and the definition of what impact means. Regarding the impact of FFS and technology adoption on food security much less evidence can be found, and several authors have criticized the limited availability of consistent empirical evidence of these linkages. Critics argue that factors such as allocation of time for training activities as opposed to other important food security related household activities (Larsen & Lilleør, 2014), inappropriate distribution of food between members of the household, and women's limited capacity to make decisions on how increased incomes are used (Kennedy & Cogill, 1987; Quisumbing & Maluccio, 2000) may seriously condition the impact of training and technology adoption on household food insecurity and improve dietary diversity.

Within the context of JENGA II, a USAID funded Multi-Year Assistance Program (MYAP) implemented by a consortium led by ADRA in Eastern DRC,

1

I empirically study in this thesis the threaded relationships among agricultural training, input subsidies, adoption of agricultural technologies, crop yields and household food security and diet diversity. The thesis firstly assesses the impact of one-shot free input starter packs on the long-term use of improved crop varieties and other productivity enhancing technologies. Secondly, it builds more understanding on how FFS, a costly extension method, can be made more cost-effective through the introduction of informal farmer-to-farmer (F2F) training. Thirdly, it studies the impact of FFS/F2F training on the crop productivity of small-scale farmers. Finally, the thesis studies the causal relationship between agricultural training, technology adoption and household food security by assessing the impact of farm level agricultural training and the adoption of agricultural technologies on household food security indicators.

Whereas each chapter is a standalone contribution to the development economics literature, the crosscutting relationships between them are equally crucial. These relations are often related to intrinsic behavioral aspects of small-scale farmers' lives; therefore we speculate and generate more understating about them as an important feedback to policy and program design and implementation, and possibly to future research.

1.2. Agricultural extension and training

Historically, agricultural extension was a centralized system for knowledge transfer from organizations or research institutions through affiliate extension agents to farmers using an agent-farmer face-to-face approach where only few large-scale farmers were reached. The key challenges of this "training" approach are the high cost for scaling up, especially to remote areas, the weak political commitment and support, and the limited accountability of the system (Anderson & Feder, 2004). In the early 1970s, the concept of training and visit (T&V) was introduced by the World Bank through its projects in Turkey and India as the new approach to overcome key weaknesses of the traditional extension system (Anderson, Feder *et al.*, 2006). The T&V approach was characterized by a hierarchical institution with several management levels for efficient reporting, rigid bi-weekly scheduled visits to pre-identified farmers, regular training of agents by specialists, and regular interaction between extension leads, specialists and research station scientists, to create a forward and backward loop for information flow (Anderson, Feder *et al.*, 2006). The T&V system ensured that extension agents reached farmers in remote areas for wider coverage. With reported evidence of its greater impact on agricultural production, the T&V system was rapidly adopted by many countries, particularly in Asia. By the early 1990s, almost 50 developing countries in Asia and Africa had adopted the T&V extension approach (Anderson, Feder *et al.*, 2006).

Soon, the weaknesses of the T&V system became evident. Moore (1984) highlighted some of the weaknesses, including training sessions that were not held or lacked clear content, extension agents not following up on visits, designated lead farmers not aware of their role, and linkages with research stations not functioning. A rigorous study conducted by Hussain, Byerlee *et al.* (1994), found no impact of T&V in Pakistan, and several others also arrived at similar conclusions. Therefore, given the high costs of implementation, countries gradually began to reduce support for T&V extension services, and different actors including farmers bargained for a new, more participatory, and more accessible lower cost approach, which is also more gender sensitive and pro-poor (Anandajayasekeram, Davis *et al.*, 2007). This required a paradigm shift towards decentralization, farmers' empowerment, more voice for farmers and their priorities, and peer learning (Anandajayasekeram, Davis *et al.*, 2007). Under this paradigm, extensionists are no longer agents that impose concepts or technologies from outside, but rather catalysts and facilitators of a learning and dynamic process to help farmers to achieve their farming goals (Anandajayasekeram, Mweri *et al.*, 2001).

The farmer field school (FFS) approach emerged in the late 1980s in Indonesia in response to threats caused by the improper use of toxic pesticides. The need for a decentralized education strategy to train and sensitize farmers to properly use pesticides (integrated pest management - IPM) and manage their production systems prompted the Government of Indonesia, with support from the United

States Agency for International Development (USAID) and technical assistance from the Food and Agriculture Organization of the United Nations (FAO), to adopt the FFS approach as a key extension strategy (Anandajayasekeram, Davis *et al.*, 2007). Since the 1980s the FFS approach has spread rapidly into many countries, been adapted for a wide range of crops, and used to address different land productivity, environmental, livestock, social and health issues. Currently, at least 10 million farmers in more than 90 countries have attended FFSs (Waddington, Snilstveit *et al.*, 2014).

Several authors define the purpose of FFSs according to their views and institutional goals. The literature largely agrees that the defining characteristics of FFSs include the development of critical thinking, discovery learning and farmer experimentation, and empowerment by encouraging farmers to develop problem-solving skills, while the dynamics of joint activities empower them through increased cooperation (Anandajayasekeram, Davis *et al.*, 2007; Braun & Duveskog, 2011; Waddington, Snilstveit *et al.*, 2014). Feder, Murgai *et al.* (2004b) highlight that the goal of FFS training is to enhance farmers' analytical skills, critical thinking, knowledge of agricultural practices, and understanding of the interactions in their ecosystems, enabling farmers to make informed production decisions and resulting in higher crop yields. Based on a variety of FFS studies, Waddington, Snilstveit *et al.* (2014) also indicated that FFSs have been used as platforms for promoting IPM methods ranging from simple practices such as no early pesticide spraying to complex agro-ecological and crop management concepts. In practice however, not everyone supports this view. A group of authors, including Braun, Jiggins *et al.* (2006); Feder, Murgai *et al.*(2004a, 2004b); Waddington, Snilstveit *et al.* (2014), see FFSs as an intensive participatory farmer-centered approach which focuses on knowledge transfer and the promotion of specific packages of technologies. Therefore, although FFS are still tailored towards knowledge building, the scope of topics addressed vary widely depending on the type of crop and the interest of the target groups.

While farmers' empowerment and development of critical thinking and decision making skills to enable farmers to address their own farming problems are the cornerstone of JENGA II's FFS strategy, the promotion of specific packages of improved agricultural practices and input technologies is an equally important component of the program's FFS strategy.

1.3. Farmer field school impact and cost-effectiveness

Clearly, FFS is a contested approach but the contrasts go beyond its purpose and include candid discussions about the levels of results that FFS generates. Some of the most prominent studies have conflicting positions regarding the impacts of FFSs. Van den Berg and Jiggins (2007) suggest that FFS have widespread and lasting developmental impacts; while Davis, Nkonya *et al.* (2012) show positive impacts of FFSs on the production and income of small-scale farmers in West Africa; and Ameua, Hirea *et al.* (2013) conclude that in countries like Angola, DRC, Kenya, Sierra Leone, and Uganda the FFS approach has empowered farmers with knowledge and skills, made them experts in their fields, honed their ability to make critical farming decisions, and equipped them with new ways of thinking and solving problems. Conversely, Feder, Murgai *et al.* (2004b) argue that FFS graduates and especially their neighbors do not significantly improve their agricultural performance. More generally, based on a thorough systematic review of over a hundred studies, Waddington, Snilstveit *et al.* (2014) suggest that FFSs have positive impacts on intermediate knowledge-related outcomes and adoption of beneficial practices, and on higher level outcomes such as agricultural production and incomes. Yet, the authors conclude that very few studies are rigorous and none have a low risk of bias.

A major drawback of the FFS approach is its cost, and according to several studies, its limited capacity to promote knowledge dissemination beyond FFS training graduates. Because this is a decentralized approach, FFSs seem to be less costly than the more traditional approaches. However, the intensiveness of training activities requires high investments in salaries, transportation, inputs and training materials, still making FFSs a costly undertaking. Therefore, the viability of FFS training largely depends on the effectiveness of knowledge transmission from farmers trained in FFS to other farmers in their nucleus of influence (Feder,

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Murgai *et al*., 2004a). Unfortunately, FFS's knowledge dissemination capacity has been largely criticized (Quizon, Feder *et al*., 2001; Rola, Jamias *et al*., 2002), and intentional attempts to create higher spillover effects are likely to be needed.

As pointed out by Anderson and Feder (2004), the cost-effectiveness of FFSs may improve through informal farmer-to-farmer interactions. However, this may not be easily materialized. Based on an extensive review of the literature, Davis, Nkonya *et al*. (2012) conclude that even when FFS has a positive effect on the adoption of technologies or practices by the participants, proof of effective dissemination is not evident. Rola, Jamias *et al*. (2002) argue that FFS training subjects are probably too complex to transmit through unstructured communications. Given the skills-based nature of the technologies promoted in FFSs, intentional attempts to encourage FFS graduates to train other farmers are likely needed. According to Pontius, Dilts *et al*. (2002), formal approaches involving FFS alumni are necessary to transmit knowledge more efficiently. However, the literature does not currently document whether the implementation of these approaches has been effective (Waddington, Snilstveit *et al*., 2014). In *Chapter 4* we study the levels of impact that FFS training has had in the context of the JENGA II project in DRC, and the effectiveness of knowledge transmission from FFS farmers through farmer-to-farmer training (F2F).

1.4. Agricultural productivity and its determinants

Currently, agriculture, which has unique potential to spur growth and increase incomes relative to other major sectors in DRC, is by far the most unproductive economic sector in the country. DRC is one of the countries in SSA with the largest gap between the share of agricultural employment (60 percent of labor force) and the sector's contribution to national gross domestic product (GDP) of about 21 percent (Otchia, 2014). Agricultural production in DRC, and particularly South Kivu, has declined steadily after the country's independence, limiting the availability of staple crops such as cassava, maize and plantain. The production of cassava, the most important staple crop in the country declined by 20 percent in the 1990s (Ameua, Hirea *et al*., 2013); with current yearly production (from 2000 to 2014) below the production levels in the 1990s (FAO, 2016a). Both cassava and banana production have been severely impacted by widespread diseases, which has been an important determinant of their yield decline.

During the period 1991 to 2014, the yields of major crops in DRC have either declined or stagnated. The average yields of banana, plantain, rice (paddy) and soybeans declined by 5.0, 4.8, 5.7 and 22.9 percent, respectively, compared to the levels in 1961-1990 (FAO, 2016a). Only maize and cassava experienced slight increases in the average yields in the same period. Cassava yields increased by 13.5 percent from 1961-1990 to 1991-2014 while the yields of maize increased by 5.8 percent over the same periods (FAO, 2016a). The yields of all major crops in 2013 were far below potential levels. According to Badibanga (2013), the yields of these crops are only about 14-22 percent of the potential yields; with yield gaps ranging from about 78 percent for maize and rice to 86 percent for cassava and plantain. Murphy, Glaeser *et al.* (2015) indicate that cassava is the main crop in terms of cropped area and energy intake, while banana plays an important role in income generation among small-scale farmers, particularly in South Kivu. The reduction in crop production and yields have impacted both domestic food availability and the country's export potential, resulting in a considerable increase in the commercial trade deficit. From 2009 to 2011, about 37 percent of cereals consumed in DRC were imported, which is much higher than the 21 percent imported in the early 1990s (FAO, 2015a). Cash crop exports declined drastically from 1980-2000, with minor cash crops such as coffee and wheat dominating DRC's exports (63 percent of exports) (Otchia, 2013).

The evidently low agricultural production and performance in DRC is widespread for a reason. It largely corresponds to farmers' lack of access to capacity building opportunities, low use of improved technologies including seeds and fertilizers, small landholdings and economies of scale, the informal character of agriculture, and the rudimentary nature of technologies used in the sector (Otchia, 2014). According to AGRA (2013), yield gaps for most crops in Sub-Saharan Africa could be reduced by appropriate use of improved crop varieties; adequate application of fertilizers; and appropriate management of soil nutrients, water resources, pests, and diseases. Yet, the adoption of these technologies and farm management practices have remained low, in large extent because public and private sector driven extension have failed to assist small-scale farmers to adopt these improved technologies and increase farm productivity (Anderson, 2007; Birkhaeuser, Evenson *et al.*, 1991). This is certainly the case in DRC. In *Chapter 3* we study how one-shot input starter packs impact farmers' long term adoption of improved crop varieties and the use of other yield enhancing technologies, and in *Chapter 5* we study how the FFS combined with F2F training impact yields in eastern DRC.

1.5. Technology adoption and household food security

Since agriculture, particularly food crop farming, is the main source of incomes for most Congolese – 62 percent of the men and 84 percent of the women – the production and yield decrease of most crops over the last 30 years has resulted in widespread food insecurity in the country. These statistics are particularly high in the rural areas where agriculture employs nearly 97 percent of the population and the levels of food insecurity exceed the national average. Nationally, about 67 percent of household income is spent on food (Akakpo, Randriamamonjy *et al.*, 2014). Average daily food consumption in the country is estimated at less than 1,500 kilocalories per person, which is below the minimum calories required for an average person to live healthily (USAID, 2015). A recent World Food Program (WFP) assessment in several provinces in DRC, including South Kivu, indicated that one third of households have poor or limited food consumption (Akakpo, Randriamamonjy *et al.*, 2014). Currently, South Kivu has the highest level of food insecurity in DRC, with 64 percent of its population considered food insecure (Akakpo, Randriamamonjy *et al.*, 2014); 43 percent of children under-5 years of age stunted and 23 percent suffering from acute malnutrition (FAO, 2015a). The global acute malnutrition rates in South Kivu is above 10 percent, which underscores the intense undernourishment in the area. Due to the poor nutritional status of households, the mortality rates of children under-5 and infant are high in South Kivu, bordering 139 per 1000 births, and 92 per 1000 births, respectively (Murphy, Glaeser *et al.*, 2015).

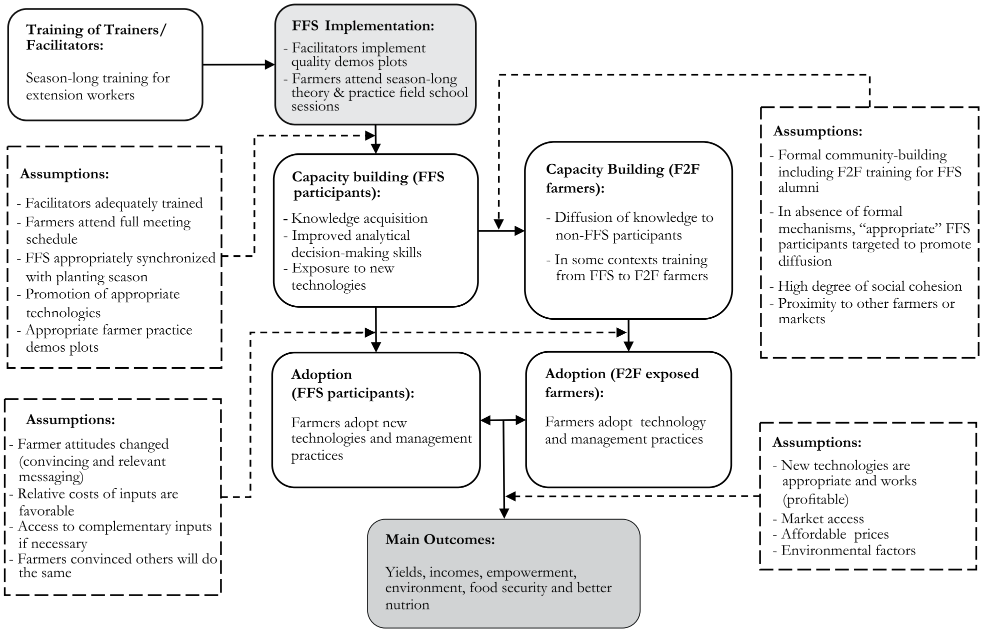
The threads between agriculture, household food security and nutrition are particularly strong for agricultural producers or laborers, through incomes and production for self-consumption. Agricultural growth is considered a best-fit conduit for reducing food insecurity as it directly impacts the household's capacity to produce a major share of the food that they need and impacts the amount, type, stability, and control of incomes. According to Von Braun, Ruel *et al.* (2011), these have important implications for the food security and nutrition of rural households. Achieving direct reductions in hunger requires prioritizing to address factors that prevent the economic growth in the agricultural sector (FAO, 2015b). This particularly affects rural consumers whose food entitlement primarily comes from self-production (Adekambi, Diagne *et al.*, 2009). Thus, increasing and diversifying farmer level agricultural productivity is paramount to reducing household food insecurity and often results in spillover benefits for other individuals not directly depending on agriculture.

The adoption of agricultural innovations is crucial to increasing agricultural productivity and growth (Blein, Bwalya *et al.*, 2013). Several studies have associated agricultural technologies with a number of outcomes, including higher yields (Gonzales, Ibarrarán *et al.*, 2009; Waddington, Snilstveit *et al.*, 2014); increased employment (Rola, Jamias *et al.*, 2002); higher incomes and poverty reduction (Kassie, Shiferaw *et al.*, 2011). Nevertheless, several authors argue that agricultural training, adoption of agricultural technologies, and even higher levels of agricultural growth have not resulted in reductions of household food insecurity. Larsen and Lilleør (2014) highlight that households may choose to divert resources from other activities toward project training. While Kennedy and Cogill (1987) and Quisumbing and Maluccio (2000) point out that expenditure allocations by women, as opposed to men, favor investments in the health, nutrition, and education of their children. The intra-household distribution of food and the allocation of incomes are also critical, as food may not be distributed based on the needs of each individual member (Pinstrup-Andersen, 2009), and households may prioritize the acquisition of other goods and services over investments in food. Based on the hypothesis that smallholder farmers' production can be a channel through which food insecurity is addressed, via household's increased capacity to produce for self-consumption, and/or greater purchasing power, we study the impact of farm level agricultural training and adoption of agricultural technologies on household food security in *Chapter 6*.

1.6. Objectives and thesis outline

I largely base the empirical questions of this thesis on the hypothetical farmer field school causal chain developed by Waddington, Snilstveit *et al.* (2014), which to some extent is rooted in the transfer-of-technology models of extension discussed by (Bennett, 1975); and cited in Funnell and Rogers (2011). On one hand, I hypothesize that farmer field school interventions generate capacity building – knowledge – and technology adoption outcomes; and on the other hand, that increased knowledge and adoption of agricultural technologies generate higher level outcomes such as increased yields, incomes, and food security. I assume that these changes are all affected by a series of individual, household and farm enabling factors, which condition the extent of these linkages. The causal model assumes that both FFS participants and neighboring non-participants are subject to changes in their capacity building related outcomes, either because of direct participation on FFS, or through natural knowledge spillovers or deliberate farmer-to-farmer interactions, which may benefit non-FFS participants (refer to *Figure 1.1*).

Figure 1.1. Farmer field schools hypothetical causal model: inception, training and dissemination



Source: Adapted from Waddington, Snilstveit *et al.*, 2014

As an overarching objective, this thesis seeks to contribute to a better understanding of the complex inter-relations between agricultural training, technology adoption, crop yields and food insecurity in the context of a post-conflict situation in South Kivu DRC, which is the ultimate goal of JENGA II's program. Following the sequence of expected change originated from JENGA II's farmer field school intervention and having household food security and dietary diversity as overarching goals, the following empirical questions will be studied throughout the four main chapters of this thesis:

a) Chapter 3: Do one-shot input starter packs impact small-scale farmer's long term adoption of improved crop varieties and the use of other productivity enhancing technologies?

b) Chapter 4: What are the effects of FFS training on small-scale farmer's adoption of agricultural technologies? Additionally, is F2F training an effective option to formalize the dissemination of agricultural technologies from FFS graduate to neighboring farmers and reduce training costs?

c) Chapter 5: What is the impact of agricultural training on crop productivity?

d) Chapter 6: What is the impact of farm level agricultural training and adoption of farming technologies on household food insecurity and dietary diversity?

1.7. Methodology

Evidence across the literature suggests that evaluating the impact of a program, especially when dealing with endogeneity and reverse causality issues, is very difficult. These issues normally arise when the program design does not identify the participants randomly (Davis, Nkonya *et al.*, 2012). In the absence of randomization, the estimation of the counterfactual – what would have happened to the participants had they not participated in the program– becomes problematic, and the treatment effect estimations may be biased. In the context of the sample used in this thesis, the estimations are exposed to two main types of bias. Selection bias is in this case likely to occur when farmers self-select to participate or not participate in specific interventions. Such participation decisions are not random and are likely influenced by the participant's characteristics such as age, education, land tenure, entrepreneurial skills, motivation, wealth, and previous experiences with other projects. The non-random placement of project interventions also creates issues of endogeneity of the regressors and may bias the estimations of average treatment effect.

The analysis in *Chapter 3* is exempt of most of these biases because the starter pack intervention was randomly assigned to participants. However, we still use fixed effect (FE) and Difference-in-Difference (DID) panel data regressions combined with probability propensity score based weighting to mitigate the effect of the remaining systematic pre-treatment differences. *Chapters 4-6* use a quasi-experimental setting, so we extensively discuss in each chapter the threats of self-selection and non-random project placement and alleviate potential biases through the use of diverse econometric specifications and methods, to include FE, DID, IV, and Propensity Score Matching (PSM), combined with inverse probability weighting (Lilleør and Larsen, 2013; Nyangena and Juma, 2014; Davis *et al.*, 2010; Alene and Manyong, 2006; Angrist and Pischke 2008, Imbens and Wooldridge 2009).

In *Chapters 4* and *5*, we argue that the primary source of bias comes from non-random placement of FFS and F2F training activities and that these are mitigated using DID and FE models – which eliminate individual specific fixed effects – combined with propensity score based weights, which makes the participants similar based on their pre-treatment characteristics and thus eliminating the effect of the covariates on the error term. Technology adoption is endogenous, so in *Chapter 6* we face additional sources of bias which we deal with applying an instrumental variable (IV) approach to estimate the impact of training, through adoption, on household food insecurity (Angrist & Krueger, 2001).

The IV model attempts to solve the issue of omitted variables that affect food security, by using part of the variation in the farmer level of technology adoption that is uncorrelated with the omitted variables, to explain the relationship between technology adoption and food security. The validity of the instrument that we use, which is the participation in FFS/F2F training, may be questioned. Therefore, we use a semi-parametric propensity score matching (PSM) approach, and differences-in-difference regressions combined with probability propensity score weighting as robustness checks. These approaches mitigate the impact of potential biases on our estimations, so we can make unbiased estimates of the impact of training and adoption on household food insecurity.

2
Setting the stage

2.1. JENGA II Project

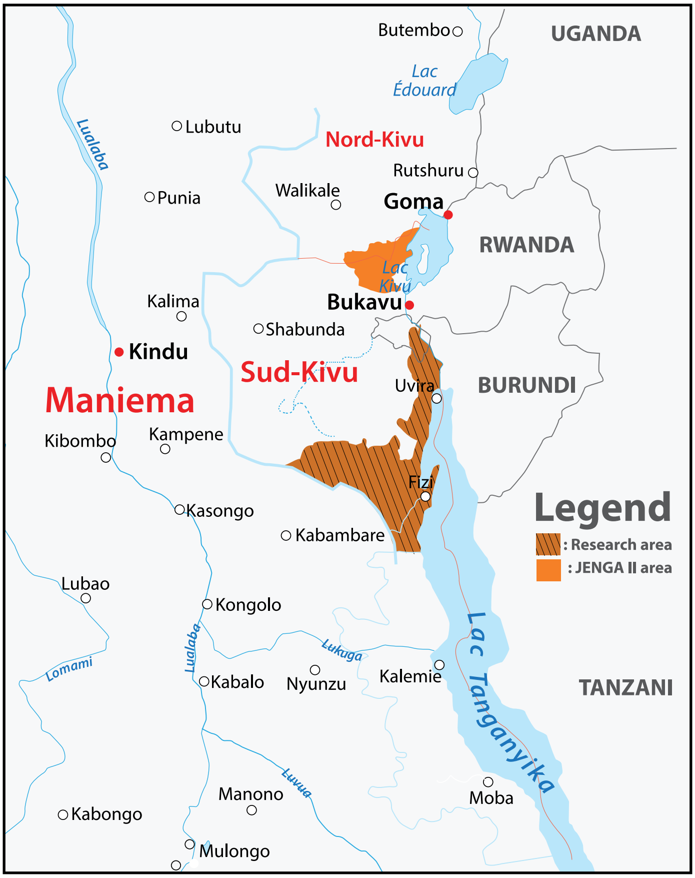
This research was conducted as part of ADRA's JENGA II project in the DRC. Jenga means "to build" in Swahili, the predominant language in the project area. The full project name in Swahili is: Jenga nguvu za jamaa katika maeneo ya Fizi na Uvira, wilaya ya Sud Kivu, or "Building the strength of communities in Fizi and Uvira, South Kivu Province." In the United States, many are familiar with the popular game Jenga which uses a set of wooden blocks that must be built as high as possible, symbolizing the importance of involving all blocks (stakeholders interacting and working together towards a common goal) and integrated programming (the different elements that are needed to build the strength of communities). ADRA started the project in July of 2011 and ended it in June 2016. The program's overall goal was to substantially reduce food insecurity among vulnerable households in Fizi, Kalehe and Uvira territories of South Kivu, DRC.

The Democratic Republic of Congo is composed by 26 provinces and has a total population of about 82 million inhabitants. The poverty level is considered very high, and the Human Development Index is one of the lowest in the world. In its 2015 report of global food security the United Nations Food and Agriculture Organization describes the rate of undernourishment in DRC to be "very high" (McGuire, 2015). Recently gathered data through the FAO project "Voices of the Hungry" indicate that the levels of severe food insecurity in 2014 affected 50% of rural population in the country. The province of South Kivu, one of the poorest in the country, was created in 1969 when the existing Kivu Province was divided into north and south. As well as sharing borders with North Kivu, Maniema, and Katanga provinces, South Kivu also has access to Rwanda, Burundi, and Tanzania through its eastern border. The province has three main cities: the provincial capital Bukavu, Fizi and Uvira. The population in these cities, has grown recently due to numerous factors, including insecurity and incidence of natural disasters. It is estimated that the city of Bukavu alone has more than 800,000 inhabitants currently.

The JENGA II project was implemented in three territories of South Kivu, namely Fizi, Kaleje and Uvira. However, as highlighted in *Figure 2.1*, the research only covered the Fizi and Uvira territories which are known for having high levels of food insecurity, similar agro-climatic characteristics, and high presence of small-scale agricultural producers. Fizi is located in the south of the province, on the shore of Lake Tanganyika and Baraka is the main town in this territory, which is composed of three municipalities (Baraka, Katanga and Kalundja). The population of Fizi is estimated at 490,000 people. Uvira is located on the northern shore of Lake Tanganyika, close to the border with Burundi. The main city is Uvira which is located 120 km from Bukavu and with an estimatedpopulation of 396,000.

JENGA II was designed to achieve its food security goals through three main strategic objectives, namely: (1) increasing the agricultural productivity and production diversification of small-scale farmers; (2) enhancing small-scale farmers' commercialization of agricultural products; (3) strengthening community resilience to food security shocks. This thesis focuses on the first objective of increasing the crop productivity of small-scale farmers in the target area and analyzes how the levels of achievements of this objective affects the levels of household food insecurity.

Figure 2.1. Map of the research area



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To accomplish this objective, JENGA II engaged small-scale farmers in a participatory learning process using non-formal education methods – FFS and F2F – and a field-based, experiential learning process using crop demonstration plots. The farmers experienced how to improve crop management and commercialization, from soil preparation through harvest, post-harvest, storage and marketing, with an emphasis on the improvement of product marketability and access to markets. In collaboration with FAO DRC, which led the development of the FFS crop-specific training curriculum, the project engaged groups of farmers in a participatory process to identify the content to be prioritized in the curriculum and ran field tests of the manual to receive feedback from farmers on areas needing improvement. JENGA II trained about 15,000 farmers through the FFS training methodology and more than 45,000 through F2F training. The majority of target farmers were from female-headed households (about 70 percent) in remote rural communities with limited access to inputs, and credit markets. Most of these farmers were illiterate and had limited to no access to technical assistance other than that provided by the JENGA II project.

2.2. JENGA II technologies promoted

Agricultural productivity in Eastern DRC is remarkably low (Thaddée, 2013) which, according to Otchia (2014), is largely due to the poor use of improved farming technologies such as fertilizers and germplasm, and the rudimentary nature of the equipment used for cultivation. The increase in population density and the overexploitation of land without proper nutrient management are increasingly leading to severe impoverishment of soil fertility and erosion (Pypers, Sanginga *et al.*, 2011), which has a direct impact on land productivity and ultimately on poverty and food insecurity (Lambrecht, Vanlauwe *et al.*, 2016b). Given the pressing need for agricultural intensification and productivity growth in Eastern DRC (Lambrecht, Vanlauwe *et al.*, 2016b), as the conflict has eased in the last 10 years several organizations have strived to expose farmers to new agricultural technologies (Rossi, Hoerz *et al.*, 2006), and a number of authors have studied their impact in the context of integrated soil fertility management (ISFM) (Lambrecht, Vanlauwe *et al.*, 2016a, 2016b; Schut, van Asten *et al.*, 2016; Vanlauwe & Zingore, 2011).

Pypers, Sanginga *et al.* (2011) found that in central Africa, the productivity and net economic returns of cassava–legume intercropping could be increased with the joint introduction of different components of ISFM, including proper agronomic practices such as row planting, the use of disease-free improved germplasm, adequate crop arrangement, and fertilizer application.

The introduction of improved cassava germplasm resulted in a yield increase of 49 percent compared to regular varieties used in Sub-Sharan Africa (Manyong, 2000). Similarly, the adoption of improved crop varieties was found to increase crop yields and lead to increased household consumption and income and reduced poverty and inequality in different settings (Asfaw, Shiferaw *et al.*, 2012; Kassie, Shiferaw *et al.*, 2011; Mathenge, Smale *et al.*, 2014; Mendola, 2007). According to Kalyebara and Buruchara (2008), the use of improved bean varieties augmented yields in seven African countries, with an average increase of about 44 percent. Malawi showed the smallest increase (2 percent) while the highest (137 percent) was found in Western Kenya.

Intercropping has also been found to have an impact in crop performance. Hine, Pretty *et al.* (2008) predicted in a sample from Kenya that intercropping increased the yields of both maize and bean by 71% and 158%, respectively. Pypers, Sanginga *et al.* (2011) also estimated significant increases in bean yields when intercropped with cassava, in addition to reducing disease severity, benefiting weed control and increasing soil fertility. Generally, intercropping is also associated with higher yield stability (Dapaah, Asafu-Agyei *et al.*, 2003).

Crop rotation has also shown promising results compared to monoculture. Thierfelder, Cheesman *et al.* (2013) found that crop rotation increases soil water infiltration, soil moisture, soil carbon, and crop productivity in the cultivation of maize in Malawi, Mozambique, Zambia and Zimbabwe. Similarly, Aziz, Ashraf *et al.* (2011) documented that the adoption of corn–soybean-wheat-cowpea crop rotation results in substantial improvements in soil fertility. The author sustains that management practices to sustain crop yields are necessary to conserve or enhance soil quality, and suggest that multiple cropping systems is more effective for maintaining and enhancing soil quality than sole-cropping systems.

Mulch from crop residues has been reported to lead to significant increases in crop yields of bananas (Wairegi & Van Asten, 2010), plantains (Salau, Opara-Nadi *et al.*, 1992) and maize (Kaumbutho & Kienzle, 2007). Ramakrishna, Tam *et al.* (2006) find it to be a powerful tool to inhibit the proliferation of weeds, which leads to labor savings. In addition, the use of cover crops leads to higher yields by reducing on-farm erosion, nutrient leaching, and grain losses due to pest attack (Branca, McCarthy *et al.*, 2011). The use of organic fertilizer, mainly compost and animal manure, has shown to significantly increase crop yields. The impact in maize has been as high as 100 percent (Hine, Pretty *et al.*, 2008); in millet between 75-195 percent (Parrott & Marsden, 2002); and in groundnuts it ranged from 100-200 percent (Parrott & Marsden, 2002).

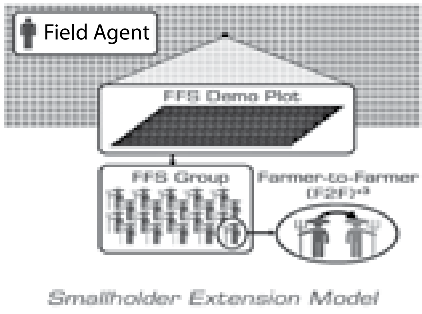
Row planting not only has the potential to reduce the labor requirement for weeding, but also enables the introduction of proper intercropping, which leads to additional economic benefits for the farmers (Pypers, Sanginga *et al.*, 2011; Vandercasteelen, Dereje *et al.*, 2016). Additionally, it has been found to reduce seed costs and increase yields, with can increase the average levels up to three times (Berhe, Gebretsadik *et al.*, 2011).

Evidently these technologies have had a variety of positive impacts in different settings and agro-climatic conditions, including in some cases South Kivu. However, according to Rossi, Hoerz *et al.* (2006) these technologies have only been introduced to South Kivu in the last 5-10 years and according to JENGA II's baseline data, the levels of adoption were still very low at the start of the program (*see Table 3.1 and 4.1, and Appendix 3.1*). JENGA II promoted a set of these type of agricultural technologies. On the one hand focusing on technologies that help to sustainably improve soil fertility as a means to increase crop productivity. These technologies include agronomic practices and inputs, namely: improved crop seeds[1], crop rotation, intercropping, mounding, mulching, organic fertilizers (composting and animal manure), organic pesticides, sprayers and weed control. On the other hand, the project also promoted row planting and the use of an improved hoe intended to increase labor productivity and consequently reduce farming costs. Agronomically, most of these technologies have been studied at large, but in this thesis, we study which of these technologies are actually adopted by the farmers.

1. JENGAII promoted the following improved germplasm for the target crops: (a) Cassava, Mosaic Resitant Sawa Sawa and Liyayi; Maize, Ekavel e Kasaï; Peanuts, JL24; Beans, Bio-fortified CODML001 and CODML005; and Rice, IRAT 112.

2.3. Farmer field schools

Figure 2.2. JENGA II FFS/F2F extension model



In JENGA II's farmer field school methodology each FFS group was comprised of 30 participants on average, and each group was supported by the project to set up a demonstration plot in a site donated by the community. These sites served as venues for on-site training in improved techniques and experience exchanges between FFS beneficiaries. The FFS approach uses project field agents (FA) to train beneficiaries and familiarize them with improved technologies (see *Figure 2.2*). The FAs held, on average, bi-weekly training sessions and were responsible for on-site monitoring of individual farms.

Each FA assisted an average of 10 FFS groups, or about 300 farmers in total. The FFS training used a multi-module crop-specific training curriculum, and the topics were taught at the appropriate time along the season. JENGA II's FFSs held a two-year training cycle, where the first year was key to developing farmers' critical thinking and understanding of their production systems and imparting knowledge about the promoted technologies. The second year was a crucial consolidation stage as farmers started to change their behaviors and truly adopt the technologies. In that context, technology adoption in period two is expected to be higher than that in period one when farmers were still experimenting and ill-prepared to make a favorable decision towards adoption.

2.4. Farmer-to-farmer training

Attempting to expand project outreach and potentially reduce cost per beneficiary, JENGA II promoted the dissemination of best practices and technologies introduced to FFSs through farmer-to-farmer training. In other words, farmers that were systematically trained by project FAs in the FFS groups became F2F trainers and were expected to train three other farmers in the same topics that they were trained in the FFSs. The project deliberately attempted to institutionalize the F2F training as part of its FFS methodology rather than expecting that knowledge acquired at FFSs would be naturally disseminated through informal communications between neighboring farmers. However, all that JENGA II did was remind FFS participants of their commitment to train their sponsored farmers and monitor their activities with no real enforcement to farmers that did not comply. The project did not provide real incentives either to FFS members to train their farmers or to F2F farmers to participate in the training. Despite that, the false expectation to receive further benefits from the project such as starter packs or other types of handouts may have incentivized farmers to participate in the F2F training.

The positive messages about technologies transmitted in FFSs may be mixed with other experiential negative messages as the FFS trainees train their F2F farmers. Therefore, to make sure that information received by both FFS and F2F farmers are similar, the FFS farmers were expected to train their sponsored farmers in the same topic immediately (the same week) after they were trained at the FFSs. The following mechanisms were implemented by the project to monitor the activities of the F2F training: (a) implementation of a F2F training form which tracks the activities of F2F farmers after each FFS training session. The FAs asked the FFS members if they trained their F2F farmers after the last FFS training session and if they had trained them in the same topics treated in the FFS session and the responses entered in the activity track sheet; (b) the FAs conducted random spot-checks to F2F fields to cross-check information reported against the reality in the F2F farms. This seems to have contributed to increased accountability of F2F trainers, which in turn contributed to increasing the quality of training and ensuring that sponsored farmers were trained in a timely fashion; and (c) the project monitoring and evaluation (M&E) field agents conducted data quality analysis to make sure that the tracking forms were filled out correctly and that FAs reported accurate information. The M&E agents sampled some of the forms that the FAs completed and cross-checked the information with observations in the field.

2.5. Input starter packs

As part of its extension strategy, JENGA II also provided a one-time free starter pack to each FFS participant. The starter-pack contained improved crop seeds, multiplication materials for cassava, and tools. Based on apparent positive experiences in other projects, the underlying assumption behind the promotion of these starter-packs is two-fold. Firstly, starter-packs serve as an input for farmers to improve yields in the first season and increase their desire and financial capacity to persistently purchase improved seeds in subsequent seasons. Secondly, they positively impact farmers' adoption of other project promoted productivity-enhancing technologies as farmers are motivated to use these technologies to exploit the full potential of starter-pack inputs. The project strategy did not originally consider the delivery of free starter packs to F2F farmers. However, for the purpose of our study, a randomly selected group of 210 F2F farmers received starter-packs and we compared these farmers with the 180 F2F farmers who did not receive starter-packs.

2.6. Research setup

JENGA II followed two steps to select the intervention area and its beneficiaries, namely: (a) selection of target villages; and (b) selection of beneficiary target groups within the villages. As indicated in *Table 2.1*, based on the pool of JENGA II villages we selected a reduced number of 25 villages for the research and randomly enrolled a subset of beneficiaries in each village in the research. The selection of the villages followed project criteria related to the level of engagement in agriculture activities and these same criteria were applied for the selection of the control villages. Overall, 13 intervention villages were sampled for the study. For all but one of the 13 intervention villages, a comparable village was selected as the control group village. Only 12 control villages met all the criteria to be selected as control villages in the study area, so one village contained all the three comparison groups –FFS, F2F and control. The villages were also selected based on project interventions received, the agro-climatic zone (mountain, plains or lakeside), relative proximity to one another and perceived similarities.

Table 2.1. Sample design

Site	Agro-Climatic Zone	*FFS*		*F2F*		*Control*		Total Sample
		Village	*Sample*	*Village*	*Sample*	*Village*	*Sample*	
1	Mountain	Lemera Center	30	Lemera Center	30	Lemera Center	25	85
2	Mountain	Mugogo	30	Mugogo	30	Ndolera Center	25	85
3	Plains	Kabumenge	30	Kabumenge	30	Langala	25	85
4	Plains	Nyakabere	30	Nyakabere	30	Nyamutiri	25	85
5	Plains	Kibirizi	30	Kibirizi	30	Q. Ruzizi	25	85
6	Plains	Kirindagumi	30	Kirindagumi	30	Rugobagoba	25	85
7	Plains	Bwegera	30	Bwegera	30	Itara 2	25	85
8	Lakeside	Ilakala	30	Ilakala	30	Kabobe II	25	85
9	Lakeside	Kalundja	30	Kalundja	30	Bitobolo Center	25	85
10	Lakeside	Mwandiga	30	Mwandiga	30	Katanga I	25	85
11	Plains	Simbi	30	Simbi	30	Kananda I/II	25	85
12	Plains	Buzimba	30	Buzimba	30	Kianda	25	85
13	Plains	Kenya Market	30	Kenya Market	30	Tchonwe	25	85
Grand Total			**390**		**390**		**325**	**1,105**

2

From a larger group of farmers that qualified to participate in the program, 30 farmers were selected to participate in FFS in each of the 13 FFS villages (for a total of 390 farmers). From each of the same 13 villages, a group of 30 out of the 90 F2F farmers were randomly selected and enrolled in the study (total of 390 farmers). For each of the 13 control group villages, 25 farmers that were not participating in any project activity (325 farmers) were enrolled. These farmers were also randomly selected from a large list of village members made available to the project by the local leaders. The F2F farmers were sampled from 13 villages, from which we randomly selected 7 villages to receive the one-time starter pack intervention, while the remaining 6 villages did not receive or serve as the control group to starter pack recipients. All the FFS farmers and 210 out of the 390 F2F farmers received a one-time input starter pack containing improved seeds and tools at the beginning of their participation in the project, but none of the control farmers received these goods.

2.7. Data collection design

A well-structured questionnaire was used to collect data from all the project groups. The questionnaire contained two main subdivisions, namely the general questionnaire, and the agricultural supplemental form. The general questionnaire included questions on household characteristics and composition; such as household size, age, sex and level of education of the head of household; and food security questions on levels of access to food (HFIAS) and household dietary diversity (HDDS). The supplemental form collected information about farm characteristics, crop production, adoption of improved practices, and marketing. These included questions on land endowments, area cultivated, quantities of crops harvested, farmer capacity to store crops, percentage of harvest sold, access to financial services, types of crops produced during the season (crop diversification), and marketing; and detailed questions related to the farming practices and input technologies used by the farmers.

In February/March 2013 the first cross-sectional survey (CSS1) was conducted. This survey served as the baseline since none of the farmers had participated in any intervention at that time and trainings were just about to start. The second cross sectional survey (CSS2) was conducted in February/March 2014, and the third (CSS3) in February/March 2015 to collect the same information from the same people (see *Figure 2.3*). The CSS2 and CSS3 data were used as the post-treatment information to contrast with the baseline for estimation of treatment impact. In the chapters, we refer to period one as the one year time period between CSS1 and CSS2, and period two as that between CSS2 and CSS3. During period one, the farmers had two entire seasons for semi-annual crops (beans, maize, peanuts and rice), and one season for cassava. In period two, the same thing happened; therefore, we cover a total of four seasons for semi-annual crops and two seasons for cassava between baseline and the final cross-sectional survey (CSS3).

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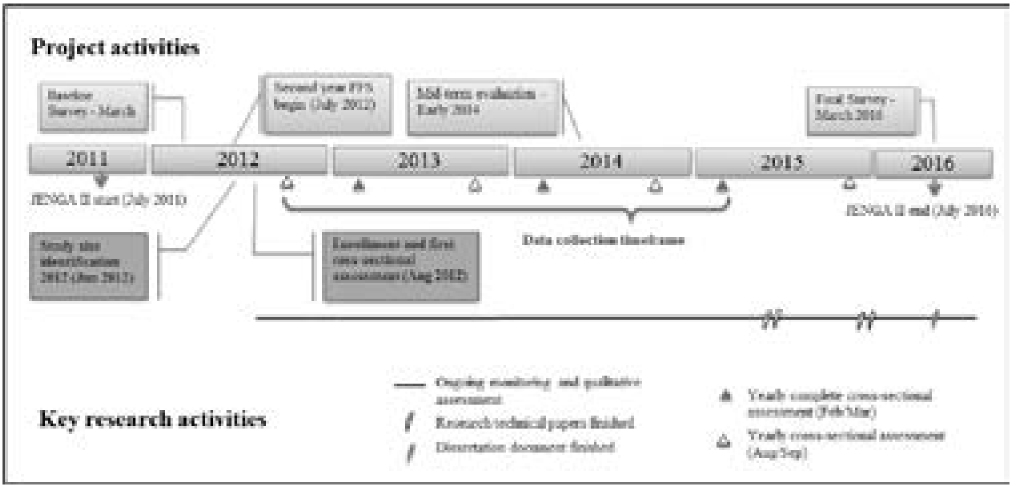
Figure 2.3. JENGA II activities and research timeline



3

Can one-time provision of free inputs boost adoption of agricultural technologies?

ABSTRACT

This paper reports the results of an experimental study in Eastern DRC which analyses the impact of one-time input starter packs on the adoption of productivity-enhancing practices which condition the performance of starter pack inputs. In addition, the paper assesses the levels of persistence over time on the use of improved crop varieties included in the starter packs. Overall there is no evidence of starter packs influencing smallholder farmers' adoption of productivity-enhancing technologies. While both recipients and non-recipients of starter packs experienced increases in the use of the technologies promoted from previous levels, the increase does not differ between the recipient groups and thus, cannot be attributed to the starter packs. Similarly, the levels of persistence with regards to the use of improved seeds following the delivery of starter packs were found not to be significant. This result is somewhat consistent with other studies, which also found minimal or no persistence on the use of inputs following the provision of one-time input subsidies (Duflo, Kremer et al., 2011). The fact that yields were not different between the two groups after the first year seems to logically explain why farmers refrained from using improved seeds in the following seasons.

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3.1. Introduction

The literature has reached a consensus that agricultural technologies such as improved farming techniques, high-yielding crop varieties and fertilizers can dramatically improve agricultural performance and reduce food insecurity (Conley & Udry, 2010; Duflo, Kremer et al., 2008; Foster & Rosenzweig, 1995). Green revolution technologies, including hybrids and high-yielding varieties, have resulted in great gains in agricultural productivity in Asia and have the potential to substantially increase productivity across Africa as well (Bank, 2008). For the past 50 years, crop production has expanded threefold globally, mostly through higher yields and crop intensification (FAO, 2013). The index of food production per capita for developing countries shows a 50 percent increase from the 1970s to the 1990s (Evenson & Gollin, 2003a).

The adoption of green revolution technologies, however, greatly varies between regions, and in the case of Sub-Saharan Africa (SSA), it has been sub-optimal and slow. Despite large numbers of modern crop varieties (MV) released in SSA in the 1960s and 1970s, there has been little adoption by farmers (Evenson & Gollin, 2003a). The use of new maize varieties in the 1990s, for example, was 17 percent of the total area harvested in SSA compared to 90 percent in Asia and the Pacific (Gollin, Morris *et al.*, 2005). Sub-Saharan Africa had less than one-third the level of modern varieties adoption attained in Asia by 1998 (Evenson & Gollin, 2003a). This coincides with remarkably low usage of fertilizers. The average use of fertilizers in SSA was only 8 kilograms per hectare of cultivated land, which is starkly lower than in other developing regions (Morris, Kelly *et al.*, 2007). Crop yields and agricultural growth are correspondingly lower. Between 1960 and 2000, SSA experienced the world smallest agricultural growth (Evenson & Gollin, 2003b) and has the largest yield gap for major crops of all regions (FAO, 2014)[2].

2. Crops included are: cereals, roots and tubers, pulses, sugar crops, oil crops and vegetables.

There are many potential demand and supply side reasons for the low technology uptake in SSA, and they have been subject to an extensive body of analysis. Researchers have studied barriers such as informational inefficiencies and learning challenges, affordability, agro-ecological conditions, local costs and benefits (Becerril & Abdulai, 2010; Conley & Udry, 2001; Hanna, Mullainathan *et al.*, 2012; Jack, 2013; Marenya & Barrett, 2009; Morris, Kelly *et al.*, 2007), farmer procrastination (Duflo, Kremer *et al.*, 2008), credit constraints (Karlan, Osei *et al.*, 2012), and risk (Just & Zilberman, 1983; Smale, Just *et al.*, 1994).

Subsidies could play an important role in helping farmers to overcome both information gaps and limited finance. Direct incentives to farmers in the form of market-smart subsidies can be used to encourage farmers to test fertilizers and other improved agricultural technologies which otherwise would be regarded as too risky (Morris, Kelly *et al.*, 2007). These kinds of subsidies are temporary direct incentives to farmers to lower the price and/or improve the availability of inputs at the farm level in ways that encourage efficient use while strengthening the market. In the last few years there has been a resurgence of subsidy programs in SSA to kick-start fertilizer use and stimulate input markets. In 2011, about 10 countries spent nearly $1.05 billion (or 28.6 percent) of their public expenditure in agriculture on input subsidy programs (Carter, Laajaj *et al.*, 2014). However, empirical evidence of the effects of these programs is still limited.

The discussion on input subsidies is starkly divided along ideological lines, and academic impact studies are limited and provide inconsistent results. The study of Carter, Laajaj *et al.* (2014) in Mozambique favors the use of subsidies, as they found that a one-time provision of fertilizers and seeds led to persistent increase in fertilizer use and agricultural production. This is contrary to the findings of Duflo, Kremer *et al.* (2011), who concluded that one-time small subsidies of fertilizers increased use from pre-existing levels in the same season, but the increase was not persistent. Given the high cost of these subsidy interventions, policymakers are interested in more evidence of their efficacy.

We study the impact that one-shot free input starter packs – the extreme case of input subsidies – have on long-term use of improved crop varieties and other productivity-enhancing technologies. We argue that starter packs have a role to play in addressing knowledge gaps through the generation of incentives for farmers to proactively increase their knowledge about other technologies such as row planting, weed control and proper soil preparation, which condition the performance of the inputs. We also study the influence of starter packs on the levels of persistence on the use of improved crop varieties, which is the main component of the project's starter packs. If adoption of improved technologies leads to increased yields (Carter, Laajaj et al., 2014; Duflo, Kremer *et al.*, 2011), this may be an important avenue for farmers to grow interest and financial capacity to invest in technologies in subsequent seasons.

As part of JENGA II, a Unites States Agency for International Development (USAID) funded Multi-Year Assistance Program (MYAP) in the Democratic Republic of Congo (DRC), we studied 390 small scale farmers using a randomized controlled trial (RCT). In this three-year experiment, on one hand, we study the impact of one-shot input starter packs on the adoption of productivity-enhancing practices which may condition the performance of starter pack inputs, and on the other hand, we assess the levels of persistence on the use of improved crop varieties included in the starter packs. Answers to these questions have practical implications for the use of this type of subsidies in the future, and contribute to the literature in many ways. First, they expand the literature on the use of randomized control trials in the agricultural context and more specifically to improved seeds. Many studies have researched subsidies in the context of health products or services (Berry, Fischer *et al.*, 2015; Cohen & Dupas, 2008; Dupas, 2014), and in the agricultural sector the focus has largely been on subsidies (Duflo, Kremer *et al.*, 2004, 2011). Second, they also contribute to a better understanding of the impact of the subsidy beyond the mere persistence on the use of the technology promoted. We also see its impact on the adoption of complementary technologies. Lastly, it also provides insightful indications of the great challenges that resource and knowledge-constrained farmers face to persistently adopt improved technologies in post-conflict situations such as that of eastern DRC.

The paper is structured as follows. In Section 2 we present the research settings and program description. Section 3 describes the methodology used to estimate treatment-effect. Section 4 describes the data collection process and descriptive statistics. Section 5 presents the empirical results and discussions, and we finish the paper outlining our main conclusions in Section 6.

3.2. Research settings and program description

This study was conducted in the context of the JENGA II Project, which ran from July 2011 through June 2016 in three territories of the South Kivu province in eastern DRC. It integrated a group of studies aimed at both informing project implementation and generating empirical evidence to improve the design and implementation of future interventions in similar settings.

Many years of unfortunate political choices, mismanagement, and armed conflicts have reduced the once diversified and productive agricultural sector in DRC to an informal subsistence system. Government policies implemented since 1966 have distorted economic incentives against agriculture, which led to the collapse of commercial agriculture in favor of subsistence agriculture (Otchia, 2013). Additionally, the deteriorated transportation infrastructure coupled with an incipient private sector have made it difficult for farmers to both commercialize their products and readily access available inputs. In 2002, the government also removed all kinds of subsidies to agriculture, creating a worsening environment for farmers in DRC (Otchia, 2014).

Currently, agriculture, which has unique potential to spur growth and increase incomes relative to other major sectors in DRC, is by far the most unproductive sector in the country. DRC is one of the countries in SSA with the largest gap between the share of agricultural employment which makes up 60 percent of labor force and the sector's contribution to national gross domestic product (GDP), which is only about 21 percent (Otchia, 2014). This stems mainly from farmers practicing small scale, labor-intensive rudimentary agriculture, mostly based on the application of outdated production practices and use of poorly productive technologies.

Small scale agriculture in DRC is largely characterized by highly fragmented landholdings (while 93 percent of households in DRC have land, the majority cultivate less than a hectare), low use of improved inputs, limited knowledge and use of appropriate agricultural practices, inadequate access to formal credit, and limited extension services (Akakpo, Randriamamonjy *et al.*, 2014). These have all contributed to remarkably low yields for most crops. The production of cassava, the most important staple crop in the country, declined by 20 percent in the 1990s (Ameua, Hirea *et al.*, 2013); with current yearly production (from 2000 to 2014) below production levels in the 1990s by 14.5percent (FAO, 2016a). Poor availability of healthy multiplication materials has exacerbated the effect of cassava and banana endemic diseases, contributing to the drastic reductions in cassava and banana production in recent years.

The use of fertilizers and improved seed varieties in DRC is one of the lowest in the continent. The average use of fertilizer between 2006 and 2010 was only 0.47 kg/ha, while countries like South Africa and Morocco reached 46.51 and 36.69 kg/ha, respectively (Otchia, 2014). Similarly, the use of improved seeds is the privilege of a few, certainly not small scale farmers. Farmers in DRC have low incentive to invest in fertilizers because imported agricultural products from nearby countries are available at very competitive prices (Nweke, 2000); Most farmers obtain their planting materials from their own old seed stocks, old stock of neighbors and friends and local seed businesses (Mastaki, 2006). Such planting materials are usually of low quality with poor germination and yield potentials.

While the systemic availability of fertilizers and quality improved seed varieties is a major bottleneck in DRC and largely explains low adoption, there is also a demand side issue which is not trivial. According to (Otchia, 2014) farmers' limited access to credit and lack of appropriate knowledge about fertilizers play a major role in the incipient use of fertilizers in the country. It has become imperative for farmers to receive some kind of assistance to be able to increase the use of more productive technologies. Consequently, different assistance mechanisms (most free delivery and subsidies) have been implemented by donors, NGOs and, in some exceptional cases, the private sector in many parts of the country, but not without some level of criticism from actors that find these mechanisms counterproductive.

3.2.1. Free input starter packs

JENGA II provided a one-time free starter pack containing improved crop seeds, multiplication materials (cassava) and tools to each participant at the start of the FFSs. These starter packs were assumed to improve yields in the first season and increase thus increase the desire and financial capacity of farmers to persistently purchase improved seeds in subsequent seasons. In addition, they would increase farmers' adoption of complementary productivity-enhancing technologies. F2F farmers generally did not get starter packs. However, for the purpose of this study a randomly selected group of F2F farmers did receive starter packs, so that we could compare their behavior with that of F2F farmers who did not receive starter packs.

The starter packs included 125 lineal meters of cassava mosaic disease (CMD) tolerant cassava cuttings; 7.5 kg of improved peanut seeds; 4 kg of improved beans seeds and 1.5 kg of improved maize seeds. The average area under cultivation in the project area is around 0.5 ha per farmer and the seeds that the project provided in the starter packs are enough to cultivate 40 percent of this area (0.2 hectare). JENGA II targets smallholder farmers that are ill-equipped and use very rudimentary and inefficient farming tools. This often leads farmers to take a full day to carry out the same activity which could be executed in a couple of hours using more appropriate hand tools. Hence, the starter packs also included a more efficient hoe, a machete and roll of rope so farmers could increase their labor productivity and implement simple but effective techniques such as row planting.

3.3. Data collection and descriptive statistics

3.3.1. Data collection

The 390 participants for this study were part of the group of F2F farmers who started in the second year of the JENGA II project. A randomly selected group of 210 of these farmers received starter-packs. In February/March 2013, before the farmers began their training and the distribution of the one-time starter packs occurred, the first cross-sectional survey (CSS1) was conducted. A year later, in February/March 2014 – when the farmers had gone through at least one growing cycle for all crops promoted (beans, cassava, maize, and peanuts), the second cross-sectional survey (CSS2) was administered. In February/March 2015, the third cross-sectional survey (CSS3) was administered to the same group of farmers. The CSS3 covered the second year after the starter packs were distributed, so no free inputs were distributed that time. Hence the study period covers a total of four seasons for semi-annual crops (beans, maize and peanuts) and two for cassava, which help us to have a better understanding of the dynamics beyond the immediate effect of starter packs.

A well-structured questionnaire was used to solicit information on the demographic characteristics of the individuals –such as age, level of education, experience, and marital status; household and farm characteristics –such as household size, economic activities, food security status, production activities including perceived soil quality, plot size, crop production, yields, and marketing; and questions related to the use of improved agricultural practices and inputs. For the purpose of our analysis, we classify project-promoted technologies into two groups: (1) practices, which include mulching, crop rotation, row planting, weeding, hoeing, intercropping, and mounding; and (2) inputs, comprising improved crop varieties, organic fertilizers, organic pesticides, and sprayers.

3.3.2. Measuring technology adoption and yields

Technology adoption is measured through alternative indexes (see *Table 3.1*), which can be classified into two main groups. The first group, measures the number of practices/inputs that the farmer used in the previous season, including: (a) the total number of technologies (practices + inputs), which ranges from 0 to 11; (b) the number of practices, ranging from 0 to 7; and (c) the number of inputs, ranging from 0 to 4. The second group, includes three binary indicators, which classify farmers as adopters or non-adopters of agricultural technologies based on the use of technologies in the previous season: 1 indicating that the farmer adopted a minimum of 4 technologies (practices + inputs), a minimum of 4 practices, or a minimum of 2 inputs, and zero otherwise. Additionally, we use another binary indicator which takes the value of 1 if the farmer used improved seeds in the preceding season and zero otherwise. We also calculated multi crop yield index to assess the impact of starter packs on crop performance. Following Working (1940) we calculate an index that compares how the yields of several different crops vary, on average between farms in our sample, and between the different periods. To standardize the quantities of the different crops to one unit for aggregation purposes, each crop yield is weighted by the product of its median market price and median land area for all farms considered in the sample.

3.3.3. Descriptive statistics and program participation

The F2F-SP and F2F-only are highly similar in their main characteristics (see *Table 3.1*). From the CSS1 data, we find that the vast majority of participants in both groups are female, while more than 95 percent of households in each group were engaged in agriculture as their main livelihood. About 97 percent of F2F farmers have access to farm land with no statistical difference between the two groups. There are no differences in the proportions of households owning land across both groups.

The farmers cultivated an average of about 2,000 m^2 of land, and the crop-yield index of the F2F-only farmers is slightly higher than of the F2F-SP farmers, although the difference is not statistically significant. About 85 percent of the farmers cultivated cassava, followed by maize (35 percent), beans (20 percent) and peanuts (18 percent). Across the two groups of farmers, only the proportion of farmers cultivating cassava significantly differed: 88 percent of F2F-only farmers cultivated cassava compared to 81 percent of F2F-SP farmers. Similarly, there are no significant differences in the proportion of crops sold by the F2F-only and F2F-SP farmers. On average farmers sold approximately 18 percent of their harvests. Less than 4 percent of households participated in any other development programs, and there was no significant difference in participation between the groups. The most common programs included agriculture, small businesses and livestock.

Table 3.1. Summary of main descriptive statistics

Variables	CSS1: Feb/March 2013 F2F-Only (n=155) ¥	CSS1: F2F-SP (n=161)	CSS1: P-Value*	CSS2: Feb/March 2014 F2F-Only (n=149)	CSS2: F2F-SP (n=169)	CSS2: P-Value*	CSS3: Feb/March 2015 F2F-Only (n=141)	CSS3: F2F-SP (n=155)	CSS3: P-Value*
Household demographics									
Household (HH) size	6.09	5.64	0.074	6.43	5.69	0.003	6.57	6.51	0.877
% of children under 5 in the HH	35%	32%	0.324	35%	31%	0.301	35%	31%	0.241
% of adults working in HH	84%	81%	0.256	84%	81%	0.250	84%	80%	0.195
% of HHs where farmer is women	39%	30%	0.076	41%	32%	0.087	43%	33%	0.107
Women's years of education	3.68	3.51	0.775	3.77	3.65	0.808	3.71	3.76	0.941
% of HHs participating in other agric. activities	23%	20%	0.482	22%	20%	0.729	21%	20%	0.905
% of HHs with savings	13%	12%	0.775	24%	26%	0.707	24%	26%	0.746
Farm characteristics									
% of farmers with access to land	98%	97%	0.548	97%	95%	0.357	94%	93%	0.813
% of land owner farmers	65%	58%	0.136	59%	57%	0.747	67%	70%	0.646
Cultivated area (square meters)	2,007	1,952	0.514	2,190	2,161	0.794	2,774	3,044	0.274
Crop production (kg)	431	428	0.727	348	330	0.867	475	566	0.587
% of crop production sold	18%	19%	0.710	28%	22%	0.079	25%	31%	0.114
% of production stored	22%	31%	0.075	48%	45%	0.680	91%	98%	0.202
% of farmers selling individually	66%	60%	0.227	70%	66%	0.502	75%	64%	0.041
% of farmers with access to financial services	28%	29%	0.807	37%	36%	0.880	42%	45%	0.561
Indexes of technology adoption									
Average number of technologies adopted	3.44	3.29	0.307	3.72	3.89	0.257	4.91	5.02	0.521
% of farmers adopted min. four technologies	46%	42%	0.523	60%	63%	0.545	84%	86%	0.734
Average number of practices adopted	3.41	3.28	0.373	3.66	3.86	0.180	4.72	4.65	0.500
% of farmers adopted min. four practices	45%	42%	0.683	58%	62%	0.568	83%	86%	0.503
Average number of inputs adopted	0.03	0.01	0.232	0.05	0.04	0.431	0.19	0.38	0.150
% of farmers adopted min. two inputs	3.2%	1.2%	0.232	5.4%	3.6%	0.431	16%	28%	0.022
% of farmers adopted improved seeds	44%	45%	0.841	66%	69%	0.587	74%	74%	0.907

*Non-parametric test for three samples: chi-squared, using Kruskal-Wallis equality-of-populations rank test.
¥ in this case n reflects the average number of observations for all indicators

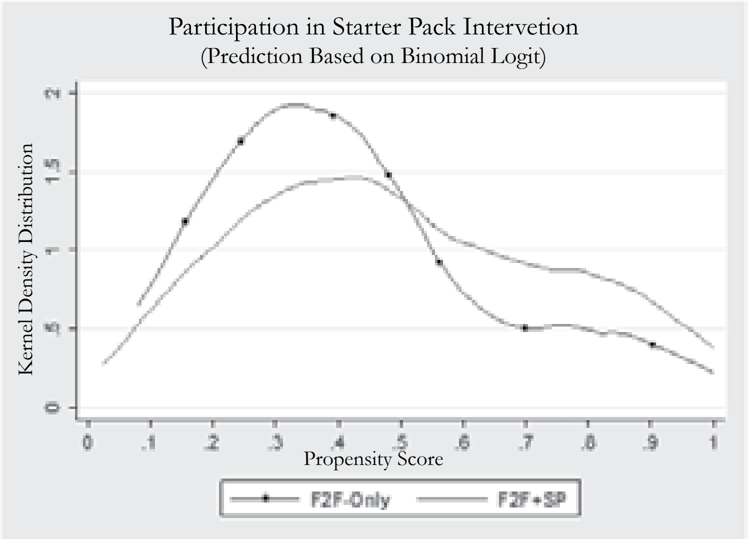
The baseline figures (CSS1) for different technology adoption indexes help us to understand from which point the treatment and control groups started. On average, from a total of 11 technologies promoted by the project, F2F-only and F2F-SP farmers were using at baseline 3.44 and 3.29 technologies respectively. These small differences are not statistically significant as displayed in *Table 3.1*.

The same holds for the other six indicators of technology adoption, as both groups were using the same level of technologies on average. When considering the adoption of individual technologies such as mulching, crop rotation and row planting, farmers on average were using the same technologies across the two groups (*see Appendix 3.1*). While the levels of adoption are the same for the two groups before the project intervention, some practices like hoeing and weeding were already highly practiced, and the use of other technologies like crop rotation and organic fertilizers was very low.

Overall the two groups are very similar in their household and farm pre-treatment characteristics, despite differences in some variables. Likewise, the pre-treatment values of the technology adoption indexes are quite similar between the two groups. This is in line with the distribution of the propensity scores for participation in F2F-Only and F2F-SP (see *Graphic 3.1*). While the distributions of these scores are slightly different, the differences are not drastic. This is a good indication that the groups were properly selected randomly and that the use of the propensity-score based weights may account for the remaining systematic differences. The distribution of the propensity scores for participation in starter pack intervention have an ample common support area [0.078 – 0.976].

In period one, or one year after the baseline (CSS2), F2F farmers had adopted significantly more agricultural technologies compared to baseline levels, however there are no significant differences between the F2F-Only's adoption levels and that of F2F-SP farmers. The number of technologies adopted by F2F farmers accentuates in period two, but again there are no significant differences between recipient and non-recipient of starter packs. This situation is very similar for all the seven indexes of technology adoption calculated in the study and the crop yield index, and for the adoption of individual technologies detailed in *Appendix 3.1*. The significant increase experienced in the technology adoption by the two groups, was highly influenced by an increased adoption of mulching, crop rotation, row planting, improved germplasm and organic fertilizers, but again these increases are not significantly different between recipients and non-recipients of starter packs.

Graphic 3.1. Propensity score and common support area (Kernel Distribution)



3.4. Methodology

3.4.1. Experimental identification

Random assignment of treatment allows for the estimation of starter packs' impact on adoption with no major inference issues. Following (Angrist & Pischke (2008) and Wooldridge (2010), the general regression equation for our technology adoption model can be stated as:

$$TA_{it} = \alpha + \delta_t d_t + \gamma SP_i + \varphi_t SP_i * d_t + \lambda X_{it} + v_i + \varepsilon_{it}, \ t = 0,1,2 \qquad (1)$$

where TA_{it} represents an index of technology adoption for participant i in time t; SP_i ϵ [1;0] is a binary variable denoting participation in the starter pack intervention, with 1 implying farmer i is the recipient of the starter pack and 0 otherwise. While SP_i is constant over time –the household is either part of the treatment group or not – the impact of the intervention measured as φ_t differs between the time periods. X_{it} is a vector of time-variant control variables. Note that this model includes three main effects, which measures the time trend effect related to time variable d_t , γ_t the effect of starter packs, and the interaction effect which looks at the period-specific impacts of starter pack. Additionally, ν_i denotes individual fixed effects; and ε_{it} an independent and identically distributed random error.

Since starter packs are randomly assigned in our experiment, we may assume that $E(\varepsilon_{it} | SP, X)=0$, implying that SP_i, X_{it}, and ε_{it} are independently distributed. Yet, there may still be some level of correlation between ν_{it} and X_{it}. We adopt the Difference-in-Differences (DID) estimator to deal with this issue and eliminate the influence of ν_i in our predictions (Angrist & Pischke, 2008; Bertrand, Duflo *et al.*, 2002; Imbens & Wooldridge, 2009; Meyer, Viscusi *et al.*, 1995). Based on *Equation 1* we derive our DID technology adoption model with time and treatment (starter pack) interactions for individual *i* at time *t*. In *Equation 2* we conduct the first difference from period one to period zero,

$$\begin{aligned} TA_{i1} - TA_{i0} &= (\delta_1 d_1 + \varphi_1 SP_i * d_1 + \lambda X_{i1} + v_i + \varepsilon_{i1}) - (\delta_0 d_0 + \varphi_0 SP_i * d_0 + \lambda X_{i0} + v_i + \varepsilon_{i0}) \\ &= \delta_1 d_1 - \delta_0 d_0 + (\varphi_1 - \varphi_0) SP_i * d_t + \lambda \Delta X_{i1} + \Delta\varepsilon_{i1} \end{aligned} \tag{2}$$

and then in *Equation 3* the first difference from period two to period one,

$$\begin{aligned} TA_{i2} - TA_{i1} &= (\delta_2 d_2 + \varphi_2 SP_i * d_2 + \lambda X_{i2} + v_i + \varepsilon_{i2}) - (\delta_1 d_1 + \varphi_1 SP_i * d_1 + \lambda X_{i1} + v_i + \varepsilon_{i1}) \\ &= \delta_2 d_2 - \delta_1 d_1 + (\varphi_2 - \varphi_1) SP_i * d_t + \lambda \Delta X_{i2} + \Delta\varepsilon_{i2} \end{aligned} \tag{3}$$

Taking *Equation 2* and *3* together results in the following:

$$\Delta TA_{it} = \delta_1^* + \delta_2^* d_2 + \varphi_1^* SP_i * d_1 + \varphi_2^* SP_i * d_2 + \lambda \Delta X_{it} + \Delta\varepsilon_{it}, \ t = 1,2 \tag{4}$$

where ΔTA_{it} is now the difference of technology adoption for the individual *i* between time *t* and *t-1*; ΔX_{it} denotes the difference of the vector of characteristics specific to individuals, their farms and households, and $\Delta\varepsilon_i$ is the difference of the term of the i.i.d error. The δ_1^* and δ_2^* represent the time trend effect for periods one and two. Note that in *Equation 4* is a parameter that in the undifferenced version represents a constant time trend parameter.

The parameters φ_t^* in *Equation 4* estimate the period-specific double difference treatment effect of the use of starter pack inputs on the adoption of agricultural technology. This estimator however, is identical to that estimated in the context

3

of repeated cross-sectional data which does not directly exploit the panel nature of our dataset (Imbens & Wooldridge, 2009). *Equation 4* ignores the fact that the magnitude of the effect of starter pack on technology adoption could be overestimated because the level of adoption of farmer i in time t may be partially determined by the level of adoption it had in time *t-1*.

One approach to address this issue, while profiting from the rich features of panel data, is to assume unconfoundedness based on lagged outcomes. In this case the levels of technology adoption in period *t-1*, are included as an explanatory variable in the model Imbens and Wooldridge (2009). The unconfoundedness assumption postulates that treatment assignment is independent of potential outcomes and the stochastic error, so controlling for differences in a set of covariates, including the levels of technology adoption before treatment, removes biases in comparisons between treated and control groups (Rubin, 1990). This unconfoundedness-based approach seems to be more attractive than DID in the context of panel data (Imbens & Wooldridge, 2009). Thus, we added the lagged observation of the dependent variable (TA_{it-1}) to control for unknown time-variant confounding variables which may influence the potential levels of technology adoption in period *t* (Angrist & Pischke, 2008) to give:

$$\Delta TA_{it} = \delta_1^{*} + \delta_2^{*} d_2 + \varphi_1^{uncon f} SP_i * d_1 + \varphi_2^{uncon f} SP_i * d_2 + \lambda \Delta X_{it} + \rho TA_{it-1} + \Delta \varepsilon_{it}, \quad t = 1,2 \qquad (5)$$

3.4.2. Inverse probability-based weighted estimations

DID causal effect estimators are unbiased only if the statistical model in correctly specified and if there are no biases originated because of non-random project placement and self-selection. In other words, when the goal is to adjust for confounding variables, the estimator is asymptotically unbiased if the model reflects the true relations among exposure and confounders with the outcome (Funk, Westreich *et al.*, 2011). In practice however, finding the appropriate model that accurately depicts these relations is particularly challenging. Therefore, we adopted a strategy that combines regressions with probability propensity score-based weights to achieve additional robustness to potential misspecification of

3

our parametric models (Imbens & Wooldridge, 2009; Wooldridge, 2007).

Inverse probability weighted (IPW) regressions is a double robustness method suggested by Robins, Rotnitzky *et al.* (1995). Let z_i be a time-variant variable omitted in *Equation 1*. As proposed by Imbens and Wooldridge (2009), regressions would help to eliminate the direct effect of z_i on the dependent variable *TA*, while weighting would remove the correlation between z_i and included treatment *SP* and covariate variables (*X*). Combining our DID regressions with weighting could lead to additional robustness as it removes the correlation between omitted covariates and reduces the correlation between omitted (z_i) and included covariates. This has proven to improve consistency of the estimators and leads to efficient predictions of average treatment effects (Hirano, Imbens *et al.*, 2003; Wooldridge, 2007).

3

In IPW method, each observation in the treatment group is weighted using the inverse of the predicted probability propensity score ($1/p\ (X_i\ ;\ \gamma^*$), and the inverse of one minus the propensity score $(1/[1 - p\ (X_i; \gamma^*)]$ for the non-treated group (Imbens & Wooldridge, 2009). While in randomized experiments like in this case, the individuals are expected to have the same probability to participate in the different treatments and thus are subjected to similar weights, we still use IPW in this paper to offset any remaining differences.

3.5. Results and discussion

Following *Equation 5*, we regressed the seven indexes of technology adoption against the treatment variables and several covariates. To assess the robustness of our main results, we employ four variations of our model using a panel with three periods: (a) Simple DID; (b) Simple DID with covariates; (c) Weighed DID; and Weighed DID with covariates. We also applied the same variations for a Fixed-Effect (FE) estimators to compare with the DID results. A summary of all regression results is included in *Table 3.2* below. In *Appendixes 3.2-3.6* we also show the full regression results. The estimation of the DID model in three periods is especially important to analyze the persistence on the use of improved inputs after the delivery of the starter pack.

We used various socio-demographic variables of the household and farm characteristics as control variables in the regressions. The summary statistics of most of the technology adoption indexes, use of individual technologies, and the covariates are presented in *Table 3.1* and *Appendix 3.1*.

3.5.1. Impact of starter packs on overall adoption of agricultural technologies

Overall, we find no impact of starter packs on adoption of productivity-enhancing technologies. Regardless of the specification and index used, the results consistently suggest no significant impact of starter pack on farmers' adoption of productivity-enhancing technologies (see *Table 3.2* and *Appendixes 3.2-3.6*). We detect a positive time trend effect: farmers in the treated and non-treated groups both increased the use of practices and inputs from baseline levels. However, there is no evidence of an increase due to the use of starter packs in any period. The overall enhancement in the two groups is most likely an effect of F2F training, since farmers participating in F2F training significantly increased their levels of adoption compared to that of farmers in the pure control group *(see Chapter 4)*

To assess whether the lack of statistically significant impact could be due to limited sample size, we calculated the Minimum Detectable Effect Size (MDES), which is the minimum true effect-size that our study can detect with the expected level of statistical precision and power (Dong & Maynard, 2013). We basically calculated the MDES for each impact explanatory variable and compared that with the minimum relevant effect size (MRES), which in this case is the size of the parameters of impact estimated in the DID regressions. To estimate the MDES we used the standard deviation for the treatment and control groups, a power level of 0.80 and adopted a two-tailed testing which is most commonly used in the literature compared (Dong & Maynard, 2013). Despite some indications that the sample size may compromise the detection of starter packs' effect on adoption – where the MDES is smaller than MERS –the MDES calculations showed that the sample offers enough power to detect the true treatment effect of starter packs on the great majority of technology adoption indexes, given the level of significance. This seems to indicate that the lack of significance in the regressions is just because starter packs do not properly predict the heterogeneity on farmers' levels of technology adoption.

3

Table 3.2. Impact of starter packs on technology adoption

Dependent Variable	Simple DID	MDES	DID with Covariates	MDES	DID Weighted	MDES	DID Weighted and with Covariates	MDES
Index of technology adoption (practices+inputs)								
Starter-pack first period	0.220	0.052	0.157	0.051	0.064	0.068	0.021	0.064
	(0.137)		(0.144)		(0.182)		(0.181)	
Starter-pack second period	0.051	0.061	-0.003	0.059	-0.034	0.087	-0.105	0.081
	(0.166)		(0.160)		(0.273)		(0.238)	
Minimum of four technologies adopted								
Starter-pack first period	0.032	0.015	-0.003	0.016	0.026	0.0245	-0.005	0.022
	(0.060)		(0.064)		(0.094)		(0.089)	
Starter-pack second period	0.007	0.012	0.001	0.012	-0.017	0.0158	-0.028	0.017
	(0.041)		(0.042)		(0.065)		(0.065)	
Total umber of practices adopted								
Starter-pack first period	0.224*	0.049	0.156	0.048	0.065	0.064	0.027	0.058
	(0.135)		(0.141)		(0.181)		(0.174)	
Starter-pack second period	-0.110	0.054	-0.118	0.052	-0.229	0.0754	-0.233	0.069
	(0.141)		(0.134)		(0.221)		(0.193)	
Minimum of four practices								
Starter-pack first period	0.031	0.016	-0.008	0.016	0.039	0.024	0.008	0.023
	(0.06)		(0.06)		(0.09)		(0.09)	
Starter-pack second period	0.021	0.013	0.016	0.011	-0.009	0.0157	-0.019	0.017
	(0.04)		(0.04)		(0.07)		(0.07)	
Total number of inputs adopted								
Starter-pack first period	-0.008	0.007	-0.003	0.007	-0.004	0.0072	-0.012	0.010
	(0.03)		(0.03)		(0.03)		(0.04)	
Starter-pack second period	0.165**	0.016	0.114*	0.016	0.198*	0.0275	0.133	0.026
	(0.07)		(0.07)		(0.12)		(0.10)	
Minimum of two inputs adopted								
Starter-pack first period	-0.008	0.007	-0.003	0.007	-0.005	0.0072	-0.003	0.010
	(0.03)		(0.03)		(0.03)		(0.03)	
Starter-pack second period	0.098**	0.012	0.071	0.013	0.108	0.0172	0.072	0.019
	(0.05)		(0.05)		(0.08)		(0.08)	

* p<0.10, ** p<0.05, *** p<0.01

Values in parenthesis are standard errors adjusted for clusters in household id

3.5.2. Persistent use of improved crop varieties

We find no evidence of one-shot free starter packs' structural changes on the use of inputs, in this case improved seeds. The use of improved seeds is no different between starter pack recipients and non-recipients in any of the two periods following the SP free delivery. Again, there is a significant time trend impact as both recipients and non-recipients increased their use of improved seeds in periods 1 and 2. Yet, there is no significant difference on the levels of adoption that can be attributed to the starter pack intervention in any period (*see Table 3.3*). As described previously, the farmers participated in two entire seasons for semi-annual crops (beans, maize, peanuts and rice) in period one, so the impact seen at the end of period one actually corresponds to that of the second season in which farmers were no longer using free-starter packs.

3

Table 3.3. Impact of starter packs on adoption of improved crop varieties

Variables	Simple DID	DID with Covariates	DID Weighted	DID Weighted and with Covariates
Dummy period 1	0.664***	0.673***	0.685***	0.706***
	(0.05)	(0.05)	(0.07)	(0.07)
Dummy period 2	0.746***	0.798***	0.758***	0.808***
	(0.05)	(0.05)	(0.07)	(0.06)
Interaction of starter-pack and period 1	0.033	0.032	0.076	0.046
	(0.06)	(0.06)	(0.08)	(0.08)
Interaction of starter-pack and period 2	-0.019	-0.050	-0.080	-0.107
	(0.05)	(0.05)	(0.09)	(0.08)
Lag of technology adoption index	-1.000***	-1.026***	-1.028***	-1.038***
	(0.04)	(0.04)	(0.05)	(0.05)
Time variant control variables	No	Yes	No	Yes
R2_adjusted	0.552	0.590	0.563	0.600
RMSE	0.450	0.440	0.460	0.440
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	548	501	297	290
Starter-pack*t1 - Starter-pack*t2 =0 ¥	0.505	0.302	0.221	0.178

* p<0.10, ** p<0.05, *** p<0.01

¥ values for Wald test are the p-value

In this section, we mostly focus on the adoption of improved practices that may maximize the effect of improved inputs on farmers' output. In our theoretical model, we hypothesized that the *SP* play a role in persuading farmers that the improved technology (improved seeds) would at least generate the same levels of production as the traditional technology ($QI\ \ Q$). Since farmers' expectation of production after experimenting the technology would now be higher than before, this would create incentives for the farmer to learn more about the other yield enhancing practices, mostly through farmer-to-farmer training. Overall, farmers' participation in F2F training significantly increased their levels of adoption compared to pure control farmers, probably because of updated knowledge about the practices, however SP-recipients' levels of adoption are not significantly different from that of non-recipients.

3

3.5.3. Starter packs and yields

Evidently, only positive information about the returns of the new technology would be relevant to incentivize farmers to persistently adopt that technology, and possibly others that may help to maximize the impact of the new technology. As indicated in *Table 3.4* below, the starter packs did not result in increased yields for the farmers in our sample in any of the periods. Note that we refer here to the yields of cassava shown in *Table 3.4*. Cassava takes 9-12 months to be harvested so it was the only crop that befitted from the starter-packs and whose yields were reported at the moment of the CSS2 survey one year after the baseline. There is a time trend effect where the levels of yields for the entire sample increased in both periods, however we find no evidence that participation in the starter pack intervention predicts higher levels of yields. While, we also estimated the impact of starter-packs on the crop yield index which also include the semi-annual crops beans, maize, and peanuts, these estimations results may be biased as the yields reported for these semi-annual crops are from the second season after the farmers received the starter packs. Anyways, these results also found no difference on the yields between recipients and non-recipients of starter packs. The fact that the new technology did not generate higher yields in the first period may potentially explain why starter-pack recipients did not adopt the technology in the second period.

Table 3.4. Impact of starter packs on cassava yields (DID)

Variables	Simple DID	DID + Covariates	DID + Weighted	DID + Weighted + Covariates
Dummy period 1	2,264***	2,242***	2,060***	2,065***
	(246)	(280)	(295)	(326)
Dummy period 2	2,346***	2,489***	1,822***	1,991***
	(250)	(264)	(259)	(265)
Inter. starter-pack and period 1	1.155	-4.824	263	132
	(266)	(292)	(397)	(388)
Inter. starter-pack and period 2	-197	-191	209	287
	(325)	(354)	(436)	(471)
Lag of cassava yield	-0.941***	-0.932***	-0.927***	-0.913***
	(0.056)	(0.061)	(0.078)	(0.067)
Household size		11.111		-52.537
		(52.028)		(78.324)
Access to farmland		711		809
		(505)		(545)
Area cultivated		-0.164***		-0.154*
		(0.051)		(0.079)
Market products individually		20.159		210
		(192)		(210)
Access to financial services		-124		123
		(177)		(233)
Farmer produces maize		379**		241
		(172)		(231)
Farmer produces beans		-256		-624**
		(204)		(268)
Farmer produces peanuts		1.579		206
		(204)		(346)
Farmer produces rice		34.191		780
		(378)		(533)
R2_adj	0.416	0.414	0.422	0.440
RMSE	1,985	1,989	1,849	1,828
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	358	327	201	198

* p<0.10, ** p<0.05, *** p<0.01

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3.5.4. Discussion

The free starter packs were distributed under the assumption that: 1) they would increase the adoption of the other technologies disseminated through the project; and 2) they would result in a persistent use of the technologies in the starter packs – especially improved seeds. Our results discard both assumptions. In this section, we explore the conditions under which the assumptions would hold and what could cause the rejection in this case.

Starter packs increase the adoption of other technologies in the presence of complementarity. Suppose a free starter pack (*SP*) that increases the returns (*R)* to traditional production (*T,0*) and an improved technology (*I*) that increases returns, but only when combined with the starter pack (*Condition 1*).

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$$R_{I,SP} > R_{T,SP} > R_{T,0} \geq R_{I,0} \tag{C.1}$$

Then farmers will adopt the technology only in combination with the starter pack. In our case, we find similar adoption for farmers with and without starter packs, which is not consistent with complementarity. We now turn to the use of one-shot free starter pack technologies. Persistent use is conditional on the benefits of the technology. Farmers will not continue to use the technologies unless the additional returns exceed the additional costs (*Condition 2*):

$$R_{SP} - R_0 > c_{SP} \tag{C.2}$$

Yet if this condition holds, why then do farmers not use the starter pack technology to begin with? One possibility is that farmers are not sufficiently aware of the benefits of the new technology, so that its expected returns are not sufficient to cover the additional costs. Free starter packs will then induce a one-shot use if the expected additional benefits are larger than zero (*Condition 3*):

$$0 < c_{SP} < E(R_{SP}) - R_0 \tag{C.3}$$

If both condition (2) and (3) hold, one-shot free starter packs will induce persistent use of the new technology. A second possibility is that farmers are aware of the benefits of the new technology, but do not have the financial means (F) to purchase the starter-pack technology (*Condition 4*):

$$c_{SP} > F \quad \text{(C.4)}$$

The additional income from the free starter pack can then be used to purchase the inputs for the following season. This means that, conditional on the assumption of higher returns to the improved technology (C.2), the one-shot free provision of the technology may result in continued use of the technology for two reasons: better knowledge about the real returns of the technology (C.3), and lower cash constraints (C.4).

The question is which of these conditions does not hold for the farmers in our sample. In principle, the conditions in the area seem appropriate for starter packs to be effective, as knowledge of improved technologies is limited and farmers have little or no access to financial markets. Yet, the effectiveness of starter packs depends on their contents as well. We start by assessing the validity of condition 1: are the additional returns to the improved seeds sufficient to compensate for the costs of purchasing the seeds? For this condition to hold, seeds need to generate sufficiently higher yields, and they need to be available in the market. In *Table 3.4* we estimated the impact of starter packs on yields for the two periods. Remarkably, while overall F2F farmers clearly increased yields (note that time trend estimators for periods one and two are significantly positive), no significant effect of starter packs is found on yields. In addition, while access to input dealers is still a great challenge in the area under study, especially for F2F farmers who are not normally benefiting from economies of scale through farmers' organizations, farmers still have ways to purchase inputs either individually or jointly. These levels of access to seeds is irrelevant in our case as the seeds are not economically attractive – condition 1 does not seem to hold for the current starter packs – and farmers are unlikely to bear the costs to purchase them.

3.6. Conclusions

This paper studies the impact of one-time free input starter packs on the long-term use of improved crop varieties and other productivity-enhancing technologies. We focused the analysis on two premises: firstly, that starter packs play an important role incentivizing farmers to increase adoption of complementary yield enhancing agricultural practices, so to exploit the full potential of input starter packs; and secondly, that starter packs encourage farmers to persistently increase the use of inputs. The starter packs are often expected to both address informational imperfections as they expose farmers to the benefits of improved inputs through experimentation, and to increase farmers' desire and financial capacity to persistently invest in inputs. If increased yields are potential outcomes of the adoption of improved technologies as found by Carter, Laajaj *et al.* (2014) and Duflo, Kremer *et al.* (2011), then increased yields may be an important mechanism for farmers to grow desire and financial capacity to invest in technologies in subsequent seasons. These hypotheses were tested using an experimental design involving 390 farmers for three years from 13 agricultural villages in eastern DRC. From the total number of farmers, 210 were randomly selected to receive the one-time starter pack, and 180 were used as the control group.

We found no evidence of the impact of one-time starter packs on the adoption of productivity-enhancing practices. While farmers in the two groups (recipients and non-recipients of starter packs) did increase their use of the technologies promoted by JENGA II from previous levels, these increases did not vary significantly between groups and thus cannot be attributed to the provision of starter packs. Equally, the results show no significant persistent use of improved seeds over the two periods following the delivery of starter packs. These results are somewhat consistent with other studies that also found minimum to no persistence in the use of inputs following the provision of one-time input subsidies (Duflo, Kremer *et al.*, 2011). While the results are apparently counterintuitive, the fact that the yields of the starter pack recipients were not significantly different from that of the non-recipients after the first year seems to logically explain why farmers refrained from using improved seeds in the following seasons.

The small size of the starter packs, limitations to access input markets, capital/credit constraints to invest in inputs, and paternalistic behaviors against self-investment in inputs are additional potential explanations for the low levels of adoption and lack of persistence in the use of inputs. These factors should be considered, explored further and accounted for in the design of future interventions aiming to promote adoption of agricultural technologies. However, any effort to address these constraints may be found ineffectual if farmers' use of technologies do not materialize in higher yields (revenues) for the users.

In light of these findings, ADRA and other organizations have started to address some of the potential factors that prevent farmers from adopting promising agricultural technologies. ADRA is testing "smarter" ways to subsidize the use of start-up inputs for resource-constrained small scale farmers. ADRA is currently implementing a multi-year gradual subsidy system to cost-share farmers' investment in improved seeds and fertilizers in ADRA's USAID funded project in Madagascar. The system consists of a 70 percent project subsidy in the first year, 50 percent in the second year and 30 percent in the third year. This is expected not only to increase efficiency of the donor resources, but also has the potential to create dynamics that incentivize farmers' "healthy" behaviors –efficient use of inputs, strategic use of harvest proceeds, record keeping, etc. – which in the long-run, may well generate higher results in terms of adoption and yields and stimulate the development of better input supply networks in the target area.

APPENDIXES

Appendix 3.1. Use of individual technologies by group

Variables	CSS1: Feb/March 2013			CSS2: Feb/March 2014			CSS3: Feb/March 2015		
	F2F-Only	F2F-SP	P-Value*	F2F-Only	F2F-SP	P-Value*	F2F-Only	F2F-SP	P-Value*
% of farmers using specif. technologies									
Mulching	34%	27%	0.323	38%	40%	0.751	67%	69%	0.829
Crop rotation	19%	14%	0.418	19%	33%	0.034	55%	56%	0.813
Row planting	49%	54%	0.442	54%	56%	0.846	77%	76%	0.927
Weeding	87%	82%	0.471	94%	92%	0.799	97%	95%	0.729
Hoeing	96%	96%	0.941	95%	97%	0.711	96%	97%	0.888
Intercropping	36%	38%	0.766	47%	49%	0.813	51%	49%	0.758
Mounding	21%	19%	0.668	20%	20%	1.000	30%	27%	0.655
Improved germplasm	44%	45%	0.863	66%	69%	0.659	74%	74%	0.929
Sprayers	0.0%	0.0%	1.000	0.0%	1.0%	0.928	0.0%	9.0%	0.207
Organic fertilizers	3.0%	1.0%	0.758	5.0%	2.0%	0.644	14%	22%	0.233
Organic pesticides	0.0%	0.0%	1.000	0.0%	1.0%	0.928	5.0%	7.0%	0.745
Average number of observations	154	161		149	169		140	152	

*Non-parametric test for three samples: chi-squared, using Kruskal-Wallis equality-of-populations rank test.

Appendix 3.2. Impact of starter packs on number of technologies adopted (persistence on use of inputs)

Variables	Simple DID	DID with Covariates	DID Weighted	DID Weighted and with Covariates
Dummy period 1	3.127***	3.300***	3.341***	3.516***
	(0.211)	(0.205)	(0.277)	(0.248)
Dummy period 2	4.315***	4.548***	4.449***	4.728***
	(0.248)	(0.238)	(0.343)	(0.313)
Interaction of starter-pack and period 1	0.220	0.157	0.096	0.035
	(0.137)	(0.144)	(0.184)	(0.188)
Interaction of starter-pack and period 2	0.051	-0.003	-0.099	-0.121
	(0.166)	(0.160)	(0.254)	(0.248)
Lag of technology adoption index	-0.829***	-0.866***	-0.847***	-0.898***
	(0.053)	(0.052)	(0.069)	(0.062)
Household size		0.045**		0.039
		(0.022)		(0.036)
Access to farmland		0.718		1.716*
		(0.489)		(0.894)
Area cultivated		0.000		-0.000
		(0.000)		(0.000)
Market products individually		0.024		0.087
		(0.088)		(0.099)
Access to financial services		0.101		0.155
		(0.083)		(0.102)
Farmer produces maize		0.117		0.065
		(0.093)		(0.116)
Farmer produces beans		0.100		-0.021
		(0.104)		(0.148)
Farmer produces peanuts		0.052		0.114
		(0.097)		(0.134)
Farmer produces rice		0.452		0.848*
		(0.351)		(0.441)
R2_adjusted	0.503	0.568	0.501	0.562
RMSE	1.290	1.200	1.240	1.170
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	553	504	298	291
Starter-pack*t1 - Starter-pack*t2 =0 ¥	0.426	0.470	0.485	0.593

* p<0.10, ** p<0.05, *** p<0.01

¥ values for Wald test are the p-value

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Appendix 3.3. Impact of starter packs on technology adoption (persistence in use of inputs)

Variables	Minimum of four technologies adopted				Total number of practices adopted				Minimum of four practices			
	Simple DID	DID with Covariates	DID Weighted	DID Weighted	Simple DID	DID with Covariates	DID Weighted	DID Weighted	Simple DID	DID with Covariates	DID Weighted	DID Weighted
Dummy period 1	0.558***	0.606***	0.555***	0.590***	3.125***	3.306***	3.438***	3.581***	0.542***	0.594***	0.546***	0.579***
	(0.047)	(0.052)	(0.078)	(0.070)	(0.198)	(0.190)	(0.257)	(0.225)	(0.05)	(0.05)	(0.08)	(0.07)
Dummy period 2	0.806***	0.829***	0.821***	0.839***	4.166***	4.397***	4.429***	4.679***	0.789***	0.810***	0.820***	0.837***
	(0.040)	(0.041)	(0.053)	(0.057)	(0.224)	(0.214)	(0.308)	(0.281)	(0.04)	(0.04)	(0.05)	(0.06)
Interaction of starter-pack and period 1	0.032	-0.003	0.039	0.000	0.224*	0.156	0.117	0.067	0.031	-0.008	0.053	0.014
	(0.060)	(0.064)	(0.094)	(0.086)	(0.135)	(0.141)	(0.182)	(0.176)	(0.06)	(0.06)	(0.09)	(0.09)
Interaction of starter-pack and period 2	0.007	0.001	-0.019	-0.015	-0.110	-0.118	-0.263	-0.266	0.021	0.016	-0.010	-0.007
	(0.041)	(0.042)	(0.058)	(0.059)	(0.141)	(0.134)	(0.201)	(0.191)	(0.04)	(0.04)	(0.06)	(0.06)
Lag of technology adoption index	-0.916***	-0.941***	-0.912***	-0.925***	-0.840***	-0.877***	-0.890***	-0.929***	-0.911***	-0.935***	-0.922***	-0.934***
	(0.037)	(0.039)	(0.049)	(0.053)	(0.049)	(0.047)	(0.061)	(0.057)	(0.04)	(0.04)	(0.05)	(0.05)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R2_adj	0.584	0.620	0.584	0.626	0.511	0.578	0.540	0.598	0.576	0.611	0.585	0.626
RMSE	0.420	0.410	0.420	0.410	1.160	1.070	1.070	1.010	0.420	0.410	0.420	0.410
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	553	504	298	291	553	504	298	291	553	504	298	291
Starter-pack*t1 - Starter-pack*t2 =0 ¥	0.727	0.960	0.598	0.886	0.085	0.174	0.126	0.175	0.882	0.754	0.564	0.842

* p<0.10, ** p<0.05, *** p<0.01
¥ values for Wald test are the p-value

Variables	Total number of inputs adopted				Minimum of two inputs adopted				Adoption of improved seeds			
	Simple DID	DID with Covariates	DID Weighted	DID Weighted	Simple DID	DID with Covariates	DID Weighted	DID Weighted	Simple DID	DID with Covariates	DID Weighted	DID Weighted
Dummy period 1	0.045**	0.036	0.041*	0.041	0.046**	0.038*	0.042*	0.038	0.664***	0.673***	0.685***	0.706***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)
Dummy period 2	0.195***	0.200***	0.189***	0.180**	0.168***	0.166***	0.154***	0.156***	0.746***	0.798***	0.758***	0.808***
	(0.04)	(0.04)	(0.07)	(0.07)	(0.03)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)	(0.06)
Interaction of starter-pack and period 1	-0.008	-0.003	-0.016	-0.035	-0.008	-0.003	-0.017	-0.021	0.033	0.032	0.076	0.046
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)	(0.06)	(0.08)	(0.08)
Interaction of starter-pack and period 2	0.165**	0.114*	0.169	0.144	0.098**	0.071	0.086	0.064	-0.019	-0.050	-0.080	-0.107
	(0.07)	(0.07)	(0.12)	(0.11)	(0.05)	(0.05)	(0.07)	(0.07)	(0.05)	(0.05)	(0.09)	(0.08)
Lag of technology adoption index	-0.992***	-1.077***	-0.940***	-1.096***	-1.021***	-1.061***	-0.976***	-1.045***	-1.000***	-1.026***	-1.028***	-1.038***
	(0.12)	(0.09)	(0.17)	(0.14)	(0.08)	(0.07)	(0.11)	(0.11)	(0.04)	(0.04)	(0.05)	(0.05)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R2_adj	0.240	0.289	0.191	0.253	0.307	0.328	0.268	0.299	0.552	0.590	0.563	0.600
RMSE	0.440	0.440	0.470	0.450	0.330	0.330	0.310	0.310	0.450	0.440	0.460	0.440
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	551	504	298	291	551	504	298	291	548	501	297	290
Starter-pack*t1 - Starter-pack*t2 =0 ¥	0.0172	0.1134	0.122	0.142	0.0498	0.1992	0.1976	0.261	0.5049	0.3016	0.221	0.178

* p<0.10, ** p<0.05, *** p<0.01
¥ values for Wald test are the p-value

Appendix 3.4. Impact of starter packs on total number of technology adopted (persistence on use of inputs)

Variables	Simple FE	FE with Covariates	FE Weighted	FE Weighted and with Covariates
Dummy period 1	0.208*	0.208	0.664***	0.586***
	(0.125)	(0.134)	(0.207)	(0.199)
Dummy period 2	1.452***	1.518***	1.875***	1.839***
	(0.145)	(0.164)	(0.265)	(0.277)
Interaction of starter-pack and period 1	0.307*	0.238	-0.029	0.020
	(0.185)	(0.187)	(0.259)	(0.247)
Interaction of starter-pack and period 2	0.220	-0.030	-0.232	-0.225
	(0.225)	(0.223)	(0.351)	(0.339)
Household size		0.036		0.013
		(0.030)		(0.041)
Access to farmland		0.367		1.166
		(0.531)		(0.927)
Area cultivated		0.000		0.000
		(0.000)		(0.000)
Market products individually		-0.005		0.052
		(0.115)		(0.135)
Access to financial services		0.135		0.189
		(0.102)		(0.136)
Farmer produces maize		0.198*		0.073
		(0.116)		(0.156)
Farmer produces beans		0.131		0.108
		(0.141)		(0.229)
Farmer produces peanuts		0.278**		0.387**
		(0.129)		(0.181)
Farmer produces rice		0.749*		0.797
		(0.421)		(0.578)
Constant	3.401***	2.565***	3.241***	1.712*
	(0.060)	(0.563)	(0.091)	(0.911)
R2_overall	0.217	0.317	0.251	0.315
RMSE	0.920	0.840	0.940	0.890
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	930	876	449	442
Starter-pack*t1 - Starter-pack*t2 =0 ¥	0.657	0.178	0.454	0.399

* p<0.10, ** p<0.05, *** p<0.01

¥ values for Wald test are the p-value

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Appendix 3.5. Impact of starter packs on technology adoption (persistence on use of inputs) – FE

Variables	Minimum of four technologies adopted				Total number of practices adopted				Minimum of four practices			
	Simple FE	FE with Covariates	FE Weighted	FE Weighted	Simple FE	FE with Covariates	FE Weighted	FE Weighted	Simple FE	FE with Covariates	FE Weighted	FE Weighted
Dummy period 1	0.119**	0.143**	0.236**	0.226**	0.199	0.202	0.651***	0.574***	0.119**	0.141**	0.235**	0.222**
	(0.057)	(0.063)	(0.096)	(0.092)	(0.122)	(0.132)	(0.206)	(0.192)	(0.06)	(0.06)	(0.10)	(0.09)
Dummy period 2	0.383***	0.409***	0.523***	0.521***	1.292***	1.359***	1.713***	1.689***	0.383***	0.408***	0.527***	0.522***
	(0.056)	(0.064)	(0.083)	(0.080)	(0.139)	(0.159)	(0.246)	(0.240)	(0.06)	(0.06)	(0.08)	(0.08)
Interaction of starter-pack and period 1	0.062	0.027	-0.049	-0.039	0.302*	0.243	-0.039	0.030	0.048	0.014	-0.049	-0.037
	(0.080)	(0.084)	(0.122)	(0.118)	(0.179)	(0.182)	(0.256)	(0.236)	(0.08)	(0.08)	(0.12)	(0.12)
Interaction of starter-pack and period 2	0.036	-0.054	-0.114	-0.122	0.029	-0.143	-0.425	-0.361	0.032	-0.057	-0.118	-0.123
	(0.076)	(0.081)	(0.114)	(0.102)	(0.201)	(0.204)	(0.303)	(0.285)	(0.08)	(0.08)	(0.11)	(0.10)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant	0.450***	0.195	0.404***	-0.221	3.374***	2.502***	3.227***	1.791**	0.445***	0.191	0.398***	-0.248
	(0.023)	(0.186)	(0.035)	(0.235)	(0.056)	(0.498)	(0.082)	(0.829)	(0.02)	(0.19)	(0.04)	(0.23)
R2_overall	0.120	0.176	0.128	0.158	0.181	0.287	0.218	0.280	0.119	0.178	0.125	0.159
RMSE	0.34	0.32	0.35	0.34	0.85	0.77	0.84	0.80	0.34	0.32	0.36	0.34
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	930.0	876.0	449.0	442.0	930.0	876.0	449.0	442.0	930.0	876.0	449.0	442.0
Starter-pack*t1 - Starter-pack*t2 =0 ¥	0.6923	0.2413	0.536	0.4622	0.1177	0.0303	0.106	0.118	0.7991	0.2997	0.507	0.447

* p<0.10, ** p<0.05, *** p<0.01

¥ values for Wald test are the p-value

Variables	Total number of inputs adopted				Minimum of two inputs adopted				Adoption of improved seeds			
	Simple FE	FE with Covariates	FE Weighted	FE Weighted	Simple FE	FE with Covariates	FE Weighted	FE Weighted	Simple FE	FE with Covariates	FE Weighted	FE Weighted
Dummy period 1	0.010	0.005	0.014	0.012	0.013	0.010	0.014	0.015	0.202***	0.209***	0.260***	0.193**
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)	(0.06)	(0.06)	(0.09)	(0.10)
Dummy period 2	0.162***	0.159***	0.162**	0.150*	0.136***	0.132***	0.126**	0.134**	0.303***	0.339***	0.325***	0.285**
	(0.04)	(0.05)	(0.07)	(0.08)	(0.03)	(0.04)	(0.06)	(0.07)	(0.06)	(0.07)	(0.12)	(0.12)
Interaction of starter-pack and period 1	0.006	-0.005	0.010	-0.010	0.000	-0.001	0.010	0.004	0.014	-0.024	-0.014	0.033
	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)	(0.08)	(0.09)	(0.12)	(0.13)
Interaction of starter-pack and period 2	0.198***	0.113	0.193*	0.136	0.121**	0.078	0.112	0.073	-0.056	-0.128	-0.155	-0.132
	(0.07)	(0.07)	(0.12)	(0.11)	(0.05)	(0.05)	(0.08)	(0.08)	(0.08)	(0.09)	(0.15)	(0.15)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant	0.026*	0.062	0.014	-0.078	0.026**	0.111	0.014	-0.035	0.458***	0.154	0.457***	-0.034
	(0.01)	(0.14)	(0.02)	(0.15)	(0.01)	(0.12)	(0.01)	(0.13)	(0.03)	(0.18)	(0.04)	(0.24)
R2_overall	0.116	0.153	0.095	0.117	0.104	0.122	0.092	0.096	0.065	0.103	0.048	0.079
RMSE	0.280	0.270	0.310	0.300	0.210	0.210	0.210	0.210	0.360	0.350	0.390	0.380
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	926	876	449	442	926	876	449	442	923	873	448	441
Starter-pack*t1 - Starter-pack*t2 =0 ¥	0.007	0.095	0.120	0.211	0.024	0.1541	0.198	0.386	0.330	0.162	0.269	0.182

* p<0.10, ** p<0.05, *** p<0.01

¥ values for Wald test are the p-value

3

Appendix 3.6. Impact of starter packs on technology adoption (persistence in use of inputs) – FE/RE

Variables	Minimum of four technologies adopted				Total number of practices adopted				Minimum of four practices			
	Simple FE	FE with Covariates	FE Weighted	FE Weighted	Simple FE	FE with Covariates	FE Weighted	FE Weighted	Simple FE	FE with Covariates	FE Weighted	FE Weighted
Dummy period 1	0.119**	0.143**	0.153***	0.139***	0.199	0.202	0.297***	0.232**	0.119**	0.141**	0.146***	0.128***
	(0.057)	(0.063)	(0.048)	(0.048)	(0.122)	(0.132)	(0.102)	(0.100)	(0.06)	(0.06)	(0.05)	(0.05)
Dummy period 2	0.383***	0.409***	0.402***	0.391***	1.292***	1.359***	1.357***	1.360***	0.383***	0.408***	0.395***	0.377***
	(0.056)	(0.064)	(0.043)	(0.044)	(0.139)	(0.159)	(0.123)	(0.119)	(0.06)	(0.06)	(0.04)	(0.04)
Interaction of starter-pack and period 1	0.062	0.027	0.034	0.039	0.302*	0.243	0.215*	0.231**	0.048	0.014	0.034	0.041
	(0.080)	(0.084)	(0.055)	(0.053)	(0.179)	(0.182)	(0.122)	(0.114)	(0.08)	(0.08)	(0.06)	(0.05)
Interaction of starter-pack and period 2	0.036	-0.054	0.016	-0.003	0.029	-0.143	-0.049	-0.065	0.032	-0.057	0.029	0.011
	(0.076)	(0.081)	(0.042)	(0.042)	(0.201)	(0.204)	(0.148)	(0.135)	(0.08)	(0.08)	(0.04)	(0.04)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant	0.450***	0.195	0.441***	0.160	3.374***	2.502***	3.344***	2.263***	0.445***	0.191	0.434***	0.153
	(0.023)	(0.186)	(0.028)	(0.133)	(0.056)	(0.498)	(0.065)	(0.380)	(0.02)	(0.19)	(0.03)	(0.13)
R2_overall	0.120	0.176	0.120	0.190	0.181	0.287	0.183	0.299	0.119	0.178	0.120	0.192
RMSE	0.340	0.320	0.430	0.430	0.850	0.770	1.080	1.030	0.340	0.320	0.430	0.430
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	930.0	876.0	930.0	876.0	930.0	876.0	930.0	876.0	930.0	876.0	930.0	876.0
Starter-pack*t1 - Starter-pack*t2 =0 ¥	0.692	0.241	0.788	0.527	0.118	0.030	0.131	0.083	0.799	0.300	0.933	0.646

* p<0.10, ** p<0.05, *** p<0.01

¥ values for Wald test are the p-value

Variables	Minimum of four technologies adopted				Total number of practices adopted				Minimum of four practices			
	Simple FE	FE with Covariates	FE Weighted	FE Weighted	Simple FE	FE with Covariates	FE Weighted	FE Weighted	Simple FE	FE with Covariates	FE Weighted	FE Weighted
Dummy period 1	0.010	0.005	0.032	0.036*	0.013	0.010	0.031	0.032	0.202***	0.209***	0.210***	0.199***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.06)	(0.06)	(0.05)	(0.05)
Dummy period 2	0.162***	0.159***	0.171***	0.189***	0.136***	0.132***	0.142***	0.150***	0.303***	0.339***	0.296***	0.321***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.06)	(0.07)	(0.05)	(0.05)
Interaction of starter-pack and period 1	0.006	-0.005	-0.018	-0.032	0.000	-0.001	-0.018	-0.022	0.014	-0.024	0.029	0.018
	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.08)	(0.09)	(0.05)	(0.05)
Interaction of starter-pack and period 2	0.198***	0.113	0.189***	0.112*	0.121**	0.078	0.112**	0.073	-0.056	-0.128	-0.007	-0.053
	(0.07)	(0.07)	(0.07)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.09)	(0.05)	(0.05)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant	0.026*	0.062	0.022***	0.072	0.026**	0.111	0.022***	0.094	0.458***	0.154	0.447***	0.118
	(0.01)	(0.14)	(0.01)	(0.11)	(0.01)	(0.12)	(0.01)	(0.11)	(0.03)	(0.18)	(0.03)	(0.14)
R2_overall	0.116	0.153	0.116	0.164	0.104	0.122	0.105	0.130	0.065	0.103	0.066	0.109
RMSE	0.280	0.270	0.360	0.360	0.210	0.210	0.270	0.270	0.360	0.350	0.470	0.460
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	926	876	926	876	926	876	926	876	923	873	923	873
Starter-pack*t1 - Starter-pack*t2 =0 ¥	0.007	0.095	0.0041	0.043	0.024	0.154	0.015	0.087	0.330	0.162	0.620	0.320

* p<0.10, ** p<0.05, *** p<0.01

¥ values for Wald test are the p-value

4

Increasing the cost-effectiveness of farmer field schools through formalized farmer-to-farmer training

ABSTRACT

Sub-Saharan Africa (SSA) has experienced decades of underinvestment in the generation of agricultural technologies. However, even available technologies have failed to reach smallholder farmers, also because of dysfunctional agricultural extension systems. The Farmer Field School (FFS) approach has become widespread as a decentralized alternative solution and has gained ground in many African countries lately. A major drawback of FFSs has been its cost. We study the effectiveness of knowledge transmission from farmers trained in FFS through farmer-to-farmer training (F2F), which could potentially result in lower costs per farmer trained and higher returns in terms of technology adoption. We assess the differential impacts of both FFS and F2F training on the levels of adoption of promoted technologies. Results consistently suggest significant impacts of both FFS and F2F training on smallholder farmers' adoption of improved technologies. While FFS training is more effective than F2F in the first period, we found that the magnitude of the FFS and F2F treatment effects in the second period are not statistically different, so dissemination of technologies promoted in FFS groups can well be formalized through farmer-to-farmer training. This has proven to substantially alleviate a major constraint to the large-scale introduction of FFS as a training method, the high costs per farmer trained.

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4.1. Introduction

Despite recent positive trends in some countries, the agricultural sector in Sub-Saharan Africa (SSA) has faced its fair share of challenges over the years. Yield growth in SSA has lagged behind other rain fed regions for nearly all staple and export crops. While advances in crop management have interacted positively with genetic improvement to raise potential yields and close yield gaps in Latin America and Asia, progress in SSA has been constrained by low soil fertility, weeds, limited labor, and the low use of hybrids and improved varieties (Fischer, Byerlee *et al.*, 2014). Cereal yields in SSA grew by 60 percent between 1961-2006, which is much lower than the 160 percent growth experienced in Latin America and the 230 percent in east and southeast Asia during the same period (Byerlee, 2011). The average maize yield between 2008-2010 was three times lower in SSA than the world's average (Fischer, Byerlee *et al.*, 2014), and the adoption of new maize varieties was only 17 percent of the total area harvested in SSA compared to (the) 90 percent in Asia and the Pacific (Gollin, Morris *et al.*, 2005).

The agricultural sector in SSA has experienced decades of underinvestment in the generation of agricultural technologies (Beintema & Stads, 2011). However, even available technologies have failed to reach small scale farmers because, amongst other issues, training and visit (T&V) agricultural extension systems established in many countries for the past 30 years have often been dysfunctional (Davis, 2008). The T&V model focused primarily on technology diffusion, was expensive to implement, and inept at covering extensive areas and reaching farmers in dispersed territories (Godtland, Sadoulet *et al.*, 2004). T&V-type extension models were also unable to address farmers' widely diverse needs which could seldom be fulfilled through the diffusion of a pre-defined inflexible package of technologies (Feder, Willett *et al.*, 2001; Picciotto & Anderson, 1997). More recently, in response to threats caused by the overuse of toxic agricultural pesticides and the need for a decentralized and more holistic model, the Farmer Field School (FFS) approach became prominent as an alternative, and has gained ground in many countries (Davis, 2008).

FFS is an intensive participatory farmer-centered approach which aims to build farmers' expertise to sustainably manage the ecology of their fields, resulting in fewer pest problems, higher yields and profits, and fewer health and environmental risks that affect the population (Dilts, 2001). FFS provides farmers with a more holistic view of what constitutes an agro-ecosystem and how farmers' intervention could either enhance or disrupt it (Braun & Duveskog, 2011).

Ever since 1989 when the approach was first implemented in Indonesia, FFSs have spread rapidly into many countries and have been adapted for a wide range of crops and to address different land productivity, environmental, livestock, social, and health issues. Between 1990 and 1999 over two million rice farmers in Asia participated in rice integrated pest management FFSs. During this period, farmers, agricultural extensionists, plant protection field workers, and NGOs learned how to facilitate FFSs and conducted over 75,000 FFSs (Pontius, Dilts *et al.*, 2002). Up to now, at least 10 million farmers in more than 90 countries have attended FFSs (Waddington, Snilstveit *et al.*, 2014). SSA is one of the regions where the FFS rapidly expanded, especially since the early 2000s. As of 2005 more than 27 countries in SSA had implemented FFS initiatives (Braun, Jiggins *et al.*, 2006). This rapid expansion, however, does not necessarily respond to empirical evidence on the impacts of FFSs. In fact, the FFS approach has collected a significant number of critics regarding its performance and the capacity to promote knowledge dissemination beyond graduates of FFS.

Some of the most prominent studies on the impact of FFS come to contrasting conclusions. On one hand, Van den Berg and Jiggins (2007) argues that FFSs have remarkable, widespread and lasting developmental impacts based on a review of 25 different FFS impact studies. Conversely, Feder, Murgai *et al.* (2004b) suggests that there is no significant influence of FFS on the performance of graduates and especially their neighbors. Although this divergence has dominated the policy debate, there are prevailing indications that FFSs yield positive results in a variety of outcomes. Davis, Nkonya *et al.* (2012) found positive impacts of FFSs on production and income of small-scale farmers in East Africa. While Ameua, Hirea *et al.* (2013) concluded that FFSs were effective at empowering farmers with knowledge and skills, making them experts in their fields, honing their ability to make critical decisions, and developing their critical thinking and problem solving skills in many SSA countries such as Angola, DRC, Kenya, Sierra Leone, and Uganda. More generally, a systematic review of over a hundred studies suggest that FFSs improve knowledge acquisition and the adoption of practices, as well as final outcomes related to agricultural production and incomes (Waddington, Snilstveit *et al.*, 2014). The same review, however, concludes that there are few rigorous studies and none with a low risk of bias.

A major drawback of the FFS approach is the cost. The season-long intensive training activities require high investments in salaries, transportation, inputs and training materials, and one agent cannot properly facilitate more than 10 groups (250-300 farmers) at the same time. Therefore the viability of FFS programs and the cost per beneficiary largely depend on the effectiveness of knowledge transmission from farmers trained in FFS to other farmers in their family nucleus or in the neighborhood (Feder, Murgai *et al.*, 2004a), the prevalence of which has been largely criticized (Quizon, Feder *et al.*, 2001; Rola, Jamias *et al.*, 2002).

The diffusion of knowledge from FFS participants to non-participants is limited (Davis, Nkonya et al., 2012; Quizon, Feder *et al.*, 2001; Rola, Jamias *et al.*, 2002; Thiele, Nelson *et al.*), and the reason for the lack of diffusion lies mostly in the nature of FFSs where learning is about developing problem solving and innovation skills, not simple technological messages that can easily be passed on to others (Braun & Duveskog, 2011). Rola, Jamias *et al.* (2002) argues that the content of FFS trainings may be too complex to transmit in casual, unstructured communications. As stated by Dilts (2001), "farmers do not master a specific set of contents or messages, rather, they master a process of learning that can be applied continuously to a dynamic situation: the ecology of their field".

Given the skills-based nature of the technologies promoted in FFSs and the holistic solutions required to solve complex farming problems, intentional support and attempts to institutionalize the FFS approach to encourage graduates to train other farmers are likely needed for any diffusion to neighbors. Pontius, Dilts *et al.* (2002) indicated that formal approaches involving FFS alumni are deemed necessary to disseminate knowledge more efficiently; "without post-FFS educational opportunities, there will be no community movement". However, the evidence does not suggest these approaches have been effective so far (Waddington, Snilstveit *et al.*, 2014).

In JENGA II, dissemination of technologies promoted in FFSs was institutionalized through formalized farmer-to-farmer (F2F) training, thus potentially resulting in lower cost per farmer trained and higher returns to investment in terms of technology adoption and production outcomes. We study the effectiveness of these interdependent and hopefully complementary approaches, in by assessing the differential impacts of FFS and F2F training on small scale farmers' adoption of agricultural technologies. We are particularly interested in understanding the effectiveness of knowledge transmission from FFS farmers to other neighboring farmers, through the promotion of farmer-to-farmer training. Given the widespread lack of access to extension and low adoption of technologies/practices in the study area, we assume that the technical information disseminated by JENGA II is useful for all farmers in our sample.

We use a pseudo-experimental design, and apply a series of measures to address potential sources of bias due to non-random placement of training activities, as well as farmer's self-preferences towards participation. We make use of the difference-in-differences (DID) approach combined with propensity score weighting to also deal with selection issues.

The contribution to the literature is two-fold. First, we contribute to the limited literature that robustly assesses the impact of FFS using micro-data. Despite the popularity of FFSs, few peer-reviewed studies have been able to use credible data to study the impact of FFS on adoption and agricultural performance. Second, we study the effect of a novel approach to formalize dissemination from the lessons learned from FFS participants to their peers, which could potentially alleviate a major constraint to the large-scale introduction of FFS as a training method: the high cost per farmer trained. While several authors have highlighted the importance of promoting knowledge dissemination from FFS graduates to neighboring farmers (Pontius, Dilts *et al.*, 2002), according to Waddington, Snilstveit *et al.* (2014) very few studies have studied effective strategies to foster such transference of knowledge.

4.2. Research context

JENGA II's FFS approach follows the concept of early promoters of the FFS, which envisioned it as a farmer-centered educational tool used to empower farmers with knowledge about agro-ecology, critical thinking, and decision making skills. However, given the low adoption levels of improved agricultural technologies which in the target area the project promoted crop-specific packages of technologies including improved crop seeds, row planting, mulching, weeding, organic pesticides, and fertilizer application. The project uses a two-year training cycle, where the first year is key to raising farmers' awareness of holistic agro-ecology concepts and acquaint them with promoted technologies, and the second year is a crucial stage of consolidation as farmers start to change their behaviours and adopt sustainable practices and technologies. Under this framework, the levels of technology adoption in period 2 are expected to be much higher than that in period 1, when farmers are still experimenting and ill-prepared to make a favourable decision towards adoption.

In an attempt to expand project outreach, reinforce knowledge dissemination, and potentially reduce cost per beneficiary, the project promotes the dissemination of best practices taught in FFSs through farmer-to-farmer training. In other words, farmers that are systematically trained by project field agents in the FFS groups become F2F trainers and are expected to train three other farmers in exactly the same topics that they were trained in the FFS group. Clearly, farmers need incentives to spend precious time training others, therefore the project FAs invested time to educate farmers about the benefits of training their peers –e.g. opportunity for collective actions such as joint marketing and purchasing of inputs in bulk and easier control of crop diseases. F2F training efforts were monitored but not formally incentivized. For more details about the JENGA II approach of FFSs and F2F training, please refer to *Chapter 2*.

4.3. Methodology

4.3.1 Our pseudo-experiment

This paper studies three different groups, including two treatment groups – farmers trained through FFS and farmers trained through F2F– and one control group comprised of farmers with similar characteristics that are not recipients of any project intervention. The research scope is restricted to villages with no other JENGA II or other agricultural programs implemented in the area, to avoid contamination and ensure treatment-effects can be properly isolated.

Farmers are likely to self-select into FFS and F2F groups based on their pre-treatment characteristics such as age, education, land tenure, entrepreneurial skills, motivation, wealth, and previous experiences. For instance, contrary to F2F, the FFS training sessions have theory slots presented by the project technician, so less educated farmers may feel less motivated to participate in "formal" FFS training and possibly prefer to learn in a less structured way than farmers that received the training in the FFS. Similarly, less motivated farmers may not see the benefit of spending several hours in trainings and may decide to participate in F2F training which receives less monitoring from the project extensionists, or simply not participate in the trainings at all. Therefore, comparison of technology adoption patters among FFS, F2F and control farmers is not straightforward. This makes it difficult to isolate the causal effects of the treatments (FFS and F2F) from other determinants of technology adoption. This paper uses quasi-experimental methods to mitigate the effect of selection-bias and other inference issues (Alene & Manyong, 2006).

4.3.2. Technology adoption empirical model

Difference-In-Differences (DID) forms the basis of our approach. DID methods have become widespread in impact evaluation of policies and programs (Angrist & Pischke, 2008; Bertrand, Duflo *et al.*, 2002; Imbens & Wooldridge, 2009; Meyer, Viscusi *et al.*, 1995). In their simplest form, DID models observe outcomes for two comparison groups at two different moments in time: baseline, and followup. No units are exposed to the treatment in the baseline and only units in one of the two groups are exposed to the treatment afterwards. Subtracting the gain over time of the non-exposed group from the gain over-time of the treatment group, yields a double-difference estimator that removes two sets of biases:

1) biases due to permanent differences between treatment and control group

2) biases due to common time trends unrelated to the treatment (Imbens & Wooldridge, 2009).

We specify our technology adoption model with time (three periods) and treatment (FFS and F2F) interactions for technology adoption TA, for household i and time t as follows:

$$TA_{it} = \alpha + \delta_t d_t + \gamma_1 FFS_i + \gamma_2 F2F_i + \lambda_t FFS_i * d_t + \varphi_t F2F_{it} * d_t + \lambda X_{it} + v_i + \varepsilon_{it}, t = 0,1,2 \quad (1)$$

where $FFS_i \in [0;1]$ and $F2F_i \in [0;1]$ represent the individuals' participation in FFS or F2F, respectively (1 indicating participation); and X_{it} reflects a matrix of individual, household and farm specific characteristics; δ_t is vector of fixed time effects $t=1,2,3$; γ_1 and γ_2 estimates the overall effect of participation in FFS_i and FFS_i on adoption; and the coefficients λ_t and φ_t represent the period-specific impacts of program participation (FFS and F2F). In year 0, the intervention has not started yet, and the effects in period 2 compared to period 0 are expected to be larger than in period 1, but not necessarily exactly twice as large. As in *Chapter 3*, v_i represents time-invariant unobserved characteristics of the individuals, their farms and households; and is an *i.i.d* error term.

Following *Chapter 3*, after we derive the model in first differences for periods [1;0] and [2;1], we come to the following overall DID model:

$$\Delta TA_{it} = \delta_1^* + \delta_2^* d_2 + \lambda_t^* FFS_t * d_t + \varphi_t^* F2F_{it} * d_t + \Delta\lambda X_{it} + \rho TA_{it-1} + \Delta\varepsilon_{it}, \ t = 1,2 \quad (2)$$

where ΔTA_{it} is now the difference of technology adoption for the individual *i* between time *t* and *t-1;* ΔX_{it} denotes the difference of the vector of characteristics specific to individuals, their farms and households, and $\Delta\varepsilon_{it}$ is the difference of the term of error, which follows a normal distribution and has a mean equal to zero. The coefficients λ_i^* and φ_t^* in *Equation 2*, estimate the treatment effect of FFS/F2F on technology adoption, and note that following *Chapter 3*, and Imbens and Wooldridge (2009), it includes the lagged effect of (TA_{it-1}) to account for potential overestimation of treatment effect due to the fact that the level of adoption in time *t* may be partially determined by the level of adoption that the farmer had in time *t-1*. The δ_1^* and δ_2^* represent the time trend effect for periods one and two.

This paper uses observational data, so an individual's likelihood to participate in a given group (FFS, F2F or control) is likely to differ from that of others. Therefore, following *Chapter 3*, we use different propensity-score based weights to level the observations for everyone according to their probability to participate. Accordingly, individuals with lower propensity scores receive higher weights to bring them to the same level as the individuals with a higher propensity to participate. Since we have two participation decisions in our model, i.e. participation in FFS and participation in F2F, we use a Multinomial Logit model to estimate the propensity scores for participation in the treatment groups (FFS or F2F) using a vector of baseline characteristics (Sloane & Morgan, 1996).

4.4. Data

4.4.1. Measuring program outcomes and technology adoption

As indicated in Section 2.1, FFS training may yield different types of impacts, ranging from intermediate outcomes such as knowledge and adoption of technologies; and final outcomes such as yields, food security, total incomes and net revenues; to secondary outcomes including health, environmental and empowerment outcomes (Waddington, Snilstveit *et al.*, 2014). While we do analyze alternative outcomes trying to explain the results and the way that farmers respond to training, this paper is bound by data availability, and we focus on studying the impact of training through both FFS and F2F modalities on small scale farmers' adoption of improved agricultural technologies.

The definition of "adopter" of a technology or group of technologies varies greatly across studies. An important factor to consider is whether adoption is considered a discrete measure to indicate status (a farmer either is, or is not, an adopter) or a continuous index to portray dynamic degrees of adoption (Doss, 2006). Authors have used different approaches to measure technology adoption. One group, normally older studies, used dichotomous indexes to define farmers as adopters if they were cultivating any improved vegetative or seed materials (Beyene, Verkuijl *et al.*, 1998; Haile, Verkuijl *et al.*, 1998; Salasya, Mwangi *et al.*), while others chose continuous measures to better describe the dynamic nature of the on-farm decision making process where farmers increasingly allocate resources to the improved technology (Degu, Mwangi *et al.*; Gemeda, 2001; Kotu, Verkuijl *et al.*). Any approach has limitations, and the main challenge is to find the index that best epitomizes the type of technology, the context, and the research questions one is trying to answer. Given the level of arbitrariness of the indicators, we use multiple indexes.

As described in Section 2, JENGA II promoted through the FFS a set of agricultural technologies, on one side, focus on improve soil fertility, including improved crop seeds, crop rotation, intercropping, mounding, mulching, organic fertilizers (composting and animal manure), organic pesticides, sprayers and weed control. On the other side, emphasis was given to row planting and the use of an efficient hoe aiming at increasing labor productivity and reducing costs. While the emphasis of this chapter is to see the impact of FFS/F2F training on groups of technologies (the different technology adoption indexes), we also explore which is specifically technologies are the ones that farmers see their economic benefit, and thus adopt them.

4.4.2. Descriptive statistics and Kernel distributions

According to the CSS1 data (pre-treatment information) the great majority of survey participants are female. However, there are significant differences between the groups: 70 percent of FFS beneficiaries are female, compared to 78 percent of F2F beneficiaries and 75 percent of the control group. More than 95 percent of households in each group have agriculture as their main livelihood. There were no significant differences in the proportions of households with access to farm land (94-98 percent). Also, land ownership rates were similar across the three comparison groups, with 37-45 percent of households in each group reporting full ownership, 51-58 percent reporting partial ownership and 4-6 percent reporting no ownership. Of those households without land ownership, 84-86 percent rented or leased land for farming. The FFS group farmed more land than F2F or controls with average baseline cultivation areas of 2,426 m^2, 1,978 m^2 and 1,765 m^2, respectively. However, the three comparison groups on average sold about the same proportion of their agricultural production at 19 percent, 18 percent and 19 percent, respectively (*Appendix 4.1*).

The baseline figures for the different technology adoption indexes can help us to understand from which point the treatment and control groups started. From a total of 11 technologies promoted by the JENGA II project, farmers participating in FFS, F2F and control group were using at baseline 3.4, 3.6, and 3.4 technologies, respectively. Weeding and hoeing are the technologies that had the highest levels of adoption before JENGA II. About 90 percent of the farmers were already using these technologies and there were no significant differences between FFS, F2F and control groups. Conversely, sprayers, organic fertilizers, and organic pesticides were virtually not used before the project intervention. Other technologies such as row planting, crop rotation, mulching and improved germplasm had important levels of use in the baseline (ranging from 14 to 41 percent) and are also the ones that experienced the highest grow after the FFS training started. All groups had in the baseline the similar levels of indexes of technology adoption, we just some small differences which are not statistically significant (*see Table 4.1*).

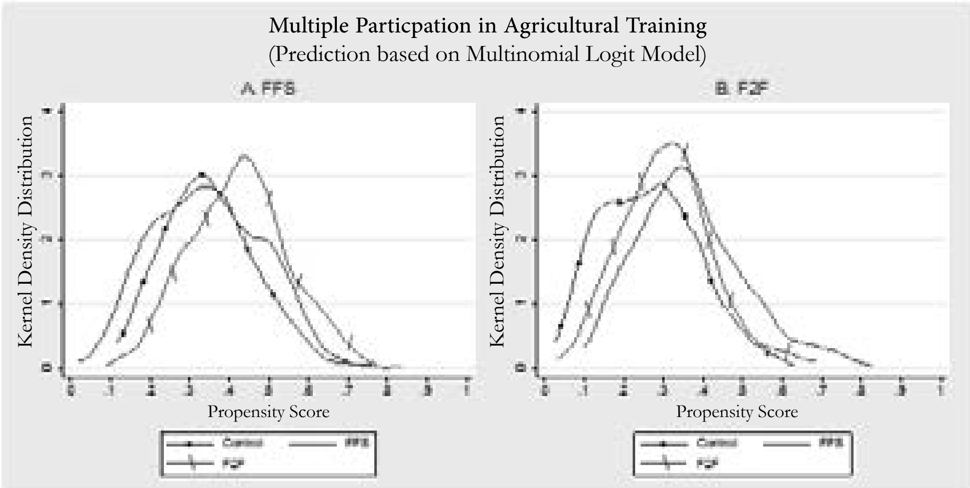
Table 4.1. Summary statistics for the main technology adoption indicators

Variables	CSS3: Feb/March 2015							
	Control	FFS	F2F	*P-Value	Control	FFS	F2F	*P-Value
of farmers using specif. technologies %								
Mulching	0.25	0.29	0.30	0.52	0.28	0.72	0.68	0.00
Crop rotation	0.14	0.18	0.16	0.74	0.21	0.59	0.55	0.00
Row planting	0.38	0.53	0.52	0.00	0.12	0.85	0.76	0.00
Weeding	0.91	0.83	0.85	0.24	0.76	0.98	0.96	0.00
Hoeing	0.95	0.93	0.96	0.85	0.92	0.98	0.97	0.55
Intercropping	0.49	0.43	0.37	0.05	0.68	0.50	0.50	0.00
Mounding	0.23	0.18	0.20	0.54	0.56	0.29	0.28	0.00
Improved germplasm	0.37	0.41	0.45	0.27	0.13	0.82	0.74	0.00
Resistant cassava cuttings	0.64	0.72	0.70	0.29	0.11	0.75	0.73	0.00
Sprayers	0.00	0.00	0.00	0.99	0.10	0.04	0.04	0.48
Organic fertilizers	0.02	0.02	0.02	0.85	0.05	0.17	0.18	0.03
Organic pesticides	0.00	0.01	0.00	0.99	0.13	0.07	0.06	0.41
Average number of observations	256	342	315		189	328	318	
Indexes of technology adoption								
Average number of technologies adopted	3.37	3.39	3.36	0.906	3.76	5.16	4.97	0.000
of farmers adopted min. four %	0.42	0.46	0.44	0.726	0.57	0.90	0.85	0.000
Average number of practices adopted	3.35	3.36	3.34	0.962	3.49	4.88	4.68	0.000
of farmers adopted min. four practices %	0.41	0.44	0.43	0.749	0.51	0.89	0.84	0.000
Average number of inputs adopted	0.02	0.03	0.02	0.959	0.28	0.28	0.29	0.901
of farmers adopted min. two inputs %	0.02	0.03	0.02	0.959	0.19	0.21	0.22	0.846
of farmers adopted improved seeds %	0.37	0.41	0.45	0.271	0.13	0.82	0.74	0.000
(Yield of cassava (dry kg/ha	2041	2233	2358	0.228	1456	2867	2386	0.000
Crop yield index	0.47	0.53	0.53	0.285	0.54	0.73	0.65	0.002
Average number of observations	286	361	353		211	346	368	

Non-parametric test for three samples: chi-squared, using Kruskal-Wallis equality-of-populations rank test

In summary, despite significant differences in some variables, in general the three groups are fairly similar in their household and farm pre-treatment characteristics. Notably there are no significant differences in the pre-project values of the impact indicators. This is in line with the distribution of the propensity scores estimated through the Multinomial Logit for participation in FFS, F2F and control (see in *Graphic 4.1*). While the distributions of these scores are not identical, meaning that some individuals are somewhat more likely to self-select into a specific treatment group based on their characteristics, the differences are not drastic. Clearly, this is a good indication that the groups were properly selected and that DID, and the use of the propensity-score based weighted models may account for remaining differences. The covariates chosen for the estimation of the propensity scores are the same as the set of controls used in the DID regressions in *Table 4.2* (see also *Appendix 4.2* for the list of covariates). The distributions of the propensity scores have a wide common support with the great majority of observations falling within [0.116 – 0.636].

Graphic 4.1. Kernel distribution of propensity scores



In CSS3, or two years after the baseline, FFS farmers had adopted significantly more agricultural technologies (5.16) compared to F2F households (4.97) and control households (3.76). Most of the adoption indexes evolved from no differences in the levels of adoption in the baseline to significant differences in CSS3. Compared to the control the FFS and F2F farmers had significantly more levels of adoption in CSS3 for all, but one index. Note that this increase in the levels of technology adoption is dominated for a few number of technologies, namely crop rotation, improved germplasm, mulching, and row planting. This may be an indication that these technologies have a higher impact on the crop performance thus farmers choose to prioritize their adoption. The summary statistics of the technology adoption indexes are presented in *Table 4.1* and for the covariates in *Appendix 4.1*.

4.5. Results and discussion

Following the econometric Equation 3 of the DID model, we regressed the seven indexes of technology adoption on the treatment variables and several covariates. To assess the robustness of our main results we employ four variations of our model using a panel with three periods: (a) Simple DID; (b) Simple DID with covariates; (c) Weighted DID; and (d) Weighted DID with covariates. We also applied the same variations for a fixed-effect (FE) technology adoption model to compare the results with the DID models. The results of these regressions for all technology adoption indexes are summarized in *Tables 4.2* and *4.3* below. In *Appendixes 4.2* through 4.7 we show the full regression results for both DID and FE specifications. The estimation of the DID model in two periods allows us to analyze farmers' dynamic adoption patterns since intervention started through the subsequent periods.

4.5.1. Treatment effect in first period

We tested the effect of FFS and F2F training on farmers' adoption of agricultural technologies in the first period. We found that FFS trainings clearly had a positive impact on farmer's adoption. An average farmer in the control group used 3.4 of the 11 promoted technologies in period 1 (see *Table 4.1* and *4.2*), while FFS farmers used on average 0.54 more technologies. This is an average difference of 16 percent in the number technologies adopted by FFS farmers compared to their counterpart in the control group. Similarly, more FFS farmers adopted a minimum number of technologies than control farmers. Fifteen percentage points more of the FFS farmers adopted a minimum of four technologies and 14 percentage points more a minimum four practices. This represents a difference of about 26 and 28 percent in the number of farmers that adopted a minimum of 4 technologies and a minimum of four practices, respectively. The results are very robust across different DID and FE specifications (*Table 4.2 and Appendixes 4.2 – 4.7*).

We found comparable results for the effect of F2F trainings on farmer's adoption of farming technologies in period one. However, this is only true in some regressions as we could not find robust significant results across specifications and technology adoption indexes. In the best case, F2F farmers used on average 0.3 more technologies than the control group. This represents a level of adoption that is 9 percent higher respective to that of the control group. The F2F groups had a difference of 9 percentage points in the minimum of four technologies and minimum of four practices indicators. The results of

4

F2F training on adoption of improved seeds are very robust and the magnitude of effect is similar to that of FFS farmers. Adoption rates of the F2F group were 14 percentage points higher than the control group while the FFS farmers were about 19 percentage points higher for the same indicator. Although these are good indications of treatment impact, farmers that received F2F training took longer to properly engage in program activities due to the lack of pro-activeness from FFS farmers. This was confirmed in several field interviews we held with individuals and groups of farmers at the end of the first period. In these interviews, we could see that the project was still struggling to put a system in place to track the activities of F2F training and that FFS took some time to understand the real contribution of training to their business, and that also influenced their level of engagement with their F2F farmers. Farmers didn't appear as eager to respond to questions regarding the training they had received.

Overall, we find substantial impact from both FFS and F2F on farmer's adoption of agricultural practices, but the impact on input adoption is not evident. While we do find a very strong effect on the adoption of seeds, no effect was found on the indexes of input adoption. It appears that a larger number of seed adopters resisted adopting the other input technologies compared to the non-seed adopters, and this offset the impact of seeds in the overall input indexes. Given the limited capacity to access capital by farmers in our sample, it seems logical that they would prioritize investments in inputs that they perceive to bring the highest return on investment, and our results seem to indicate that farmers prioritized seeds.

Table 4.2. Treatment effect in period one

Dependent Variable	Simple DID	DID with Covariates	DID weighted	DID weighted and with Covariates
Index of technology adoption (pracitces+inputs)				
Farmer field school	0.569***	0.531***	0.539***	0.508***
	(0.106)	(0.107)	(0.129)	(0.128)
Farmer-to-Farmer	0.264**	0.306***	0.194	0.211
	(0.110)	(0.113)	(0.142)	(0.141)
Minimum of four technologies adopted				
Farmer field school	0.162***	0.149***	0.145***	.134***
	(0.044)	(0.044)	(0.050)	(0.050)
Farmer-to-Farmer	0.067	0.091*	0.035	0.047
	(0.046)	(0.047)	(0.056)	(0.055)
Total number of practices adopted				
Farmer field school	0.543***	0.515***	0.541***	0.517***
	(0.105)	(0.106)	(0.124)	(0.123)
Farmer-to-Farmer	0.253**	0.312***	0.209	0.234*
	(0.109)	(0.111)	(0.137)	(0.135)
Minimum of four practices				
Farmer field school	0.152***	0.140***	0.145***	0.134***
	(0.040)	(0.040)	(0.050)	(0.050)
Farmer-to-Farmer	0.062	0.089*	0.043	0.055
	(0.050)	(0.050)	(0.060)	(0.060)
Total number of inputs adopted				
Farmer field school	0.026	0.017	-0.005	-0.012
	(0.020)	(0.020)	(0.030)	(0.030)
Farmer-to-Farmer	0.011	-0.003	-0.017	-0.025
	(0.020)	(0.020)	(0.030)	(0.030)
Minimum of two inputs adopted				
Farmer field school	0.018	0.012	-0.006	-0.010
	(0.020)	(0.020)	(0.030)	(0.030)
Farmer-to-Farmer	0.016	0.009	-0.007	-0.011
	(0.020)	(0.020)	(0.030)	(0.030)
Adoption of improved seeds				
Farmer field school	0.185***	0.182***	0.216***	0.213***
	(0.040)	(0.040)	(0.050)	(0.050)
Farmer-to-Farmer	0.132***	0.141***	0.140**	0.144***
	(0.050)	(0.050)	(0.060)	(0.060)

* p<0.10, ** p<0.05, *** p<0.01
Values in parenthesis are standard errors adjusted for clusters in household id

We conducted a series of Wald Tests, and the results show that in most regressions the effect size of FFS and F2F trainings are different in the first period. While we see less consistent results for F2F than FFS, both FFS and F2F seem to positively impact farmers' adoption of project promoted technologies, but the differences in the magnitude of the impact are significant.

In summary, we find indications of positive treatment effect in period one, expectedly however the farmers' exposure to FFS and F2F training is yet to yield the levels of impact on adoption of agricultural technologies, especially for F2F training. Additionally, whereas we find substantial impacts of both FFS and F2F on farmer's adoption of agricultural practices, the impact on input adoption is less evident.

4.5.2. Treatment effect in second period

Examining the progression of impact across the three periods gives us a much better understanding of the relationship between training and technology adoption in the context of this study. Notably, in the second period the impact of both FFS and F2F training accentuated from that of levels registered in the first period. FFS farmers used on average 1.3 more technologies than the control group over the two periods (see *Table 4.3*). This is a 40 percent increase in the number of technologies adopted by FFS farmers over the two periods, in contrast with the 15 percent achieved in period one. For the indexes of minimum of four technologies and minimum of four practices, FFS farmers had 30 and 34 percentage point difference over control group farmers, respectively. This is a substantial increase compared to the 19 and 15 percentage point difference achieved in period one.

The level of improvement experienced by F2F farmers over the two periods is particularly interesting. While F2F farmers used on average 0.3 more technologies than the control group in the first period, this increased to 1.1 technologies in the second period. This represents a level of adoption that is nine percent higher than the control group in the first period and 30 percent higher in the second period. For the indexes of minimum of four technologies and minimum of four practices, F2F farmers had a 25 and 30 percentage point difference over the control farmers, respectively. This is a substantial increase compared to the nine-percentage point difference achieved in period one for both indicators. Whereas in the first period the predictions of F2F training impact are not conclusive, in the second period the impact is evident, and robust across specifications.

Table 4.3. Treatment effect in period two

Dependent Variable	Simple DID	DID with Covariates	DID weighted	DID weighted and with Covariates
Index of technology adoption (pracitces+inputs)				
Farmer field school	1.322***	1.301***	1.163***	1.263***
	(0.135)	(0.137)	(0.168)	(0.173)
Farmer-to-Farmer	1.182***	1.141***	1.045***	1.090***
	(0.139)	(0.140)	(0.186)	(0.186)
Minimum of four technologies adopted				
Farmer field school	0.318***	0.327***	0.275***	0.307***
	(0.041)	(0.044)	(0.049)	(0.052)
Farmer-to-Farmer	0.286***	0.281***	0.231***	0.241***
	(0.042)	(0.046)	(0.054)	(0.056)
Total number of practices adopted				
Farmer field school	1.327***	1.343***	1.182***	1.306***
	(0.115)	(0.110)	(0.147)	(0.144)
Farmer-to-Farmer	1.183***	1.179***	1.042***	1.127***
	(0.118)	(0.114)	(0.162)	(0.154)
Minimum of four practices				
Farmer field school	0.370***	0.369***	0.319***	0.343***
	(0.04)	(0.05)	(0.05)	(0.05)
Farmer-to-Farmer	0.339***	0.327***	0.273***	0.275***
	(0.04)	(0.05)	(0.05)	(0.06)
Total number of inputs adopted				
Farmer field school	0.005	-0.028	-0.011	-0.031
	(0.060)	(0.060)	(0.070)	(0.080)
Farmer-to-Farmer	0.003	-0.033	0.008	-0.034
	(0.060)	(0.060)	(0.070)	(0.080)
Minimum of two inputs adopted				
Farmer field school	0.025	0.002	0.026	0.009
	(0.040)	(0.040)	(0.040)	(0.050)
Farmer-to-Farmer	0.029	0.007	0.050	0.027
	(0.040)	(0.040)	(0.050)	(0.050)
Adoption of improved seeds				
Farmer field school	0.676***	0.714***	0.652***	0.693***
	(0.030)	(0.040)	(0.050)	(0.050)
Farmer-to-Farmer	0.592***	0.639***	0.542***	0.599***
	(0.040)	(0.040)	(0.050)	(0.050)

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Values in parenthesis are standard errors adjusted for clusters in household id

Concisely, the effects of both F2F and FFS training have increased between period one and two, and remarkably the magnitudes of the effects of the two types of training are not statistically different in the second period. That is, in the mid-term less costly Farmer-to-Framer training can yield attractive results compared to that of a more structured and easier to monitor FFS training. The literature describes mixed results on effective dissemination of knowledge from FFSs (Davis, Nkonya *et al.*, 2012; Rola, Jamias *et al.*, 2002), however few deliberate efforts were made to stimulate such dissemination. The treatment effect detected here seems to be the result of the JENGA II's institutionalization of the F2F training as a complement to its FFS strategy, suggesting that this type of improvements to the FFS can yield important results in terms of cost reduction.

While we did not analyze the impact of FFS/F2F training on each one of the individual technologies promoted, according to the data in *Table 4.1* this increase in the levels of technology adoption is largely attributed to farmers' adoption of just a few technologies. The data show that crop rotation, improved germplasm, mulching, and row planting are the technologies that experienced the largest grow. We speculate that since these technologies have a higher impact on agricultural input, they are economically attractive and thus farmers choose to prioritize their adoption.

4.5.3. Farmer-driven initiatives as mechanisms for F2F impact

As pointed out in Section 2.1, there are a wide range of studies that have found limited to no dissemination of knowledge from FFS graduates to their families and neighbors (Feder, Murgai *et al.*, 2004b; Quizon, Feder *et al.*, 2001; Rola, Jamias *et al.*, 2002). This is partly because dissemination largely depends on the nature of the messages been delivered (Feder, Murgai *et al.*, 2004b), but it also depends on the capacity and the incentives that FFS farmers have to transfer knowledge to farmers in their circle of influence, and on the incentives that these target farmers have to obtain/adopt such knowledge (FAO, 2016b). Waddington, Snilstveit *et al.* (2014) states that "FFS graduates may be limited in their ability to transmit all but the simplest of messages effectively to other farmers through informal means", and the sustainable uptake of agricultural innovations largely depends on farmers' decision-making abilities, given the level of knowledge and information available to them (Boz & Ozcatalbas, 2010; Rahman, 2003).

Through focus groups, interviews with FFS and F2F farmers, and field spot checks we have observed a surge of clever farmer-driven initiatives that FFS farmers created to attract the interest and engagement of their sponsored farmers in the training activities that they ought to conduct. The options are limited to enforce farmers that fail to train their F2F farmers. Consequently, the project mostly based its strategy on showing farmers the benefits that training others bring even to themselves, and making use of social accountability incentives, where the fact that farmers need to report in front of others what they did in the previous week may discourage them from reporting inaccuracies. These initiatives have become important mechanisms through which a greater level of knowledge dissemination to non-FFS participants can be achieved. They incentivize F2F to further engage in trainings conducted by FFS farmers, help FFS to consolidate their knowledge, but most importantly, they create social and communal dynamics which seem to make the impact of FFS training more overarching and sustainable. We highlight two of these initiatives here.

Firstly, several FFS farmers have created a system to exchange labor days with their F2F farmers. The FFS farmers invite their F2F farmers to work on their farms when they apply the techniques that they learned in the FFS training. In compensation, the FFS farmers commit the same quantity of labor to assist their F2F farmers to apply the same techniques in the F2F farmers' fields. This creates a dynamic that allows FFS farmers to consolidate their knowledge of the techniques while at the same time training the F2F farmers.

Secondly, we noticed that several FFS groups used the seeds harvested in their FFS demonstration plots to share with their F2F farmers so that they can also further engage and apply the techniques that they are trained on. These seeds are supposed to be shared between FFS group participants, but the farmers decided to use them as an incentive for their F2F farmers. While we recognize that these initiatives are not widespread, we argue that this is anecdotal evidence that the institutionalization of the F2F training component to a traditional FFS diffusion system not only improves FFS the ability to disseminate knowledge and can reduce the training cost per beneficiary, but also creates farmer-driven dynamics that increase the direct impact of training on FFS participants.

Through our interactions with farmers during qualitative assessments we have noticed other elements besides these farmer-driven initiatives that may be used to increase the impact of F2F training, including enhancing the capacity of FFS farmers to be trainers of trainers; and promoting more engagement of F2F farmers in project complementary activities such as field days, exchange visits, fairs, and even farmer business associations which have proven to open a whole new set of opportunities to farmers through increased access to information, markets and inputs.

4.6. Conclusions

This paper empirically studies the impact of FFS training on small scale farmers' adoption of agricultural technologies and assesses if the dissemination of best practices from FFS participants can be efficiently formalized through F2F training. Our findings support an important share of the literature (Davis, Nkonya *et al.*, 2012; Dilts, 2001; Van den Berg & Jiggins, 2007) which has found a significant positive impact of FFS on farmers' adoption of improved technologies. The effect of FFS training on adoption is modest in the first period, but increases in the second period as FFS farmers adopted on average 40 percentage more technologies than the control farmers. The results are similar if we consider the number of farmers that used a minimum of four technologies or a minimum of four practices. Over the two periods the number of adopters in FFS groups increased about 30-34 percentage points compared to control groups.

Equally, while we find less consistency across regressions in the first period, we do find a significant positive effect of F2F training on sponsored farmers' adoption of technologies over the two periods. Remarkably the magnitude of the effects of both FFS and F2F training are not statistically different in the second period. This seems to indicate that dissemination of technologies promoted in FFS groups can well be formalized through this kind of farmer-to-farmer training. This aligns with Pontius, Dilts *et al.* (2002) who argued that formal approaches involving FFS alumni are deemed necessary to disseminate knowledge beyond FFS participants. The literature has found mixed results on effective dissemination of knowledge from FFSs (Davis, Nkonya *et al.*, 2012; Rola, Jamias *et al.*, 2002; Waddington, Snilstveit *et al.*, 2014). However, few deliberate efforts were made to stimulate such dissemination. The treatment effect detected here seems to be the result of JENGA II's institutionalization of the F2F training as a complement to its FFS strategy.

These results indicate that F2F training have the potential to substantially alleviate a major constraint to the large-scale introduction of FFS as a training method: the high cost per farmer trained. Feder, Murgai *et al.* (2004a) therefore, suggests that the viability of FFS training largely depends on the effectiveness of knowledge transmission from FFS farmers to other farmers. According to our results, JENGA II's F2F approach seems to offer a powerful way to do so. The institutionalization of the F2F training to expand the influence of the FFS training reduced the cost per beneficiary by three quarters.

JENGA II's experience with this mixed diffusion system generated a set of best practices which will certainly help to implement measures that can further improve the performance of F2F training. Amongst others, it includes improving monitoring of F2F participant activities; enhancing the capacity of FFS farmers to be trainers of trainers; promoting stronger participation of F2F farmers in project complementary activities such as field days, exchange visits, and fairs; and promoting sharing labor schemes to incentivize the participation of farmers in F2F trainings as well as consolidating the knowledge of FFS farmers.

This study focused on FFS/F2F individual level impact, however there is a significant amount of knowledge diffusion community/aggregate impact including the empowerment of women; environment; and social cohesion and action that should be further explored in other research. These topics are especially important to be studied in the context of farmer-to-farmer knowledge dissemination, as they have the potential to create an impact beyond the initial target population, but may be more difficult to diffuse than messages about technology. All things considered, if we were to generalize the results of this paper, the role of FFS could be adjusted from a training method focused on direct training of potential adopters of farming technologies, to one whose primary purpose is to form farmers that sustainably articulate knowledge diffusion through farmer-to-farmer communications.

APPENDIXES

Appendix 4.1. Descriptive statistics of household and farm characteristics

Variables	CSS1: Feb/March 2013				CSS2: Feb/March 2014				CSS3: Feb/March 2015			
	Control	FFS	F2F	P-Value*	Control	FFS	F2F	P-Value*	Control	FFS	F2F	P-Value*
Household demographics												
Household (HH) size	6.561	6.604	5.837	0.000	6.764	6.914	6.033	0.000	7.395	7.178	6.542	0.001
% of children under 5 in the HH	0.421	0.314	0.332	0.000	0.407	0.305	0.329	0.000	0.410	0.309	0.330	0.000
% of adults working in the HH	0.832	0.856	0.828	0.532	0.827	0.852	0.826	0.571	0.831	0.852	0.823	0.534
% of HHs where farmer is women	0.388	0.291	0.348	0.096	0.368	0.304	0.365	0.305	0.373	0.298	0.382	0.149
Women's years of education	3.037	2.451	3.606	0.070	3.050	2.361	3.729	0.440	2.904	2.232	3.768	0.023
% of HHs participating in other agric. activities	0.294	0.256	0.209	0.193	0.323	0.248	0.207	0.078	0.325	0.247	0.199	0.057
% of HHs engaged in salary activities	0.068	0.075	0.069	0.984	0.058	0.079	0.075	0.905	0.061	0.078	0.079	0.936
Farm characteristics												
% of farmers with access to land	0.940	0.986	0.977	0.582	0.952	0.977	0.964	0.870	0.970	0.932	0.935	0.743
% of land owner farmers	0.533	0.627	0.614	0.094	0.522	0.577	0.579	0.422	0.787	0.670	0.684	0.061
Cultivated area (square meters)	1,764	2,425	1,978	0.001	2,026	2,690	2,174	0.000	2,934	3,315	2,915	0.142
Crop production (kg)	340	420	429	0.015	329	365	338	0.561	340	608	522	0.000
% of crop production sold	0.194	0.191	0.185	0.982	0.190	0.303	0.244	0.000	0.312	0.320	0.279	0.224
% of production stored	0.307	0.300	0.263	0.594	0.481	0.465	0.462	0.921	1.000	0.947	0.947	0.928
% of farmers selling individually	0.673	0.637	0.630	0.632	0.669	0.713	0.679	0.614	0.829	0.629	0.696	0.001
% of farmers with access to financial services	0.401	0.334	0.288	0.067	0.331	0.327	0.365	0.670	0.265	0.458	0.437	0.000

*Non-parametric test for three samples: chi-squared, using Kruskal-Wallis equality-of-populations rank test.
¥ in this case n reflects the average number of observations for all indicators

Appendix 4.2. DID impact of training on farmer adoption of technologies (practices + inputs)

Variables	Simple DID	DID with Covariates	DID Weighted	DID Weighted and with Covariates
Dummy period 1	3.279***	3.255***	3.474***	3.405***
	(0.131)	(0.131)	(0.168)	(0.165)
Dummy period 2	3.498***	3.573***	3.821***	3.796***
	(0.156)	(0.162)	(0.218)	(0.226)
Interaction of FFS and period 1	0.569***	0.531***	0.539***	0.508***
	(0.106)	(0.107)	(0.129)	(0.128)
Interaction of F2F and period 1	0.264**	0.306***	0.194	0.211
	(0.110)	(0.113)	(0.142)	(0.141)
Interaction of FFS and period 2	1.322***	1.301***	1.163***	1.263***
	(0.135)	(0.137)	(0.168)	(0.173)
Interaction of F2F and period 2	1.182***	1.141***	1.045***	1.090***
	(0.139)	(0.140)	(0.186)	(0.186)
Lag of technology adoption index	-0.918***	-0.911***	-0.952***	-0.944***
	(0.030)	(0.029)	(0.042)	(0.041)
Household size		0.001		0.010
		(0.017)		(0.020)
Access to farmland		0.457*		0.399
		(0.250)		(0.333)
Area cultivated		0.000		0.000*
		(0.000)		(0.000)
Market products individually		-0.015		-0.025
		(0.053)		(0.069)
Access to financial services		0.042		0.029
		(0.048)		(0.064)
Farmer produces maize		0.148***		0.189***
		(0.056)		(0.070)
Farmer produces beans		0.075		0.064
		(0.063)		(0.074)
Farmer produces peanuts		0.142**		0.138*
		(0.061)		(0.076)
Farmer produces rice		0.436***		0.160
		(0.152)		(0.272)
R2_adj	0.508	0.570	0.519	0.576
RMSE	1.300	1.200	1.310	1.220
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	1559	1437	1257	1194
Wald test (p-value) ¥				
FFS*period1 - FFS*period2 = 0	0.000	0.000	0.004	0.000
F2F*period1 - F2F*period2 = 0	0.000	0.000	0.000	0.000
FFS*period1 - F2F*period1 = 0	0.001	0.0018	0.003	0.008
FFS*period2 - F2F*period2 = 0	0.219	0.131	0.446	0.233

* p<0.10, ** p<0.05, *** p<0.01

Values in parenthesis are standard errors, adjusted for clusters in household id

¥ values for Wald test are the p-value

4

Appendix 4.3. Difference-in-Differences regressions using alternative technology adoption indexes

Variables	Minimum of four technologies adopted				Total number of practices adopted				Minimum of four practices			
	Simple DID	DID with Covariates	DID Weighted	DID Weighted and with	Simple DID	DID with Covariates	DID Weighted	DID Weighted and	Simple DID	DID with Covariates	DID Weighte	DID Weighted and
Dummy period 1	0.522***	0.522***	0.566***	0.551***	3.288***	3.270***	3.470***	3.421***	0.511***	0.508***	0.549***	0.531***
	(0.037)	(0.037)	(0.042)	(0.041)	(0.126)	(0.127)	(0.162)	(0.159)	(0.04)	(0.04)	(0.04)	(0.04)
Dummy period 2	0.543***	0.546***	0.602***	0.587***	3.264***	3.327***	3.593***	3.566***	0.481***	0.492***	0.553***	0.544***
	(0.039)	(0.044)	(0.048)	(0.052)	(0.138)	(0.141)	(0.202)	(0.207)	(0.04)	(0.04)	(0.05)	(0.05)
Interaction of FFS and period 1	0.162***	0.149***	0.145***	0.134***	0.543***	0.515***	0.541***	0.517***	0.152***	0.140***	0.145***	0.134***
	(0.044)	(0.044)	(0.050)	(0.050)	(0.105)	(0.106)	(0.124)	(0.123)	(0.04)	(0.04)	(0.05)	(0.05)
Interaction of F2F and period 1	0.067	0.091*	0.035	0.047	0.253**	0.312***	0.209	0.234*	0.062	0.089*	0.043	0.055
	(0.046)	(0.047)	(0.056)	(0.055)	(0.109)	(0.111)	(0.137)	(0.135)	(0.05)	(0.05)	(0.06)	(0.06)
Interaction of FFS and period 2	0.318***	0.327***	0.275***	0.307***	1.327***	1.343***	1.183***	1.306***	0.370***	0.369***	0.319***	0.343***
	(0.041)	(0.044)	(0.049)	(0.052)	(0.115)	(0.110)	(0.147)	(0.144)	(0.04)	(0.05)	(0.05)	(0.05)
Interaction of F2F and period 2	0.286***	0.281***	0.231***	0.241***	1.183***	1.179***	1.042***	1.127***	0.339***	0.327***	0.273***	0.275***
	(0.042)	(0.046)	(0.054)	(0.056)	(0.118)	(0.114)	(0.162)	(0.154)	(0.04)	(0.05)	(0.05)	(0.06)
Lag of technology adoption index	-0.947***	-0.951***	-0.977***	-0.971***	-0.929***	-0.927***	-0.967***	-0.965***	-0.944***	-0.943***	-0.974***	-0.962***
	(0.023)	(0.024)	(0.029)	(0.030)	(0.028)	(0.027)	(0.040)	(0.038)	(0.02)	(0.02)	(0.03)	(0.03)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R2_adj	0.580	0.612	0.582	0.613	0.527	0.587	0.543	0.598	0.572	0.600	0.576	0.604
RMSE	0.430	0.410	0.430	0.420	1.170	1.080	1.180	1.100	0.430	0.420	0.440	0.430
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	1,559	1,437	1,257	1,194	1,559	1,437	1,257	1,194	1,559	1,437	1,257	1,194
Wald test (p-value) ¥												
FFS*period1 - FFS*period2 = 0	0.011	0.006	0.078	0.022	0.000	0.000	0.001	0.000	0.000	0.000	0.020	0.006
F2F*period1 - F2F*period2 = 0	0.000	0.004	0.014	0.018	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.007
FFS*period1 - F2F*period1 = 0	0.017	0.153	0.022	0.063	0.002	0.030	0.004	0.001	0.025	0.219	0.035	0.093
FFS*period2 - F2F*period2 = 0	0.215	0.076	0.234	0.068	0.139	0.064	0.276	0.107	0.259	0.112	0.216	0.067

* p<0.10, ** p<0.05, *** p<0.01

Values in parenthesis are standard errors, adjusted for clusters in household id

¥ values for Wald test are the p-value

4

Appendix 4.4. Difference-in-Differences regressions using alternative technology adoption indexes

Variables	Total number of inputs adopted				Minimum of two inputs adopted				Adoption of improved seeds			
	Simple DID	DID with Covariates	DID Weighted	DID Weighted and with	Simple DID	DID with Covariates	DID Weighte	DID Weighted and with	Simple DID	DID with Covariates	DID Weighte	DID Weighted and with
Dummy period 1	0.031**	0.043***	0.056**	0.062**	0.026**	0.032***	0.047**	0.048**	0.535***	0.527***	0.542***	0.517***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Dummy period 2	0.279***	0.313***	0.280***	0.318***	0.191***	0.208***	0.184***	0.203***	0.126***	0.100***	0.196***	0.157***
	(0.05)	(0.06)	(0.06)	(0.07)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Interaction of FFS and period 1	0.026	0.017	-0.005	-0.012	0.018	0.012	-0.006	-0.010	0.185***	0.182***	0.216***	0.213***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
Interaction of F2F and period 1	0.011	-0.003	-0.017	-0.025	0.016	0.009	-0.007	-0.011	0.132***	0.141***	0.140**	0.144***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)
Interaction of FFS and period 2	0.005	-0.028	-0.011	-0.031	0.025	0.002	0.026	0.009	0.676***	0.714***	0.652***	0.693***
	(0.06)	(0.06)	(0.07)	(0.08)	(0.04)	(0.04)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)	(0.05)
Interaction of F2F and period 2	0.003	-0.033	0.008	-0.034	0.029	0.007	0.050	0.027	0.592***	0.639***	0.542***	0.599***
	(0.06)	(0.06)	(0.07)	(0.08)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
Lag of technology adoption index	-1.042***	-1.131***	-0.920***	-1.128***	-1.066***	-1.101***	-1.007***	-1.089***	-0.971***	-0.970***	-1.026***	-1.002***
	(0.07)	(0.04)	(0.14)	(0.05)	(0.04)	(0.04)	(0.07)	(0.05)	(0.02)	(0.02)	(0.03)	(0.03)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R2_adj	0.250	0.284	0.227	0.279	0.313	0.331	0.297	0.330	0.587	0.603	0.596	0.608
RMSE	0.460	0.450	0.450	0.440	0.320	0.320	0.320	0.310	0.430	0.430	0.440	0.430
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	1,555	1,437	1,254	1,194	1,555	1,437	1,254	1,194	1,545	1,430	1,245	1,188
Wald test (p-value) ¥												
FFS*period1 - FFS*period2 = 0	0.727	0.523	0.944	0.834	0.849	0.827	0.519	0.737	0.000	0.000	0.000	0.000
F2F*period1 - F2F*period2 = 0	0.887	0.668	0.738	0.922	0.764	0.960	0.294	0.535	0.000	0.000	0.000	0.000
FFS*period1 - F2F*period1 = 0	0.487	0.379	0.589	0.590	0.942	0.872	0.965	0.962	0.171	0.305	0.144	0.133
FFS*period2 - F2F*period2 = 0	0.968	0.918	0.750	0.959	0.911	0.886	0.589	0.691	0.013	0.025	0.076	0.023

* p<0.10, ** p<0.05, *** p<0.01
Values in parenthesis are standard errors, adjusted for clusters in household id
¥ values for Wald test are the p-value

4

Appendix 4.5. Fixed Effect impact of training on farmer adoption of technologies (practice + input)

Variables	Simple FE	FE with Covariates	FE Weighted	FE Weighted and with Covariates
Dummy period 1	0.174*	0.183*	0.107	0.062
	(0.105)	(0.106)	(0.143)	(0.141)
Dummy period 2	0.401***	0.478***	0.442**	0.456**
	(0.134)	(0.141)	(0.182)	(0.186)
Interaction of FFS and period 1	0.563***	0.493***	0.723***	0.667***
	(0.141)	(0.139)	(0.179)	(0.176)
Interaction of F2F and period 1	0.190	0.169	0.276	0.302
	(0.140)	(0.142)	(0.199)	(0.196)
Interaction of FFS and period 2	1.378***	1.254***	1.415***	1.354***
	(0.169)	(0.171)	(0.218)	(0.219)
Interaction of F2F and period 2	1.161***	1.058***	1.159***	1.118***
	(0.175)	(0.177)	(0.236)	(0.227)
Household size		-0.015		-0.009
		(0.022)		(0.026)
Access to farmland		0.173		0.048
		(0.270)		(0.357)
Area cultivated		0.000**		0.000***
		(0.000)		(0.000)
Market products individually		-0.052		-0.084
		(0.067)		(0.092)
Access to financial services		0.089		0.089
		(0.064)		(0.089)
Farmer produces maize		0.312***		0.274***
		(0.071)		(0.094)
Farmer produces beans		0.191**		0.177*
		(0.083)		(0.100)
Farmer produces peanuts		0.372***		0.438***
		(0.083)		(0.103)
Farmer produces rice		0.599***		0.408
		(0.209)		(0.345)
Constant	3.385***	2.978***	3.422***	3.067***
	(0.034)	(0.280)	(0.041)	(0.400)
R2_overall	0.216	0.315	0.217	0.311
RMSE	0.940	0.860	0.970	0.900
Valor-p>F	0.000	0.000	0.000	0 .000
Obs.	2,629	2,497	2,071	2,005
Wald test (p-value) ¥				
FFS*period1 - FFS*period2 = 0	0.000	0.000	0.002	0.003
F2F*period1 - F2F*period2 = 0	0.000	0.000	0.000	0.001
FFS*period1 - F2F*period1 = 0	0.005	0.012	0.009	0.027
FFS*period2 - F2F*period2 = 0	0.155	0.174	0.192	0.177

* p<0.10, ** p<0.05, *** p<0.01
Values in parenthesis are standard errors, adjusted for clusters in household id
¥ values for Wald test are the p-value

Appendix 4.6. Fixed Effect regressions using alternative technology adoption indexes

Variables	Minimum of four technologies adopted				Total number of practices adopted				Minimum of four practices			
	Simple FE	FE with Covariates	FE Weighte	FE Weighted and with	Simple FE	FE with Covariates	FE Weighte	FE Weighted and with	Simple FE	FE with Covariates	FE Weighte	FE Weighted and with
Dummy period 1	0.138***	0.136***	0.112*	0.097*	0.152	0.147	0.062	0.014	0.139***	0.136***	0.104*	0.088
	(0.045)	(0.045)	(0.058)	(0.057)	(0.104)	(0.105)	(0.141)	(0.139)	(0.04)	(0.04)	(0.06)	(0.06)
Dummy period 2	0.154***	0.145***	0.139**	0.134**	0.137	0.171	0.177	0.159	0.106**	0.106**	0.102	0.102*
	(0.049)	(0.052)	(0.062)	(0.062)	(0.121)	(0.124)	(0.167)	(0.173)	(0.05)	(0.05)	(0.06)	(0.06)
Interaction of FFS and period 1	0.127**	0.105*	0.183**	0.163**	0.561***	0.499***	0.737***	0.689***	0.113*	0.092	0.181**	0.161**
	(0.059)	(0.058)	(0.073)	(0.071)	(0.140)	(0.138)	(0.177)	(0.175)	(0.06)	(0.06)	(0.07)	(0.07)
Interaction of F2F and period 1	0.013	0.022	0.031	0.047	0.204	0.198	0.301	0.338*	0.005	0.015	0.036	0.052
	(0.060)	(0.061)	(0.080)	(0.078)	(0.138)	(0.139)	(0.195)	(0.192)	(0.06)	(0.06)	(0.08)	(0.08)
Interaction of FFS and period 2	0.299***	0.273***	0.333***	0.303***	1.391***	1.321***	1.428***	1.405***	0.342***	0.309***	0.372***	0.340***
	(0.059)	(0.061)	(0.073)	(0.073)	(0.153)	(0.153)	(0.199)	(0.202)	(0.06)	(0.06)	(0.07)	(0.07)
Interaction of F2F and period 2	0.247***	0.239***	0.236***	0.222***	1.167***	1.124***	1.149***	1.161***	0.293***	0.281***	0.272***	0.255***
	(0.062)	(0.065)	(0.080)	(0.078)	(0.157)	(0.159)	(0.214)	(0.208)	(0.06)	(0.07)	(0.08)	(0.08)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant	0.439***	0.302***	0.452***	0.312***	3.360***	2.928***	3.403***	3.026***	0.431***	0.307***	0.445***	0.313***
	(0.013)	(0.094)	(0.016)	(0.118)	(0.033)	(0.250)	(0.039)	(0.357)	(0.01)	(0.09)	(0.02)	(0.12)
R2_overall	0.122	0.184	0.120	0.178	0.190	0.284	0.193	0.282	0.123	0.183	0.123	0.181
RMSE	0.340	0.320	0.350	0.340	0.870	0.800	0.900	0.840	0.340	0.330	0.350	0.340
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	2,629	2,497	2,071	2,005	2,629	2,497	2,073	2,007	2,629	2,497	2,071	2,005
Wald test (p-value) ¥												
FFS*period1 - FFS*period2 = 0	0.003	0.007	0.044	0.068	0.000	0.000	0.000	0.000	0.000	0.000	0.012	0.019
F2F*period1 - F2F*period2 = 0	0.000	0.000	0.011	0.037	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.014
FFS*period1 - F2F*period1 = 0	0.040	0.135	0.032	0.082	0.006	0.017	0.012	0.030	0.053	0.175	0.039	0.106
FFS*period2 - F2F*period2 = 0	0.290	0.503	0.123	0.182	0.103	0.135	0.107	0.126	0.322	0.5766	0.114	0.166

* p<0.10, ** p<0.05, *** p<0.01
Values in parenthesis are standard errors, adjusted for clusters in household id
¥ values for Wald test are the p-value

4

Appendix 4.7. Fixed Effect regressions using alternative technology adoption indexes

Variables	Total number of inputs adopted				Minimum of two inputs adopted				Adoption of improved seeds			
	Simple FE	FE with Covariates	FE Weighte	FE Weighted and with	Simple FE	FE with Covariates	FE Weighte	FE Weighted and with	Simple FE	FE with Covariates	FE Weighte	FE Weighted and with
Dummy period 1	0.023	0.036*	0.044	0.049	0.018	0.025	0.035	0.038	0.164***	0.162***	0.149**	0.128**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.06)	(0.06)
Dummy period 2	0.264***	0.307***	0.265***	0.296***	0.177***	0.199***	0.166***	0.183***	-0.226***	-0.253***	-0.173***	-0.218***
	(0.05)	(0.05)	(0.06)	(0.07)	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)
Interaction of FFS and period 1	0.002	-0.006	-0.014	-0.022	-0.000	-0.003	-0.012	-0.017	0.164***	0.140**	0.176**	0.170**
	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)	(0.06)	(0.08)	(0.08)
Interaction of F2F and period 1	-0.012	-0.028	-0.023	-0.035	-0.006	-0.012	-0.014	-0.021	0.046	0.033	0.069	0.073
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)	(0.07)	(0.09)	(0.09)
Interaction of FFS and period 2	-0.012	-0.067	-0.011	-0.051	0.012	-0.022	0.027	-0.001	0.639***	0.651***	0.569***	0.610***
	(0.06)	(0.06)	(0.07)	(0.08)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.08)	(0.08)
Interaction of F2F and period 2	-0.003	-0.066	0.015	-0.043	0.019	-0.014	0.053	0.022	0.501***	0.534***	0.449***	0.507***
	(0.06)	(0.06)	(0.07)	(0.08)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.07)	(0.08)	(0.08)
Time variant control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant	0.025***	0.050	0.020**	0.040	0.023***	0.097	0.019***	0.083	0.416***	0.134	0.416***	0.100
	(0.01)	(0.08)	(0.01)	(0.10)	(0.01)	(0.07)	(0.01)	(0.09)	(0.01)	(0.10)	(0.02)	(0.11)
R2_overall	0.088	0.125	0.090	0.128	0.088	0.108	0.087	0.109	0.154	0.182	0.150	0.179
RMSE	0.290	0.280	0.290	0.280	0.210	0.210	0.210	0.210	0.350	0.340	0.360	0.350
Valor-p>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	2,622	2,497	2,066	2,005	2,622	2,497	2,066	2,005	2,612	2,490	2,057	1,999
Wald test (p-value) ¥												
FFS*period1 - FFS*period2 = 0	0.817	0.371	0.969	0.738	0.753	0.681	0.435	0.083	0.000	0.000	0.000	0.000
F2F*period1 - F2F*period2 = 0	0.871	0.576	0.615	0.931	0.535	0.958	0.222	0.491	0.000	0.000	0.000	0.000
FFS*period1 - F2F*period1 = 0	0.570	0.406	0.721	0.627	0.778	0.677	0.949	0.856	0.036	0.070	0.144	0.175
FFS*period2 - F2F*period2 = 0	0.857	0.980	0.665	0.894	0.847	0.831	0.565	0.619	0.012	0.044	0.076	0.123

* p<0.10, ** p<0.05, *** p<0.01
Values in parenthesis are standard errors, adjusted for clusters in household id
¥ values for Wald test are the p-value

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Impact of farmer field school training on small-scale farmer crop yields in DRC

ABSTRACT

Using a three-period set of data collected through annual cross-sectional surveys from 1,105 small-scale farmers in eastern DRC we study the impact of farmer's participation in FFS and F2F training on small-scale farmers' yields. We use two yield indexes; a multi-crop yield-index and the yields of cassava as impact measures, and the Difference-in-Differences method combined with inverse propensity score weighting to offset potential selection biases due to non-random placement of FFS and F2F training or farmers' preference towards participation. Our results consistently indicate that both FFS and F2F trainings contribute to a significant increase in farmers' yields, especially in the second period. We also learned that the effect size does not differ between the two training approaches in either period, suggesting that F2F communications are a suitable alternative to FFS training. We are unable to confirm if training materializes in higher yields through technology adoption, however, we do speculate that the increased adoption of productivity-enhancing practices and inputs is likely the most important impact mechanism.

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5.1. Introduction

Agriculture is the single most important economic sector in the Democratic Republic of Congo (DRC). It accounts for more than 42 percent of the gross domestic product, employs 62 percent of its men and 84 percent of its women (D'Haese, Banea-Mayambu *et al.*, 2013), and provides income for 97 percent of rural households (WFP, 2014). The country is endowed with abundant fertile arable land, bodies of water, and climatic conditions which make agriculture the sector with the highest potential to spur growth and increase household incomes, especially for food crop farmers which are prevalent in DRC. Food crop production is a common livelihood among rural populations in all provinces in DRC (USAID, 2015). According to WFP (2014), food crop farming is the most common agricultural activity (69 percent), followed by livestock production (9 percent), fishing and forestry resources (7 percent respectively), and cash crop production (5 percent). Yet, food crop producers constitute the second highest proportion of poor households in the country (57 percent), following fishermen (70 percent) (WFP, 2014).

5

The yields of most food crops have either marginally grown or simply decreased over the last five decades in DRC. According to Chauvin, Mulangu *et al.* (2012), since the 1960s, the cereal and tuber crop yields experienced an average annual growth rate of 0.25 percent and 0.42 percent, respectively. However, the rate of growth was not sustainable after the 1970s, when the yields for most crops remained stagnant until the end of the 1990s and decreased from 2000-2008 (Thaddée, 2013). Accordingly, the yields of major crops remain far from the potential, with a gap that ranges from 78 percent for maize and rice to 86 percent for cassava and plantain (Thaddée, 2013).

Poor agricultural productivity is systematic in DRC and this largely corresponds to a lack of investment in accumulating capabilities, limited use of improved technologies including fertilizer, small landholdings, the informal character of agriculture, and the rudimentary nature of technologies used in the sector (Otchia, 2014). Yield gaps for most crops in Sub-Saharan Africa could be reduced by the appropriate use of improved crop varieties; appropriate application of fertilizers;

and adequate management of nutrients, water, pests, and diseases (AGRA, 2013). However, the adoption of these technologies and farm management practices has remained low, mostly because extension has failed to achieve its technology adoption and farm productivity goals (Anderson, 2007; Birkhaeuser, Evenson *et al.*, 1991). This is certainly the case in DRC, and particularly affects small-scale farmers who face the greatest challenges to access innovation.

In the last three decades agricultural extension has increasingly evolved into more decentralized and participatory approaches, of which farmer field schools (FFS) became prominent (Godtland, Sadoulet *et al.*, 2004; Van den Berg & Jiggins, 2007). Since then, the FFS approach has spread across Asia, and Latin America and has gained ground in more than 27 African countries (Braun, Jiggins *et al.*, 2006; Nelson, Orrego *et al.*, 2001). FFS is a participatory farmer-centered approach first introduced in the late 1980s in Asia as a way of diffusing integrated pest management practices to rice farmers (Godtland, Sadoulet *et al.*, 2004). The FFS approach uses extensionists as facilitators who conduct participatory learning activities and field experimentation. According to Kenmore (2002) the FFS approach represents a paradigm shift, unlike other traditional government-led extension modalities, as it incentivizes farmers to develop their critical thinking and creativity, and consequently help them make better farming decisions.

Many authors have found that FFS training had a positive effect on agricultural performance and productivity, through farmers' adoption of environmentally friendly practices and sustainable use of input technologies (Davis, Nkonya *et al.*, 2012; Van den Berg & Jiggins, 2007; Waddington, Snilstveit *et al.*, 2014). Assessing the impact of FFSs on knowledge acquisition and agricultural productivity in Peru, Godtland, Sadoulet *et al.* (2004) found that participation in FFS training increased the productivity of treated groups by 52 percent. Correspondingly, Davis, Nkonya *et al.* (2012) suggests that the value of crop for FFS members increased by about 80 percent in Kenya and 23 percent in Tanzania. In Uganda however, the same study was not able to predict a significant impact of FFS on crop productivity. Feder, Murgai *et al.* (2004b) also indicates that the FFS program in Indonesia did not have a significant impact on the performance of graduates and their neighbors. The results of FFS impact evaluations greatly differ according to the settings, the impact evaluation methods, and the definition of what impact means (Godtland, Sadoulet *et al.*, 2004). Nevertheless, FFS are costly undertakings and assessing their real impact is desirable.

This chapter studies the impact of FFS and the associated Farmer to Farmer training (F2F) on the crop productivity of 1,105 small-scale farmers in eastern DRC. *Chapter 4* found that both FFS and F2F training increase small scale farmers' adoption of improved technologies, and this chapter goes a step further by assessing if adoption also results in an increase in yields. It uses a three-period panel data set collected through annual cross-sectional surveys which begun in 2013, as the baseline, continued in 2014, which was the mid-term survey, and ended in 2015, the end-line survey. We face important threats of selection bias due to non-random placement of FFS and F2F training and potential farmers' preference towards participation. To offset the impact of these biases we adopted a Difference-in-Differences model with three periods combined with inverse propensity score weighting. Assessing the impact of FFS beyond knowledge acquisition and adoption helps us to get a better sense of how FFS/F2F influences farmers' decision making capacity, and how it impacts the outcomes which create incentives for farmers to persistently adopt the set of knowledge and technologies promoted in FFS/F2F.

The paper continues with Section 5.2 which describes our sample, research settings and the descriptive statistics; Section 5.3 defines our yield productivity index; Section 5.4 describes our empirical strategy; Section 5.5 the results and discussion; and in Section 5.6 we conclude with the final remarks.

5.2. Research setup

5.2.1. Sample and setting

We used the same three groups of farmers studied in *Chapter 4* to participate in this study, namely an FFS, F2F and a control groups (see Section 2.6). We selected the beneficiary –FFS and F2F– and control group villages, followed by the selection of the beneficiary households and finally, the enrollment of the beneficiary households to the project. A total of 390 farmers participated in FFS activities, 390 farmers in F2F activities, and 325 were enrolled as the control group. In addition to the project interventions received by the FFS and F2F farmer groups, all the FFS and 210 of the 390 F2F farmers received a one-time input starter pack containing improved seeds and tools at the start of the project. However, *Chapter 3* evaluated the impact of one-shot free input starter packs using the same dataset and found no impact of that on a participant's adoption of productivity-enhancing technologies. This implies that any observed post-treatment differences in the farmers' levels of technology adoption may be attributable to participation in the training and not the starter packs. Refer to Section 2.7 for more detailed information about the data collection process.

5.2.2. Descriptive statistics

As described in *Chapter 4*, overall the baseline data (CSS1) shows that the three farmer groups are very similar in terms of their household and farm characteristics before treatment, with just a few variables that had statistically significant differences between the groups. This is in line with the distribution of the participation propensity scores estimated through the Multinomial Logit for the different groups in our sample (see in *Graphic 4.1*). While some individuals are somewhat more likely to belong to a specific group based on their characteristics, the differences are small and we may account for these differences in our regressions in order to reduce the threat of selection bias.

As indicated in *Table 4.1* in *Chapter 4*, the levels of technology adoption are not statistically different between groups in the baseline. The total number of technologies adopted by the three farmer groups ranges from 3.37-3.39. Similarly, the proportion of farmers adopting a minimum of four technologies, a minimum of four practices, and a minimum of two inputs, are statistically the same across all three farmer groups.

Table 5.1 also shows that the farmer groups are very similar in terms of the crops that they produce, with cassava being the most important crop produced by the three groups, maize the second, followed by beans, peanuts and rice in order of importance. About 86 percent of the farmers participating in the study cropped cassava and 26 percent cultivated maize the second most import crop in the project area. The crop-index and the yields of cassava were also very similar across the three groups, with no statistically significant differences.

Table 5.1. Descriptive statistics for different comparison groups

Variables	CSS1: Feb/March 2013				CSS2: Feb/March 2014				CSS3: Feb/March 2015			
	Control (n=286)¥	FFS (n=361)	F2F (n=353)	P-Value*	Control (n=200)	FFS (n=337)	F2F (n=343)	P-Value*	Control (n=211)	FFS (n=346)	F2F (n=368)	P-Value*
Percentage of farmers producing cassava	85%	88%	84%	0.570	96%	97%	97%	0.984	86%	95%	93%	0.246
Percentage of farmers producing maize	33%	39%	35%	0.425	41%	52%	44%	0.648	48%	49%	45%	0.644
Percentage of farmers producing beans	20%	21%	20%	0.943	21%	23%	21%	0.786	22%	24%	24%	0.873
Percentage of farmers producing peanuts	12%	16%	18%	0.417	14%	23%	21%	0.200	24%	28%	23%	0.440
Percentage of farmers producing rice	4.9%	5.0%	1.7%	0.697	2.5%	4.1%	2.2%	0.905	4.1%	6.9%	7.3%	0.816
Crop production (kg)	340	420	430	0.015	329	366	338	0.561	340	608	522	0.000
Crop-yield Index	0.47	0.53	0.53	0.285	0.52	0.55	0.56	0.358	0.54	0.73	0.65	0.002
Yield of cassava (dry kg/ha)	2,041	2,233	2,358	0.228	2,487	2,175	2,308	0.363	1,456	2,867	2,386	0.000
Yield of maize (kg/ha)	1,160	1,145	1,169	0.732	1,126	1,054	1,157	0.577	1,717	1,444	1,458	0.090
Yield of beans (kg/ha)	594	607	418	0.006	690	622	648	0.838	837	639	715	0.502
Yield of peanuts (kg/ha)	948	1,328	816	0.030	812	1,084	992	0.128	1,376	1,347	1,319	0.609
Yield of rice (kg/ha)	1,708	1,691	880	0.529	1,621	1,261	1,700	0.689	2,219	1,730	2,842	0.030

*Non-parametric test for three samples: chi-squared, using Kruskal-Wallis equality-of-populations rank test.
¥ in this case n reflects the average number of observations for all indicators

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Across the three periods, the number of technologies adopted by the three groups gradually increased. Except for the input adoption indexes, all adoption indicators significantly increase in CSS3 in all three groups. The FFS farmers adopted an average of 5.16 technologies which is higher than the number of technologies adopted by the F2F (4.97) and control farmers (3.76). The null hypothesis of no difference in yields across the three farmer groups is rejected in CSS3. In this period the crop-yield index for the FFS farmers is 0.73, while the F2F farmers is 0.65 control farmers 0.54, and these numbers are statistically different. In summary, our main descriptive statistics show that while the groups of farmers are quite similar on their household and farm characteristics in the baseline, after the intervention starts the FFS and F2F start to positively differentiate themselves from the control group in terms of technology adoption and yields.

5.3. Yield measurement

Historically, the definition of crop productivity or yield has evolved from the commonly established definition of an energy ratio to the ratio between the numbers of seeds harvested and seed sown (Evans, 1996); to the mass of product per unit land area (FAO & DWFI, 2015). Considering yield as the mass of product per unit of land, yield can be classified into three main types: theoretical yield; the maximum crop yield determined by the crop biophysical nature, potential yield; the yield of a cultivar under suitable environmental conditions, and actual yields; which is the yield obtained due to the use of available technologies and under prevailing environmental conditions.

Most development studies, including Davis, Nkonya *et al.* (2012); Gonzales, Ibarrarán *et al.* (2009); Larsen and Lilleør (2014); Morris, Tripp *et al.* (1999); Nyangena and Juma (2014), assess crop productivity from the actual yield perspective, as it allows one to capture the performance of multiple crops after exposure to program intervention and the adoption of new technologies. Generally, actual yields are measured as the quantity of crops harvested per unit of area cultivated.

According to FAO and DWFI (2015), the increasing cropping intensity and multi-crop nature of agricultural systems make the concept of yield as amount harvested over area cultivated inappropriate. This is because individual crop yield measurement doesn't correctly account for the actual land, time, labor, and resource invested (Connor & Mínguez, 2012). Egli (2008) confirmed this in a study that found an inverse relationship between the rate of soybean yield growth and the intensity of cropping measured as the percentage of double crops in the system. Therefore, it is essential that current measures of productivity focus on the entire production system rather than individual crops, especially for small-scale farmers whose system tend to be more diversified (Rosset, 1999). One crop yield index that fulfills this requirement is the crop yield index developed by Working (1940) and applied by Rehman (2014).

The crop yield index compares yields of a number of crops on a given farm with the average yields of the same crops on other farms or in previous years (Working, 1940). Hence, the crop-yield index measures how the yields of several different crops vary on average between farms, between geographical areas and between years (Working, 1940). To standardize the quantities of the different crops to one unit for aggregation purposes, the price index approach is used in which each crop yield is weighted by the product of its median market price and median land area for all farms considered.

Therefore, our crop-yield index is calculated by first estimating the quantity of each field crop produced on the farm and weighting this by the product of the median market price and median land area devoted to the crop. This statistic is then summed across all the different crops under production in the farm (farm-level statistic). Similarly, the average yield of each crop on all the farms is weighted by the product of its median market price and median land size and summed across all crops under consideration (mean farm statistic). The farm-level statistic is then divided by the mean farm statistics to calculate the crop-yield index. Our crop-yield index is calculated as follows:

$$Y_j = \frac{\sum\left[\frac{y_{ij}}{y_{i0}} * (y_{i0} * A_{i0} * P_{i0})\right]}{\sum(y_{i0} * A_{i0} * P_{i0})} = \frac{\sum_{k=1}^{4}(y_{ij} * A_{i0} * P_{i0})}{\sum_{k=1}^{4}(y_{i0} * A_{i0} * P_{i0})} \quad (1)$$

Where, Y_j represents the crop yield index for the farm j ; γ_{ij} the yield of crop i in the given farm j ; γ_{i0} is the median yield of crop i in all the farms; A_{i0} denotes the farm size median; P_{i0} the median price for crop I and k is the number of crops considered, which are cassava, maize, beans and peanuts ($k=4$).[3] According to Working (1940), this crop yield index is the best "general purpose" index for crop yield as it considers all the key characteristics; hectares, number of crops per farm, output and crop prices, that influence a particular production level.

5.4. Empirical strategy

We estimate the impact of farmer field school (FFS) and farmer-to-framer (F2F) training on the yields of small-scale farmers in our sample. The empirical challenge we face is identifying a proper counterfactual outcome to the participation outcome, that is, a group of non-FFS/F2F participants whose outcomes, on average, would represent unbiased predictions of the outcomes of FFS/F2F participants, had they not participated in the program. We use a group of farmers –control group– that did not participate in any training intervention to simulate the non-treated condition of training participants. However, this poses an additional set of challenges for estimating the impact of the program on yields as the distribution of the observed participants' characteristics differ from that of non-participants due to non-random selection of JENGA II villages and farmers' self-selection. Under the unconfoundedness assumption, a simple comparison of the yields of FFS/F2F participants and non-participants in our sample would produce biased estimates of the average program effect.

Using our data set with three periods, we adopt the following general framework to measure the impact of our training treatment (FFS and F2F) on crop yields Y_{it} , where i indexes individuals and t the time years, $t=0,1$ and 2.

3. Given the similarities of the market conditions across the sampled villages, we used the area average price for each crop as the median crop price ($Pi0$).

$$Y_{it} = \delta_t + \chi_t FFS_i + \varphi_t F2F_i + \gamma_1 L_{it} FFS_i + \gamma_2 L_{it} F2F_i + \lambda X_{it} + v_i + \varepsilon_{it}, \; t = 0,1,2 \qquad (1)$$

This model has a full set of time effects, δ_t; a full set of year-specific program effects χ_t and φ_t; an interaction term between FFS_{it} / $F2F_{it}$ and the size of land cultivated L_{it}; individual-specific covariates, X_{it}; unobserved individual-specific factors, v_t; and an i.i.d. error term, ε_{it}. Our primary goal is to obtain an unbiased estimate of the treatment effects χ_t, and φ_t. Therefore, since we have a three-period data panel with information for all individuals in our sample –including for the control group– we adopt a Difference-In-Differences (DID) approach to estimate the treatment effect (Angrist & Pischke, 2008; Bertrand, Duflo *et al.*, 2002; Imbens & Wooldridge, 2009; Meyer, Viscusi *et al.*, 1995).

Note that under unconfoundedness the treatment is assumed to be independent of potential outcomes and the random error, so controlling for differences in a set of covariates removes biases in comparisons between treated and control groups (Rubin, 1990). In our case, we control for several covariates X_{it}, but since the yield in period (*t-1*) is likely to condition the farmer's yield in period *t*, following Imbens and Wooldridge (2009) we added the lagged observation of the yield index (Y_{it-1}) to our DID specification in *Equation 1* as an additional control. This allows controlling for unknown time-variant confounding variables, which may influence the post-treatment levels of yields (Angrist & Pischke, 2008).

The first difference removes the biases caused by unobserved time-invariant variables (v_i - v_i = 0). However, as discussed by Godtland, Sadoulet *et al.* (2004), in our research settings we may face several sources of biases, including that of differences on the distribution of observable characteristics of the farmers in the different groups; and biases originated due to unobserved time variant and invariant characteristics of the individuals, which may be correlated with the idiosyncratic error term.

Rosenbaum and Rubin (1983) demonstrates that under unconfoundedness, conditional on the propensity score of being treated, the potential outcomes and treatment variables may be considered independent, that is $e(x) = pr(D_i{=}1 \mid X_i{=}x)$. As quoted by Imbens and Wooldridge (2009), this means "that within subpopulations homogenous in the propensity score there are no biases in comparisons between treated and control units". Hence, to make our treated and non-treated groups more comparable, it suffices to exclusively adjust for differences in the propensity score between participants of FFS/F2F and the individuals in the control group, which can be achieved through diverse manners. Given that the distribution of our covariates does not differ drastically, following *Chapter 3* and *4*, we chose inverse probability weighting (IPW) estimates to weight our DID regressions. IPW is a double robustness method suggested by Robins, Rotnitzky *et al.* (1995), which combined with our DID regressions could lead to additional robustness as it removes the correlation between omitted covariates, and reduces the correlation between omitted and included covariates (Imbens & Wooldridge, 2009). Hirano, Imbens *et al.* (2003) and Wooldridge (2007), argue that this approach yield efficient predictions of average treatment effects.

5.5. Results and discussion

We study the participation in FFS and F2F training as important determinants of small-scale farmers' crop productivity. As the main measure of crop productivity, I use a general purpose crop-yield index, which measures how the yields of several different crops vary between farms, geographical locations and years (Working, 1940). Since cassava is the single most important crop in our sample –more than 90 percent of farmers produce cassava– we also use the yields of cassava (kg/ha) as an alternative indicator to assess the consistency of the impact results. We also assess the robustness of our regressions by using different DID and FE specifications which combine the use of covariates and propensity score based weighting.

5.5.1. Farmer field school training and crop yields

I first focus on the impact of FFS training on crop yields and report the summary results of the fixed effect and DID regressions in *Table 5.2*. We find a positive time trend in both periods as FFS farmers increased their average yields – for all yield indicators, compared to previous levels, although the FFS training did not result in significant difference in yields for the farmers in the first period compared to the baseline. This is consistent with findings from other studies using the same dataset, which found the impact of FFS on technology adoption to be quite slow in the first period (see *Chapter 4*). According to the Wald tests included in *Appendix 5.1*, the impact of FFS on both yield measures is significantly different between the two periods, meaning that the impact of FFS on yields increased over the two periods.

In the second period, we find plausible evidence that the FFS training have a significant positive impact on farmers' crop-yield and cassava yield indexes. According to the DID and FE regressions in *Table 5.2*, the FFS farmers had an additional increase in their crop-yield index of about 0.18, compared to the control farmers. With an average baseline crop-yield index of 0.51, the FFS farmers experienced an average increase of 35 percent over the two periods. FFSs also had a significant impact on farmers' cassava yields, with FFS participants experiencing an additional increase of approximately 81 percent in their cassava yields compared to the control. Interestingly, while the FFS farmers substantially increased their yields in period two compared to their baseline levels, the control farmers actually experienced a reduction from about 2,040 kg/ha in the baseline to 1,450 kg/ha in period two. The reduction in cassava yield is probably the results of the 2014/2015 outbreak of the new cassava brown streak disease (CBSD), which greatly affected the yields of many farmers in the study area.[4] The fact that the cassava yields of the FFS participants increased while that of the control group farmers declined, seems to be a good indication that the FFS training helped the FFS farmers be much more aware of the disease and adopt improved technologies (including practices and improved seeds) to mitigate the impact of the disease on their crops.

4. Cassava brown streak disease (CBSD) causes loss of cassava root production and quality. It can affect the cassava roots that are left in the ground for over nine months. Cassava brown streak disease causes substantial root yield loss of up to 100% particularly in worst affected areas. See more about the CBSD in (Alicai, Omongo et al., 2007; Legg, Jeremiah et al., 2011)

5.5.2. Farmer-to-Farmer training and crop yields

Next, we explore the effect of F2F training on farmers' yields. We find a significant impact of F2F training on farmers' cassava yields in the second period, however in period one our results do not consistently predict any significant effect of the F2F training on any of the yield indicators. On average, over the two periods the F2F training resulted in about a 58 percent increase in the cassava yields of the F2F participants, compared to the control group farmers. We find less consistent results for the effect F2F training on the crop-yield index in both periods. While the DID estimations find no statistically significant impact of F2F training on the crop-yield index in any period, the FE estimations do. If considering the results of the FE estimations which may not be entirely accurate, we estimate an average treatment effect of F2F on the crop-yield index that ranges from 0.18 – 35 percent increase – in the FE weighted regressions, to 0.22 – 43 percent increase – in the FE weighted plus covariates models.

We run a series of Wald Tests to assess the statistical differences on the magnitude of our coefficients (*Appendix 5.2*). We find that in both periods, the FFS and F2F treatment effect size do not statistically differ for either yield indicators, under conventional confidence levels, and the results are suitably robust to different estimation methods. This is a result of special interest to our research as it, to some extent suggests that despite important differences between our two training modalities, compared to FFS, the F2F training still generates competitive levels of impact on yields. This result is in line with and to some extent complements the findings from *Chapter 4*, which suggested that after the two periods the magnitude of impact of FFS and F2F on adoption of agricultural technologies was not different.

Table 5.2. Impact of FFS and F2F training on crop yield index and cassava yields

Variables	FE Weighted	FE + Covariates + Weighted	DID Weighted	DID + Covariates + Weighted
Impact on crop yield index				
FFS training first period	0.038	0.010	0.008	-0.033
	(0.068)	(0.063)	(0.061)	(0.060)
F2F training first period	0.150**	0.148**	0.085	0.072
	(0.073)	(0.065)	(0.079)	(0.073)
FFS training second period	0.173**	0.180**	0.174**	0.126*
	(0.079)	(0.075)	(0.074)	(0.074)
F2F training second period	0.178**	0.220**	0.099	0.078
	(0.087)	(0.086)	(0.098)	(0.100)
FFS training & land cultivated	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
F2F training & land cultivated	-0.000	-0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Impact on cassava yield				
FFS training first period	-46.585	-91.109	133.950	-28.355
	(343.667)	(341.436)	(292.760)	(299.133)
F2F training first period	178.684	235.801	346.401	173.220
	(383.685)	(380.081)	(435.538)	(423.473)
FFS training second period	1608***	1565***	2048***	1907***
	(356.649)	(395.506)	(274.543)	(310.543)
F2F training second period	1474***	1625***	1284***	1106**
	(443.367)	(487.860)	(466.099)	(521.611)
FFS training & land cultivated	-0.223***	-0.122	-0.177***	-0.123**
	(0.077)	(0.121)	(0.047)	(0.053)
F2F training & land cultivated	-0.254***	-0.158	-0.093	-0.026
	(0.097)	(0.138)	(0.091)	(0.096)

* p<0.10, ** p<0.05, *** p<0.01
Values in parenthesis are standard errors, adjusted for clusters in household id

5.5.3. *Impact of land under cultivation on yields*

The size of land cultivated by the farmer does not seem to influence the impact of FFS training on crop-yield index, yet it significantly influences the extent to which FFS training impacts the cassava yield measure. According to the parameter of the interaction term between FFS and size of land cultivated (L), contingent on the area under cultivation, the participation in FFS training has a diminishing effect on the cassava yields of FFS farmers. In other words, the FFS training has a smaller impact on the yields of farmers with larger cultivations. As indicated by the area cultivated coefficient in *Appendixes 5.2* and *5.3*, the farmers with larger plots have lower cassava yields and smaller crop-yield indexes than the farmers in the opposite extreme of the spectrum. One proximate explanation to this observation is that farmers most likely make farming decisions based on production outputs rather than their actual yields. It may be the case that farmers with larger plots perceive their current outputs as good enough and may be less motivated to engage in training activities than farmers with smaller plots, who arguably pay much more attention to training activities because they are aware of their need to improve. Using evidence from southern and northern countries, Rosset (1999) argues that small farmers are more productive and efficient, and are better stewards of natural resources.[5] We find this to be true in our sample. Farmers may not realize how badly they are doing until they analyze their levels of productivity, and this may not help them to value training as they probably should.

5.6. Conclusion

Besides knowledge acquisition and the adoption of technologies, increasing yields is an important goal pursued as we implement farmer field school, and hence farmer-to-farmer training. The challenge is to understand how much of the variation in yields can be plausibly attributed to FFS and F2F farmer interventions. In this paper, we assess the impact that participation in FFS and F2F training have on small-scale farmers' yields. We use two main productivity

5. The analysis is based on total output productivity rather than monoculture yields. He concludes that "while yield almost always biases the results toward larger farms, total output allows us to see the true productivity advantage of small farms" (Rosset, 1999).

measures as impact indicators, namely a multi-crop yield-index, and the yields of cassava. Our results strongly suggest that participation in training – FFS and F2F – significantly improve the yields of small-scale farmers.

We find an overall time trend as farmers in our sample increased their average crop yield-index and cassava yields over the course of the project compared to baseline levels. While neither the FFS nor F2F training significantly predict the variation on the levels of crop yields in the first period, our results consistently indicate that both FFS and F2F trainings contributed to significant increases in farmers' yields in the second period. This is consistent with *Chapter 4* which using the same dataset found the FFSs to be slow increasing farmers' adoption of agricultural technologies in the first period. According to the Wald tests, the impact of FFS on both yield measures is significantly different between the two periods, meaning that the impact of FFS increased over the two periods.

We are unable to directly observe the role of JENGA II's training on reducing the incidence of diseases in our sample, however we do find suggestive evidence that training did play a role in offsetting the impact of an outbreak of cassava brown streak disease (CBSD), which greatly impacted the yields of most farmers in the study area during period two. This was evident in the yields of the control farmers which severely reduced in CSS3, while the FFS farmers experienced a substantial increase. We regard this difference as the impact that the FFS and F2F training had by making farmers more aware of the disease, more prepared to make decisions to combat it, and adopt improved technologies, including practices and improved seeds that allow them to mitigate the negative impacts of the disease.

From the Wald Tests results, it seems to suggest that regardless of the differences between our two training approaches –FFS and F2F, the F2F training is still able to produce similar levels of impact compared to FFS training. Studying the impact of FFS and F2F training on farmers' levels of technology adoption, *Chapter 4* shows that in the second period, the magnitude of impact of FFS training did not diverge from that of F2F. If this association can be interpreted as the F2F not trailing the FFS modality in terms of results, thus, given the evident lower costs of F2F training compared to FFS training, the farmer-to-farmer approach seems to be an attractive option to generate more adoption and sustainable crop yields, while reducing the cost of training.

APPENDIX

Appendix 5.1. Impact of FFS and F2F training on crop yield index and cassava yields

Variables	*Crop yield index*				Cassava yield			
	FE Weighted	FE + Covariates + Weighted	DID Weighted	DID + Covariates + Weighted	FE Weighted	FE + Covariates + Weighted	DID Weighted	DID + Covariates + Weighted
FFS training first period	0.038	0.010	0.008	-0.033	-46.585	-91.109	133.950	-28.355
	(0.068)	(0.063)	(0.061)	(0.060)	(344)	(341)	(293)	(299)
F2F training first period	0.150**	0.148**	0.085	0.072	179	236	346	173
	(0.073)	(0.065)	(0.079)	(0.073)	(384)	(380)	(435)	(423)
FFS training second period	0.173**	0.180**	0.174**	0.126*	1,608***	1,565***	2,048***	1,907***
	(0.079)	(0.075)	(0.074)	(0.074)	(357)	(395)	(274)	(310)
F2F training second period	0.178**	0.220**	0.099	0.078	1,474***	1,625***	1,284***	1,106**
	(0.087)	(0.086)	(0.098)	(0.100)	(443)	(488)	(466)	(522)
FFS training & land cultivated	-0.000	-0.000	0.000	0.000	-0.223***	-0.122	-0.177***	-0.123**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.077)	(0.121)	(0.047)	(0.053)
F2F training & land cultivated	-0.000	-0.000*	0.000	0.000	-0.254***	-0.158	-0.093	-0.026
	(0.000)	(0.000)	(0.000)	(0.000)	(0.097)	(0.138)	(0.091)	(0.096)
Wald test (p-value) ¥								
FFS*period1 - FFS*period2 = 0	0.059	0.017	0.025	0.040	0.000	0.000	0.000	0.000
F2F*period1 - F2F*period2 = 0	0.735	0.368	0.869	0.941	0.000	0.001	0.014	0.026
FFS*period1 - F2F*period1 = 0	0.111	0.023	0.389	0.199	0.480	0.301	0.642	0.6612
FFS*period2 - F2F*period2 = 0	0.952	0.613	0.483	0.632	0.764	0.895	0.139	0.141

* p<0.10, ** p<0.05, *** p<0.01
Values in parenthesis are standard errors, adjusted for clusters in household id
¥ values for Wald test are the p-value

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Appendix 5.2. Impact of FFS and F2F training on crop yield index

Variables	DID	DID + Covariates	DID Weighted	DID + Covariates + Weighted
Dummy period 1	0.505***	0.439***	0.469***	0.393***
	(0.037)	(0.035)	(0.038)	(0.036)
Dummy period 2	0.512***	0.438***	0.506***	0.466***
	(0.042)	(0.040)	(0.046)	(0.051)
Interaction FFS training and period 1	0.011	-0.030	0.008	-0.033
	(0.054)	(0.053)	(0.061)	(0.060)
Interaction F2F training and period 1	-0.015	-0.008	0.085	0.072
	(0.054)	(0.055)	(0.079)	(0.073)
Interaction FFS training and period 2	0.201***	0.190***	0.174**	0.126*
	(0.064)	(0.061)	(0.074)	(0.074)
Interaction F2F training and period 2	0.030	0.054	0.099	0.078
	(0.067)	(0.068)	(0.098)	(0.100)
Interaction FFS training & land cultivated	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Interaction F2F training & land cultivated	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Lag of crop yield index	-0.957***	-0.835***	-0.960***	-0.836***
	(0.031)	(0.031)	(0.032)	(0.034)
Household size (difference)		0.010		0.009
		(0.007)		(0.008)
Access to farmland (difference)		0.204***		0.277***
		(0.066)		(0.065)
Area cultivated (difference)		-0.000***		-0.000***
		(0.000)		(0.000)
Market products individually (difference)		-0.022		-0.019
		(0.023)		(0.028)
Access to financial services (difference)		0.020		0.025
		(0.022)		(0.024)
Farmer produces maize (difference)		0.107***		0.106***
		(0.025)		(0.028)
Farmer produces beans (difference)		0.045		0.055
		(0.032)		(0.033)
Farmer produces peanuts (difference)		0.345***		0.316***
		(0.032)		(0.035)
Farmer produces rice (difference)		0.206***		0.219**
		(0.070)		(0.088)
R2	0.435	0.529	0.456	0.539
RMSE	0.512	0.474	0.490	0.456
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	1,247	1,152	1,021	967
Wald test (p-value) ¥				
FFS*period1 - FFS*period2 = 0	0.007	0.002	0.025	0.040
F2F*period1 - F2F*period2 = 0	0.538	0.386	0.869	0.941
FFS*period1 - F2F*period1 = 0	0.666	0.717	0.389	0.199
FFS*period2 - F2F*period2 = 0	0.019	0.056	0.483	0.632

* p<0.10, ** p<0.05, *** p<0.01

Values in parenthesis are standard errors, adjusted for clusters in household id

¥ values for Wald test are the p-value

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Appendix 5.3. Impact of FFS and F2F training on cassava yields

Variables	DID	DID + Covariates	DID Weighted	DID + Covariates + Weighted
Dummy period 1	2,520***	2,428***	2,351***	2,270***
	(191)	(196)	(199)	(205)
Dummy period 2	1,403***	1,454***	1,431***	1,486***
	(121)	(144)	(136)	(163)
Interaction FFS training and period 1	91.766	9.132	134	-28.355
	(249)	(251)	(293)	(299)
Interaction F2F training and period 1	86.258	-12.865	346	173
	(254)	(264)	(435)	(423)
Interaction FFS training and period 2	2,157***	2,097***	2,048***	1,907***
	(243)	(266)	(274)	(310)
Interaction F2F training and period 2	1,277***	1,088***	1,284***	1,106**
	(269)	(311.343)	(466)	(521)
Interaction FFS training & land cultivated	-0.198***	-0.152***	-0.177***	-0.123**
	(0.041)	(0.046)	(0.047)	(0.053)
Interaction F2F training & land cultivated	-0.112**	-0.036	-0.093	-0.026
	(0.055)	(0.064)	(0.091)	(0.096)
Lag of cassava yield	-0.977***	-0.973***	-0.984***	-0.974***
	(0.030)	(0.032)	(0.035)	(0.038)
Household size (difference)		4.939		11.512
		(25.737)		(31.641)
Access to farmland (difference)		483		878***
		(317)		(303)
Area cultivated (difference)		-0.115***		-0.136***
		(0.037)		(0.050)
Market products individually (difference)		-8.131		-29.154
		(108)		(134)
Access to financial services (difference)		-122		-111
		(96.661)		(119)
Farmer produces maize (difference)		383***		397***
		(112)		(126)
Farmer produces beans (difference)		-192		-234
		(128)		(146)
Farmer produces peanuts (difference)		-20.299		27.146
		(126)		(130)
Farmer produces rice (difference)		21.892		279
		(217)		(240)
R2	0.521	0.526	0.529	0.542
RMSE	1,864	1,886	1,845	1,863
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	978	902	788	747
Wald test (p-value) ¥				
FFS*period1 - FFS*period2 = 0	0.000	0.000	0.000	0.000
F2F*period1 - F2F*period2 = 0	0.000	0.001	0.014	0.026
FFS*period1 - F2F*period1 = 0	0.982	0.931	0.642	0.661
FFS*period2 - F2F*period2 = 0	0.009	0.004	0.139	0.141

* p<0.10, ** p<0.05, *** p<0.01

Values in parenthesis are standard errors, adjusted for clusters in household id

¥ values for Wald test are the p-value

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6

Impact of agricultural technology adoption on household food security and dietary diversity: the case of eastern DRC

ABSTRACT

This study evaluates the relationship between agricultural training, adoption of agricultural technologies, and household food security. The analysis is based on a three-year panel data set gathered from 1,105 randomly selected farming households in eastern DRC. To mitigate for potential non-random program placement and farmer self-selection biases, we employed an instrumental variable (IV) approach, and as a robustness check we also applied Propensity Score Matching (PSM) and probability propensity score weighted Difference-in-Differences (DID) regressions. The results suggest no direct impact of FFS and F2F training on reducing household food insecurity, however training does seem impact food security through the adoption of improved agricultural technologies. While the impact on household access to food (HFIAS) is less evident, the adoption of agricultural technologies significantly predicts improvements in household dietary diversity (HDDS). The results also suggest that even though there is scope for agricultural training to reduce food insecurity and improve household dietary diversity, there are mediating factors that both constrain how training affects technology adoption and the extent to how adoption impact household food insecurity and nutrition.

6

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6.1. Introduction

Recent spikes in food prices have drawn renewed attention to food security to the extent that it has become the recent focus of most multilateral donor agencies (Larsen & Lilleør, 2014). During the last leaders' declaration, food insecurity was highlighted a priority on the G20 agenda (FAO and OECD, 2014); the United Nations African Human Development Report focused on food security as an avenue to achieve human development (UNDP, 2013), while AGRA in their Africa Agriculture Status Report, highlighted agriculture as the key sector for reducing food insecurity, employment and economic growth in Africa (AGRA, 2015).

An operational feature of this new surge of support to global food security is the shift away from focusing on aggregate food self-sufficiency towards concentrating on securing the economic demand and energy and nutrient requirements of individuals. Amartya Sen argued that the poor may lack "entitlements" to food under conditions of high food prices and low capacity to generate incomes, even if food supplies are sufficient (Sen, 1981). Food insecurity is an ex-ante status related to nutrition and health conditions as it reflects uncertain access to enough and appropriate food (Barrett, 2002). Hence, aggregate food self-sufficiency is neither a necessary nor a sufficient condition for household food security and adequate nutrition (Barrett, 2002; Cleaver, 1993). Whereas we live an era of abundant food availability, hunger, malnutrition and food insecurity remain widespread and affect an important share of the world's population.

According to The State of Food Insecurity in the World Report, about 98 percent of the world's chronically undernourished people (870 million people) live in developing countries, while about 23 percent of Africa's population are considered undernourished (FAO, 2012). Although the percentage of undernourished people in Sub-Saharan Africa (SSA) declined from about 33 percent in 1990-92 to about 23 percent in the 2014-16, the total number of undernourished people continues to increase with an estimated 220 million in 2014-16 compared to 176 million in 1990-92 (FAO, 2015a).

A predominant share of the literature frames food security under three elements measured at various levels. These are food availability, measured at the national/regional level, food accessibility, measured at the household level and food utilization, measured at the individual level (Larsen & Lilleør, 2014). If food security is to be a measure of household or individual welfare, it has to address access (Pinstrup-Andersen, 2009), which is defined as the ability to acquire sufficient quality and quantity of food to meet all household members' nutritional requirements for productive lives (Swindale, 2006). This paper focuses primarily on the access dimension of food security, which from a household perspective can be achieved through home food production and/or increased physical and economic access to food.

The links between agriculture, household food security and nutrition are particularly strong for agricultural producers or laborers, through incomes, and production for self-consumption. Since agriculture is central to the livelihoods of about 65 percent of SSA's population (AGRA, 2015), agricultural growth is considered a best-fit strategy for reducing food insecurity. Agriculture directly impacts a household's capacity to produce a major part of the food that they consume and influences the amount, type, stability, distribution and control of incomes. These factors have important implications for the food security and nutritional status of agricultural households (Von Braun, Ruel *et al.*).

According to FAO (2015b), to achieve the most direct reduction of hunger, priority must be given to economic growth in the agricultural sector. This is particularly important for rural consumers whose food entitlement is mainly based on their own production (Adekambi, Diagne *et al.*, 2009). Thus, increasing and diversifying farmer level agricultural productivity is paramount to reducing household food insecurity and often results in spillover benefits for others by contributing to their own food security concerns, broadening the food security scope and eventually promoting overall economic growth (Blein, Bwalya *et al.*, 2013).

The adoption of innovation in the form of, for example, best cultivation, harvest and post-harvest practices and improved inputs and equipment, is required to increase agricultural productivity and growth (Blein, Bwalya *et al.*, 2013). Improved agricultural technologies have been associated with a number of household and farm level outcomes including higher yields (Gonzales, Ibarrarán *et al.*, 2009; Waddington, Snilstveit *et al.*, 2014); increased employment (Binswanger & Braun, 1991); and higher incomes and reduced poverty (Kassie, 2011). The use of high yielding varieties could lead to significant increases in agricultural productivity and stimulate the transition from subsistence agriculture to a highly productive agro-industrial economy (World Bank, 2007).

Yet, economists have raised concerns that agricultural technology diffusion programs and even increased levels of technology adoption and agriculture growth, have not necessarily led to reductions in household food insecurity and/or improvements in dietary diversity. Households may choose to divert resources, including time, away from other activities toward project training activities and depending on the nature of these activities, the net impact of training on food insecurity may vary (Larsen & Lilleør, 2014). The intra-household distribution of food and the allocation of increased incomes are also critical, since increased household ability to acquire diversified food may not result in the actual purchase of food. For good reasons, households may simply not prioritize food over the acquisition of other goods and services, such as school fees and housing. A number of studies have suggested that expenditure allocations by women, as opposed to men, favored investments in the health, nutrition, and education of children in the household and that parents do not always have equitable preferences toward male and female children (Kennedy & Cogill, 1987; Quisumbing & Maluccio, 2000). The intra-household allocation of food may not be based on the needs of each individual member (Pinstrup-Andersen, 2009).

As part of ADRA's JENGA II food security program in the Democratic Republic of Congo (DRC), a set of different improved agricultural technologies (including practices and inputs) were disseminated to food insecure small scale farmers (SSF) through FFSs. A reduction in household food insecurity was the main expected outcome. This study aims to better understand the interrelationship between farmer level agricultural training, adoption of agricultural technologies, and food insecurity by using a household perspective in which smallholder farmers' production can be a way out of food insecurity, via their own produce and/or greater purchasing power (Maxwell, 1996).

We study the impact of farm level agricultural training and the adoption of agricultural technologies on Household Food Insecurity Access Scale (HFIAS) and Household Dietary Diversity Score (HDDS) while controlling for household and farm characteristics. We are especially interested in understanding if participation in FFS/F2F training impacts the levels of household food insecurity either directly or through technology adoption which we hypothesize is an important impact mechanism.

The contribution of this paper to the literature is fourfold. First, we build on a handful of recent studies focused on studying the impact of adoption of technologies on household food security and poverty (Alene & Manyong, 2006; Amare, Asfaw et al., 2012; Kassie, Jaleta *et al.*, 2014; Kumar & Quisumbing, 2010; Minten & Barrett, 2008). Second, we expand the literature committed to measuring food insecurity and the factors affecting it (Babatunde, Omotesho *et al.*, 2007; Bashir, Naeem *et al.*, 2010; Onianwa & Wheelock, 2006; Sidhua, Kaurb *et al.*, 2008). Third, unlike most studies – which primarily focus on the impact of inputs and new crop varieties – we also study the impact of farming practices on household food insecurity which normally require less startup investment. Lastly, we generate more evidence about these important links in the context of eastern DRC, where farmers have close to no access to technical assistance and training, agriculture performance has been dramatically low, and food insecurity remains pervasive. We apply current methodologies to measure and analyze technology adoption and its relationship to household food insecurity by adopting a quasi-experimental design and employing instrumental variables (IV) and propensity score matching (PSM), complemented with probability propensity score weighted regressions.

This paper continues with a brief description of the research setting, followed by a section about measurements of food insecurity, another on the methodology and empirical models, a section and about on data collection and descriptive statistics. The study concludes with the results and discussion section, and the final conclusions.

6.2. Research setting

Characterized by about 80 million hectares of fertile arable land, abundant water resources (52 percent of SSA fresh water are concentrated in DRC), and a diversity of climates, DRC has enormous agricultural potential. By exploiting this agricultural potential to its fullest, DRC would be able to feed as many as 1 billion people in the world (Bank, 2013). However, even the current relatively small domestic food demand is not met. DRC is classified among the top low-income food deficit countries (Akakpo, Randriamamonjy *et al.*, 2014) and despite some recent positive trends of recovery, the situation has deteriorated in the last three decades. About 37 percent of cereals consumed in DRC from 2009 to 2011 were imported, which is much higher than the 21 percent imported in the early 1990s (FAO, 2015a).

Since independence, agricultural production in South Kivu has declined, limiting the availability of staple crops such as cassava, maize, rice and plantain. Banana and cassava production has been severely impacted by diseases. The production of cassava, the single most important staple crop in the country, decreased by about 20 percent in the 90s because of the upsurge of pests and diseases, low performing agricultural practices, reduction in soil fertility, and political unrest (Ameua, Hirea *et al.*, 2013).

Widespread food insecurity clearly has its roots in low agricultural performance. Agricultural activities are the main sources of incomes of most Congolese, accounting for 62 percent of men and 84 percent of women. These numbers are particularly high in rural areas where agriculture employs nearly 97 percent of the population and the levels of food insecurity exceed the national average. According to Akakpo, Randriamamonjy *et al.* (2014) about 54 percent of all rural households in DRC are food insecure with 1 in every 4 children in DRC being malnourished. Generally, about 43 percent of children under 5 are chronically malnourished (stunted) in DRC and 23 percent acutely malnourished (wasted). The average daily food consumption in the country is also estimated at less than 1,500 kilocalories per person, which is below the minimum calories required to be considered healthy of 1,800 kilocalories per person (USAID, 2015). South Kivu is one of the rural areas in DRC where the proportion of food insecure households'– 64 percent – exceeds the national level. In addition, over 50 percent of children under 5 in South Kivu are either wasted or stunted (Akakpo, Randriamamonjy et al., 2014). The global acute malnutrition rates in South Kivu is above 10 percent emphasizing the intense under-nourishment in the zone. Aiming to change the farming and food insecurity situation of the participating households in South Kivu, JENGA II used the FFS/F2F methodology to train farmers and increase the adoption of productivity-enhancing agricultural technologies (see more about JENGA II's FFS/F2F methodology in *Chapter 2*).

6.3. Food insecurity measurements

The field of food security has experienced drastic paradigm shifts since the early 80s. They were triggered by (Sen, 1981), who helped redefine the way "food security" was discussed in the development literature (Webb, Coates *et al.*, 2006). Since then, thinking about food security has evolved from focusing on aggregate food availability (supply-side), through a second generation emphasizing individual and household level access to enough and appropriate food (demand-side), towards a prominent third generation thinking that places food security in a broad framework of individual behavior (Barrett, 2002). Informed by this evolution of the conceptualization of food security, the United States Agency for International Development (USAID) defined food security as “when all people at all times have both physical and economic access to sufficient food to meet their dietary needs for a productive and healthy life”. With this definition, aggregate food self-sufficiency is neither a necessary nor a sufficient condition for household food security (Cleaver, 1993), as domestic food gaps can be satisfied by imports and even in instances where the country is sufficient, people may still fall prey to food deprivation because of constraints in physical and/or economic access to food.

Food insecurity, on the other hand, can be defined as the limited or uncertain ability to procure food required to meet dietary needs for a productive and healthy life (Olaniyi, 2014). Food insecurity in eastern DRC is a problem dominated by limitations of access to food. Most agricultural households fail to produce the quantity and variety of food that they need to satisfy household food needs and/or to generate the income that allows them to acquire sufficient food in the market. One way to analyze food insecurity is from the perspective of household/individual inadequate access to food (see *Figure 6.1*), in which households with access to food are considered food secure, while those with limited access are not. A household is said to have adequate food access when it has adequate income or other resources to purchase or trade to obtain levels of appropriate foods needed to maintain consumption of an adequate diet or nutritional level (USAID, 1992).

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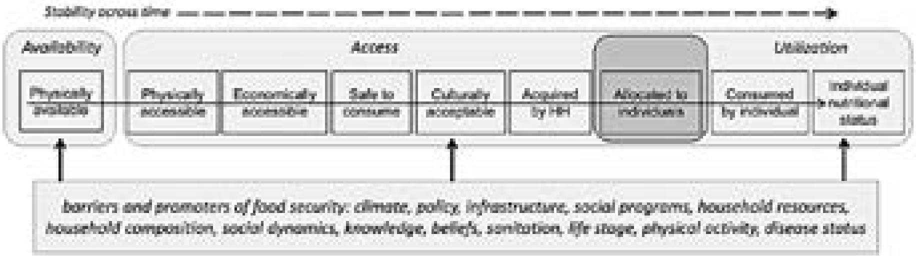
Figure 6.1. The loci within the food security conceptual pathway (Jones, Ngure et al., 2013)



While these conceptual developments have indeed contributed to identifying a more appropriate set of priorities to address food insecurity, policy-makers and program implementers remain confronted with the practical hurdles of properly assessing needs, targeting the best food security enhancement interventions, and measuring their impact. This is especially difficult without a clear understanding of how to differentiate food secure from food insecure households, and those facing immediate hunger from those who are not (Webb, Coates *et al.*, 2006). There has been a clear need to identify more precise yet simpler to use and analyze indicators of food insufficiency that are poverty-driven and not limited to clinical definitions. Responding to this demand, rigorous studies in the United States in the 1990s led to the development of empirically grounded measurement scales for food insecurity and hunger. An 18-question food insecurity module administered in 1995 allowed the measurement of both prevalence of food insecurity and the severity of hunger in the United States. The validation of this scale found that food insecurity was significantly negatively correlated with income and household food expenditures, and this qualitative food insecurity scale also correlated significantly with traditional measures such as energy intake per capita (Kennedy, 2005).

In the past several years, the food insecurity literature has been dominated by two competing (and often complementary) qualitative and quantitative approaches to measuring food insecurity. In fact, combining different methods and sources of information is increasingly desired by scholars, although not without costs due to the practical challenges of integrating qualitative and quantitative data. For instance, quantitative methods are traditionally seen as providing complementary breadth to the depth of insight generated by a qualitative approach. Coates, Wilde el al. (2006) compare a qualitative scale to measure food insecurity with an item-response model and find that based on Bangladesh data, the two approaches placed 90 percent of households in the same food insecurity category. Additionally, the results of the two scales were highly correlated which offers confidence to the use of either kind of approach (Webb, Coates *et al.*, 2006).

USAID's Food and Nutrition Technical Assistance (FANTA) project has supported a series of studies to explore simple but methodologically rigorous indicators that can be used to guide, monitor and evaluate USAID Title II and Child Survival program interventions. After several iterations and validations of a number of measures, FANTA has developed two key qualitative indicators to measure the prevalence of food insecurity and quality of diet as a proxy for food insecurity. These are the Household Food Insecurity Access Scale (HFIAS) and the Household Dietary Diversity Score (HDDS) respectively (Coates & Bilinsky, 2007; Swindale, 2006).

6.3.1. Household Food Insecurity Access Scale (HFIAS)

The HFIAS is a qualitative indicator that measures the prevalence of household food insecurity and serves to detect changes in household food insecurity over time. It is a continuous measure of the degree of food insecurity in the household. The HFIAS is calculated using a series of both occurrence and frequency of occurrence questions, with a recall period of four weeks (30 days). Broadly, the tool elicits whether households experienced anxiety about household food supply and if the quality or quantity of food consumed in the previous month was reduced (Coates & Bilinsky, 2007). These questions represent universal domains of the household food insecurity experience and can be used to assign households and populations along a continuum of severity; from severely food insecure to food secure.

The occurrence questions are grouped into three main domains, namely: (1) anxiety and uncertainty about the household food supply (e.g. did you worry that your household would not have enough food?); (2) insufficient quality, including variety and preferences of the food types (e.g. were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?, did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food?); and (3) insufficient food intake and its physical consequences (e.g. did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?, did you or any household member go to sleep at night hungry because there was not enough food?)

To each occurrence question, the respondent answers either yes or no, that is, whether the condition in the question happened at all in the past four weeks. If the respondent answers yes to an occurrence question, then a frequency-of-occurrence question is asked to determine whether the condition happened rarely (once or twice), sometimes (three to ten times) or often (more than ten). The response to each question is coded using 0 = "no" occurrence, 1 = "rare" occurrence, 2 = "sometimes" occurrence and 3 = "often" occurrence.

The HFIAS score for each household is calculated by summing the codes for all questions answered by the household. The maximum score for a household is 27 (when the household response to all nine occurrence questions was "often", coded as 3) with a minimum score of 0 (when the household responded "no", coded as 0 to all occurrence questions). Therefore, the higher the score, the more food insecure the household is and the lower the score, the less food insecure.

6.3.2. Household dietary diversity scores (HDDS)

Household dietary diversity, which is referred to as the number of different food groups consumed over a given reference period by a household, is an attractive proxy indicator to measure food insecurity (Hoddinott & Yohannes, 2002), because a diversified diet is associated with a number of outcomes including increased expenditures and incomes, birth weight, child anthropometric status, caloric and protein adequacy (Swindale, 2006). The HDDS measures the food diversity within households using the number of food groups rather than the number of different foods consumed. This is to ensure that the diet consumed by the households are diversified in its nutrient source. All food items are classified into 12 food groups and used to calculate the HDDS. The 12 food groups are: cereals; roots and tubers; vegetables; fruits; meat, poultry and offal; eggs; fish and seafood; pulses, legumes, and nuts; milk and milk products; oil and fats; sugar and honey; and miscellaneous.

The application of the survey tool is based on household food consumption in the previous 24 hours. Each head of household or the person in charge of preparing food for the household is presented with a list of all the food groups to indicate the food groups that were consumed by the household the previous day. Each food group consumed is given a score of 1, and 0 otherwise. The HDDS for a household is calculated by summing the scores of the food groups consumed by the household. Typically, the HDDS ranges from 0-12 where "0" implies the household did not consume any of the food groups (household did not eat) and "12" implies the household consumed foods in all the 12 food groups (a well-balanced diet).

6.4. Data

6.4.1. Data collection

As indicated in *Chapter 2,* we applied a questionnaire which on the one hand, collected household characteristics such as household size; age, sex and level of education of the head of household, and levels of access to food (HFIAS) and dietary diversity (HDDS). On the other hand, through the supplemental form, it collected information about farm characteristics including area cultivated, land endowments, farmer capacity to store crops, percentage of harvest sold, access to financial services, types of crops produced during the season and marketing. This form also included detailed questions related to the farming practices and input technologies used by the farmers.

6.4.2. Descriptive statistics

The baseline summary statistics indicate that our three comparison groups (FFS, F2F and control) are highly similar in their individual/household characteristics. For all technology adoption and food security indexes (HDDS and HFIAS) we fail to reject the null hypothesis that the mean difference between the three groups equals zero. The HDDS for the FFS, F2F and control group farmers were 3.46, 3.37 and 3.32 respectively, and there was no significant difference between the three groups. With regard to HFIAS, the control group was slightly more food insecure (16.71) than the F2F (16.46) and the FFS (16.44) farmers in the baseline, although the difference was not statistically significant either (see *Table 6.1*).

The number of technologies adopted increased gradually over the course of the project for all three farmer groups. In CSS3, the FFS farmers had adopted 5.16 technologies which was 3.82 percent more than the number of technologies adopted by the F2F group (4.97 technologies). The technologies adopted by the FFS and F2F farmers significantly exceeded the number of technologies adopted by the control group (3.76) by 37 percent and 32 percent, respectively. Similarly, for all the other technology indexes, there were significant changes in the adoption rates for all the three farmer groups in CSS3, with the control group having the lowest technology adoption rate.

The multi-crop yield index of the FFS and F2F farmer groups increased through CSS3 while the mean yields of the control group remained more or less the same. The yield of cassava for the control group dropped by about 25 percent from CSS1 – CSS2. The rain patterns in the second and third year of the project (years of CSS2 and CSS3) were erratic which affected agricultural production substantially. The fact that treated groups adopted new technologies may have made them more resilient and prepared to confront this climate shock.

Table 6.1. Descriptive statistics for different comparison groups

Variables	CSS1: Feb/March 2013				CSS3: Feb/March 2015			
	Control (n=286)¥	FFS (n=361)	F2F (n=353)	P-Value*	Control (n=211)	FFS (n=346)	F2F (n=368)	**P-Value***
Average number of technologies adopted	3.367	3.389	3.364	0.906	3.762	5.160	4.966	0.000
% of farmers adopted min. four technologies	0.418	0.456	0.440	0.639	0.566	0.900	0.851	0.000
Average number of practices adopted	3.352	3.360	3.342	0.962	3.487	4.882	4.679	0.000
% of farmers adopted min. four practices	0.406	0.442	0.434	0.749	0.508	0.891	0.845	0.000
Average number of inputs adopted	0.016	0.029	0.022	0.960	0.277	0.280	0.291	0.901
% of farmers adopted min. two inputs	0.016	0.029	0.022	0.960	0.191	0.213	0.223	0.846
% of farmers adopted improved seeds	0.369	0.409	0.447	0.271	0.134	0.823	0.740	0.000
Crop production (kg)	340	420	430	0.015	340	608	522	0.000
Crop-yield Index	0.470	0.530	0.530	0.285	0.540	0.730	0.650	0.002
HDDS	3.320	3.460	3.370	0.639	4.320	4.780	4.600	0.214
HFIAS	16.710	16.440	16.460	0.720	13.170	12.930	12.900	0.920

*Non-parametric test for three samples: chi-squared, using Kruskal-Wallis equality-of-populations rank test.
¥ in this case n reflects the average number of observations for all indicators

The HDDS increased gradually over the course of the project, for the FFS, F2F and control groups, reaching in CSS3 4.78, 4.60 and 4.32, respectively. Although the HDDS was highest for the FFS followed by the F2F and control group farmers, there is no significant difference among the three groups in study. Compared to the baseline (CSS1), the HFIAS declined across all the three farmer groups (for the FFS, F2F and control group farmers) reaching in CSS3 12.93, 12.90 and 13.17, respectively. However, these differences are not statistically significant in CSS3 either.

Overall these statistics indicate a time trend improvement of both HDDS and HFIAS across the three comparison groups, however the differences between groups are minimum. Despite slight differences in some food security impact indicators, the comparison groups are reasonably similar both before and after treatment. While this gives us an idea of the progression that these groups have made in improving their food security situation, given that this analysis does not account for factors that make these groups incomparable, conclusions about the impact of FFS/F2F on household food security is better made through the results of the econometric analysis in Section 6.6.

6.5. Empirical approach

The purpose of this study is to evaluate the relationships among FFS agricultural training, the adoption of agricultural technologies, and the levels of household food security (HDDS and HFIAS). The simplest way to achieve this is to compare the outcome variable of interest before and after exposure to the treatment. However, according to White, Sinha *et al.* (2006) simply estimating the difference in the outcome variable does not provide any treatment effect attribution as it only offers information on the factual and not on what would have happened in the absence of the treatment, the counterfactual. Therefore, this study uses a quasi-experimental approach which uses information from both treatment and non-treatment groups before and after the introduction of the intervention to attempt to have a valid counterfactual.

6.5.1. *Instrumental variables approach*

Given our interest to estimate the extent to which agricultural technology adoption affects household food insecurity indicators, we specify the following structural model:

6

$$FS_{it} = \alpha + \gamma TA_{it} + \lambda X_{it} + \mu_i + v_{it} \tag{1}$$

where FS_{it} is a continuous index of food security represented by either HFIAS or HDDS;[6] TA_{it} is an index of technology adoption for the household i at time t; X_{it} denotes a vector of exogenous characteristics specific to individuals, their farms and households, which determine food insecurity; μ_i represents time-invariant unobserved characteristics of the individuals; v_{it} is an idiosyncratic error term which follows a normal distribution and have mean equal to zero; and γ and λ are parameters to be estimated.

As suggested by a number of studies including Asfaw and Shiferaw (2010), TA_{it} is endogenous with respect to vit, so the *Equation 1* is not properly identified and the parameter γ should not be estimated through ordinary least square (OLS). To properly identify the model, would require finding instrumental variables (Z_{it})

6. Note that the HFIAS score ranges from 1-27 and the larger the score the more food insecure the household is. An increase in HFIAS means that the households perceive access to food to be worsening.

which do not appear in *Equation 1* but that explain the variation in technology adoption, thus making the predicted level of TA_{it} uncorrelated with v_{it}, while still correlated with FS_{it}. According to Wooldridge (2010), using this exclusion restriction in the structural *Equation 1* is the most convincing strategy to find good instruments. Our identified structural system of equations would be as follows:

$$FS_{it} = \alpha + \gamma TA_{it} + \lambda X_{it} + \mu_i + v_{it} \quad (2)$$

$$TA_{it} = \omega + \eta Z_{it} + \lambda X_{it} + u_i + \varepsilon_{it} \quad (3)$$

where Z_{it} is a vector of instrumental variables; u_i represent individual fixed effects that condition adoption; and v_{it} is an *i.i.d.* error term.

Technology adoption is an important mechanism for agricultural training to impact household food insecurity. Hence, we propose a two-stage food security model to assess the impact that the program has, through adoption of agricultural technologies, on household food insecurity. Based on *Equation 3*, in the first stage we have:

$$TA_{it} = \delta_t d_t + \eta_1 FFS_i + \eta_2 F2F_i + \chi_t FFS_i * d_t + \phi_t F2F_i * d_t + \beta_1 FFS_i * L_{i1} \\ + \beta_2 F2F_i * L_{i1} + \lambda X_{it} + u_i + \varepsilon_{it}, t = 1,2 \quad (4)$$

where FFS_{it} and $F2F_{it}$ ϵ [0;1] represent participation in FFS or F2F training, 1 indicating participation and zero otherwise; d_t represents the time dummies for periods 1 and 2; L_{it} is the size of land cultivated by individual *i* in season *t*, and β_1 and β_2 are the parameters for the interaction of program participation (FFS/F2F) and land cultivated;[7] u_i represents time-invariant unobserved characteristics of the individuals; and is the error term, which follows a normal distribution and have mean equal to zero. The parameters γ_t and ϕ_t are period-specific estimates of the effect of FFS and F2F training on technology adoption, respectively.

Based on *Equation 1*, we specify our food security second stage model using HFIAS and HDDS as indicators for food security (*FS*), as follows:

7. The land cultivated in the last season is an important variable that may impact the farmer's ability to adopt new technology, and for that reason we include an interaction term to assess if land size conditions in any extent the effect of training on adoption.

$$FS_{it} = \delta_t d_t + \gamma_t TA_{it} * d_t + \rho_1 TA_{it} * G_{it} + \rho_2 TA_{it} * L_{it} + \lambda X_{it} + \mu_i + v_{it}, t = 1,2 \quad (5)$$

Since TA_{it} in *Equation 5* is predicted through *Equation 4* and here it only represents the variation in TA_{it} that is uncorrelated with v_{it}, the estimator γ is unbiased and depicts the effect of technology adoption on household food insecurity. The estimator P_1 and P_2 are the estimators for the interactions of the variable G (dummy farmer is women) and L (size of land cultivated) with TA_{it}.

We use Two-Stage Least Square (2SLS), an instrumental variable (IV) method, to simultaneously estimate the effect of training on TA_{it}; and the effect of TA_{it} on food insecurity (Angrist & Krueger, 2001).[8] Intuitively, our IV model seeks to address the issue of omitted factors that may affect food security, by using only part of the variability in *TA* that is uncorrelated with the omitted variables, to explain the relationship between technology adoption and food security (Angrist & Krueger, 2001). For example, the quality of the soil may affect the farmer's ability to invest in new technologies, but it may also affect the household's capacity to produce and/or acquire more food.

Technology adoption has remained very low and steady for decades in the study target area and farmers' participation in FFS training resulted in significantly higher levels of adoption (*see Chapter 4*). We argue that in the context of our sample, participation in FFS training is a prevailing instrument to *TA* (inclusion requirement). We have found that when controlling for technology adoption the participation in FFS and F2F is poorly correlated with FS (see *Appendix 6.2*) so our instrument is likely not to violate our exclusion restriction. Some may argue that participation in FFS/F2F is endogenous since people were not selected randomly and farmers may self-select into both treatment and control groups. We make two considerations regarding to this. First, the fact that non-participant farmers came from villages with very similar characteristics[9] but with no FFS/F2F interventions, the sample of non-participants is very likely to also include people who would participate in the program had the FFS/F2F training been

8. Given that we use interactions of TA with time, G and L, running the IVREG2 and XTIVREG2 commands in Stata becomes challenging. It would require having the endogenous variable (TA) interacted with an exogenous one (time, G and L) being instrumented in the first phase, however this is not correct (see Wooldridge (2010)). We could overcome this by estimating the 2SLS manually, however the standard errors in the second stage would be incorrect. We use an alternative solution, which is predicting in a separate first stage the TA index, build the interaction between TAhat and time, G and L, and used these interactions as the instruments in our IVREG2 2SLS regressions.

more widely available. A similar argument was made by (Godtland, Sadoulet *et al.*, 2004) in their FFS impact study in Peru.[10] Second, each FFS village selected for the study just had one FFS, and the farmers selected for the FFS activities in the village are as likely to participate, had the FFS activity been more available. For possible remaining differences among the participant groups in the baseline, is mitigated by weighting the first stage regressions by the inverse probability propensity score to participate (*see IPW in Chapter 3*). We also use different specifications including variations of the IV 2SLS, with OLS and FE.

As an alternative to the structural model in Equations 3 and 4 we can estimate a reduced form of the food insecurity model which would only include as independent variables exogenous regressors. While this opens the possibility to estimate the FS model through OLS, reduced forms do not usually have easy economic interpretation. Yet, given that our main instrument is farmer participation in JENGA II training, our reduced form can estimate the direct impact of FFS/F2F training (not through adoption) on household food insecurity which is of interest. We run the reduced form using Difference-in-Differences combined with propensity score weighting to offset remaining differences between participant groups. In order to check on the appropriateness of using IV regressions in our analysis we run a series of endogeneity and identification tests. These tests allow us to assess the capacity of our instruments to eliminate omitted variable biases; and if OLS is preferable over IV. We used the following tests: Anderson Canonic Corr. LM Statistic for under-identification; Cragg-Donald Wald F Statistic and Anderson-Rubin Wald Test for weak-identification; Sargan Statistic for over-identification; and Durbin-Wu-Hausman Endogeneity Test.

9. The non-FFS/F2F villages were purposely selected to have similar characteristics to FFS/F2F villages in terms of prevalence of food insecurity, agro-climatic conditions, access to markets, and access to public services and main roads.
10. We also used the propensity score of participation in FFS/F2F estimated based on pre-treatment household and farm characteristics, and the results do not differ considerably.

6.5.2. *Propensity score matching approach*

As an alternative to the IV estimations we also use a semi-parametric method to check the robustness of our results. To estimate the impact of the intervention, the following linear regression function can be specified, where a treatment variable is included as an explanatory dummy variable together with other covariates that influence the outcome variable in the model (Imbens & Wooldridge, 2007).

$$FS_i = \propto + \beta_i X_i + \tau p_i + u_i \qquad (6)$$

Where
τ = the effect of participation in FFS or F2F
(or being an adopter) on food security
FS_i = food security status of the individual *i*
p_i = participation in the program/adoption status ($p \in [0;1]$)
X_i = other covariates that influence the outcome variable

According to Imbens and Wooldridge (2007), two separate regression functions can be specified for the control and treatment groups and the predicted estimates used to calculate the overall impact. However, the challenge is that these regressions can be sensitive to differences in covariate distribution across the two groups which will affect the predicted values based on the model specified (Imbens & Wooldridge, 2007). Additionally, according to (White, Sinha *et al.*), it is possible to underestimating the treatment effect when some of the covariates included as explanatory variables are channels through which the treatment affects the outcome variables, or overestimating the treatment effect if these covariates are not accounted for in the regression. Based on these challenges, some non-parametric approaches have been proposed to estimate the treatment effects (Imbens & Wooldridge, 2007; Imbens, 2004). One methods is the differencing approach which has commonly been used to evaluate the impact of programs. For a differencing approach, the average treatment effect on the treated (ATT) which measures the impact of participation in the program on the participants is given as:

$$ATT = E(FS_{i1} \mid p = 1) - E(FS_{i0} \mid p = 1) \quad (7)$$

where $p = 1$ indicates that the individual i participated in the FFS or F2F training or is considered an adopter of agricultural technologies; FS_{i1} is the food security status of participant i after participating in the training; and represents the food security status of participant i had he/she not participated in the training or not been an adopter.

Given the impossibility to observe F0, the study employs a comparable control group to estimate this counterfactual outcome. According to Davis, Nkonya *et al.* (2012), using the control group helps to account for other factors that could also affect the outcome variable, but the control group needs to be comparable to the treatment group on observed characteristics that influence participation. The challenge with our evaluation design is that the selection of program villages and participants was not random, therefore simply comparing the food security levels between participants and non-participants would yield biased estimates of the program impact (Godtland, Sadoulet *et al.*, 2004) due to the existence of program placement and self-selection bias (Davis, Nkonya *et al.*, 2012). Program placement bias occurs when the location or target population of the program is not randomly selected, while self-selection bias occurs when participants decide whether to participate in the program, which is usually influenced by their individual characteristics, abilities, endowments and some unobserved characteristics (Davis *et al.*, 2010). Several approaches have been developed to deal with these issues which primarily vary by their underlying assumptions regarding how to resolve the placement and self-selection biases in estimating intervention effect (Davis, Nkonya *et al.*, 2012; Imbens & Wooldridge, 2007; Khandker, Koolwal *et al.*, 2010).

Matching on observables is an attractive potential solution (Caliendo & Kopeinig, 2008) which uses pre-treatment characteristics of the treatment and control groups, to estimate balancing scores which are used to match similar participant and non-participant individuals before the estimation of treatment effect. To alleviate the biases in the estimation of treatment effect in this study, we primarily use propensity score matching (PSM), which is a prominent balancing method developed by (Rosenbaum & Rubin, 1983). However, in order to compare the robustness of the results we also adopted probability propensity score-based weighted regressions to alternatively estimate treatment effect.

6.5.3. Propensity score matching estimations

PSM evaluates the impact of a program by comparing the outcomes of the treated groups to a control group based on the observable characteristics that affect participation in the program and the outcome variable being measured (Davis, Nkonya *et al.*, 2012; Rosenbaum & Rubin, 1983). According to Abadie and Imbens (2016), PSM addresses the problem of placement and selection bias by assuming: (a) conditional independence which suggests that selection into the intervention is based only on observable characteristics of the target individuals and that after conditioning on the observed characteristics influencing participation, the expected outcome in the absence of treatment does not depend on treatment status; and (b) a sizable common support or overlap in the propensity scores across treated and untreated groups to allow for possible matching of the treated individuals to closely related untreated ones. Once these conditions are met and the biases have been corrected, the effect of participation in the program on the outcome variable can be estimated. The main steps in PSM are: (1) estimation of the probability propensity scores; (2) matching of the treated individuals with the untreated based on the propensity scores; and (3) estimation of the treatment effect by comparing the outcomes of the treated with the untreated individuals (Caliendo & Kopeinig, 2008).

Estimation of the propensity scores requires selection of the model to use and a set of variables to be included as covariates in the model (Caliendo & Kopeinig, 2008). The most preferred discrete choice models used are the Probit and the Logit Models. Although there are no critical reasons to choose any model over the other, the Probit Model has been used by most impact evaluation studies (Awotide, Diagne *et al.*, 2012; Davis, Nkonya *et al.*, 2012; Gonzales, Ibarrarán *et al.*, 2009; Khonje, Mkandawire *et al.*).

In choosing the covariates to include in the model Heckman, Ichimura *et al.* (1997) shows that only variables that simultaneously influence the participation decision and the outcome variables should be included in the model. This is because the matching strategy builds on the assumption that outcome variables are independent to treatment, conditioned on the propensity scores (Caliendo & Kopeinig, 2008). The Probit Model employed in this study is specified as:

$$P_k(x_j) = f\left[\beta_{0,k} + \Sigma(\beta_{j,k} X_j)\right] \tag{8}$$

Where β_0 represents the intercept; β_j the regression coefficients; k are the different binary dependent variables for the Probit Model which are participation in FFS, participation in F2F, adoption of a minimum of four technologies, adoption of a minimum of four practices, and use of improved seeds; P_k denotes a binary dependent variable which takes the value of 1 if the participant receives the treatment (participated in FFS, F2F or is an adopter) and 0 if it is a control farmer or non-adopter; X_j is a set of pre-treatment covariates.

From the estimated Probit Model, the predicted coefficients of the significant variables influencing participation in the training or adoption of technologies are used to calculate the propensity scores for each farmer. Steiner and Cook (2013) defines propensity scores as the conditional probability of participating in the training given pre-treatment characteristics (X_j). The propensity scores, according to Thavaneswaran (2008) can be calculated using the equation:

$$\hat{e}(X_j) = \frac{1}{1+e^{-(B_0+B_j Z_j)}} \tag{9}$$

Where $\hat{e}(X_j)$ equals the predicted probability propensity score based on the covariates; where $0 < \hat{e}(X_j) < 1$. Exact matching on $\hat{e}(X_j)$ eliminates biases originated by non-random project placement and self-selection.

Once the propensity scores are estimated, the next step is to match the participant group to the control group. Several methods can be used to match the participant and control individuals based on their propensity scores. These include the Caliper Matching, Radius Matching, Near-Neighbor Matching, Kernel Matching and Mahalanobis Metric Matching. Of these, the Near-Neighbor and Kernel Matching are the most commonly used matching methods. The Nearest-

Neighbor Matching is the simplest method (Caliendo & Kopeinig, 2008). It involves matching control group individuals to participants that are closest in terms of their propensity scores (Caliendo & Kopeinig, 2008; Thavaneswaran, 2008). The control group can be matched with or without replacement, although matching with replacement is generally preferred as it leads to greater overlap of propensity scores, especially when the control group is small (Heinrich, Maffioli *et al.*, 2010; Thavaneswaran, 2008). Also, more than one near-neighbor can be used to match each participant. Davis, Nkonya *et al.* (2012) suggest that the nearest-neighbor matching efficiency improves as the number of matches increases. For the Kernel matching, weighted averages of all individuals in the control group are used to construct the counterfactual outcome (Caliendo & Kopeinig, 2008). The weights depend on the distance between each individual in the control group and the treated groups for which the counterfactual is estimated.

Since the Kernel method uses all individuals in the control sample, it produces the most efficient estimates of the treatment effect due to reduced variance, and it's considered by many the most ideal matching method (Sianesi, 2001). We use two matching methods in this study, namely Near-Neighbor and Kernel. After matching and all matching quality test performed, the effect of participation in the treatment on the outcome variable is estimated.

Benefiting from the estimation of the probability propensity score described above, we also adopted the strategy that combines regression with probability propensity score weighting (*see Chapter 3 and 4*) as an alternative way to estimate the average treatment effect of training and adoption on household food security. This approach helps alleviate biases caused by the non-random project intervention placement and farmers' self-selection. This also achieves better levels of robustness to potential misspecification of our parametric model in *Equation 6* and omitted variables (Imbens & Wooldridge, 2009; Wooldridge, 2007).

6.6. Results and discussion

We explore two main routes to measure the impact of training on household food security. On the one hand, we use a two-stage IV method to address the issue of omitted factors that may influence food security, and thus bias the estimation of the effect of technology adoption on household food security. On the other hand, we estimate the treatment effect making use of propensity score matching, which mitigates selection and project placement biases by making treated and control groups comparable based on their observed characteristics.

6.6.1. Instrumental variable results

Before running the IV regressions to test the impact of JENGA II training participation on FS through technology adoption, we analyzed the direct impact of training on the two food security indicators using the reduced form of our food security model. In both simple and weighted DID regressions (*see Appendix 6.1),* when controlling by the levels of technology adoption, the participation in training is poorly correlated with HFIAS. This indicates that in the case of our sample, the participation in training does not have any direct effect on household food insecurity other than through technology adoption. Hence, participation meets the exclusion criteria and can well be used to explain the variation of *TA* in the IV first stage in *Equation 3*.

We find in the first-stage of our IV regressions however, plausible indications that participation in JENGA II's agricultural training is significantly associated with increased levels of technology adoption. We observed that participation in training significantly predicts the variation on the levels of technology adoption, especially in the second period where the levels of significance and magnitude of effect are substantially larger (*see Chapter 4*).

Studying the mechanisms through which agricultural training and other factors impact household food insecurity, seems to be more attractive and is key for the design and implementation of programs and policies. Accordingly, we evaluated using IV 2SLS how the households in our sample respond to different levels of technology adoption, which is explained to a great extent by farmers' participation in the JENGA II training. We regress the HFIAS and HDDS scores against the value of technology adoption which is simultaneously predicted using instruments in the first stage (*Equations 4* and *5*). To check the consistency of the results we used both the regular 2SLS (based on OLS) and a combination of 2SLS + fixed effect (FE), which we found to be correspondingly consistent (see *Appendix 6.2, 6.3, 6.5* and *6.6*).

We run a series of endogeneity and identification tests to assess the capacity of our instruments to eliminate omitted variable biases; and to analyze if OLS is preferred over IV in the case that our regressors can be considered exogenous. As shown in *Appendix 6.4*, the tests related to the HDDS regressions steadily indicate that our IV model is identified, the endogenous regressors cannot be deemed exogenous, and that the instruments are relevant. In this case, OLS is inconsistent and IV regressions generate more consistent estimates. In the case of HFIAS, the tests indicate that the instruments are weak and that any potential endogeneity among the regressors would not have deleterious effects on OLS estimates. In that case, IV is consistent but inefficient which could be affecting our results. We run the HFIAS model through OLS and the levels of impact are consistent with that of the IV regressions *(see Appendix 6.6)*.

While we find very limited and inconsistent evidence regarding the impact of technology adoption on household access to food (HFIAS), as shown in *Table 6.2*, higher levels of adoption are significantly associated with higher household dietary diversity (HDDS). On average, one additional technology adopted by farmers resulted in an increase in HDDS that ranges from 0.95 (OLS) to 1.2 (FE). Based on the *TA* index's average increase over the three periods, which is 1.26 technologies (*Table 6.1*), the HDDS experienced an increase ranging from 1.2 (35 percent) to 1.5 (44 percent).

Table 6.2. Impact of technology adoption on household food insecurity (IV 2SLS second stage)

Variables	Technology Adoption Index Instrumented			
	Number Technologies	Min. Four Technologies	Number Practices	Min. Four Practices
Dependent Variable (HDDS)				
Tech. adoption index ¥	-0.586**	-1.069	-0.508*	-1.079
	(0.290)	(0.729)	(0.267)	(0.790)
Tech. adoption index & period 1 ¥	0.346	0.941	0.416*	0.915
	(0.240)	(0.633)	(0.235)	(0.637)
Tech. adoption index & period 2 ¥	0.952***	2.193***	0.801***	2.082**
	(0.299)	(0.765)	(0.296)	(0.931)
Tech. adoption index & farmer women	0.070	-0.017	0.061	-0.052
	(0.101)	(0.363)	(0.111)	(0.411)
Tech. adoption index & land cultivated	-0.000**	-0.000**	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Dependent Variable (HFIAS)				
Tech. adoption index	1.320*	2.761	1.243*	2.675
	(0.793)	(2.009)	(0.735)	(2.125)
Tech. adoption index & period 1 ¥	-1.337**	-2.791*	-1.122*	-2.496
	(0.638)	(1.682)	(0.636)	(1.726)
Tech. adoption index & period 2 ¥	-1.170	-1.505	-1.119	-1.684
	(0.823)	(2.080)	(0.823)	(2.275)
Tech. adoption index & farmer women	-0.009	0.461	0.020	0.450
	(0.273)	(0.963)	(0.302)	(0.938)
Tech. adoption index & land cultivated	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)

***** p<0.10, ** p<0.05, ***p<0.01
¥ first stage predicted value of the tech. adoption index

6.6.2. Estimation of treatment effect through PSM and IPW based regressions

Using a combination of two probability propensity score based methods, we estimated the impact of participation in FFS and F2F training and the effect of technology adoption on two household food security indicators (HFIAS and HDDS). Since increased technology adoption is an expected outcome of participation in FFS and F2F training, we refer to the results in *Chapter 4* where we found plausible indications that participation in JENGA II's agricultural training is significantly associated with increased levels of technology adoption.

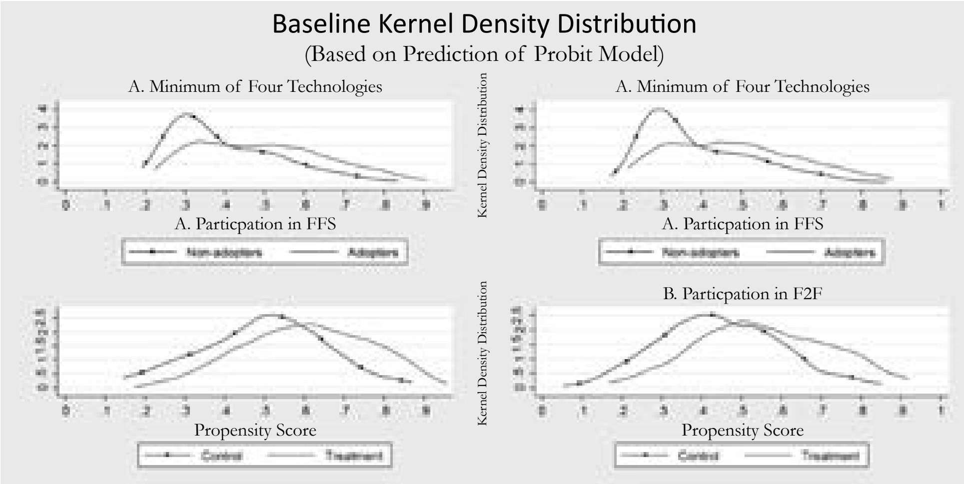
6.6.2.1. PSM balancing and treatment effect estimations

Using the Probit Model in *Equation 3*, we estimated a flexible lineal model to obtain the individual specific probability propensity score to participate in FFS or F2F training compared to the control group. Using the same specification, we also estimated the propensity score of being an adopter or non-adopter of the promoted technologies.[11] As we analyze the Kernel propensity score distributions for participation in FFS or F2F compared to the control group and that of being an adopter or non-adopter of a minimum of four practices or minimum of four technologies (see in *Graphic 6.2*), we observe that while the distributions show some divergence, the differences are not drastic and can be accounted for through the use of the propensity score matching and weighted regressions.

Additionally, the distributions of the propensity scores present a large overlap of the propensity scores between treated and untreated individuals (adopters and non-adopters), which means a sizable common support area that will allow for an appropriate matching of the treated individuals to similar untreated ones or the use of the propensity scores to weight the regressions. To predict the propensity scores, we used the variables included in *Appendixes 6.8* and *6.9* as covariates. These covariates comprise the pre-treatment household and farm specific characteristics, including the levels of food security as measured by the HFIAS and HDDS.

11. Note that we used three binary indicators of adoption, namely: adoption of minimum of four technologies; adoption of minimum of four practices; and adoption of improved seeds.

Graphic 6.2. Baseline Kernel propensity score distributions for treatment groups



We used the PSM as the primary average treatment effect estimation method, and before the calculation of the ATT in the end line we analyzed the balancing capacity of the probability propensity scores. Balancing tests reveal the capacity of the propensity scores to create a comparison group which resembles the treatment group (Smith & Todd, 2005). The test evaluates whether the means of the observable variables are significantly different between treated and un-treated units. As shown in *Appendixes 6.8* and *6.9,* after matching for both program participation and technology adoption variables, we fail to reject the null hypothesis of no difference of means between treated and untreated groups for most of the variables. Moreover, the results also indicate that the mean bias decreased significantly for all the balancing tests, and this is graphically presented in *Appendix 6.7*. Both Nearest-Neighbor and Kernel Matching yielded very similar results.

Following the estimation of the propensity scores, we estimated the ATT for both participation and adoption on household food security. Since we have three time periods in our sample (baseline, first period and second period), we calculated the mean difference for the treatment effect variables in the baseline and the ATT for the for the second period, both before (U) and after (M) matching (see *Table 6.3*). This gives us an idea of whether or not the sample

6

was balanced on the outcome indicators in the baseline and tells the levels of impact (ATT) of participation in FFS/F2F training and adoption on HFIAS and HDDS after the intervention started. While the unmatched sample showed some differences in the outcomes of treated and control groups, after matching there are no significant statistical differences between the two groups for any the outcome indicators. This is another indication that the PSM was able to account for possible systematic differences between the groups.

Both Nearest-Neighbor and Kernel matching (see *Table 6.3* and *Appendix 6.10*) show that participation in FFS and F2F training is very poorly correlated with a reduction in household food insecurity (HFIAS) and improvements in household dietary diversity (HDDS). While we noticed an overall increase in the HDDS of 26 percent for FFS participants and 34 percent for F2F from baseline to period two, these do not differ significantly from the control group. The same is true for HFIAS as the FFS farmers increased their indexes by about 20 percent and the F2F by about 23 percent from baseline to period 2, yet no significant differences are found between participants and the control group neither before nor after the treatment. This confirms that in our sample, the participation in training does not have a large enough impact on household food insecurity other than potential indirect effects through other variables such as technology adoption.

Table 6.3. Baseline balance and impact of participation/adoption on HDDS/HFIAS (Kernel PSM)

Variables		Baseline				Period 2			
		Treated	Control	Balance	t-stat	Treated	Control	Balance	t-stat
HH Food Insecurity Access Scale (HFIAS)									
Minimum of Four Technologies	*U*	3.732	3.15	0.582***	5.65	4.595	3.388	1.208***	4.00
	M	3.678	3.666	0.012	0.11	4.594	3.425	1.169***	4.29
Minimum of Four Practices	*U*	3.753	3.147	0.606***	5.88	4.602	3.392	1.210***	4.08
	M	3.706	3.684	0.022	0.19	4.602	3.502	1.100***	4.18
Use of Improved Seeds	*U*	3.518	3.332	0.186*	1.76	4.577	4.000	0.577**	2.40
	M	3.518	3.421	0.097	0.84	4.560	3.975	0.585**	2.45
Participation in Farmer Field Schools	*U*	3.480	3.355	0.126	1.17	4.373	4.441	-0.068	-0.40
	M	3.480	3.490	-0.009	-0.08	4.367	4.467	-0.099	-0.55
Participation in Farmer-to-Farmer	*U*	3.412	3.399	0.013	0.11	4.586	4.330	0.257	1.43
	M	3.402	3.460	-0.058	-0.50	4.586	4.401	0.185	0.87
HH Food Insecurity Access Scale (HFIAS)									
Minimum of Four Technologies	*U*	16.664	16.329	0.334	1.12	12.622	14.224	-1.603**	-2.03
	M	16.688	16.702	-0.014	-0.04	12.636	14.653	-2.016***	-2.66
Minimum of Four Practices	*U*	16.683	16.322	0.360	1.21	12.631	14.098	-1.467*	-1.89
	M	16.690	16.694	-0.005	-0.01	12.660	14.626	-1.965***	-2.62
Use of Improved Seeds	*U*	16.977	16.129	0.847***	2.86	12.676	13.242	-0.566	-0.90
	M	16.977	17.033	-0.057	-0.18	12.760	13.331	-0.571	-0.86
Participation in Farmer Field Schools	*U*	16.448	16.498	-0.049	-0.16	13.031	12.671	0.360	0.79
	M	16.448	16.445	0.003	0.01	13.106	12.829	0.277	0.57
Participation in Farmer-to-Farmer	*U*	16.243	16.583	-0.340	-1.07	12.644	12.907	-0.264	-0.55
	M	16.348	16.242	0.106	0.32	12.644	13.567	-0.923*	-1.72

* p<0.10, ** p<0.05, ***p<0.01

We also evaluated how the households in our sample respond to agricultural technology adoption through PSM estimations. As shown in *Table 6.3,* adoption is significantly associated with higher household dietary diversity (HDDS) and household food access (HFIAS), although we find less consistent evidence on the impact of technology adoption on HFIAS. On average, the HDDS ATT for adopters of agricultural technologies ranged from 0.585 for improved seeds to 1.169 for a minimum of four technologies. This represents approximately a 15–34 percent increase in HDDS (improvement in household dietary diversity) as a result of adopting the improved agricultural technologies. In the case of HFIAS, the ATT ranged from -1.965 for adoption of a minimum of four practices to -2.016 for minimum of four technologies. This is approximately a 13 percent reduction in the HFIAS (reduction of food insecurity) as a result of adopting the improved agricultural technologies. In the case of HFIAS, the ATT for use of improved seeds is very small and non-significant at conventional error levels. In most of the impact indicators the matched ATT is slightly smaller than the unmatched one, but the levels of significance remained similar and in some cases even improved.

6.6.2.2. Treatment effect estimations based on weighted regressions

We also estimated the treatment effect using DID combined with probability propensity scores weighting to mitigate the effect of pre-treatment systematic differences between the control and treatments groups. We used inverse probability propensity scores to weight the observations. *Table 6.4* presents a summary of the results of the regressions which overall are fairly consistent with the findings in the PSM estimations, except for the impact of adoption on HFIAS, which are less evident in the DID weighted estimations.

As in the PSM estimations, farmers' participation in FFS and F2F training have no significant effect on HDDS and HFIAS in any period. While the estimators indicate an increase in HDDS and reduction in HFIAS, none of them are statistically significant at conventional levels of error. For the impact of agricultural technology adoption on the food security indicators, the regression shows clear significant impacts, especially in the second period when all three indicators of adoption are statistically significant and the size of the impact accentuates. On average, given the adoption of technologies the households increased their HDDS indexes from baseline to period 2 within a range from 0.572 for adoption of improved seeds to 0.744 for adoption of a minimum of four technologies. This represents an increase that ranges from 16 – 22 percent compared to the non-adopter households.

Table 6.4. Impact of participation and adoption on HDDS/HFIAS (DID + weighting)

Variables	*Technology Adoption*			*Program Participation*	
	Min. of Four Technologies	**Min. Four Practices**	**Improved Seeds**	**FFS**	**F2F**
HH Dietary Diversity Score (HDDS)					
Impact in first period (DID)	0.539***	0.531***	-0.010	0.323	0.528
Impact in first period (DID+weighted)	0.577***	0.571***	0.013	0.175	0.251
Impact of second period (DID)	0.683***	0.745***	0.584***	0.220	0.443
Impact of second period (DID +weighted)	0.744***	0.743***	0.572***	0.066	0.326
HH Food Insecurity Access Scale (HFIAS)					
Impact in first period (DID)	0.158	0.164	-0.607	-0.267	0.218
Impact in first period (DID+weighted)	0.450	0.454	-0.514	-0.338	-0.279
Impact of second period (DID)	-1.214**	-1.388***	-0.254	-0.238	0.068
Impact of second period (DID +weighted)	-0.450	-0.635	-0.266	-1.109	-0.737

** p<0.10, ** p<0.05, *** p<0.01*

6

We find however, much less consistency in the results regarding the impact of adoption on HFIAS compared to the PSM estimations. This is especially true for the weighted regressions where we find no significant effects. This lack of consistency in the results between the two treatment effect estimation methods may also indicate some features of our interventions and the way that households make decisions. Some of these potential features are discussed in the following section.

6.6. General discussion

The two routes that we use to measure the impact of FFS/F2F training and technology adoption on household food security indicators show very similar and consistent results. That is, that FFS/F2F training does not have much direct effect on household food security, but participation in this training does have an impact through the farmers' adoption of agricultural technologies. While we see less evidence of this impact in HFIAS, we do find consistent impact of adoption on household dietary diversity score (HDDS), regardless of the method of estimation.

The fact that our study finds participation in FFS/F2F training to have a significant impact on technology adoption and adoption on food security without any direct impact of participation on food security seems to be because the levels of treatment effect are not large enough yet. Given that participation has a small effect on adoption and that adoption has a limited effect on food security, the direct impact from participation to food security is too small to be detected in the short term, but this could change in the long run if adoption continues to increase and play an important role in household food security.

The effects on HDDS are encouraging, yet the poor impact of adoption on HFIAS is puzzling. While the farmers in our sample substantially increased crop yields (see *Chapter 5* for yield results), it is not clear if they resulted in higher profits, and if they did, how much of it was spent on food. In any case, farming households such as the ones in our sample – which on average cultivate less than 0.5 hectare – likely have to choose between investing their incomes in more access to food (e.g. more meals a day, fewer events where the household does not have food), or better diversity of their household food basket.

This is especially important considering that households have other non-food related priorities like children's education and health, which for a good reason may be even more imperative for them than food security. This restricts what farmers can do with the extra income, and given this limitation our results seem to indicate that the households prioritized diet diversification over increasing the frequency of meals per day. While it is rational to expect households to prioritize quantity over quality in a context where households do not have enough to eat, their perception of their food security situation may differ from reality. Maes, Hadley *et al.* (2009) found that respondents to an HFIAS questionnaire in Ethiopia adjusted their internal standards of food security because of their exposure to increasingly food-insecure households as part of their volunteer work as caregivers. In our sample, the average HFIAS in the second period (13) is relatively close to the cutoff point for adequate food access, which according to Olaniyi (2014) is 11. Consequently, the current levels of access to food is probably not as far from what they perceive to be ideal. Macharia, Lange *et al.*

(2013) pointed out that surveyed farmers in DRC and Burundi largely indicated having access to enough food but not of the desired type, which is also consistent with other studies reporting that households in DRC have very non-diversified diets, but access to carbohydrate-rich foods is decent (Ekesa, Blomme *et al.*, 2011).

Most households in our sample have been living with less than ideal access to food for a long time, and the current situation for many is probably better than it has ever been. Hence, their current access to food is probably not as far from what they perceive to be their ideal level of food accessibility. A study by Macharia, Lange *et al.* (2013), suggests that the majority of households surveyed in DRC and Burundi indicated having enough food but not of the desired type. Similarly, findings from other studies which reported that households in the two countries have very non-diversified diets, but access to carbohydrate foods – roots, tubers and banana – is reasonable (Ekesa, Blomme *et al.*, 2011). This may explain why households decided to prioritize investing the extra income, at least partially, towards consuming other food groups which otherwise had not been part of their diets. Given their current levels of access to food, diet diversification seems to be preferred by households as long as they cannot afford to fund both.

A considerable portion of the literature on household food security and nutrition have found poor correlations between an increase in food production/ incomes and reduction in household food insecurity. In many cases, increases in food production and incomes did not necessarily translate into improvements in access to food, diets and/or nutrition. In the absence of social and behavioral changes, food storage, preparation practices and consumption patterns may remain unchanged, even with increases in production, productivity and incomes (Garrett & Kennedy, 2015). As suggested by Fan and Pandya-Lorch (2012), agricultural growth alone is not sufficient to address undernutrition. It is also important to pursue other objectives such as targeted nutrition programs. In order for increased household income or food availability to be translated into more significant changes in nutrition, the increased food availability, normally, would have to be accompanied by some combination of improved caring and feeding patterns and better access to health services (Levinson, 2011).

In view of this, the levels of impact that we find on HDDS actually imply that the households in our sample know about food security much more than one can assume. The fact that their diets have been remarkably undiversified is probably due to resource constraints rather than lack of knowledge and/or willingness to consume other food groups. In the DID regression in *Appendixes 6.13* and 6.14, the parameter of HDDSit-1 suggests that households with a higher diet diversification in the previous period experienced smaller increases in their HDDS over the two periods. This seems to suggest that households decrease their desire to invest further into diet diversification as their HDDS increases. That being the case; according to their knowledge about feeding practices, nutrition and health; households may adopt unconscious thresholds which may impact their decision to invest their allocable incomes to further diversify their diets or to prioritize investment in other pressing needs. This adds credence to the importance of health and nutrition behavior change education to layer at the household and community levels with agricultural trainings.

Food taste is also an important factor to food preferences and may also play a role in household's prioritization of HDDS over HFIAS. Stewart and Blisard (2008) found that even before small increases in incomes, low-income households tend to add at least two other food groups to their diets, arguably because they place a higher value on these food groups due to taste. Taste preferences are often considered a primary motivator of food choices (Drewnowski, 1997; Drewnowski, Henderson *et al.*, 1999).

The underlying premise of the ADRA JENGA II project was to integrate both nutrition behavior change training/sensitization with the FFS training. However, since our primary goal in this research was to isolate the effect of training on different production and food security outcomes, the households sampled in our study did not benefit from both agricultural and health and nutrition trainings. This may well have affected the households' ability and even motivation to maximize the effect of training and technology adoption on reducing household food insecurity. This overlap of activities is certainly an important area of research which can complement our finding in this thesis.

6.7. Conclusions

Our results suggest an overall positive trend in household access to food and dietary diversity for all groups in our sample. While impact on household access to food (HFIAS) is less evident, farmers' participation in agricultural trainings seem to predict improvements in household dietary diversity (HDDS) through increased adoption of agricultural technologies. This confirms that FFS/F2F trainings can well play a key role in reducing household food insecurity through the mediating mechanism of the adoption of improved agricultural technologies. This finding is critical to inform the design of future technology transfer programs. Historically, significant resources have been allocated to similar training programs aimed at reducing household food insecurity. However, one common feature in most programs is that they neglect to deal with underlying factors that condition the impact of training on adoption. Our findings suggest that training will not have much impact on household food insecurity if it first does not materialize in adoption.

We also learned that increased yields and incomes may not have been adequate to meet all pressing household expenses. Hence, households prioritize where to spend their extra agricultural incomes and they seem to decide towards diet diversification rather than increasing the quantity of food that they consume. This decision itself seems to indicate that households know about the importance of including other food groups in their diets more than we probably expected, that they place higher value on some food groups that they were not consuming, and that households may be subjected to adjustments of the perception of their food security situation, given their historic exposure to food insecurity (Maes, Hadley *et al.*, 2009). Most households analyzed have long been exposed to limited access to food and the current situation for many is probably better now than it has been for a long time. Hence, their current access to food as measured by the HFIAS is probably closer to what they perceive to be their ideal level than their degree of diet diversification (HDDS) is.

Increased adoption had a significant positive impact on yields in our sample (*Chapter 5*). However, while increased agricultural production and incomes are important mechanisms through which training seems to impact FS, during the implementation of the interventions we observed that the existence of household and community factors, such as, cultural norms, nutrition knowledge gaps, status of women in the household, husband-wife relationships, and landholding size, condition the extent of these impacts.

Overall, our results in *Chapter 4* do indicate that transference of agricultural technologies can play a role in increasing small scale farmers' adoption of improved technologies, and here we find that adoption can also play a preponderant role in increasing household dietary diversity. However, an important share of the literature suggests that the impact could be enhanced by combining agricultural extension with nutrition-specific interventions. According to many authors, standalone agricultural trainings have not necessarily resulted in a reduction of household food insecurity or an improvement of nutrition (Fan & Pandya-Lorch, 2012; Garrett & Kennedy, 2015; Levinson, 2011).

This study sheds light on several questions that have been dominating the debate regarding the interrelation between agricultural technology adoption and household food insecurity, but at the same time it underscores the importance of generating a better understanding of the impact that integrated agricultural and nutrition-specific interventions may have on household food insecurity, dietary diversity and even nutritional status.

APPENDIXES

Appendix 6.1. Impact of JENGA II FFS/F2F training on HDDS and HFIAS (controlling for adoption)

Variables	HDDS		HFIAS	
	DID	DID Weighted	DID	DID Weighted
Dummy period 1	2.837***	2.837***	12.322***	12.322***
	-0.213	-0.213	-0.739	-0.739
Dummy period 2	3.855***	3.855***	10.883***	10.883***
	-0.27	-0.27	-0.817	-0.817
Participation in FFS period 1	-0.338*	-0.338*	1.129**	1.129**
	-0.18	-0.18	-0.519	-0.519
Participation in F2F period 1	-0.258	-0.258	-0.231	-0.231
	-0.194	-0.194	-0.595	-0.595
Participation in FFS period 2	-0.316	-0.316	1.428*	1.428*
	-0.298	-0.298	-0.822	-0.822
Participation in F2F period 2	-0.12	-0.12	0.323	0.323
	-0.312	-0.312	-0.849	-0.849
Interaction FFS & land cultivated	0.000**	0.000**	-0.000***	-0.000***
	0.000	0.000	0.000	0.000
Interaction F2F & land cultivated	0.000*	0.000*	0.000	0.000
	0.000	0.000	0.000	0.000
Household size	0.002	0.002	-0.065	-0.065
	-0.036	-0.036	-0.07	-0.07
Access to farmland	1.555***	1.555***	-0.785	-0.785
	-0.325	-0.325	-0.91	-0.91
Area cultivated	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000
Market products individually	0.041	0.041	-0.455*	-0.455*
	-0.105	-0.105	-0.269	-0.269
Access to financial services	0.032	0.032	-0.636***	-0.636***
	-0.097	-0.097	-0.216	-0.216
Farmer produces maize	0.235**	0.235**	-0.391	-0.391
	-0.107	-0.107	-0.274	-0.274
Farmer produces beans	0.198	0.198	0.237	0.237
	-0.128	-0.128	-0.332	-0.332
Farmer produces peanuts	0.17	0.17	0.108	0.108
	-0.124	-0.124	-0.333	-0.333
Farmer produces rice	0.750***	0.750***	-1.065	-1.065
	-0.279	-0.279	-0.69	-0.69
Farmer is women	0.006	0.006	0.465	0.465
	-0.118	-0.118	-0.33	-0.33
Lag of HDDS	-0.830***	-0.830***		
	-0.04	-0.04		
Lag of HFIAS			-0.867***	-0.867***
			-0.039	-0.039
Technology adoption index	0.202***	0.202***	0.003	0.003
	-0.047	-0.047	-0.106	-0.106
R2	0.436	0.436	0.440	0.440
RMSE	1.784	1.784	4.828	4.828
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	1195	1195	1151	1151

* p<0.10, ** p<0.05, *** p<0.01

6

Appendix 6.2. Impact of technology adoption on HFIAS (IV 2SLS – second-stage)

Variables	*Technology Adoption Index*			
	Number Technologie	**Min. Four Technologie**	**Number Practices**	**Min. Four Practices**
Dummy period 1	2.346	-0.945	1.567	-1.143
	(2.183)	(0.885)	(2.177)	(0.853)
Dummy period 2	-0.103	-3.514***	-0.081	-3.349***
	(2.866)	(1.265)	(2.898)	(1.295)
Tech. adoption index ¥	1.320*	2.761	1.243*	2.675
	(0.793)	(2.009)	(0.735)	(2.125)
Tech. adoption index & period 1 ¥	-1.337**	-2.791*	-1.122*	-2.496
	(0.638)	(1.682)	(0.636)	(1.726)
Tech. adoption index & period 2 ¥	-1.170	-1.505	-1.119	-1.684
	(0.823)	(2.080)	(0.823)	(2.275)
Tech. adoption index & farmer women	-0.009	0.461	0.020	0.450
	(0.273)	(0.963)	(0.302)	(0.938)
Tech. adoption index & land cultivated	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Household size	0.063*	0.067*	0.062	0.066*
	(0.039)	(0.039)	(0.038)	(0.039)
Access to farmland	-1.854**	-1.712**	-1.838**	-1.656**
	(0.745)	(0.727)	(0.734)	(0.830)
Area cultivated	-0.001*	-0.000	-0.001	-0.000*
	(0.000)	(0.000)	(0.001)	(0.000)
Market products individually	-0.804***	-0.857***	-0.838***	-0.836***
	(0.226)	(0.222)	(0.223)	(0.226)
Access to financial services	-0.862***	-0.816***	-0.828***	-0.793***
	(0.210)	(0.205)	(0.205)	(0.209)
Farmer produces maize	-0.246	-0.173	-0.229	-0.192
	(0.356)	(0.338)	(0.340)	(0.366)
Farmer produces beans	-0.727**	-0.698**	-0.698**	-0.690**
	(0.284)	(0.287)	(0.272)	(0.294)
Farmer produces peanuts	-0.039	-0.041	-0.009	-0.098
	(0.314)	(0.334)	(0.303)	(0.386)
Farmer produces rice	-1.158**	-1.053**	-0.916*	-1.018*
	(0.540)	(0.526)	(0.502)	(0.542)
Farmer is women	0.782	0.480	0.673	0.482
	(1.096)	(0.619)	(1.176)	(0.562)
Constant	15.157***	18.155***	15.372***	18.167***
	(2.424)	(1.032)	(2.284)	(1.112)
R2	0.087	0.095	0.094	0.095
RMSE	4.663	4.642	4.644	4.642
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	2338	2338	2338	2338

* p<0.10, ** p<0.05, ***p<0.01

¥ first stage predicted value of adoption

6

Appendix 6.3. Impact of technology adoption on HDDS (IV 2SLS – second-stage)

Variables	Technology Adoption Index Predicted			
	Number Technologie	Min. Four Technologie	Number Practices	Min. Four Practices
Dummy period 1	-0.949	-0.253	-1.273	-0.239
	(0.828)	(0.339)	(0.809)	(0.297)
Dummy period 2	-2.392**	-0.065	-1.773*	0.040
	(1.036)	(0.459)	(1.043)	(0.512)
Tech. adoption index ¥	-0.586**	-1.069	-0.508*	-1.079
	(0.290)	(0.729)	(0.267)	(0.790)
Tech. adoption index & period 1 ¥	0.346	0.941	0.416*	0.915
	(0.240)	(0.633)	(0.235)	(0.637)
Tech. adoption index & period 2 ¥	0.952***	2.193***	0.801***	2.082**
	(0.299)	(0.765)	(0.296)	(0.931)
Tech. adoption index & farmer women	0.070	-0.017	0.061	-0.052
	(0.101)	(0.363)	(0.111)	(0.411)
Tech. adoption index & land cultivated	-0.000**	-0.000**	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Household size	0.010	0.008	0.007	0.006
	(0.015)	(0.015)	(0.014)	(0.016)
Access to farmland	1.245***	1.214***	1.301***	1.222***
	(0.285)	(0.279)	(0.276)	(0.242)
Area cultivated	0.000***	0.000**	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Market products individually	-0.156*	-0.159*	-0.152*	-0.158*
	(0.085)	(0.084)	(0.082)	(0.090)
Access to financial services	0.263***	0.249***	0.259***	0.243***
	(0.080)	(0.078)	(0.076)	(0.080)
Farmer produces maize	0.560***	0.517***	0.517***	0.518***
	(0.129)	(0.123)	(0.122)	(0.138)
Farmer produces beans	0.303***	0.288***	0.289***	0.293***
	(0.105)	(0.106)	(0.099)	(0.113)
Farmer produces peanuts	0.463***	0.472***	0.452***	0.495***
	(0.118)	(0.122)	(0.111)	(0.147)
Farmer produces rice	0.883***	0.891***	0.822***	0.847***
	(0.202)	(0.199)	(0.186)	(0.248)
Farmer is women	-0.177	0.102	-0.138	0.125
	(0.408)	(0.235)	(0.433)	(0.238)
Constant	3.427***	2.024***	3.203***	2.029***
	(0.896)	(0.391)	(0.837)	(0.369)
R2	-0.020	-0.008	0.030	-0.008
RMSE	1.797	1.786	1.752	1.786
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	2394	2394	2394	2394

* p<0.10, ** p<0.05, ***p<0.01

¥ first stage predicted value of the tech. adoption index

6

Appendix 6.4. IV 2SLS endogeneity and identification tests

Tests	*Technology Adoption Index Instrumented* ‡			
	Number Technologies	**Min. Four** Technologies	**Number** Practices	**Min. Four** Practices
Dependent Variable (HDDS)				
Anderson Canonic Corr. LM Statistic - Ho: Equation under-identified	R	R	R	R
Cragg-Donald Wald F Statistic) - Ho: Equation weakly identified	R	NR	R	NR
Sargan statistic Ho: Equation is over-identified	EI	EI	EI	EI
Endogeneity test - Ho: Regressors can be treated as exogenous	R	R	R	NR
Anderson-Rubin Wald test - Ho: Instruments are weak	R	R	R	NR
Dependent Variable (HFIAS)				
Anderson Canonic Corr. LM Statistic - Ho: Equation under-identified	R	R	R	R
Cragg-Donald Wald F Statistic) - Ho: Equation weakly identified	NR	NR	R	NR
Sargan statistic Ho: Equation is over-identified	EI	EI	EI	EI
Endogeneity test - Ho: Regressors can be treated as exogenous	NR	NR	NR	NR
Anderson-Rubin Wald test - Ho: Instruments are weak	NR	NR	NR	NR

R: Null hypothesis rejected; NR: Null hypothesis non-rejected; and EI: Equation exactly identified

‡ The null hyphothesis in most cases is rejected at %5 confidence, but the threshold for rejection is NR is %10.

6

Appendix 6.5. Impact of technology adoption on household food insecurity (IV FE – second-stage)

Variables	*Technology Adoption Index Instrumented*			
	Number Technologies	**Min. Four Technologies**	**Number Practices**	**Min. Four Practices**
Dependent Variable (HDDS)				
Tech. adoption index ¥	-0.984**	-2.717*	-0.788*	-2.809*
	(0.456)	(1.562)	(0.405)	(1.629)
Tech. adoption index & period 1 ¥	0.596*	1.738*	0.553*	1.798*
	(0.332)	(1.014)	(0.310)	(1.035)
Tech. adoption index & period 2 ¥	1.192***	2.842**	0.991**	3.020**
	(0.407)	(1.184)	(0.391)	(1.311)
Tech. adoption index & farmer women	0.148	0.192	0.129	0.149
	(0.137)	(0.532)	(0.150)	(0.544)
Tech. adoption index & land cultivated	-0.000**	-0.000**	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Dependent Variable (HFIAS)				
Tech. adoption index	1.115	3.733	1.071	4.176
	(1.115)	(3.996)	(1.034)	(4.118)
Tech. adoption index & period 1 ¥	1.170-	3.387-	1.059-	3.283-
	(0.803)	(2.485)	(0.792)	(2.519)
Tech. adoption index & period 2 ¥	0.831-	1.080-	0.871-	2.045-
	(0.992)	(2.876)	(1.015)	(3.222)
Tech. adoption index & farmer women	0.044-	0.178	0.040-	0.126
	(0.340)	(1.231)	(0.386)	(1.262)
Tech. adoption index & land cultivated	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)

* p<0.10, ** p<0.05, ***p<0.01

¥ first stage predicted value of the tech. adoption index

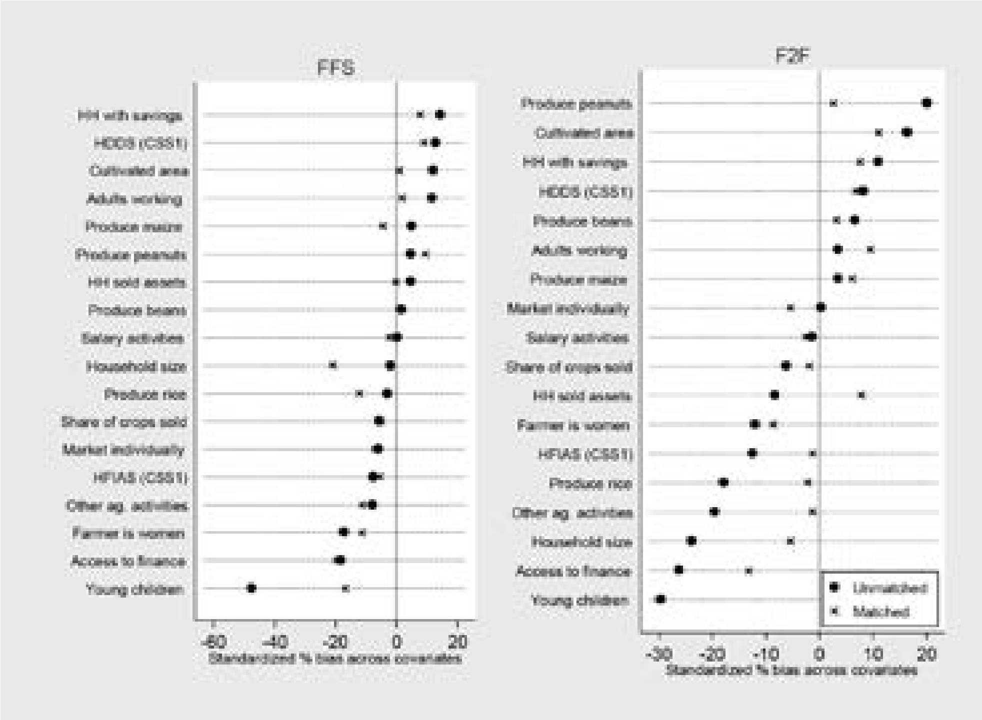
Appendix 6.6. Impact of technology adoption on HDDS and HFIAS (IV OLS)

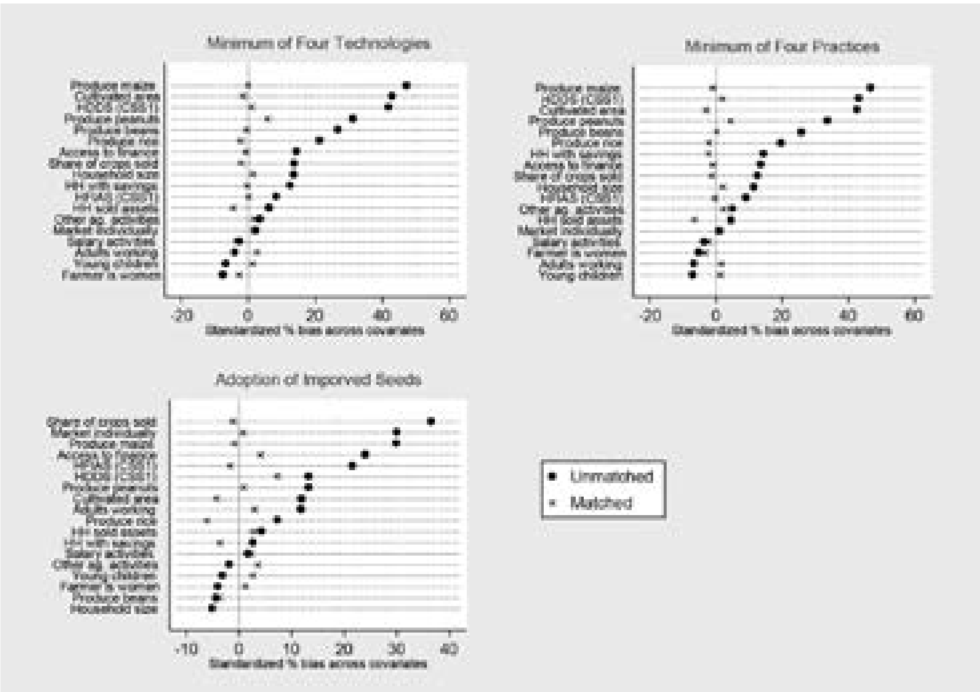
Variables	*Technology Adoption Index Instrumented*			
	Number Technologies	**Min. Four Technologies**	**Number Practices**	**Min. Four Practices**
Dependent Variable (HDDS)				
Tech. adoption index ¥	0.189**	0.456***	0.187***	0.463***
	(0.078)	(0.172)	(0.055)	(0.174)
Tech. adoption index & period 1 ¥	0.099	0.165	0.078	0.129
	(0.074)	(0.175)	(0.060)	(0.172)
Tech. adoption index & period 2 ¥	0.278**	0.329	0.147*	0.299
	(0.108)	(0.261)	(0.084)	(0.256)
Tech. adoption index & farmer women	-0.061	-0.067	-0.043	-0.038
	(0.074)	(0.160)	(0.058)	(0.161)
Tech. adoption index & land cultivated	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Dependent Variable (HFIAS)				
Tech. adoption index	0.027	0.466	0.116	0.404
	(0.227)	(0.478)	(0.165)	(0.476)
Tech. adoption index & period 1 ¥	-0.065	-0.018	-0.302	0.015
	(0.248)	(0.543)	(0.188)	(0.536)
Tech. adoption index & period 2 ¥	-0.159	-0.324	-0.530**	-0.514
	(0.312)	(0.864)	(0.224)	(0.836)
Tech. adoption index & farmer women	0.102	0.442	0.167	0.439
	(0.179)	(0.444)	(0.158)	(0.438)
Tech. adoption index & land cultivated	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)

* p<0.10, ** p<0.05, ***p<0.01
¥ first stage predicted value of the tech. adoption index

6

Appendix 6.7. Baseline standardized bias across covariates using Kernel Distribution





Appendix 6.8. Descriptive statistics and five nearest neighbor balancing tests (baseline)

Variables	Unmatched/ Matched	Technology Adoption									Program Participation					
		Min. of Four Technologies			Min. Four Practices			Use of Improved Seeds			FFS			F2F		
		Treated	Control	p > |t|	Treated	Control	p > |t|	Treated	Control	p > |t|	Treated	Control	p > |t|	Treated	Control	p > |t|
HDDS (CSS1)	U	3.732	3.150	0.000	3.753	3.147	0.000	3.518	3.332	0.079	3.480	3.298	0.152	3.412	3.298	0.387
	M	3.678	3.750	0.536	3.706	3.678	0.816	3.518	3.422	0.406	3.480	3.399	0.582	3.402	3.246	0.369
HFIAS (CSS1)	U	16.664	16.329	0.261	16.683	16.322	0.227	16.977	16.129	0.004	16.448	16.750	0.384	16.243	16.750	0.184
	M	16.688	16.650	0.906	16.690	16.544	0.658	16.977	17.056	0.805	16.448	16.693	0.547	16.348	16.415	0.893
Household (HH) size	U	6.324	6.002	0.068	6.301	6.026	0.120	6.086	6.207	0.497	6.292	6.338	0.825	5.770	6.338	0.011
	M	6.290	6.303	0.945	6.278	6.117	0.403	6.086	6.137	0.792	6.292	6.683	0.109	5.759	5.717	0.886
% of HHs where farmer is women	U	0.330	0.370	0.258	0.337	0.365	0.427	0.340	0.362	0.533	0.320	0.404	0.052	0.341	0.404	0.167
	M	0.338	0.371	0.377	0.343	0.381	0.330	0.340	0.341	0.986	0.320	0.402	0.096	0.344	0.333	0.850
% of children under 5 in the HH	U	0.353	0.368	0.426	0.353	0.368	0.419	0.359	0.365	0.758	0.314	0.425	0.000	0.355	0.425	0.003
	M	0.356	0.351	0.804	0.355	0.349	0.754	0.359	0.363	0.864	0.314	0.350	0.130	0.358	0.443	0.008
% of adults working in HH	U	0.831	0.841	0.595	0.827	0.843	0.380	0.852	0.824	0.123	0.851	0.822	0.186	0.831	0.822	0.712
	M	0.832	0.810	0.269	0.828	0.810	0.394	0.852	0.847	0.784	0.851	0.853	0.940	0.834	0.821	0.670
% of HHs participating in other agric. act	U	0.274	0.257	0.595	0.279	0.254	0.443	0.261	0.266	0.877	0.267	0.303	0.374	0.221	0.303	0.049
	M	0.268	0.274	0.858	0.271	0.247	0.496	0.261	0.231	0.397	0.267	0.308	0.376	0.223	0.220	0.955
% of HHs engaged in salary activities	U	0.065	0.073	0.703	0.064	0.073	0.623	0.073	0.068	0.820	0.071	0.070	0.965	0.066	0.070	0.873
	M	0.067	0.097	0.164	0.065	0.048	0.365	0.073	0.065	0.725	0.071	0.071	0.995	0.063	0.067	0.883
% of HH sold any asset	U	0.231	0.206	0.421	0.228	0.209	0.537	0.224	0.207	0.574	0.238	0.219	0.611	0.186	0.219	0.376
	M	0.229	0.265	0.301	0.229	0.274	0.199	0.224	0.221	0.922	0.238	0.238	0.996	0.188	0.140	0.316
% of HHs with savings	U	0.159	0.116	0.094	0.163	0.114	0.051	0.139	0.129	0.719	0.153	0.105	0.113	0.142	0.105	0.240
	M	0.153	0.145	0.771	0.157	0.156	0.982	0.139	0.156	0.552	0.153	0.127	0.474	0.143	0.112	0.469
Cultivated area (square meters)	U	7.595	7.271	0.000	7.598	7.275	0.000	7.464	7.373	0.117	7.432	7.339	0.178	7.461	7.339	0.083
	M	7.572	7.600	0.637	7.579	7.579	0.990	7.464	7.505	0.517	7.432	7.444	0.887	7.465	7.368	0.302
% of crop production sold	U	0.207	0.175	0.066	0.206	0.176	0.091	0.240	0.153	0.000	0.185	0.199	0.515	0.184	0.199	0.508
	M	0.209	0.204	0.789	0.209	0.201	0.683	0.240	0.245	0.803	0.185	0.206	0.384	0.182	0.172	0.730
% of farmers selling individually	U	0.676	0.666	0.772	0.673	0.668	0.891	0.752	0.614	0.000	0.651	0.680	0.498	0.681	0.680	0.971
	M	0.675	0.643	0.391	0.673	0.635	0.325	0.752	0.761	0.806	0.651	0.706	0.260	0.679	0.659	0.733
% of farmers with access to financial serv	U	0.383	0.315	0.053	0.381	0.318	0.072	0.413	0.299	0.001	0.327	0.417	0.038	0.292	0.417	0.005
	M	0.379	0.396	0.659	0.379	0.358	0.592	0.413	0.409	0.921	0.327	0.444	0.020	0.290	0.328	0.503
Percentage of farmers producing maize	U	0.523	0.298	0.000	0.526	0.301	0.000	0.482	0.336	0.000	0.406	0.382	0.581	0.398	0.382	0.717
	M	0.516	0.503	0.738	0.520	0.528	0.834	0.482	0.488	0.884	0.406	0.431	0.623	0.397	0.354	0.475
Percentage of farmers producing beans	U	0.308	0.194	0.000	0.308	0.197	0.001	0.231	0.249	0.568	0.238	0.232	0.875	0.261	0.232	0.481
	M	0.293	0.307	0.702	0.294	0.299	0.888	0.231	0.259	0.418	0.238	0.223	0.717	0.263	0.246	0.752
Percentage of farmers producing peanuts	U	0.237	0.119	0.000	0.244	0.116	0.000	0.198	0.148	0.077	0.157	0.140	0.610	0.217	0.140	0.033
	M	0.226	0.196	0.348	0.232	0.228	0.908	0.198	0.197	0.984	0.157	0.140	0.651	0.214	0.188	0.599
Percentage of farmers producing rice	U	0.069	0.024	0.003	0.067	0.026	0.007	0.053	0.038	0.326	0.050	0.057	0.719	0.022	0.057	0.057
	M	0.061	0.070	0.629	0.062	0.069	0.720	0.053	0.066	0.493	0.050	0.071	0.371	0.018	0.019	0.924
Mean Bias	U		17.000			17.000			12.500			10.200			12.600	
	M		4.700			4.300			3.000			8.200			7.200	
Median Bias	U		13.000			12.100			9.500			6.900			11.800	
	M		3.700			3.500			2.200			7.000			4.700	
p>chi2	U		0.000			0.000			0.000			0.000			0.000	
	M		0.974			0.994			1.000			0.357			0.733	

* p<0.10, ** p<0.05, *** p<0.01

6

Appendix 6.9. Descriptive statistics and five nearest neighbor balancing tests (end line)

Variables		Technology Adoption									Program Participation					
		Min. of Four Technologies			Min. Four Practices			Use of Improved Seeds			FFS			F2F		
		Treated	Control	p > |t|	Treated	Control	p > |t|	Treated	Control	p > |t|	Treated	Control	p > |t|	Treated	Control	p > |t|
HDDS (CSS1)	U	3.428	3.429	0.998	3.431	3.412	0.929	3.416	3.440	0.892	3.487	3.201	0.060	3.362	3.201	0.286
	M	3.427	3.380	0.665	3.423	3.512	0.425	3.396	3.321	0.538	3.482	3.292	0.266	3.362	3.442	0.693
HFIAS (CSS1)	U	16.232	16.531	0.635	16.212	16.647	0.483	16.433	15.967	0.345	16.518	16.504	0.973	16.115	16.504	0.397
	M	16.333	17.047	0.013	16.373	16.907	0.072	16.335	16.247	0.811	16.509	16.783	0.573	16.115	15.748	0.550
Household (HH) size	U	5.938	6.327	0.285	5.950	6.235	0.424	6.014	5.857	0.582	6.202	6.410	0.396	5.661	6.410	0.005
	M	5.967	6.072	0.616	5.978	6.161	0.389	5.986	5.891	0.633	6.204	6.906	0.013	5.661	6.028	0.277
% of HHs where farmer is women	U	0.346	0.408	0.396	0.345	0.412	0.355	0.365	0.319	0.419	0.329	0.360	0.548	0.385	0.360	0.646
	M	0.352	0.375	0.529	0.355	0.402	0.213	0.360	0.335	0.543	0.332	0.340	0.883	0.385	0.414	0.683
% of children under 5 in the HH	U	0.325	0.299	0.498	0.325	0.294	0.393	0.319	0.321	0.938	0.302	0.418	0.000	0.348	0.418	0.012
	M	0.322	0.320	0.916	0.322	0.319	0.859	0.321	0.311	0.630	0.304	0.352	0.083	0.348	0.447	0.008
% of adults working in HH	U	0.834	0.835	0.996	0.835	0.831	0.922	0.835	0.831	0.875	0.840	0.831	0.719	0.819	0.831	0.695
	M	0.830	0.817	0.508	0.829	0.827	0.913	0.827	0.842	0.477	0.839	0.837	0.964	0.819	0.831	0.762
% of HHs participating in other agric. ac	U	0.255	0.163	0.162	0.257	0.157	0.122	0.256	0.187	0.178	0.272	0.331	0.230	0.201	0.331	0.009
	M	0.239	0.297	0.095	0.235	0.327	0.009	0.229	0.245	0.660	0.274	0.351	0.172	0.201	0.206	0.940
% of HHs engaged in salary activities	U	0.067	0.102	0.382	0.068	0.098	0.437	0.075	0.055	0.513	0.070	0.072	0.949	0.069	0.072	0.919
	M	0.067	0.089	0.283	0.068	0.087	0.363	0.069	0.052	0.391	0.066	0.102	0.276	0.069	0.093	0.528
% of HH sold any asset	U	0.220	0.204	0.802	0.221	0.196	0.686	0.225	0.198	0.581	0.250	0.187	0.163	0.172	0.187	0.738
	M	0.224	0.139	0.005	0.219	0.138	0.007	0.207	0.219	0.740	0.248	0.200	0.359	0.172	0.097	0.149
% of HHs with savings	U	0.164	0.041	0.023	0.165	0.039	0.018	0.167	0.099	0.112	0.154	0.079	0.037	0.132	0.079	0.135
	M	0.139	0.052	0.000	0.130	0.062	0.004	0.124	0.124	1.000	0.146	0.134	0.781	0.132	0.134	0.972
Cultivated area (square meters)	U	7.461	7.451	0.934	7.462	7.446	0.898	7.487	7.408	0.408	7.430	7.316	0.181	7.454	7.316	0.107
	M	7.452	7.460	0.908	7.453	7.407	0.471	7.463	7.499	0.593	7.430	7.445	0.874	7.454	7.336	0.284
% of crop production sold	U	0.187	0.165	0.537	0.188	0.166	0.539	0.190	0.171	0.509	0.186	0.190	0.866	0.181	0.190	0.746
	M	0.178	0.211	0.091	0.180	0.225	0.020	0.190	0.196	0.784	0.187	0.206	0.519	0.181	0.189	0.822
% of farmers selling individually	U	0.645	0.673	0.699	0.646	0.667	0.774	0.669	0.582	0.132	0.645	0.662	0.739	0.661	0.662	0.986
	M	0.642	0.604	0.312	0.642	0.640	0.948	0.647	0.642	0.901	0.642	0.683	0.480	0.661	0.704	0.531
% of farmers with access to financial services	U	0.299	0.327	0.697	0.298	0.333	0.609	0.317	0.253	0.242	0.325	0.403	0.129	0.276	0.403	0.018
	M	0.306	0.330	0.515	0.309	0.358	0.183	0.309	0.337	0.489	0.327	0.419	0.119	0.276	0.368	0.172
Percentage of farmers producing maize	U	0.419	0.306	0.132	0.419	0.314	0.155	0.410	0.396	0.813	0.417	0.353	0.223	0.385	0.353	0.555
	M	0.415	0.442	0.480	0.414	0.417	0.937	0.400	0.450	0.235	0.412	0.426	0.817	0.385	0.299	0.222
Percentage of farmers producing beans	U	0.255	0.204	0.441	0.257	0.196	0.352	0.263	0.209	0.300	0.241	0.201	0.378	0.247	0.201	0.339
	M	0.258	0.210	0.147	0.256	0.209	0.158	0.247	0.247	0.984	0.239	0.277	0.480	0.247	0.140	0.077
Percentage of farmers producing peanuts	U	0.176	0.224	0.412	0.177	0.216	0.506	0.184	0.176	0.855	0.145	0.108	0.311	0.218	0.108	0.010
	M	0.173	0.144	0.307	0.173	0.141	0.262	0.178	0.191	0.693	0.142	0.087	0.183	0.218	0.224	0.923
Percentage of farmers producing rice	U	0.035	0.061	0.377	0.035	0.059	0.419	0.041	0.033	0.732	0.053	0.058	0.841	0.017	0.058	0.055
	M	0.027	0.008	0.069	0.028	0.012	0.162	0.040	0.028	0.423	0.049	0.102	0.076	0.017	0.034	0.427
Mean Bias	U		11.600			12.000			8.600			12.000			14.600	
	M		9.400			9.700			4.200			11.700			12.000	
Median Bias	U		11.500			10.900			8.000			10.300			11.600	
	M		7.600			7.600			4.000			10.300			9.100	
p>chi2	U		0.435			0.418			0.596			0.000			0.000	
	M		0.001			0.006			0.995			0.125			0.306	

* p<0.10, ** p<0.05, *** p<0.01

6

Appendix 6.10. Impact of training and adoption on HDDS/HFIAS (using Nearest-Neighbor)

Variables		Baseline				Period 2			
		Treated	Control	Balance	t-stat	Treated	Control	ATT	t-stat
HH dietary diversity score (HDDS)									
Minimum of Four Technologies	U	3.732	3.15	0.582***	5.65	4.595	3.388	1.208***	4.00
	M	3.678	3.750	-0.072	-0.58	4.594	3.585	1.009***	3.48
Minimum of Four Practices	U	3.753	3.147	0.606***	5.88	4.602	3.392	1.210***	4.08
	M	3.706	3.678	0.027	0.22	4.602	3.634	0.968***	3.48
Use of Improved Seeds	U	3.518	3.332	0.186*	1.76	4.577	4.000	0.577**	2.40
	M	3.518	3.422	0.096	0.78	4.560	3.979	0.581**	2.25
Participation in Farmer Field Schools	U	3.480	3.355	0.126	1.17	4.373	4.441	-0.068	-0.40
	M	3.480	3.527	-0.047	-0.39	4.367	4.507	-0.140	-0.72
Participation in Farmer-to-Farmer	U	3.412	3.399	0.013	0.11	4.586	4.330	0.257	1.43
	M	3.402	3.414	-0.013	-0.10	4.586	4.248	0.338	1.56
HH Food Insecurity Access Scale (HFIAS)									
Minimum of Four Technologies	U	16.664	16.329	0.334	1.12	12.622	14.224	-1.603**	-2.03
	M	16.688	16.650	0.038	0.11	12.636	14.793	-2.156**	-2.68
Minimum of Four Practices	U	16.683	16.322	0.360	1.21	12.631	14.098	-1.467*	-1.89
	M	16.690	16.544	0.145	0.40	12.660	14.651	-1.990**	-2.51
Use of Improved Seeds	U	16.977	16.129	0.847***	2.86	12.760	13.187	-0.427	-0.59
	M	16.977	17.056	-0.079	-0.23	12.760	13.187	-0.427	-0.59
Participation in Farmer Field Schools	U	16.448	16.498	-0.049	-0.16	13.031	12.671	0.360	0.79
	M	16.448	16.453	-0.004	-0.01	13.106	12.820	0.286	0.55
Participation in Farmer-to-Farmer	U	16.243	16.583	-0.340	-1.07	12.644	12.907	-0.264	-0.55
	M	16.348	16.211	0.138	0.38	12.644	13.313	-0.669	-1.20

* p<0.10, ** p<0.05, ***p<0.01

Appendix 6.11. Impact of FFS/F2F training on HDDS and HFIAS (DID + PS weighting)

Variables	HDDS		HFIAS	
	DID	DID Weighted	DID	DID Weighted
Dummy period 1	2.700***	2.610***	12.221***	12.987***
	(0.317)	(0.355)	(0.948)	(1.068)
Dummy period 2	3.691***	3.725***	10.712***	11.654***
	(0.384)	(0.425)	(0.989)	(1.062)
Participation in FFS period 1	0.323	0.175	-0.267	-0.338
	(0.372)	(0.464)	(1.484)	(1.404)
Participation in F2F period 1	0.220	0.066	-0.238	-1.109
	(0.357)	(0.447)	(1.462)	(1.377)
Participation in FFS period 2	0.528	0.251	0.218	-0.279
Participation in F2F period 2	(0.397)	(0.481)	(1.603)	(1.561)
	0.443	0.326	0.068	-0.737
Household size	(0.377)	(0.459)	(1.552)	(1.464)
	0.016	0.008	-0.014	-0.075
Access to farmland	(0.026)	(0.036)	(0.061)	(0.066)
	1.448***	1.613***	-1.223	-0.637
Area cultivated	(0.283)	(0.303)	(0.901)	(0.930)
	-0.000	-0.000	-0.000**	-0.000
Market products individually	(0.000)	(0.000)	(0.000)	(0.000)
	-0.051	0.045	-0.619***	-0.497*
Access to financial services	(0.077)	(0.101)	(0.231)	(0.270)
	0.121*	0.015	-0.527***	-0.704***
Farmer produces maize	(0.070)	(0.086)	(0.203)	(0.221)
	0.190**	0.226**	-0.260	-0.309
Farmer produces beans	(0.085)	(0.103)	(0.229)	(0.269)
	0.134	0.187	0.322	0.282
Farmer produces peanuts	(0.104)	(0.127)	(0.280)	(0.325)
Farmer produces rice	0.201*	0.259**	0.280	0.000
	(0.105)	(0.122)	(0.288)	(0.333)
Farmer is women (proportion)	0.908***	0.839***	-0.667	-1.059
	(0.246)	(0.244)	(0.599)	(0.691)
Lag of HDDS	0.003	0.077	0.629**	0.399
	(0.102)	(0.120)	(0.291)	(0.348)
Lag of HFIAS	-0.875***	-0.886***	-0.853***	-0.872***
	(0.038)	(0.041)	(0.033)	(0.037)
Village fixed effect	Yes	Yes	Yes	Yes
R2	0.452	0.456	0.441	0.456
RMSE	1.741	1.764	4.877	4.809
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	1412	1210	1359	1166

* p<0.10, ** p<0.05, *** p<0.01

Appendix 6.12. Impact of technology adoption on HDDS and HFIAS (DID + PS weighting)

Variables	HDDS		HFIAS	
	DID	DID Weighted	DID	DID Weighted
Dummy period 1	2.700***	2.610***	12.221***	12.987***
	(0.317)	(0.355)	(0.948)	(1.068)
Dummy period 2	3.691***	3.725***	10.712***	11.654***
	(0.384)	(0.425)	(0.989)	(1.062)
Participation in FFS period 1	0.323	0.175	-0.267	-0.338
	(0.372)	(0.464)	(1.484)	(1.404)
Participation in F2F period 1	0.220	0.066	-0.238	-1.109
	(0.357)	(0.447)	(1.462)	(1.377)
Participation in FFS period 2	0.528	0.251	0.218	-0.279
	(0.397)	(0.481)	(1.603)	(1.561)
Participation in F2F period 2	0.443	0.326	0.068	-0.737
	(0.377)	(0.459)	(1.552)	(1.464)
Household size	0.016	0.008	-0.014	-0.075
	(0.026)	(0.036)	(0.061)	(0.066)
Access to farmland	1.448***	1.613***	-1.223	-0.637
	(0.283)	(0.303)	(0.901)	(0.930)
Area cultivated	-0.000	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Market products individually	-0.051	0.045	-0.619***	-0.497*
	(0.077)	(0.101)	(0.231)	(0.270)
Access to financial services	0.121*	0.015	-0.527***	-0.704***
	(0.070)	(0.086)	(0.203)	(0.221)
Farmer produces maize	0.190**	0.226**	-0.260	-0.309
	(0.085)	(0.103)	(0.229)	(0.269)
Farmer produces beans	0.134	0.187	0.322	0.282
	(0.104)	(0.127)	(0.280)	(0.325)
Farmer produces peanuts	0.201*	0.259**	0.280	0.000
	(0.105)	(0.122)	(0.288)	(0.333)
Farmer produces rice	0.908***	0.839***	-0.667	-1.059
	(0.246)	(0.244)	(0.599)	(0.691)
Farmer is women (proportion)	0.003	0.077	0.629**	0.399
	(0.102)	(0.120)	(0.291)	(0.348)
Lag of HDDS	-0.875***	-0.886***		
	(0.038)	(0.041)		
Lag of HFIAS			-0.853***	-0.872***
			(0.033)	(0.037)
Village fixed effect	Yes	Yes	Yes	Yes
R2	0.452	0.456	0.441	0.456
RMSE	1.741	1.764	4.877	4.809
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	1412	1210	1359	1166

* p<0.10, ** p<0.05, *** p<0.01

6

Appendix 6.13. Impact of adoption of practices on HDDS and HFIAS (DID + PS weighting)

Variables	HDDS		HFIAS	
	DID	DID Weighted	DID	DID Weighted
Dummy period 1	2.474***	2.342***	11.807***	12.563***
	(0.323)	(0.364)	(0.976)	(1.113)
Dummy period 2	3.359***	3.333***	11.848***	12.199***
	(0.382)	(0.433)	(1.007)	(1.125)
Minimum of four practices period 1	0.531***	0.571***	0.164	0.454
	(0.102)	(0.116)	(0.389)	(0.436)
Minimum of four practices period 2	0.745***	0.743***	-1.388***	-0.635
	(0.174)	(0.217)	(0.497)	(0.634)
Household size	0.015	0.007	-0.028	-0.082
	(0.026)	(0.035)	(0.060)	(0.066)
Access to farmland	1.346***	1.525***	-1.114	-0.625
	(0.273)	(0.295)	(0.876)	(0.921)
Area cultivated	-0.000	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Market products individually	-0.066	0.042	-0.627***	-0.505*
	(0.076)	(0.099)	(0.230)	(0.270)
Access to financial services	0.132*	0.038	-0.525***	-0.705***
	(0.069)	(0.084)	(0.202)	(0.220)
Farmer produces maize	0.193**	0.221**	-0.259	-0.282
	(0.084)	(0.101)	(0.228)	(0.271)
Farmer produces beans	0.116	0.167	0.342	0.294
	(0.104)	(0.126)	(0.281)	(0.328)
Farmer produces peanuts	0.179*	0.229*	0.302	0.014
	(0.105)	(0.122)	(0.288)	(0.334)
Farmer produces rice	0.845***	0.819***	-0.628	-1.086
	(0.243)	(0.250)	(0.598)	(0.687)
Farmer is women (proportion)	0.013	0.089	0.605**	0.409
	(0.101)	(0.119)	(0.289)	(0.349)
Lag of HDDS	-0.879***	-0.890***		
	(0.038)	(0.040)		
Lag of HFIAS			-0.853***	-0.869***
			(0.032)	(0.038)
Village fixed effect	Yes	Yes	Yes	Yes
R2	0.463	0.468	0.444	0.455
RMSE	1.721	1.743	4.861	4.807
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	1412	1210	1359	1166

* p<0.10, ** p<0.05, *** p<0.01

Appendix 6.14. Impact of adoption of improved seeds on HDDS/HFIAS (DID + PS weighting)

Variables	HDDS		HFIAS	
	DID	DID Weighted	DID	DID Weighted
Dummy period 1	2.745***	2.675***	12.344***	13.096***
	(0.334)	(0.368)	(0.937)	(1.073)
Dummy period 2	3.513***	3.552***	10.904***	11.755***
	(0.368)	(0.405)	(0.929)	(1.034)
Use of improved seed period 1	-0.010	0.013	-0.607	-0.514
	(0.109)	(0.131)	(0.385)	(0.428)
Use of improved seed period 2	0.584***	0.572***	-0.254	-0.266
	(0.164)	(0.203)	(0.461)	(0.524)
Household size	0.018	0.010	-0.015	-0.072
	(0.026)	(0.035)	(0.061)	(0.066)
Access to farmland	1.342***	1.541***	-1.215	-0.621
	(0.283)	(0.297)	(0.899)	(0.927)
Area cultivated	-0.000	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Market products individually	-0.042	0.054	-0.609***	-0.473*
	(0.076)	(0.101)	(0.231)	(0.274)
Access to financial services	0.110	-0.000	-0.502**	-0.702***
	(0.070)	(0.085)	(0.203)	(0.222)
Farmer produces maize	0.184**	0.218**	-0.239	-0.267
	(0.085)	(0.103)	(0.228)	(0.267)
Farmer produces beans	0.133	0.184	0.343	0.317
	(0.104)	(0.127)	(0.280)	(0.324)
Farmer produces peanuts	0.199*	0.256**	0.272	0.010
	(0.105)	(0.122)	(0.289)	(0.334)
Farmer produces rice	0.917***	0.874***	-0.670	-1.074
	(0.245)	(0.246)	(0.599)	(0.697)
Farmer is women (proportion)	-0.007	0.063	0.638**	0.411
	(0.101)	(0.119)	(0.288)	(0.348)
Lag of HDDS	-0.872***	-0.886***		
	(0.038)	(0.040)		
Lag of HFIAS			-0.852***	-0.870***
			(0.033)	(0.038)
Village fixed effect	Yes	Yes	Yes	Yes
R2	0.457	0.460	0.442	0.455
RMSE	1.731	1.756	4.870	4.808
Valor-p>F	0.000	0.000	0.000	0.000
Obs.	1412	1210	1359	1166

* p<0.10, ** p<0.05, *** p<0.01

7

Synthesis

7

7.1. General introduction

For the vast majority of small-scale farmers in DRC, agricultural training and the adoption of agricultural technologies are arguably the most certain and shortest pathway to change their farming conditions and, (through higher increased technology adoption, crop productivity, and connections with markets) provide a better present and future for their families. Having the privilege to visit a considerable number of JENGA II's villages on various occasions, I have witnessed the upside of the program's interventions, when families wrote their own story of success. The participation in FFS and F2F activities apparently opened them to an array of opportunities, and resulted in changes in the way that they live, see their production systems, commercialize their products, and interact with other players in their own social and business environment. Sadly, I have also seen those not so few cases where the opportunity to participate in something novel and exciting soon became part of the inertia and another failed attempt to experience a change in their farms, change which at times farmers do not even comprehend. It appears that there is something in people's mindset and in the way that they engage in externally promoted development activities, and/or in the intervention itself, which seems to make a significant difference in terms of the outcome. This raises the question about what is it that makes a program like JENGA II achieve its goals for some farmers, while failing to make a difference to others.

Small-scale agriculture is the main source of incomes in DRC but farmers are between the poorest in the region. Agricultural productivity and incomes must urgently improve, but this needs to be linked to improvements in household food security and living standards. The primary goal of this research is to better understand the close relationship between agricultural training, the adoption of agricultural technologies, crop productivity, and household food insecurity and quality of diets. It also helps narrow the literature gap on the role of input subsidies to foster small-scale farmers' uptake of input technologies and other productivity-enhancing complementary practices. Studying these relationships may reveal features of the intervention that contributed (or did not contribute) to the achievement of expected impacts, while also shedding light on behavioral aspects, and some farmer-driven initiatives which may condition the extent of the impact. Throughout the main chapters, I identify practical implications that are highly important for the design and implementation of new development programs and policies.

This research is part of a wide collection of studies dedicated to appraise the impact of FFS on different types of outcomes (Davis, Nkonya *et al.*, 2012; Feder, Murgai *et al.*, 2004a, 2004b; Feder, Willett *et al.*, 2001; Godtland, Sadoulet *et al.*, 2004; Van den Berg & Jiggins, 2007; Waddington, Snilstveit *et al.*, 2014). Our findings support the large body of the literature which has found positive impacts of FFS on technology adoption, crop productivity, incomes and food security, but also expands the literature in two main areas. First, it explores the role of F2F training as an important avenue to alleviate the cost of FFSs while maintaining comparable levels of impact. Because of its low capacity to transmit knowledge from its graduates to other farmers (Davis, Nkonya *et al.*, 2012; Quizon, Feder *et al.*, 2001; Rola, Jamias *et al.*, 2002), the high cost of FFS have been largely criticized (Feder, Murgai *et al.*, 2004a), yet virtually neglected by researchers. Second, we add to the literature by evaluating the impact of FFS using a three-period sizable panel dataset which allows us to better address issues of self-selection. Most studies have analyzed FFSs and their impact from a macro standpoint. But even the studies that used farm level information have been questioned given their limited capacity to build an appropriate counterfactual, and due to bias towards institutional interests and ideological viewpoints (Waddington, Snilstveit *et al.*, 2014). Davis, Nkonya *et al.* (2012), one of the most prominent recent studies on the impact of FFS, arrived at important conclusions using a similar sample size but spread in three different countries, and a dataset with just two periods.

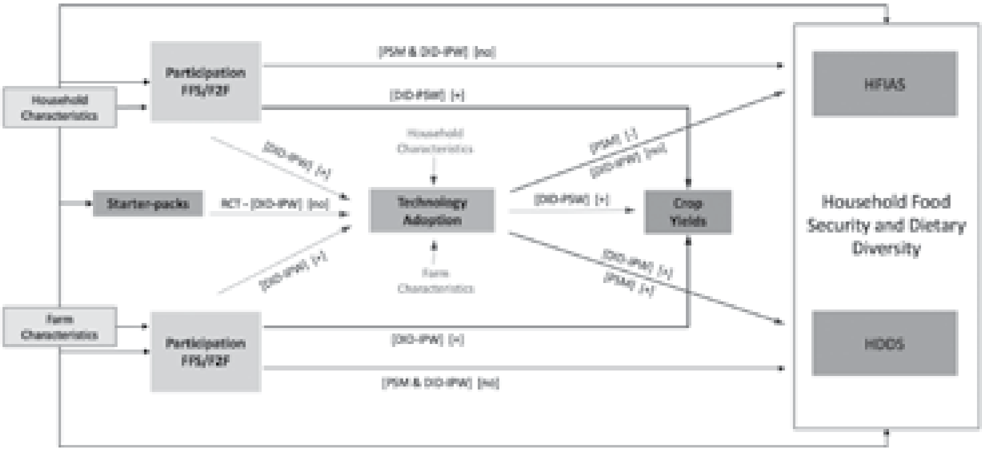
Another important contribution of this thesis is the use of experimental data to evaluate the micro-level impact of a one-shot input starter pack on farmers' adoption of agricultural technologies and crop productivity. The literature on input subsidies is also lengthy, but most of the studies have traditionally focused on national subsidy policies. We have seen a surge in rigorous studies of more localized program subsidy initiatives recently, including Carter, Laajaj *et al.* (2014); Duflo, Kremer *et al.* (2011). However, the evidence of impact is still highly mixed and much more must be done to better understand the role that input subsidies can play in accelerating adoption and productivity grow.

As obvious as the linkages between agriculture and household food security and diet diversification may appear, there has been ample criticism that in many cases agricultural outcomes have not resulted in improved household food security and improved diets. This thesis also contributes to some recent studies dedicated to these threads between agriculture and household food insecurity and nutrition (Larsen & Lilleør, 2014), and highlights how these missed opportunities can be overcome in the context of development projects like JENGA II.

7.2. Key findings and policy implications

Analyzing the sequence of results from the four main chapters in this thesis through the lens of our farmer field school causal model (see Figure 1.1) adapted from Waddington, Snilstveit *et al.* (2014), I can see how the JENGA II program was able generate positive changes in farmers' adoption of improved agricultural technologies in line with (Bunyatta, Mureithi *et al.*; Feder, Murgai *et al.*, 2004a), increased crop productivity (Davis, Nkonya et al., 2012; Van den Berg & Jiggins, 2007) and better household food security through appropriate provision of agricultural training (Larsen & Lilleør, 2014). We have also seen how expensive interventions such as input starter packs are not able to generate the expected levels of impact on yields and consequently on adoption, as also suggested by (Duflo, Kremer *et al.*, 2011). Our findings also underscore several limiting factors that conditioned the extent of the impact of the program, and how even those interventions that generated significant impacts were not able to make substantial differences in the food security and dietary situation of the households. These findings certainly have program and policy implications, so we discuss them in the following sections.

Figure 7.1. JENGA II farmer field schools result pathways



7.2.1. *Addressing a key issue in impact evaluation*

Determining the counterfactual (what would have happened to the beneficiaries had they not participated in the project intervention) is a key challenge that economists often face when estimating the impact of agricultural programs (Duflo, Glennerster *et al.*, 2007; Kakwani, 2000). In the absence of a valid counterfactual it is unfeasible to predict the treatment effect by just differencing the mean outcome of individuals exposed to the intervention from that of the control group. This difference could well be attributed to the impact of the intervention, but also to important systematic differences in pre-existing characteristics of participants and non-participants (Duflo, Glennerster *et al.*, 2007).

Randomized controlled trials (RCT) are considered the gold standard to address this issue as the selection bias can be entirely removed by assigning individuals randomly to the treatment or control group. When the RCT is correctly implemented, it yields unbiased estimates of the mean treatment effect of the program in the target population (Duflo, Glennerster *et al.*, 2007) as both treated and control groups are identical on their pre-treatment characteristics. RCTs however, are highly criticized because of their high implementation costs at large scale (De Janvry, Dustan *et al.*, 2010; Smith & Todd, 2005), and due to logistical constraints when implemented as part of a broader program like JENGA II. In situations when randomized experiments are not possible, alternative pseudo-experimental impact evaluation methods such as propensity score matching, inverse probability score weighted regressions, difference-in-differences, fixed effect, and instrumental variables are used to address the selection bias problem (Duflo, Glennerster *et al.*, 2007).

This thesis expands the use of both RCT and pseudo-experimental methods to estimate the causal effect of field level agricultural interventions on indicators such as technology adoption, crop yields and household food security. *Chapter 3,* uses random assignment of starter packs to small-scale farmers to improve comparability between recipients and non-recipients of the starter packs. The data showed that both groups were very similar on their pre-treatment characteristics which mitigated biases on the estimation of treatment effects. One important weakness related to the rollout of our RCT, which may bias our estimations and affect internal validity of our results, relates to the fact that our F2F control group (non-recipients of starter packs) were exposed to information regarding starter packs through interactions with their FFS farmers. It is possible that the control group of F2F farmers are influenced by the starter packs that their FFS farmers receive, which might create downward bias in the estimates of the impact of the starter pack on technology adoption. This is indeed a threat to our results but difficult to solve given the way our data collection strategy was set up.

The literature only presents a handful of studies which use RCTs to estimate the impact of agricultural subsidies (Carter, Laajaj *et al.*, 2014; Duflo, Kremer *et al.*, 2011), and this thesis contributes to this literature implementing a RCT in the context of a NGO development project which indeed is unconventional, yet a great step towards more evidence-based programing.

Using a quasi-experimental approach to deal with selection bias threats to causal inference in *Chapters 4-6*, this research also generates more understanding about the use of methods such as PSM, DID, IPW, and IV. This effort is part of a rich literature on the use of these methods (Angrist & Krueger, 2001; De Janvry, Dustan *et al.*, 2010; Duflo, Glennerster *et al.*, 2007; Hirano, Imbens *et al.*, 2003;

Imbens & Wooldridge, 2007; Imbens & Wooldridge, 2009; Imbens, 2004). We experienced firsthand how these methods can yield richer results with additional information. Analyzing adoption at the farm level helps us to better understand processes that affect the performance of agriculture and other household outcomes (Bidogeza, 2011).However it can benefit from more information about these key areas that trigger heterogenous response to training, adoption, and other outcomes. This is an important limitation of our research, while we controlled for some levels of heterogeneity at the farm and household level, key information on markets, prices, soil quality, training attendance, etc., was not collected and thus not accounted for in our analysis.

7.2.2. Free handouts to accelerate technology adoption?

In *Chapter 3*, we study the impact of one-shot free input starter packs on the long-term use of improved crop varieties, and the adoption of other productivity-enhancing improved practices. The study assumed two potential channels of impact: firstly, that starter packs play an important role in incentivizing small-scale farmers to adopt complementary productivity-enhancing agricultural practices which arguably help farmers to exploit the full potential of the inputs received in starter packs; and secondly, that starter packs encourage farmers to persistently increase the use of inputs by narrowing knowledge gaps and addressing farmers' capital constraint to invest in inputs. We learned that starter packs did not have the expected levels of impact on farmers' adoption of productivity-enhancing technologies. Although all farmer groups in the study experienced an increase in the use of improved technologies over the three years, no significant differences between recipients and non-recipients of starter packs can be attributed to starter packs. The starter packs did not make recipients more likely to persistently increase the use of improved seeds over the two periods either. This result on the one the hand, is consistent with the finding from Duflo, Kremer et al. (2011) of minimal to no persistence of the provision of one-time input subsidies on the use of inputs. On the other hand, it contradicts Carter, Laajaj *et al.* (2014) who found that one-time provision of a voucher of fertilizer and improved seeds led to substantial increases in fertilizer use through two subsequent cropping seasons. The positive thing about the findings in Carter, Laajaj *et al.* (2014) is that it also finds a positive impact of the subsidy on other outcomes such as agricultural output, farm output, household consumption, and assets. These are indeed the types of higher level outcomes which justify the introduction of these subsidy schemes. However they may not have been achieved had the inputs not been persistently adopted or economically attractive to farmers.

The small size of the starter packs, limitations to access input markets, capital/credit constraints to invest in inputs, and paternalistic behaviors against self-investment in inputs are potential explanations for the lack of impact of starter packs found in the study. However, the fact that the starter packs did not result in higher returns for farmers and thus are not economically attractive is what really seems to be weighing on the results. The starter pack is 100 percent subsidized by the project and this may have also influenced the results, as farmers may have adopted irresponsible behaviors on the use of the starter packs leading to less effect of the seeds on yields. The subsidy in Carter, Laajaj *et al.* (2014) had a farmer 27 percent cost share and this may have influenced the outcomes.

Logically, technologies promoted to farmers must be economically attractive. Hence, the type of technology and the way that they are promoted are key to their sustainable adoption. The use of smart subsidy schemes could reduce input startup costs during the introduction of the technology. We speculate that two key features absent in our subsidy program could positively change the impact of the subsidy. First, introducing the use of a voucher system connected to a network of inputs providers could allow farmers to choose the combination of inputs (mix of fertilizer, seed varieties, quantities, etc.) that is more economically attractive to his farming conditions. Secondly, requiring a cost-share from the farmer could avoid farmers' negative behaviors towards the use of inputs. While the subsidy would still help farmers to overcome their immediate investment constraint and convince them of the returns of the inputs, farmers are still required to cost-share the inputs which may incentivize them to be more accountable about the use of the inputs. These are two characteristics absent in our subsidy scheme, but included in Carter, Laajaj *et al.* (2014), which may have played a role in the different capacities of the interventions to secure a positive impact.

The non-effect of the starter packs on adoption and yields contrasts with the rather consistent effects of FFS/F2F on the same indicators found in *Chapter 4* and *5*. The starter packs were designed to complement the FFS/F2F intervention by helping farmers increase the use of improved inputs and adoption of productivity-enhancing practices. While the starter packs did not achieve these objectives, apparently, they did not discourage farmers from adopting the practices either, or at least not to the extent to offset the effect of the FFS/F2F training.

7.2.3. Farmer-to-farmer training, can it alleviate the costs of farmer field schools?

In *Chapter 4*, we evaluate the levels of impact of FFS and F2F training on small scale farmers' adoption of agricultural technologies. We attempted to use F2F training to improve the dissemination of information and knowledge from FFS participants to several other neighboring farmers, potentially resulting in a lower cost per farmer trained and higher returns to investment (in terms of technology adoption and other higher level outcomes). We learned that FFS and F2F trainings have robust and significant effects on farmer's adoption of agricultural technologies, including the adoption of improved seeds. In the first period, FFS farmers adopted significantly more technologies than the F2F farmers. In the second period, the levels of impact of both FFS and F2F accentuated, however they are statistically the same.

These results are consistent with findings from prominent studies like Davis, Nkonya *et al.* (2012); Van den Berg and Jiggins (2007); Waddington, Snilstveit *et al.* (2014), who have found positive effects of FFS on several outcomes including adoption; and suggest that dissemination of technologies promoted in FFS groups can well be formalized through farmer-to-farmer training (Pontius, Dilts *et al.*, 2002). Feder, Murgai *et al.* (2004b), argue that the viability of FFS training largely depends on the effectiveness of knowledge transmission from FFS farmers to other farmers. Thus, a similar F2F approach has the potential to expand the scope of extension impact whereas substantially alleviating a major constraint to the large-scale introduction of FFS training: the high costs.

Note that the overall increase in the levels adoption is dominated for a small group of technologies, including crop rotation, improved germplasm, mulching, and row planting. This mean that the levels of adoption substantially increased for less than half of the 11 technologies promoted by JENGA II. This seems to be indicate that these technologies are economically attractive to farmers because of their higher impact on the crop performance, thus farmers choose to prioritize their adoption. Another reason for the increase in adoption to be largely dominated by these few technologies is the fact that some of the 11 technologies (e.g. hoeing and weeding) were already used by the great majority of the farmers in the sample. That means that these technologies were not really introduced by the JENGA II to the target area, and thus it did not have a significant effect on their adoption. The results seem also to indicate that the project was fairly effective to boost the adoption of technologies that the farmers are less acquainted with, indicating that JENGA II's extension system played a role on eliminating information and knowledge gaps which prevent farmer's adoption of this type of technologies.

Much more needs to be studied regarding the joint impact of the FFS/F2F approach versus that of a standalone FFS method. Nonetheless, in this chapter we have learned that streamlining the role of FFS from being a training method focused on direct training of potential adopters of farming technologies to one whose primary purpose is to form farmers that sustainably articulate knowledge diffusion through farmer-to-farmer communications, may yield attractive and probably more sustainable results while reducing the costs of training delivery. Although the F2F training was only enforced by fairly cursory monitoring, the F2F training activities and the implementation of this 'novel' mixed training approach was relatively successful. I argue that much better results could be achieved by: (1) building the capacity of FFS farmers to be better trainers of trainers; (2) promoting stronger participation of F2F farmers in project complementary activities such as field days, exchange visits, fairs and nutrition related activities; (3) improving the monitoring of F2F participant activities; and (4) promoting novel initiatives such as labor sharing schemes which may incentivize the participation of farmers in F2F trainings and consolidate the knowledge of the FFS farmers.

7.2.4. From training to impact in yields

In *Chapter 5*, I look at the impact of FFS and F2F trainings on the crop productivity of small-scale farmers. Two key indicators of yield are considered, namely a multi crop-yield index and the cassava yield. The crop yield index considers the yields of the four main crops cultivated in the area, while the alternative measure is the yields of cassava, which is the single most important crop produced in South Kivu. Our results show that both FFS and F2F training have a slow start and the impact on yields is very feeble in the first period. However, both FFS and F2F trainings significantly contributed to increasing farmers' yields in the second period. Overall, participation in FFS and F2F training increased the multi crop-yield index of the FFS and F2F farmers by about 35 and 39 percent respectively, compared to the control group. Similarly, participation in the FFS and F2F training increased the cassava yields of FFS and F2F farmers by about 81 and 58 percent respectively, compared to the yields of control farmers. We also learned that the average yields of the FFS and F2F farmers are not statistically different, which means that farmer-to-farmer training is not less effective than the FFS and can be an attractive improvement to enhance the cost-effectiveness of FFS training.

Our results support two key studies which have found significant effect of FFS training on agricultural productivity. Godtland, Sadoulet *et al.* (2004) concluded that FFS increased the agricultural productivity of FFS participants in Peru by 52 percent, and our results are in line with these levels of achievement. Similarly, Davis, Nkonya *et al.* (2012) found that the value of crop (their measure of crop productivity) grew by about 80 percent in Kenya and 23 percent in Tanzania among FFS members.

The impact of FFS and F2F training in the context of this thesis can also be looked at from a different angle, which may be more illustrative of how this kind of training can make a difference in building farmers' capacity to analyze the issues that they face and make decisions to address them. In the second year of the project an outbreak of the cassava brown streak disease (CBSD) affected large areas of the project, including farms under research. I learned that in the third year of the research – when the disease was at its peak – the cassava yields of the control farmers substantially dropped, while FFS and F2F farmers increased their yields. This may be an important indication of how the training helped the FFS and F2F farmers better mitigate the effects of the CBSD through increased knowledge of the disease and the use of appropriate improved technologies, including practices and seeds.

Two important policy takeaways of this chapter are that on one end, agricultural training seems to play an important role in closing yield gaps through farmers' adoption of improved technologies, and on the other end, F2F approaches can substantially alleviate the costs of training while maintaining comparable levels of impact on yields, which is also one of the conclusions made in *Chapter 4*.

7.2.5. Agricultural training, technology adoption and household food security

Chapter 6 studies the relationships between agricultural training, technology adoption and household food security by assessing the impact of farm level agricultural training and adoption of agricultural technologies on two food security indicators: Household Food Insecurity Access Scale (HFIAS) and Household Dietary Diversity Score (HDDS). Overall, we learned that FFS/F2F training indirectly impact household food security status. As found in *Chapter 4*, participation in FFS/F2F training is found to increase small scale farmers' adoption of improved technologies, and we find in *Chapter 6* that adoption in turn, plays a preponderant role in reducing household food insecurity, specifically the index of dietary diversity (HDDS). This finding supports several studies which have found technology adoption to improve the food security status of households (Alene & Manyong, 2006; Asfaw & Shiferaw, 2010; Kassie, Jaleta *et al.*, 2014; Kumar & Quisumbing, 2010; Minten & Barrett, 2005).

A prominent study on the topic is Larsen and Lilleør (2014). The study found significant impacts of FFS training on food security. The authors suggest that the reallocation of household labor towards own agricultural production and increased agricultural performance are potential mechanisms through which training impacted the levels of food security. Our results are similar, at least those related to improved production. We find that FFS/F2F training had a significant impact on household food security (HDDS), through increased adoption of new agricultural technologies, and increased crop productivity (refer to *Chapter 5*).

In our study technology adoption is significantly associated with higher household dietary diversity (HDDS), which is also concluded by Kassie, Jaleta *et al.* (2014); however we find no consistent evidence of impact on household access to food (HFIAS). Despite the significant impact on HDDS, there is still much room for improvement. In period 2, the food security levels of the households, indicated by the HDDS, are still far below potential levels. Although the households experienced an average increase of about 28 percent in their dietary diversity, the actual mean HDDS obtained in period 2 was just 4.7, which is far below the ideal level (the maximum is 12). While this may indicate that the results on food security are just as good as the impact of FFS on adoption, we may also consider that to achieve a better impact of agricultural activities on food security (especially dietary diversity) more efforts must be made on nutrition behavior change sensitization. According to Wesley and Faminow (2014), even when food is available in the household, its appropriate use may be conditioned by factors such as lack of knowledge about adequate diets. These authors highlight nutrition education as one of the key pathways to promote food security and better nutrition through agriculture production. While our results support the findings of Lashgarara, Mirdamadi *et al.* (2009) that agricultural training plays an important role in promoting food security through increasing farmers' adoption of improved agricultural practices, it also emphasizes the strong need to accompany these agricultural trainings with nutrition behavior change education/sensitization.

By promoting nutrition-specific behavior change, two critical issues that affect household food security may be addressed. First, it helps to shape the perceptions of households on what constitutes food security, and bridges the gap between farmers' own perceived thresholds of food security and the acceptable levels. This can help households to make more realistic decisions based on their real household food security conditions and commit more resources to improve their access to food (HFIAS) and to diversify their food basket (HDDS). While this is not to prevent the farmers from investing the extra income to other equally important factors such as health care and children's education, it helps to sensitize households to invest in their own critical food security needs which are usually the overall goal of development programs. Second, behavior change communications conducted along with the agricultural trainings may help to demystify some of the social and cultural norms that affect the household capacity to satisfy their nutritional needs. This may also provide the opportunity for households to overcome these barriers to attain the expected food security outcomes.

7.3. Final remarks

This thesis to some extent epitomizes an individual and institutional attempt to implement development activities that create more meaningful and sustainable changes in the way that small-scale farmers perform their farming activities in Sub-Saharan Africa. Evidently, several relevant questions are still to be addressed. However, those that were answered in this thesis will hopefully have practical policy and program design implications. Most of our findings in this research have already been studied in the literature, and we either find evidence to support existing findings or contradict them, which should motivate further research on these topics. I conclude this thesis with the following remarks.

Firstly, subsidies can play a key role boosting adoption of improved technologies (Carter, Laajaj *et al.*, 2013), but the free-handout types of subsidies largely promoted by NGOs today must be reconsidered as they seem not to yield the expected levels of impact on adoption and yields. Decisions makers should pay attention to the fact that technologies need to be economically attractive to farmers considering their economies and farming characteristics. We see threats to the validity of our findings related to starter packs which we believe we have dealt with, however we also see important indications in the literature showing results that support ours (Duflo, Kremer *et al.*, 2011).

Secondly, farmer-to-farmer training seems to be a plausible alternative to expand the scope of impact of FFS and reduce the cost of training. This has important implications for stakeholders committed to accelerating growth of small-scale agriculture.

Thirdly, FFS training can have significant impacts on household food security when farmers' participation in training result in higher levels of technology adoption. While this is contrary to critics who contend that agricultural interventions do not have an impact on household food security, it also stresses the need for agricultural programs to pay more attention to how to make FFS training more effective in accelerating adoption.

This research was implemented in eastern DRC, which is an area that is still in a post-conflict situation, where the fears of new conflicts are imminent, the infrastructure is very poor, and farmers' access to private and public services is limited. Therefore, these findings should be looked at through a lens that considers potential key differences which may alter their applicability in other contexts. Because of data constraints we were not able to deeply analyze the heterogeneity of responses of the different types of farmers in the sample. As a result, the findings may exclude differential effects that training and subsidies may have on adoption and household food security.

The definition of impact used in this research is intentionally narrowly focused on technology adoption, yields and food security. But there are other types of impacts and byproducts, such as collective action, capacity development, and the empowerment of women, which are as important but were not considered in the thesis.

The chapters found and discussed significant impacts of FFS and F2F training on several farm and household indicators, but note that this is not a declaration that FFS is the solution to increase technology adoption and close the yield gaps for small scale farmers. There are still a series of pending issues, including cost-effectiveness, sustainability of the system, and knowledge dissemination, which after a closer look may indicate the need to consider alternative approaches that present a better formula to solve these important concerns. Surely, these considerations are, by themselves, areas of further research which, from this end, I encourage other researchers to engage in.

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Summary

The promotion of improved agricultural technologies has been an important area of focus as governments and policy makers seek to increase agricultural productivity and reduce national and household food insecurity. Nevertheless, the effectiveness of the extension program to generate higher levels of technology adoption as well as the impact of adoption on productivity and household food insecurity have often been questioned, and there is still much to be understood about these interrelationships. In this thesis, I use experimental and quasi-experimental data from 25 villages and a total of 1,105 farmers from eastern DRC to investigate the relationship among agricultural training, the adoption of agricultural technologies, crop productivity, and household food insecurity and dietary diversity. I present evidence that contributes to narrow the gap in the literature on the role of input subsidies fostering small-scale farmers' uptake of productivity-enhancing technologies, how farmer field school and farmer-to-farmer trainings affect the adoption of agricultural technologies, how F2F training may reduce the costs of FFS implementation, how adoption materializes on yields of food crops, and how training through the adoption of improved agricultural technologies impacts household food insecurity and the diet diversification of target households.

As a complement to econometric evidence and in order to understand the main findings, I also discuss behavioral features and farmer driven initiatives which somehow condition these impacts. Throughout the four main chapters, I identify practical implications that are highly important for the design and implementation of new programs and policies aimed to address agricultural productivity issues and reduce household food insecurity. In *Chapter 1* I develop a general introduction to the research which discusses the evolution of agricultural extension in the last few decades, and describe FFS and F2F training methodologies. *Chapter 2* provides a detailed description of the project intervention, technologies promoted, research settings and the data collection process. In *Chapter 3*, I report the results of an experimental study that analyses the impact of one-shot input starter packs on the adoption of productivity-

enhancing complementary practices, which have the potential to maximize the impact of starter pack inputs. Additionally, I assess the levels of persistence on farmers' use of improved crop seeds which are included in the starter packs. Overall, I find no evidence of starter packs' impact on small-scale farmers' adoption of productivity-enhancing technologies. Over the two periods, both recipients and non-recipients of starter packs experienced increases in the use of the improved practices promoted, however there is no significant difference between the groups that can be attributed to the starter packs. Similarly, the levels of persistence regarding the use of seeds following the delivery of starter packs were not significant. These results are consistent with studies that have found minimal or no persistence on the use of inputs following the provision of subsidies, including Duflo, Kremer *et al.* (2011). One may argue that the lack of impact of the starter packs is because the non-recipients bought the seeds or that the seeds were not effective, but only the practices. However, the limited impact that starter packs had on yields in the first year may logically explain that farmers refrained from using improved seeds subsequently because the inputs are not economically attractive.

Using a sizable sample of farmers, *Chapter 4* studies the effectiveness of knowledge transmission from farmers trained in FFS through farmer-to-farmer training (F2F), which could potentially result in lower extension costs and higher impacts. The chapter look at the differential impacts of both FFS and F2F training on the levels of adoption of project promoted input and practice technologies. The results robustly suggest that both FFS and F2F training had a significant impact on smallholder farmers' adoption of improved technologies. I find that FFS training has a higher impact than F2F training in the first period, but the magnitude of the treatment effect in the second period is not statistically different between the two training methods. I argue that the dissemination of technologies promoted in FFS groups can well be formalized through farmer-to-farmer deliberate training attached to the FFS approach. Given the low costs of F2F training compared to FFS, the introduction of F2F training may substantially alleviate a major constraint to the large-scale introduction of

FFS as a training method, its high costs, while also potentially increasing the sustainability of knowledge transmission.

In *Chapter 5*, I study the impact of farmer's participation in FFS and F2F training on small-scale agricultural productivity. A multi-crop yield-index and the yields of cassava were used as impact indicators. The results indicate that both FFS and F2F trainings contribute to a significant increase in farmers' yields, especially in the second period when the magnitude of the effect substantially increased. We also learned that the effect size does not differ between the two training approaches in neither period, suggesting that F2F communications are a suitable alternative or complement to FFS training. While the chapter was unable to confirm if training materializes in higher yields through technology adoption, I argue that in the context of the sample the adoption of productivity-enhancing practices and inputs are likely the most important impact mechanism.

Aiming to analyze the impact of the FFS/F2F intervention on higher level household outcomes, I also study the relationship between agricultural training, the adoption of improved technologies and household food insecurity. To mitigate for potential biases caused by non-random placement of training participants and adopters; and self-selection, I employ IV, PSM and probability propensity score weighted DID regressions. I find that farmers' participation in agricultural trainings has a positive effect, through the adoption of improved technologies, on improvements in household dietary diversity (HDDS). Nonetheless, the impact on household access to food (HFIAS) is less evident. These results suggest that FFS/F2F training can well reduce household food insecurity, which is mostly achieved through the adoption of improved agricultural technologies. Yet, there are farm and household specific factors such as landholding size, crop diversification, education, sex of the head of household, and levels of product sales which constrain how training impacts technology adoption and how adoption affect household food insecurity and diet diversification.

In *Chapter 7*, I synthesize the results of the four main chapters and articulate the sequence of results from training to adoption to productivity to food security. I also highlight the direct effects that training and adoption have on household food security. I conclude this chapter and the thesis with a set of final remarks on the main findings of the research, and highlighting issues such as, the level of applicability of the results to other contexts; the limits of the definition of impact used in the chapters which focused on adoption, yields and household food security; and pending issues related to the implementation feature of the FFS approach, including cost-effectiveness, sustainability of the system, and knowledge dissemination.

Samenvatting

Het stimuleren van verbeterde landbouwtechnieken is een belangrijk aandachtspunt voor overheden en beleidsmakers die streven naar een verbeterde landbouwproductiviteit en een verlaagde voedselonzekerheid op huishoud en nationaal niveau. Desalniettemin worden de effectiviteit van voorlichtingsprogramma's en het effect van adoptie op productiviteit en voedselzekerheid vaak in twijfel getrokken en is er nog veel onbegrepen over deze relaties. In dit proefschrift gebruik ik experimentele en quasi-experimentele data van 25 dorpen en in totaal 1.105 boeren uit Oost DRC om de relatie tussen landbouwtraining, de adoptie van landbouwtechnologieën, gewasproductiviteit en voedselonzekerheid en diversiteit van het dieet op huishoudniveau te onderzoeken. Ik presenteer bewijs dat bijdraagt aan het verkleinen van het gat in de literatuur over de rol van inputsubsidies bij het stimuleren van het gebruik van productiviteitsverhogende technologieën, hoe farmer field schools (FFS) en trainingen van boer-tot-boer (F2F) de implementatiekosten van FFS verlagen, hoe adoptie zich vertaald in de opbrengst van voedselgewassen, en hoe training effect heeft op voedselzekerheid en diversiteit van het dieet van huishoudens door de adoptie van verbeterde landbouwtechnieken.

Als complement voor het statistische bewijs en om de belangrijkste bevindingen te begrijpen, bespreek ik ook gedragskenmerken en boereninitiatieven die de effecten op een of andere manier conditioneren. In de vier kernhoofdstukken identificeer ik praktische implicaties die van groot belang zijn voor het ontwerp en de implementatie van nieuwe programma's en beleid met als doel het oplossen van problemen met landbouwproductiviteit en het verlagen van voedselonzekerheid op huishoudniveau. In Hoofdstuk 1 ontwikkel ik een algemene introductie op het onderzoek en bespreek ik de evolutie van landbouwvoorlichting in laatste paar decennia en de FFS en F2F trainingsmethodes. Hoofdstuk 2 geeft een gedetailleerde beschrijving van het project, de context van het onderzoek en het proces van dataverzameling. In Hoofdstuk 3 rapporteer ik de resultaten van een experimentele studie naar het effect van eenmalige startpakketten met inputs op de adoptie van productiviteitsverhogende complementaire praktijken die het

effect van de inputs kunnen maximaliseren. Bovendien bepaal ik de continuïteit van het gebruik van de verbeterde zaden uit het startpakket. Over het geheel genomen vind ik geen bewijs van een effect van startpakketten op de adoptie van productiviteitsverhogende praktijken door kleine boeren. Over de twee periodes vergroten zowel de ontvangers als de niet-ontvangers van startpakketten het gebruik van de verbeterde praktijken, maar er is geen significant verschil tussen de groepen dat kan worden toegewezen aan de startpakketten. Ook het niveau van continuïteit van zaakgebruik na de levering van startpakketten was niet significant. Deze resultaten komen overeen met een deel van de literatuur dat minimale of geen continuïteit vindt in het gebruik van inputs na het verstrekken van subsidies, zoals Duflo, Kremer *et al.* (2011). Je kunt beredeneren dat het gebrek aan effect van startpakketten komt doordat de niet-ontvangers de zaden hebben gekocht of doordat de zaden niet effectief waren, maar alleen de praktijken. Het beperkte effect van de startpakketten op de opbrengst in het eerste jaar kan echter logisch verklaren dat boeren hebben afgezien van het gebruik van verbeterde zaden omdat de inputs niet economisch aantrekkelijk zijn.

Gebruik makend van een ruime steekproef van boeren, bestudeer ik in hoofdstuk 4 de effectiviteit van kennisoverdracht van boeren getraind in FFS via boer-tot-boer (F2F) training, wat in potentie leidt tot lagere voorlichtingskosten en hogere impact. Met andere woorden, ik bekijk de verschillende effecten van zowel FFS als F2F training op de adoptieniveaus van de inputs en praktijken die het project promoot. De resultaten suggereren dat zowel FFS als F2F training een significante impact hadden op de adoptie van verbeterde technologieën door kleine boeren. Ik vind dat FFS training een groter effect had dan F2F training in de eerste periode, maar de grootte van het behandelingseffect in de tweede periode is niet statistisch verschillend tussen de twee trainingsmethodes. Ik beargumenteer dat de verspreiding van technologieën gepromoot in FFS groepen goed kan worden geformaliseerd door bewuste boer-tot-boer training verbonden aan de FFS benadering. Gezien de lage kosten van F2F training vergeleken met FFS, zou de introductie van F2F training een belangrijke restrictie voor de grootschalige introductie van FFS als een trainingsmethode kunnen verminderen en mogelijkerwijs tegelijkertijd de duurzaamheid van kennisoverdracht kunnen verhogen.

In Hoofdstuk 5 bestudeer ik de impact van de participatie van boeren in FFS en F2F training op kleinschalige landbouwproductie. Een meergewassenproductiviteitsindex en de productiviteit van cassave zijn gebruikt als impactindicatoren. De resultaten tonen aan dat zowel FFS als F2F trainingen bijdragen aan een significante toename van de productiviteit van boeren, in het bijzonder in de tweede periode toen de grootte van het effect substantieel toenam. We hebben ook geleerd dat de grootte van het effect in geen van beide periodes verschilt tussen de twee trainingsmethoden, wat suggereert dat F2F communicatie een geschikt alternatief of complement is voor FFS training. Hoewel het hoofdstuk niet kon aantonen dat training leidt tot hogere opbrengsten door technologieadoptie, beredeneer ik dat in de context van de steekproef de adoptie van productiviteitsverhogende praktijken en inputs waarschijnlijk het belangrijkste mechanisme is.

Met als doel het analyseren van de impact van de FFS/F2F interventie op huishouduitkomsten op hoger niveau, bestudeer ik ook de relatie tussen landbouwtraining, de adoptie van verbeterde technologieën en voedselonzekerheid op huishoudniveau. Om potentiële afwijkingen veroorzaakt door niet-willekeurige plaatsing van deelnemers aan training en toepassers van technologie; en zelf-selectie, gebruik ik IV, PSM en DID regressies gewogen met probability propensity scores. Ik vind dat de deelname van boeren aan landbouwtrainingen een positief effect heeft, door de adoptie van verbeterde technologieën, op verbeteringen in de diversiteit van het dieet van huishoudens. Desalniettemin is de impact op de toegang van huishoudens tot voedsel (HFIAS) minder duidelijk. Deze resultaten suggereren dat FFS/F2F training de voedselonzekerheid van huishoudens kan verminderen, wat vooral bereikt wordt door de adoptie van verbeterde technologieën. Er zijn echter boerderij- en huishoud-specifieke factoren, zoals bedrijfsgrootte, gewasdiversificatie, opleiding, geslacht van het hoofd van het huishouden, en het verkoopniveau van gewassen, die het effect van training op technologieadoptie en het effect van adoptie op voedselonzekerheid en diversiteit van het dieet beperken.

In Hoofdstuk 7, ontwikkel ik een synthese om de resultaten van de vier kernhoofdstukken samen te voegen en de sequentie van de resultaten van training via adoptie naar productiviteit naar voedselzekerheid over te brengen, naast de directe effecten die training en adoptie hebben op voedselzekerheid. Ik eindig dit hoofdstuk en het proefschrift met een aantal eindopmerkingen over de belangrijkste lessen van het onderzoek en benadruk zaken als de toepasbaarheid van de resultaten in andere contexten, de beperkingen van de definitie van impact gebruikt in de hoofdstukken die focussen op adoptie, productiviteit en voedselzekerheid, en nog openstaande zaken gerelateerd aan de implementatie van de FFS benadering, inclusief kosteneffectiviteit, duurzaamheid van het systeem en kennisverspreiding.

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