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ESSAYS ON THE USE OF AGRICULTURAL TECHNOLOGIES IN DEVELOPING COUNTRIES

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Summary*

Adopting new technologies and agricultural practices can help smallholder farmers improving their livelihoods, increasing their income and other aspects of their well-being, such as nutrition. Despite this, adoption rates in developing countries are still low, especially in Africa. Factors affecting the adoption and the use of these practices are manifold and include elements such as access to information, risk aversion and sufficient liquidity. Among them, special attention in the recent debate has been paid to information and market access, which will be two of the core elements in this thesis. Indeed, here I try to provide a comprehensive picture of technology adoption, analyzing its determinants and the specific consequences on household food security and nutrition for women. Technology will be defined throughout the essays as something not necessarily new to the context under analysis but as an improved product (good or service) or process.

This work contributes to a deeper understanding of the debate on technology adoption in developing countries in several ways. Firstly, this thesis wants to contribute by pointing out benefits deriving from the use of agricultural technologies using a gender perspective and evaluating the impact of agricultural practices on women's nutrition and household food security, improving evidence that is still scarce. Secondly, it contributes to the debate around the determinants of the adoption of agricultural practices with peculiar reference to access to information and to the market for small farmers. Another relevant contribution of this thesis is the use, along the three essays, of several approaches to analyze transmission channels through formal or informal mediation analysis. Mediation analysis is a statistical framework used to analyze the mechanism through which a variable of interest, the treatment, affects an outcome through one or more intermediate variables called mediators. This methodology is commonly used in sociology, psychology, and epidemiology, but despite the importance of knowing transmission mechanisms of economic phenomena, few studies use this approach in economics. Indeed, many studies estimated the magnitude and the significance of an impact but cannot disentangle what are the causes of that impact, leaving the causal effect as what was called a "black box" in the mediation analysis literature. In principle, mediation analysis implies a sequence in the influence among variables. The treatment affects the outcome directly, and indirectly it has an influence on the mediator that in turn impacts the outcome. In real cases, it is not always so straightforward as there could be reverse causality and the use of cross-sectional data can create problems related to the temporal order of the variables in the analysis. The

* I hereby declare that this thesis has not been and will not be submitted in whole or in part to another university for the award of any other degree. Material included in Essays 1 and 2 has been incorporated in working papers, one of them co-authored with one of my advisor and other researchers. However, I hereby state that the bulk of the original research presented in this thesis, including all the empirical applications in each of the following essays, is my own work.

analyses will be performed using both cross-sectional and panel data. Overall, throughout the three essays, some regularities emerged. However, the frameworks under examination in this thesis are quite complex and many variables could play a role, making the analysis complicated. Therefore, it is no surprise that across the manuscript results could lead to different conclusions depending on the context considered and requiring to approach them with caution.

This thesis is built by three independent, although related, empirical essays investigating both the determinants and the impact of agricultural technology and agricultural practices.

Essay 1 examines the link between agricultural technology use, food security and nutrition, using new panel data on smallholder oil palm growers in Ghana collected by the Agricultural Policy Research in Africa (APRA) consortium in 2017 and 2019. In this essay, I introduce a gender perspective, focusing on women and the possible mediating role of women's empowerment that could be an important mechanism in driving the results. Here, technology use will be defined firstly as the use of one practice among agrochemicals, irrigation, and intercropping, three relevant practices for oil palm cultivation in the country. Secondly, I narrowed the definition to the use of irrigation and agrochemicals only due to possible heterogeneity when including also intercropping. Using fixed effect models with interaction terms and a Heckman's model, the core results are: i) for oil palm producers in south-western Ghana, the use of at least one agricultural practice among irrigation and agrochemicals is significantly linked with women's dietary diversity; ii) women empowerment appears to be a positive factor for household food security, regardless of the technological use status and iii) women empowerment mediates the relationship between technology use and women's dietary diversity.

Essay 2 shifts the focus to another country and a different type of technology. One of the main barriers to technology adoption identified in the literature is limited knowledge about the technology, a barrier that could be reduced by increasing and improving extension services. In this essay, I assess the role of extension services on the adoption of laser land leveling (LLL) among 604 households in the Indian state of Karnataka using cross-sectional data collected by the South Asia Regional (SAR) division of IFPRI. The empirical analysis includes propensity score matching and causal mediation analysis. The core results are: i) having visited at least once the extension center (or received a visit by its officials) increases the likelihood of using LLL; ii) after explaining the advantages of the technology and its cost, farmers develop a perception about the affordability of laser land leveling that mediates the treatment effects of the extension service on laser land leveling adoption.

Finally, essay 3 includes the role of market access in determining the use of agricultural technologies. This essay wants to shed light on the nexus between market access, the three main constraints to technology adoption detected in the literature (i.e., limited knowledge, farmers' risk aversion and limited liquidity and access to credit), and the final adoption. Using the four waves of the LSMS-ISA for Nigeria, I firstly identify the local governmental areas (LGAs) that can be classified as hot spots and cold spots for the main crops grown in the country - cereals, cassava or tubers. To do so, I use the Getis and Ord statistic to detect how the geographical concentration of certain crops and agricultural commercialization are linked. Then, I employ an instrumental variables mediation analysis to account for non-random selection and possible simultaneity between market access and the use of agrochemicals. Results show a positive correlation between selling on the market and the outcome variable, and this is confirmed also by the instrumental variable mediation. The primary transmission channel identified seems to be the possibility to access to credit.

Essay 1

Agricultural technology, food security and nutrition: the role of female empowerment for oil palm growers in Ghana

Abstract

Several agricultural technologies could facilitate the gains from agricultural commercialization for smallholder farmers in Africa. The dissemination of such technologies plays a relevant role in tackling poverty and food insecurity in Sub-Saharan Africa. The causal link between agricultural technology use, food security, and nutrition has become an important research question with relevant implications for policy making. Using new panel data on oil palm growers in Ghana from the Agricultural Policy Research in Africa (APRA) consortium, this research aims to shed light on food security and nutrition, focusing mainly on women and on the mediating role of female empowerment. I define technology use based on agrochemicals, irrigation and intercropping, which have a correspondingly higher potential in increasing the quantity and quality of oil palm yield. Then, since there could be heterogeneous effects due to the different practices included in the first definition of technology, I also perform the analysis considering only agrochemicals and irrigation. Using a fixed effects model with interaction terms, along with a Heckman's model, the main findings highlight that the use of at least one agricultural practice (irrigation or agrochemicals) is significantly linked with women's dietary diversity, and this relationship is mediated by the measure of women empowerment adopted in the analysis - with the group of women who scored better in terms of empowerment facing an improvement of their dietary diversity. Women empowerment appears to be a positive factor also for household food security, regardless of the technological use status.

1. Introduction

The use and dissemination of agricultural technologies can play an important role in tackling poverty and food insecurity in Sub-Saharan Africa. Agricultural technology can affect household nutrition and potentially have specific impacts on women's bargaining power within the household, their nutritional status, and household food security. Evaluating whether technology use relevant to a specific crop is associated with improvement in household food security and women's dietary diversity is a relevant issue. However, there has been scant attention to localized evidence on these aspects.

Further, while technology use, household food security, and - to a lesser extent - women's dietary diversity are broadly studied in the literature, few studies consider the role of women's empowerment in mediating the relationship (Passarelli *et al.*, 2018; Kassie *et al.*, 2020). In this essay, I address this research gap by studying the impact of technology use on the two outcomes (women's nutrition and household food security), including the mediating role of women empowerment in both analyses. To this aim, I use panel data collected in two districts of Southwestern Ghana by the Agriculture Policy Research in Africa (APRA) consortium.

Previous studies investigating agricultural technology adoption and the impact on the welfare of small farmers (Beshir *et al.*, 2012; Ghimire and Huang, 2016; Sinyolo, 2020) indicate farmer characteristics and physical characteristics of the area where each household lives as the elements through which technology affects farmers' welfare. Therefore, local evidence is critical to foster and strengthening the related knowledge (Saha, Sabates-Wheeler and Thompson, 2021).

What also emerges from previous studies is that women's primary interest is often ensuring household food security (Aryal *et al.*, 2020) and "non-priced values" concerning nutritional, ecological, institutional, and educational matters. In order to ensure these outcomes, their position and empowerment in the household play a significant role. However, there may be situations where women cannot ensure both household food security and improved nutrition for themselves at the same time, and I explore this aspect in this paper.

In the oil palm sector in Ghana, gender roles are clearly defined. Usually, women are in charge of rodent control, aggregating and carrying of harvested fruits, collection of loose fruits, marketing, and receiving money from sales, whereas activities such as nursery management and fertilizer application are carried out by both men and women (Ministry of Food and Agriculture of Ghana, 2011; Ofosu-budu and Sarpong, 2013). Several studies focus on the adoption of agricultural technologies by female farmers (Damisa and Igonoh, 2007; Tanellari *et al.*, 2014; Namonje-kapembwa and Chapoto, 2016; Mensah, Villamor and Vlek, 2018; Aryal *et al.*, 2020) highlighting the specific barriers that women in smallholder farmer households face, such as lower education and opportunities to learn new technologies and agricultural practices and in general lower bargaining power within the household.

This study links with Kassie et al. (2020), which analyzed the moderating effect of women's empowerment on the relationship between the adoption of a push-pull organic pest control system and women's dietary diversity in Western Kenya. I build on it in several ways: first, technology will be defined as the use of agrochemicals, irrigation or intercropping as a preliminary and technical analysis about how to grow oil palm in Ghana suggests these practices as essential in order to increase its productivity. The definition of technology used in this essay is justified by the fact that the main problems related to oil palm management in this country include poor water availability, insufficient drainage and poor nutrient management, namely the failure to consider the proper nutrient requirement of the crop and to use fertilizers and crop residues correctly. Indeed, many smallholder farmers apply little mineral fertilizer and do not recycle crop residues, leading to lower yields than the potentially possible ones (IPNI, 2015). Focusing the attention on the three selected practices can provide valuable insights into their contribution to oil palm small farmers' food security and nutrition. Second, I use new panel data from household surveys representative of oil palm producers in a specific area in Ghana. Further, I capture empowerment by combining women's inputs on personal decisions, on the use of their wages and on minor household expenditures, decisions on sales, on inputs and outputs use.

To understand the direct nexus between technology use, nutrition and food security but also the indirect effect mediated by female empowerment, I run some panel regressions where women empowerment is interacted with technology use and a Heckman model.

The remainder of this essay is organized as follows. Section 2 reviews the literature and presents the background. Section 3 firstly presents the data and discusses some summary statistics, then the empirical framework is presented. In section 4, the empirical results are presented and discussed. Section 5 concludes with policy recommendations and suggestions for future research.

2.Background and review of the literature

2.1 Brief Overview of Literature

Drawing from both the literature on the impact of technology adoption on farmers' wellbeing and the literature on technology and gender, I address the main research question of how farmer households are affected in terms of female nutrition and food security by the use of certain agricultural techniques in South-Western Ghana.

Technology use and farmers' wellbeing

Several previous studies investigated agricultural technology adoption and its impact on the productivity and wellbeing of small-holder farmers in developing countries. Beshir *et al.* (2012) investigated the determinants of adoption and intensity of inorganic fertilizer in two districts of South Wollo, in Ethiopia, using a double hurdle model with cross-sectional data. They found a positive impact of extension and credit services, age, farm size, education, livestock, off-farm income, and gender in enhancing the adoption of inorganic fertilizer. Physical characteristics like distance from farmers' homes to markets, roads, credit and inputs supply played a critical role in the adoption of inorganic fertilizer since proximity to information, sources of input, credit supply and markets save time and reduce transportation costs.

Furthermore, Sinyolo (2020) investigated the impact of the adoption of improved maize varieties on household food security among smallholder farmers in KwaZulu-Natal, South Africa. Food security was measured in terms of total annual household food expenditures plus the estimated monetary value of the food consumed from home production, in Rands per capita, using a 30-day recall period. The author found that an additional one hectare of land under improved maize varieties increases annual food expenditure per capita levels by over R4000. Female farmers are more likely to adopt improved maize varieties and benefit more from them than their male counterparts. After the adoption, they also spend more to ensure household food security. Ghimire and Huang (2016) focused on the impact of the adoption of new-generation modern rice varieties (MRVs) on family welfare among rural farm households in central Nepal. They used farm (annual) income among farm households as a proxy for farmers' welfare and the Heckman sample selection model with cross-sectional data. They found a positive and significant impact of MRVs on farm income.

Technology use by gender

Several studies focus on the adoption of agricultural technologies (such as integrated soil fertility management, inorganic fertilizer, herbicides and improved seeds) by female farmers (Damisa and Igonoh, 2007; Tanellari *et al.*, 2014; Namonje-kapembwa and Chapoto, 2016; Mensah, Villamor and Vlek, 2018; Aryal *et al.*, 2020) finding that factors such as farming experience, dependency ratio, family remittance and income positively influence female farmers' adoption. Households with female participation in decision-making are more likely to adopt a technology, as emerged from Aryal et al. (2020) about climate-smart agriculture (CSA). They also highlight that women usually have a weaker understanding of CSA, which affects their ability and willingness to influence intra-household decision-making processes around adoption. This leads us to an important factor affecting female adoption that concerns their level of education, their access to extension and learning opportunities (Matshe, Zikhali and Chilonda, 2010; Ragasa *et al.*, 2013; Mishra *et al.*, 2020).

Matshe et al. (2010) studied the role of female education levels on female farmers' decisions to purchase chemical fertilizers in Zimbabwe, finding a positive and significant effect of education on female farmers' adoption. Ragasa et al. (2013) investigated gender differences in access to extension services and how this translates to observed differences in technology adoption and agricultural productivity in Ethiopia. A distinction was made between de jure female heads (widow, single, divorced or separated) and de facto female heads (wives of male migrants or with ill spouses) and they also considered the gender of who in the household has the right to decide what to grow on the parcel. They found that receiving advice from extension agents is positively related to the adoption of improved seed and fertilizer for both females and males. Lastly, Mishra et al. (2020) investigated the role of self-learning in explaining the female adoption of hybrid seeds, inorganic fertilizers or pesticides decision in the Ugandan context. Farmers' self-experimentation matters, but they found a weaker impact of self-learning for female-headed households that face fewer opportunities for learning than male-headed households.

Other studies compared the agricultural technologies adoption outcome between male and female farmers (Doss and Morris, 2001; Diiro, Ker and Sam, 2015). Doss and Morris (2001) investigated farmers' decisions about adopting modern varieties (MVs) and chemical fertilizers, considering male farmers living in male-headed households, female farmers living in male-headed households, and female farmers in female-headed households. Although the gender of the household head may be important, they found that gender per se is not significantly associated with MV or fertilizer adoption rates. Diiro et al. (2015) considered female- vs. male-headed households and their inorganic fertilizer adoption outcome. Male-headed households were more likely to adopt fertilizer than female-headed households, for which education and distance from the market were significant factors affecting their choice.

Further studies also add joint control over land in their analysis, obtaining different results (Ndiritu, Kassie and Shiferaw, 2014; Marenya, Kassie and Tostao, 2015; Haider, Smale and Theriault, 2018; Theis *et al.*, 2018; Gebre *et al.*, 2019). Focusing on multiple sustainable intensification practices, Ndiritu et al. (2014) found that female managers are less likely to adopt minimum tillage and animal manure in crop production, indicating the existence of certain socioeconomic inequalities and barriers for them. On the other hand, no gender differences in the adoption of soil and water conservation measures, improved seed varieties, chemical fertilizers, maize-legume intercropping, and maize-legume rotations were found. Controlling for the demographics of the manager and plot characteristics, Marenya et al. (2015) found that joint management of agricultural plots is associated with higher fertilizer application rates on maize plots but with lower fertilizer application on non-food cash plots. Joint management would work well under the assumption that the benefits from additional production would be available to all household members equally. Theis et al. (2018) explored who within the household uses and controls a small-scale irrigation technology in Ethiopia, Ghana, and Tanzania, focusing on women living in countries where they often depend on husbands for access to land and typically cultivate both joint and individually managed plots with some independent control over income. Overall, rights over technology are distributed differently among the households considered. Women value irrigation, especially for crops and plots where they control management and have the right to derive profit. However, this right is particularly weak when there is information asymmetry over the sales of joint production.

Furthermore, the right to use a technology does not necessarily confer other rights and may represent a greater labor burden for women. Gebre et al. (2019) found that the intensity of adoption of improved maize varieties is lower for female-headed households, where decisions are made jointly by men and women, compared to male-headed households, where decisions are made jointly. Haider et al. (2018) investigated how technology adoption, particularly fertilizer adoption on maize plots, can influence farmers' bargaining processes in West Africa. They test the nature of the relationship between the decision to use fertilizer on jointly managed fields and on individually managed fields. Bargaining is inadequate to sustain an efficient fertilizer allocation but providing inputs to women and young men may increase their influence on other decisions and lead to greater equity within the household, enhancing production efficiency through a better allocation of inputs.

Technology use, gender and nutrition

However, the works presented above only estimate either the impact of technology use or of female empowerment on the outcomes of interest, whereas only few studies try to provide a comprehensive analysis of the three elements(Njuguna *et al.*, 2016; Passarelli *et al.*, 2018; Kassie *et al.*, 2020; Nkonya, Kato and Ru, 2020). Indeed, women are often more interested in nutrition for their household rather than income (Aryal *et al.*, 2020) and the level at which they can ensure that the gain deriving from the use of technologies is translated into improvements in the diets is affected by their position and empowerment within the household. Kassie et al. (2020) investigated the moderating effect of women's empowerment, measured by the Abbreviated Women's Empowerment in Agriculture Index (A-WEAI), on the relationship between the adoption of a push-pull organic pest control system and women's dietary diversity in Western Kenya. To this aim, they used an endogenous switching regression (ESR) framework, and they found that women's empowerment has a positive and significant effect on the women's dietary diversity score regardless of technology adoption status. Furthermore, although technology adoption positively impacts women's dietary diversity regardless of empowerment status, its effect is stronger for households with empowered compared to disempowered women. The main limitation of their study is that they used cross-sectional data that are not nationally representative. Nkonya, Kato and Ru (2020) analyzed the characteristics of irrigation adoption in Mali and its impact on nutrition (household dietary diversity) across the sex of irrigators, considering the household head. The share of women irrigators is significantly lower than their male counterparts. The authors highlight the importance of participation in farmer groups to increase the propensity to adopt irrigation since they might be an entry point for capacity building on this practice. Additionally, they find that irrigation increases the consumption of nutrient-rich food groups, which significantly improves household nutrition in addition to increasing income. Passarelli et al. (2018) investigated the potential for small-scale irrigation to contribute to improved diets and the pathways through which irrigation affects dietary diversity using the Household Dietary Diversity Score (HDDS) in Ethiopia and Tanzania. One of the potential pathways through which irrigation can influence food security and nutrition considered in the study is the women's empowerment pathway – decision-making authority and access to and control over resources – which can ultimately lead to changes in child and maternal nutritional outcomes. They found a positive association between irrigation, production (both yields and quality), and food security of adopter households. Dietary diversity was higher in woman-headed households in Ethiopia, while woman-headship was associated with lower participation in irrigation and lower production diversity in Tanzania. Again, data were cross-sectional, and some limitations can be noticed in how the household dietary diversity index is built. Njuguna et al. (2016) examined the dynamics of the adoption of drought-tolerant, early-maturing seeds in relation to improvements in food security (as the number of months per year of sufficiency in the provisioning of food for all members of the household). The analysis considered what women adopt, under what terms and conditions, and with what results for household food security. They observed that "non-priced values" (e.g., nutritional, ecological, institutional, educational) are key drivers of women's adoption decisions. Additionally, they noted gains in a range of household food and nutrition security measures after technology adoption.

My empirical framework belongs to this strand of the literature. However, most of the studies cited in this subsection used cross-sectional data failing to capture the temporal link between the outcome and the predictor. In contrast to them, I contribute to this literature using panel data to investigate the effect of the use of agricultural practices and their interaction with female empowerment on women's nutrition and household food security for small oil palm growers in South-Western Ghana.

2.2 Oil Palm Cultivation

The analysis focuses on oil palm cultivation in Ghana, which requires some specific practices and inputs to provide successful harvesting and yields. Oil palm is a modern crop and as such it needs growers to ask for advice, plan the work on farm to carry out the proper tasks at the right time. This kind of cultivation requires much more attention than natural trees, but if properly managed, it also yields more. Seeds germinate after 90 to 100 days if kept in a room where it is very hot; then, each seed is planted in a small plastic container. The young seedling stays there for 4 to 5 months; after that, it is transplanted out into the nursery, where it will stay for 16 to 18 months when it becomes ready to be planted in the field. It starts to produce 3 or 4 years after it has been planted. Therefore, for a long period, farmers must invest in this cultivation without harvesting any fruit or earning money. Investments involve buying seeds and fertilizers that should be applied since the oil palm is still young. Oil palms require much time to be cultivated, especially in the first phases where farmers have to sow the cover crop, dig holes in the plantation, take care of the seedlings and then plant them. They also have to put wire netting around young trees, spread fertilizer, and take care of them properly. This could imply that farmers could not have enough time to look after other crops and probably not enough money to buy food for the household from the market. The only thing that farmers could do before harvesting oil palm fruits is to use the green fodder from the cover crop in the palm groves or the palm-kernel oil cake (i.e., what is left over after the extraction of the palm kernel oil) to feed beef cattle (FAO, 1990). Furthermore, key climatic factors to cultivate oil palm in Ghana are a good level of rainfall, five hours per day of sunshine in all months, and a temperature between 18°C and 32°C (Ministry of Food and Agriculture of Ghana, 2011). Concerning land preparation, manual or mechanized methods can be used: in the former, workers employ a cutlass to remove the vegetation. On the opposite, the mechanical method uses bulldozers to remove vegetation and uproot the trees. Usually, 143 palms per hectare are planted, keeping a space of 9 meters between trees (Ministry of Food and Agriculture of Ghana, 2011). A crucial requirement is soil suitability. *Highly suitable soils* are the ones that are well-drained or moderately well-drained; their topsoil is made of sandy loam, loam, or silty loam, and the subsoil by sandy clay loam. These types of soil contain no or very few gravels and concretions. Soils that are imperfectly drained are classified as *moderately suitable*. Their topsoil is composed of loamy sand or sandy clay loam, while their subsoil of clay or sandy loam; gravel and concretions are few. Lastly, soils poorly drained with the topsoil made by sandy clay or silty clay and subsoil by loamy sand, sandy loam or silty clay where many gravels and concretions are present are classified as *marginally suitable*. In Ghana, most soils in climatically suitable areas for oil palm are middle to lower-slope and valley-bottom soils. These soils tend to be very acidic (with a low ph), and fertility levels of most of them are inherently poor. Without the appropriate supplement of soil nutrients and sound management practices, a steady decline in production and crop failures could be observed (Ministry of Food and Agriculture of Ghana, 2011). Between 2014 and 2015, several experiments including a fertilizer, irrigation and soil moisture trial were established in Ghana to understand the interaction of water and nutrients in oil palm cultivation (IPNI, 2015). Weeds are allowed to regenerate for a few weeks after plantation; then, they are controlled using hand weeding during the immature phase. Herbicides, added to hand weeding, are used during the mature phase. Chemical control is the most effective method to eradicate weeds (Ministry of Food and Agriculture of Ghana, 2011). Another necessary operation is manuring, which involves the application of crop residues (empty fruit bunches) and chemical fertilizers to enhance soil fertility. The poor quality of soils in Ghana highlights the importance of a constant fertilizer supply. The most important fertilizer is muriate of potash to supplement potassium lost after harvesting (Ministry of Food and Agriculture of Ghana, 2011). For smallholder farmers, a baseline application of NPK 10-10-30 and an application of urea, tsp, kcl and borate are recommended to correct the extreme soil deficiencies. Also, the use of crop residues, such as pruned fronds aligned in a box pattern around the palm and empty fruit bunches –not always available for them – is suggested (IPNI, 2015). However, especially in the Western region, many planters cannot afford the high cost of high-quality fertilizers and use cheaper types (Ministry of Food and Agriculture of Ghana, 2011). Leaf miner, the most dangerous pest of oil palm in Ghana, can be detected through regular census and suitable control measures starting from biological agents to the use of pesticides in the correct quantity (Ministry of Food and Agriculture of Ghana, 2011). A leguminous cover crop is often sown to eliminate weeds and provide nitrogen and organic matter. Oil palm is predominantly grown as a monocrop, but small-scale oil palm farmers in Ghana often intercrop their oil palm with food crops (cassava, plantain, maize, rice, and so on), especially during the palms' first four years. To continuously intercrop palms and food crops, farmers can prune the oil palm excessive fronds at the beginning of the cropping season to allow maximum sunlight penetration for effective growth of the other food crops (Ministry of Food and Agriculture of Ghana, 2011). Overall, the main problems related to oil palm management include poor water availability and the lack of (or insufficient) drainage. An additional issue is poor nutrient management, namely the failure to correctly consider the right nutrient requirement of the crop and to use fertilizers and crop residues. Many smallholder farmers apply little mineral fertilizer and do not recycle crop residues. This leads to lower yields than potentially available, and further research on these issues is important to improve yields in Ghana (IPNI, 2015).

Another issue that will be discussed in this analysis concerns gender. Gender roles are clearly defined in the oil palm sector, and an imbalance between sexes can be noticed. In 2010, in large estates, up to 60% of workers on the plantations were female. In general, women are in charge of rodent control, aggregating and carrying of harvested fruits, collection of loose fruits, marketing and receiving money from sales, whereas activities such as nursery management and fertilizer application are carried out by both women and men (Ministry of Food and Agriculture of Ghana, 2011; Ofosu-budu and Sarpong, 2013).

2.3. Conceptual Framework

The theoretical framework guiding my analysis is similar to the one by Kassie et al. (2020), who investigated the moderating effect of women's empowerment on the relationship between the adoption of a push-pull organic pest control system and women's dietary diversity in Western Kenya. It presents three pathways related to the study's research questions (RQ) that will be shown later. I will also report a figure in section 3.4 that explains the conceptual framework graphically. The first pathway relates to the effect of technology use on women's dietary diversity and household food security, which could operate through many mechanisms such as production or income (Kidane, Maetz and Dardel, 2006; Sanchez, 2019; Bairagi, Mishra and Durand-Morat, 2020; Obayelu *et al.*, 2021). I decided to focus on women's nutrition since they are often in a weaker position within the household and improving their level of empowerment could have a positive effect on their health and on their nutrition.

The second pathway encompasses the idea that women's empowerment in rural areas directly affects their dietary diversity and household food security. This reflects the fact that women play essential roles in their family's nutrition. The underlying hypothesis is that empowered women are expected to have better general knowledge of nutrition and health. They also have more control over household resources to apply that knowledge to the quality of their diets and to the household's food security. This is because they may be able to afford nutritious food through their own production or purchasing it on the market. Doss (2006), analyzing Ghana, showed that women's share of assets, mainly farmland, significantly increased food budget shares. Thus, women's empowerment can lead to improved nutrition for them and all the household members (Malapit and Quisumbing, 2015; Malapit *et al.*, 2015).

Lastly, the third pathway concerns the role of women's empowerment in mediating the effects of technology adoption on household food security. Many previous studies agree that women are more interested in nutrition and the quality of household diets. Women that participate more in household decisions or have more control over resources can ensure that the potential increase in food availability or income due to the use of agricultural practices is translated in strong household food security (Passarelli *et al.*, 2018). Finally, a related pathway represents the interaction of women's empowerment in determining whether any increased income or other crop production due to the use of agricultural technologies impacts women's dietary diversity. In fact, they can secure improvements in the quantity and quality of food eaten equally shared among household members, including women (Kassie *et al.*, 2020).

Based on what was discussed above, I analyze the following research questions:

RQ1: What is the link between agricultural technology use and dietary diversity for women? What is the link between agricultural technology use and household food security?

RQ2: What is the influence of female empowerment on women's dietary diversity and household food security?

RQ3: What is the mediating effect of female empowerment on the relationship between technology use and nutrition or food security?

To answer them, I use panel data and context-specific from Ghana. I capture technologies specific to oil palm as described in the related section above. Lastly, I capture empowerment combining input on wages and minor household expenditures with decisions on crops' sales, use of inputs on the plot managed, and use of outputs.

3. Methods

3.1 Sampling and data

The essay uses panel data from household surveys conducted in 2017 and 2019 by the *Agriculture Policy Research in Africa* (APRA) consortium. The districts involved are the Ahanta West and Mpohor Districts, located within the oil palm belt of South-Western Ghana. They were selected because of the high concentration of oil palm production by smallholder farmers and because two of Ghana's "big four" oil palm companies (Norpalm Ghana Ltd and Benso Oil Palm Plantation Ltd) and a medium-scale oil palm processing company (Building Business on Values, Integrity and Dignity, B-BOVID) are based in this area. The consortium created a list of communities in which farmers were engaging with the various commercialization channels after reviewing the literature, two visits in the area, and the identification of the broader channels through which oil palm producers sell their fruits after harvesting. Since a reliable sampling frame was unavailable, twenty communities were randomly selected, and a census for constructing a frame was carried out. Based on sample size calculation[1], the original idea was to draw on a sample of 600 oil palm grower households at random to represent each ex-ante group. Nevertheless, a larger sample was needed due to the heterogeneity within the sale channels; thus, a sample of 700 households was targeted (Dzanku *et al.*, 2020).

The first survey round was conducted in 2017 and covered 726 oil palm farm households (Dzanku *et al.*, 2020). The second survey round was conducted in 2019 when 137 households were added to the sample. Attrition in the sample was very low, as only 60 households were not re-interviewed.

Household Survey

The survey used a structured core questionnaire to collect data from the randomly selected households on plots cultivated, agricultural production and marketing, non-farm activities and income sources, household assets, food security, and dietary diversity. Information at the individual and at the household level are included in the questionnaire, and specific sections about female income, female nutrition, women's decisions within the household and information about care work are embodied. Data were collected through face-to-face interviews with the household head or another adult family member with relevant knowledge of the questions when the head was unavailable. The senior researchers trained and supervised a team of enumerators (Saha, Sabates and John, 2021).

[1] The sample size calculations were based on four statistical assumptions: (a) A 5% level of significance (i.e., $a = 0.05$); (b) A 0.144 standard deviation of the outcome variables of interest for rural Western region, which was estimated using household dietary diversity scores based on the Ghana Living Standards Survey data (GLSS6); (c) less than 0.10 expected change (or difference) in the outcome variable (i.e., effect size < 0.10); and (d) statistical power of 80 per cent (Dzanku et al, 2020).

3.2. Measurement of key variables

Technology use

The main explanatory variable is the use of at least one among intercropping, irrigation and agrochemicals, selected according to the considerations in the specific technical section about how to grow oil palm. The use of these practices is captured through a dummy variable at the household level equal one if the household adopts at least one of the three practices and as a count variable (from 0 to 3). Tables 1 displays the number of households in the sample using and not using the practices considered on plots with oil palm. For other crops see table A2 in appendix.

Since there could be heterogeneity in the use of the three practices, I will also analyze the use of single practices, except for irrigation (due to the lower number of adopters in the sample). Lastly, I will also perform the analysis considering only the use of agrochemicals and irrigation (both creating a dummy equal one if the household uses at least one of the two practices and a count variable from 0 to 2).

Table 1. Number of households in the sample using and not using agricultural practices considered on oil palm plots.

	2017		2019		Pooled sample	
	Non-user	Users	Non-user	Users	Non-user	Users
At least one of the three practices	387	336	412	382	799	718
	(53.53)	(46.47)	(51.89)	(48.11)	(52.67)	(47.33)
Intercropping	468	255	512	282	980	537
	(64.73)	(35.27)	(64.48)	(35.52)	(64.60)	(35.40)
Irrigation	703	20	781	13	1484	33
	(91.70)	(8.30)	(91.06)	(8.94)	(91.36)	(8.64)
Agrochemicals	561	162	649	145	1210	307
	(77.59)	(22.41)	(81.74)	(18.26)	(79.76)	(20.24)

Percentage shares are shown in parentheses

Female Empowerment

Based on the literature review and the data available, I defined female empowerment firstly creating a score - called "empowerment score" - that goes from 0 to 5 according to the number of the domains reported in table 4 in which women said they had some control. This variable is missing if no information about all five domains is available. If an interviewed woman's reply is missing only for one to four domains, I consider those replies zero (i.e., no control for the specific domain). I then use this measure to identify two groups of women: one with women who score better in terms of empowerment and the second with women who score lower in terms of empowerment. To represent these two groups, I created a dummy equal to 1 if the empowerment score is equal or greater than a certain threshold, zero otherwise.

Women Dietary Diversity

In the literature, indicators about dietary diversity are often used at the household level, but I go further and use this score at the individual level since we have information on female dietary diversity. Particularly, I use as one of the outcome variables the dietary diversity for women developed by FAO (Kennedy, Ballard and Dop, 2011). The dietary diversity score is calculated by summing the number of food groups consumed by the individual respondent over the 24-hour recall period. Nine food categories are considered: starchy staples (grains and white roots); other vitamin A fruits and vegetables; other fruits and vegetables; organ meat; meat and fish; legumes, nuts and seeds; eggs; milk and milk products. Thus, the Women Dietary Diversity Score (WDDS) is a variable that ranges from 0 to 9. This variable was created firstly generating food group variables for those food groups that need to be aggregated; secondly, the variable WDDS was generated as the sum of all food groups included in the dietary diversity score. In the dataset, this variable goes from 0 to 8, meaning that no woman in the sample consumed food from all the nine food groups.

Household Food Security

To represent the household food security status, I used the Food Insecurity Experience Scale (FIES) created by FAO (Cafiero, Viviani and Nord, 2018). The FIES fits SDG target 2.1 (*by 2030 end hunger and ensure access by all people, in particular the poor and people in vulnerable situations including infants, to safe, nutritious and sufficient food all year round*) as it provides an indication of people's access to food. The FIES represents a statistical measurement scale of severity of food insecurity at the household or individual level and it is based on people's direct yes/no responses to eight questions related to their access to adequate food, reported in Table A3(Appendix). Analyzed together, these questions form a quantitative tool to measure the prevalence of food insecurity in a population: they cover different food-related experiences and are associated with different levels of severity of food insecurity. A valuable contribution of the FIES is that it also captures psychosocial aspects related to anxiety or uncertainty regarding the ability to obtain enough food. A second key innovation of FIES is that it produces estimates that can be compared across countries (FAO, 2021). Using the Rash test, I obtain the raw score from 0 to 8.

3.3. Descriptive Statistics

Table 2 briefly defines the main variables for this analysis. Table 3 shows the summary statistics for the two outcomes by technology use (top of the table) and empowerment status (bottom of the table). In all the samples considered, users had higher Women Dietary Diversity Score and lower Food Insecurity Experience Scale, a difference which is significant for the pooled sample. Empowered women had on average higher Women Dietary Diversity Score in 2017 but not in 2019 and in the pooled sample.

However, they had a lower Food Insecurity Experience Scale compared to the disempowered women, and this difference is significant in 2017 and in the pooled sample.

Table 2. Definition of the main variables used in the analysis.

Indicator	Definition of the indicator
Technology	
Technology Use	Dummy =1 if household uses at least one among intercropping, irrigation, and agrochemicals
	Count variable from zero to 3 (intercropping, irrigation and agrochemicals)
Women's outcome	
Women Dietary Diversity Score	Number of food groups consumed based on 24-h recall out of 9: (1) starchy staples; (2) green leafy vegetables; (3) other vitamin-A rich fruits and vegetables; (4) other fruits and vegetables; (5) organ meat; (6) meat and fish; (7) eggs; (8) legumes and nuts; (9) milk and milk products.
Household outcome	
Food Insecurity Experience Scale	Number of food insecurity sub-indicators in the past 12 months out of 8: (1) worry about not having enough food to eat because of a lack of money or other resources; (2) unable to eat healthy and nutritious food because of a lack of money or other resources; (3) ate only a few kinds of foods because of a lack of money or other resources; (4) skip a meal because there was not enough money or other resources to get food; (5) ate less than you thought you should because of a lack of money or other resources; (6) ran out of food because of a lack of money or other resources; (7) hungry but did not eat because there was not enough money or other resources; (8) went without eating for a whole day because of a lack of money or other resources.
Empowerment	
Empowerment	
Female empowerment	Dummy=1 if the empowerment score is equal or greater than 2 or 3
Empowerment Score	Score from 0 to 5 according to the number of domains in which women have some control. Missing values for any single subdomain are considered as zero. The score is missing if all the five subdomains are missing.
Subdomain indicators	
Main manager of the household's plots	Dummy=1 if at least one female household member makes decisions about which crops to grow and which inputs to be used on the plot
Decision making on outputs use	Dummy=1 if at least one female household member makes decisions about how to use the output from the plot
Decision making on crops sale	Dummy=1 if at least one female household member makes decisions about whether to sell crops
Inputs on wage use	Dummy=1 if women in the household feel they can make at least some personal decisions regarding the use of wage, if they want to
Inputs on minor expenditure	Dummy=1 if women in the household feel they can make at least some personal decisions regarding minor expenditures, if they want to

Table 3. Descriptives of the outcome variables by technology use[2] and female empowerment[3]

	2017		2019		Pooled sample	
	Non-users	Users	Non-users	Users	Non-users	Users
Women Dietary Diversity Score	2.990	3.563	2.91	3.036	2.949	3.292
	(1.260)	(1.130)	(1.079)	(1.028)	(1.172)	(1.110)
Food Insecurity Experience Scale	1.669	1.402	1.629	1.274	1.649	1.336*
	(2.142)	(1.849)	(2.399)	(2.159)	(2.275)	(2.014)
N	290	261	302	277	592	538
	2017		2019		Pooled sample	
	Empowerment level		Empowerment level		Empowerment level	
	Low	High	Low	High	Low	High
Women Dietary Diversity Score	3.190	3.275	3.071	2.952	3.136	3.104
	(1.029)	(1.279)	(.884)	(1.081)	(.966)	(1.189)
Food Insecurity Experience Scale	1.962	1.444*	1.709	1.423	1.848	1.433*
	(2.024)	(1.996)	(2.305)	(2.304)	(2.153)	(2.162)
N	105	448	86	496	191	944

Users-non users refer to the three practices combined on oil palm plots. Mean values are shown with standard deviations in parentheses. Differences in means between the groups considered are tested for statistical significance. * p<0.05, ** p<0.01, *** p<0.001.

Table 4 shows descriptive statistics for the samples of users and non-users. A greater percentage of women in non-user households than those in user ones is considered empowered (according to my two definitions), but the difference is not significant. On average, it seems that women in the user households spend slightly more time on all care work, but the difference is again not significant. However, some statistical differences in socio-economic characteristics between these two groups can be observed. Users of at least one agricultural practice are younger and slightly more educated than their non-user counterparts. The average number of household members and female members in each household is similar but slightly higher for users. User households cultivated more hectares of land and dedicated a slightly higher number of plots to oil palm (but the difference is not significant this time). Concerning wealth, adopter households have a slightly larger asset ownership score, and the difference is significant in the pooled and in the sample of 2017.

[2] On oil palm plots
[3] Empowerment score equal or greater than 2

Table 4. Socio-economic characteristics (oil palm plots only)

	2017		2019		Pooled sample	
	Non-users	Users	Non-users	Users	Non-users	Users
Female empowerment (dummy)	.663	.574	.655	.598	.659	.587
[empowerment score at least 2]	(.473)	(.495)	(.476)	(.491)	(.474)	(.493)
Female empowerment (dummy)	.215	.155	.204	.178	.210	.167
[empowerment score at least 3]	(.411)	(.362	(.403)	(.383)	(.407)	(.374)
Time spent on all care work by	8.237	8.267	5.318	6.471	6.748	7.344
women(hours)	(5.441)	(5.789)	(3.308)	(3.432)	(4.710)	(4.807)
Age of household head (years)	51.842	51.932	54.029	51.599*	52.970	51.755**
	(13.276)	(12.814)	(12.666)	(12.468)	(13.003)	(12.624)
Education of the household head	7.124	7.735*	7.347	8.236*	7.239	8**
(years)	(4.712)	(4.804)	(4.691)	(4.882)	(4.700)	(4.849)
Household size	4.300	4.560*	4.667	4.796	4.489	4.685
	(2.238)	(2.282)	(2.276)	(2.389)	(2.264)	(2.341)
Number of female household	2.479	2.571	2.399	2.465	2.437	2.515*
members	(1.335)	(1.319)	(1.284)	(1.221)	(1.308)	(1.268)
Land cultivated by the household	7.968	10.106***	7.870	9.135**	7.917	9.589***
(ha)	(7.791)	(10.364)	(7.450)	(8.364)	(7.612)	(9.359)
No. Plots cultivated with oil palm by	1.142	1.321	1.191	1.353	1.172	1.338
households	(.423)	(.626)	(.424)	(.658)	(.424)	(0.643)
Asset Score	.370	.377*	.379	.389	.375	.383*
	(.148)	(.160)	(.149)	(.164)	(.149)	(.162)
N[4]	387	336	412	382	799	718

Users-non users refer to the three practices combined on oil palm plots. Mean values are shown with standard deviations in parentheses. Differences in means between users and non-users are tested for statistical significance. * p<0.05, ** p<0.01, *** p<0.001.

[4] Number of observations is lower for some variables.

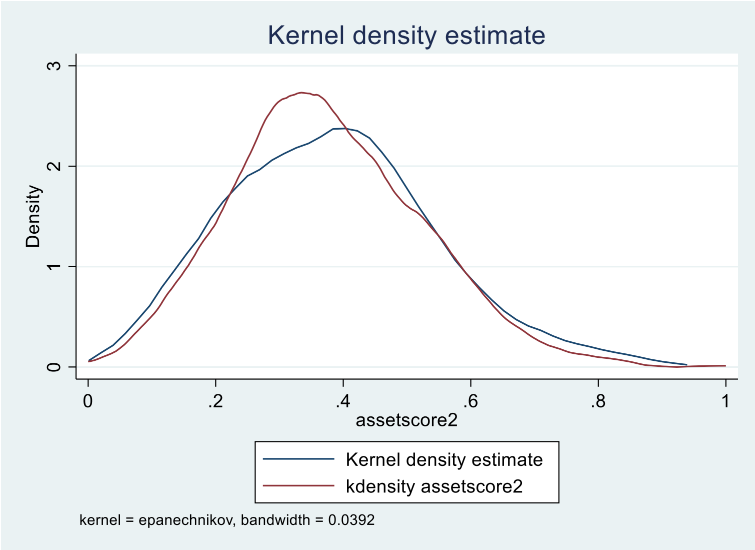


Figure 1. Kernel density of assets score (pooled sample)

Figure 1 shows the kernel density of the assets score both for users of at least one of the practices considered on oil palm plots (blue line) and non-users (red line). The distribution of the variable for the second group reaches the peak earlier than what happens to the other group, displaying a lower asset score. Figure 2 shows the kernel density for the Women Dietary Diversity Score and figure 3 for the Food Insecurity Experience Scale for the group of households using at least one of the three practices (blue line) and for the other group of households not using any of the practices (red line). In the Women Dietary Diversity Score case, it is possible to observe a multimodal distribution for both groups. However, the majority of households not using any of the practices under analysis (red line) shows a lower level of WDDS than the other group (blue line). For Food Insecurity Experience Scale, the distribution is unimodal and right-skewed, meaning that the mean is greater than the median. In this case, the two groups show similar levels of food insecurity.

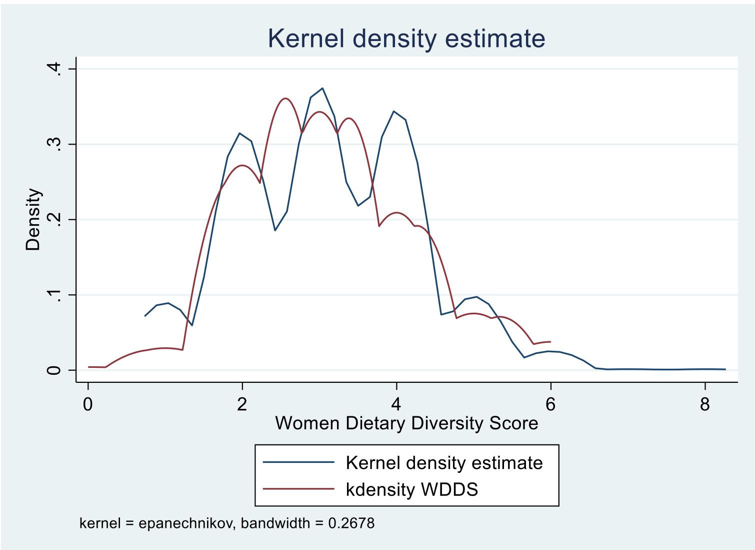


Figure 2. Kernel density of Women Dietary Diversity Score(pooled sample)

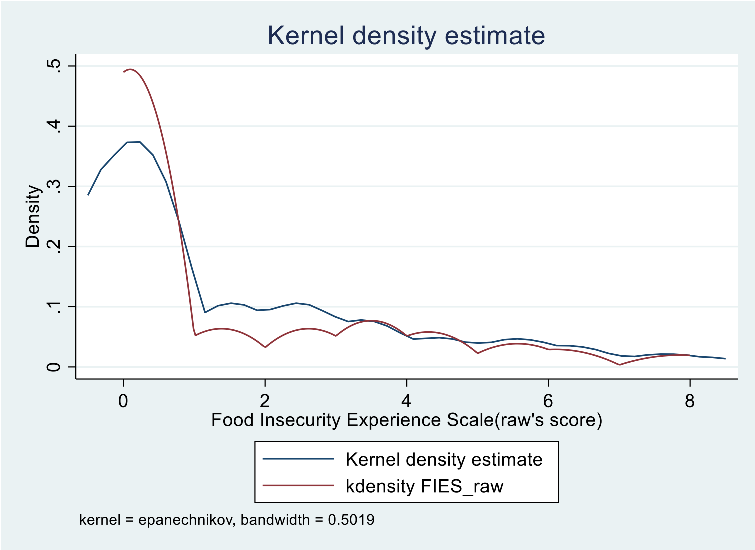
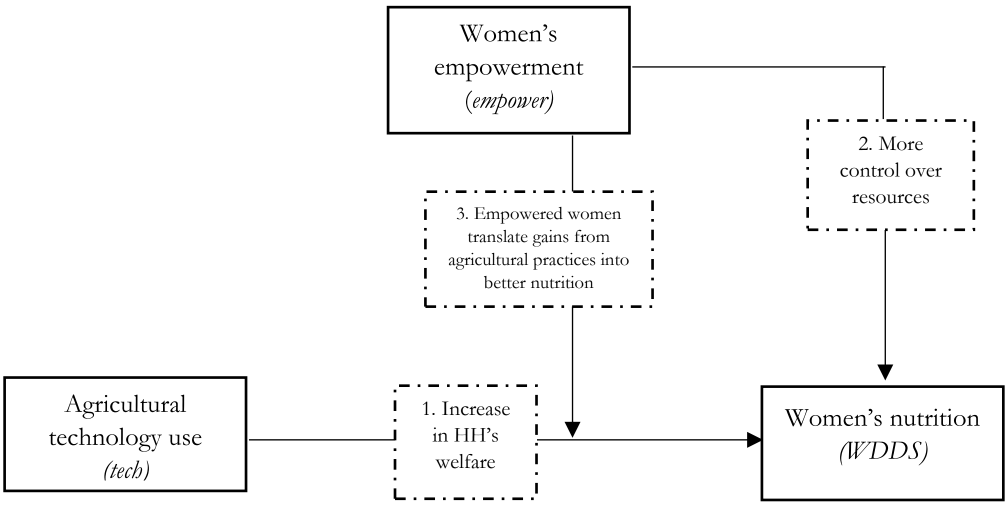


Figure 3. Kernel density for FIES(pooled sample)

3.4. Empirical Strategy

Figure 4 shows the conceptual framework used for understanding direct and indirect links between agricultural technology use, women's empowerment, and the two outcomes of interest: women's dietary diversity and household food security, following the theoretical discussion in section 2.3. To test the theoretical pathways presented there, I use panel regressions and Heckman models, as explained in the following subsections.

Outcome 1: Women Dietary Diversity



OUTCOME 2: HOUSEHOLD FOOD SECURITY

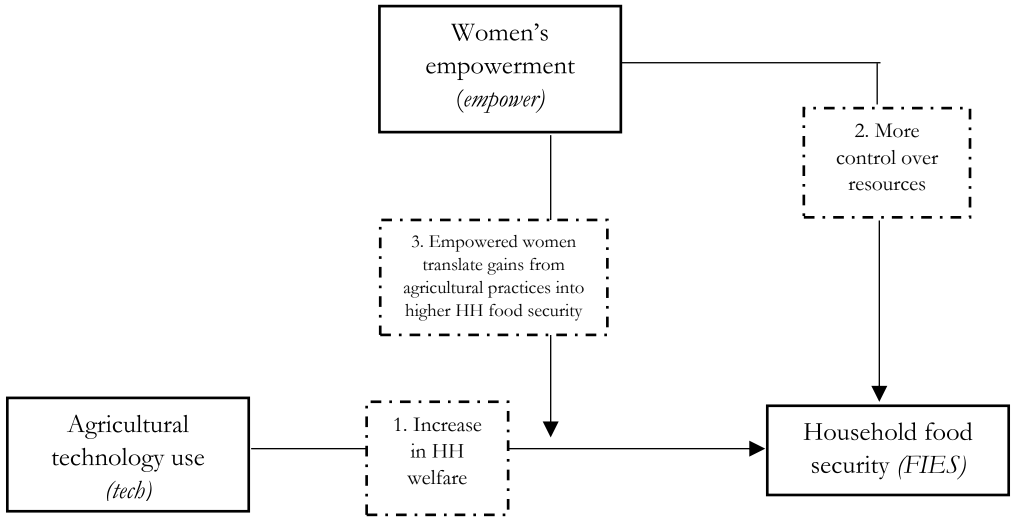


Figure 4. Conceptual Framework. Source: own elaboration. 1,2,3 refer to pathways described in section 2.3.

<u>Pooled Ordinary Least Squares</u>

A panel OLS regression model with an interaction term was carried out for each of the outcome variables under analysis:

$$WDDS_{it} = \alpha + \beta_1 \cdot tech_{it} + \beta_2 \cdot \ empower_{it} + \beta_3 \ \cdot tech * empower_{it} \ + \beta_4 X_{it} + \varepsilon_{it} \ (1)$$

$$FIES_{it} = \alpha + \beta_1 \cdot tech_{it} + \beta_2 \cdot empower_{it} \ + \beta_3 \ \cdot tech * empower_{it} \ + \beta_4 X_{it} + \varepsilon_{it} \ (2)$$

Where *WDDS* is the Women Dietary Diversity Score, *FIES* is Food Insecurity Experience Scale, *tech* is the technology variable indicating the number of practices used by the household(from 0 to 3), *empower* is a dummy indicating whether the empowerment score is above or below a threshold, *tech*empower* is the interaction term, and *X* is a vector of control variables that include the household characteristics: time spent on all care work by women, age and education of the household head, number of household members, number of female members in the households, female headed households, hectares of land cultivated, number of plots cultivated with oil palm and asset score. Lastly, *t* indicates the time periods (in this case, 2) and *i* the individuals.

FE models

Afterward, the same specifications expressed above were used in a fixed effect model:

$$WDDS\text{it}=\alpha+\beta 1\cdot tech\text{it} +\beta 2\cdot empower\text{it} +\beta 3 \cdot tech*empower\text{it} +\beta 4\ X\text{it} +\sum_{j=1}^{N-1}\mu_j D_{ji}+\varepsilon\text{it} \quad (1')$$

$$FIES\textit{it}=\alpha+\beta 1\cdot tech\text{it} +\beta 2\cdot empower\text{it} +\beta 3 \cdot tech*empower\text{it} +\beta 4\ X\text{it} + \sum_{j=1}^{N-1}\mu_j D_{ji} +\varepsilon\text{it} \quad (2')$$

Finally, we also add time dummies:

$$WDDS\text{it}=\alpha+\beta 1\cdot tech\text{it} +\beta 2\cdot empower\text{it} +\beta 3 \cdot tech*empower\text{it} +\beta 4\ X\text{it} + \sum_{j=1}^{N-1}\mu_j D_{ji} + \sum_{s=1}^{T-1}\tau_s D_{st} +\varepsilon\text{it} \quad (1'')$$

$$FIES\textit{it}=\alpha+\beta 1\cdot tech\text{it} +\beta 2\cdot empower\text{it} +\beta 3 \cdot tech*empower\text{it} +\beta 4\ X\text{it} + \sum_{j=1}^{N-1}\mu_j D_{ji} + \sum_{s=1}^{T-1}\tau_s D_{st}+\varepsilon\text{it} \quad (2'')$$

Heckman's Model

Since standard regression techniques can be biased as in this context there could be potential selection bias in the use of the technologies considered and in the empowerment status, self-selection or endogeneity models are needed to account for time-varying unobserved heterogeneity in the household. A major problem in estimating the outcomes equations (WDDS and FIES equations) for women is that the empowered sample may not be a random draw from the population. In other words, the women observed in the group with higher level of empowerment may be a selective group in terms of observable (for instance, they could have different levels of education, different age, access to resources and markets and so on) and in terms of "unobservables" (for instance, motivation and abilities). The source of the problem is that "unobservable" determining empowerment and those determining dietary diversity or household food security are potentially correlated. Under such circumstances, conventional estimation of the outcomes equations by OLS may yield biased coefficient estimates, given the presence of selection bias. To solve this issue, I employ the Heckman correction procedure using a two-step approach. This approach treats the selection effect as an omitted variable problem (Heckman, 1979).

I first calculate the Inverse Mills Ratios (IMR) from the first stage equation (probit). Since I want to avoid having an extremely collinear model - that will happen if I use the same set of covariates in both the selection and the main equation of the Heckman model - I add some instruments to the first stage (selection model).

In previous literature, the variables usually identified as instruments include whether a woman has brought at least a plot to the family as an inherited asset (allocated by the woman's clan or as an inheritance from her family). Inherited assets has been considered in the literature as a bargaining measure (Quisumbing and Maluccio, 2003; Kassie *et al.*, 2020). This could have an impact on women's empowerment, but it is not automatically linked to an improvement in the diversity of female diets, that should include several components not always related to plot that they bring into marriage. Other instruments used are the death of a child in the past ten years, whether the head is widowed or single and whether the household is female-headed(Sraboni *et al.*, 2014).

In the first stage, I estimate the participation equation using a probit model for female empowerment:

$$Prob[fem\_emp=1]= \Phi\ (\alpha_0+\alpha_1 carework_i+\alpha_2 hh\_members_i+\alpha_3 land_i+\alpha_4 assets_i+\alpha_5 female\_memb_i+\alpha_6 age_i +\alpha_7 educ_i+ \alpha_8 age\_female_i+ \alpha_9 edu\_female_i+ \alpha_{10} Z_i) \text{ with } i=1,..1527 \tag{3}$$

where Z for WDDS is a vector of instruments including whether a woman has brought at least a plot to the family (allocated by the woman's clan or as an inheritance from her family) and if the household head is female. For FIES, the Z vector includes whether a woman has brought at least a plot to the family and whether a child's death in the past years occurred.

I then use the probit coefficients from first-stage equations to compute the selection term to be used in the second-stage equations for the two outcomes, computed as pooled OLS (eq. 4 and 5) and with fixed effects (eq. 4' and 5'; adding time dummies in eq. 4" and 5"). For each outcome, the second stage will be computed both for empowered and disempowered women and with robust standard errors. In this way, in addition to control for self-selection, I can obtain the technological effect of female empowerment.

$$WDDS_{it} = \alpha + \beta_1 \cdot tech_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{4}$$

$$FIES_{it} = \alpha + \beta_1 \cdot tech_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{5}$$

$$WDDS_{it} = \alpha + \beta_1 \cdot tech_{it} + \beta_2 X_{it} + \sum_{j=1}^{N-1} \mu_j D_{ji} + \varepsilon_{it} \tag{4'}$$

$$FIES_{it} = \alpha + \beta_1 \cdot tech_{it} + \beta_2 X_{it} + \sum_{j=1}^{N-1} \mu_j D_{ji} + \varepsilon_{it} \tag{5'}$$

$$WDDS_{it} = \alpha + \beta_1 \cdot tech_{it} + \beta_2 X_{it} + \sum_{j=1}^{N-1} \mu_j D_{ji} + \sum_{s=1}^{T-1} \tau_s D_{st} + \varepsilon_{it} \tag{4''}$$

$$FIES_{it} = \alpha + \beta_1 \cdot tech_{it} + \beta_2 X_{it} + \sum_{j=1}^{N-1} \mu_j D_{ji} + \sum_{s=1}^{T-1} \tau_s D_{st} + \varepsilon_{it} \tag{5''}$$

with X as a vector of variables that includes time spent on all care work by women, age and education of the household head, number of household members, number of female members in the households, hectares of land cultivated, number of plots cultivated with oil palm, asset score and the residuals from the first stage.

The selection terms

The *i*th estimated residuals is given by

$$\hat{u}_i = \frac{y_i - \Phi(\hat{\theta}_i)}{\Phi(\hat{\theta}_i)[1-\Phi(\hat{\theta}_i)]}\phi(\hat{\theta}_i)$$

The selection terms are probit residuals, the residuals from when the event occurs: if y_i=1(women with higher level of empowerment), then I obtain the inverse of the mills ratio:

$$\hat{u}_i = \frac{\phi(\hat{\theta}_i)}{\Phi(\hat{\theta}_i)}$$

If y_i=0(women with lower level of empowerment), then I get the complement of the mills ratio:

$$\hat{u}_i = \frac{\phi(\hat{\theta}_i)}{1-\Phi(\hat{\theta}_i)}$$

The inverse of mills ratio (or pseudo-residuals) variable is an empirical measure of "unobservables" in the empowerment equation. I employ this device to correct the main equations for potential selection bias into empowerment.

4. Results

4.1 Panel regressions considering the three practices on oil palm plots

This section presents the sets of results for the two outcomes considered. Table 7 shows results from the panel regression using the Women Dietary Diversity Score as dependent variable. Column I displays the coefficient for technology use, column II for technology use plus the empowerment dummy, and column III shows the results of the specification with interaction effects. Then, in column IV, control variables were added to the model with the interaction term. Column V reports coefficients for the FE model, and column VI for the FE with time dummies.

The use of one and the use of two practices on oil palm plots seems to positively affect the nutrition outcome in a significant way, and it remains significant also when I add the empowerment dummy, the interaction terms and control variables in the regression. In particular, using two practices increases the WDDS by around 0.74. However, using a fixed effect model (specifications V and VI) the effect of the technology use remains positive but significant only for the use of two practices. Female empowerment and the interaction term seem to have mixed and not significant results. Other variables that seem to play a significant role in WDDS are the asset score, the land cultivated, and the time spent by women of care works for the household.

Table 7. Regression results for the combined use of technologies on oil palm plots on WDDS

	WDDS					
	POLS	POLS	POLS	POLS	FE	FE-time dummy
Use of agricultural practices(categorical)						
Use of one practice	0.131*	0.130	0.183**	0.174*	0.054	0.033
	(0.079)	(0.079)	(0.090)	(0.090)	(0.173)	(0.167)
Use of two practices	0.748***	0.747***	0.786***	0.709***	0.734**	0.680**
	(0.125)	(0.125)	(0.143)	(0.143)	(0.296)	(0.286)
Use of three practices	0.182	0.180	-0.024	-0.070	0.004	0.261
	(0.381)	(0.381)	(0.432)	(0.425)	(0.759)	(0.736)
Female empowerment		-0.042	0.066	0.546	0.099	-0.035
		(0.087)	(0.131)	(0.342)	(0.968)	(0.936)
1 practice#1.fememp			-0.230	-0.262	-0.167	-0.081
			(0.187)	(0.184)	(0.386)	(0.374)
2 practices#1.fememp			-0.156	-0.106	0.193	0.243
			(0.291)	(0.284)	(0.549)	(0.531)
3 practices#1.fememp			0.934	1.025	1.834	0.865
			(0.916)	(0.896)	(1.438)	(1.408)
No. of household members				0.030	0.026	0.131
				(0.025)	(0.103)	(0.102)
Land cultivated(ha)				-0.006	-0.031*	-0.031*
				(0.005)	(0.017)	(0.016)
No. of plots with oil palm				0.023	-0.234	-0.167
				(0.067)	(0.185)	(0.180)
Asset score				0.874***	1.177	1.560**
				(0.267)	(0.791)	(0.769)
No. of female members				-0.070*	-0.031	-0.179
				(0.040)	(0.160)	(0.159)
Age of the head				-0.002	-0.027	0.010
				(0.003)	(0.023)	(0.024)
Education head				-0.007	-0.019	-0.003
				(0.009)	(0.026)	(0.026)
Female headed household				-0.341	-0.330	0.492
				(0.326)	(1.108)	(1.087)
Time spent on care work				0.050***	0.044***	0.026*
				(0.008)	(0.014)	(0.014)
Time dummy						0.500***
						(0.112)
Const.	3.041***	3.051***	3.024***	2.538***	4.464***	1.758
	(0.057)	(0.061)	(0.066)	(0.250)	(1.517)	(1.586)
F statistic	12.1	9.1	5.6	6.0	2.4	3.6
R-squared	0.04	0.04	0.04	0.10	0.12	0.18
N	933	933	933	932	932	932

st.errors in parenthesis, * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 8 displays the results from the panel regression using the Food Insecurity Experience Scale as dependent variable. The use of at least one of the practices provides mixed results, but in most cases, coefficients are not significant. They are significant only for the use of two practices in columns 2,3, and 4, providing evidence of a reduction in household food insecurity. Female empowerment has a positive and significant effect on the food insecurity scale, suggesting a reduction of household food insecurity ranging from 0.59 to 1.15, depending on the specification. The interaction term is significant in the pooled specification, and it suggests that for the group of women scoring lower in terms of empowerment, the FIES is expected to decrease by 1.141 due to the use f two practices, while for the other group it is expected to slightly increase (-1.141+1.161=0.02 in column 4). As the number of household members rises, the Food Insecurity Experience Scale seems to increase a little; however, this is significant only in the fourth specification. The asset score plays a significant role in greatly reducing household food insecurity (by around 3.3). The education of the household head has a significant effect on food insecurity, ever if only at 5% in the fixed effect models. Being a female-headed household seems to have a negative impact on food security, whereas spending more time on household care work seems to reduce food insecurity, but both coefficients are significant only in the POLS specification (column 4).

Table 8. Regression results for the combined use of technologies on oil palm plots on FIES

	FIES					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of agricultural practices (categorical)						
Use of one practice	0.043	-0.012	-0.310	-0.346	-0.594	-0.593
	(0.142)	(0.142)	(0.342)	(0.324)	(0.627)	(0.627)
Use of two practices	-0.359	-0.380*	-1.556***	-1.141**	-1.156	-1.092
	(0.224)	(0.223)	(0.550)	(0.520)	(0.937)	(0.941)
Use of three practices	-0.378	-0.493	-0.167	-0.236	2.384	2.392
	(0.686)	(0.683)	(1.199)	(1.132)	(1.795)	(1.796)
Female empowerment		-0.583***	-0.913***	-0.932***	-1.208**	-1.159*
		(0.172)	(0.296)	(0.283)	(0.586)	(0.591)
1 practice#1.fememp			0.346	0.410	0.910	0.913
			(0.376)	(0.356)	(0.662)	(0.662)
2 practices#1.fememp			1.407**	1.161**	1.621	1.529
			(0.602)	(0.569)	(1.006)	(1.015)
3 practices#1.fememp			-0.587	-0.437	-2.357	-2.372
			(1.459)	(1.380)	(2.106)	(2.108)
No. of household members				0.082*	0.211	0.237
				(0.044)	(0.149)	(0.154)
Land cultivated(ha)				0.005	0.036	0.036
				(0.008)	(0.024)	(0.024)
No. of plots with oil palm				-0.024	0.313	0.330
				(0.115)	(0.273)	(0.274)
Asset score				-3.496***	-3.202***	-3.099***
				(0.460)	(1.155)	(1.164)

No. of female members				-0.095	-0.059	-0.101
				(0.069)	(0.233)	(0.240)
Age of the head				-0.002	0.003	0.011
				(0.005)	(0.034)	(0.036)
Education head				-0.036**	-0.074*	-0.071*
				(0.015)	(0.039)	(0.039)
Female-headed household				0.379**	-0.896	-0.748
				(0.179)	(0.831)	(0.856)
Time spent on care work				-0.044***	-0.028	-0.033
				(0.013)	(0.021)	(0.022)
Time dummy						0.126
						(0.171)
Constant	1.378***	1.881***	2.167***	3.905***	2.669	2.032
	(0.102)	(0.180)	(0.275)	(0.477)	(2.283)	(2.443)
F statistic	1.2	3.8	3.0	9.6	2.1	2.0
R-squared	0.00	0.02	0.02	0.14	0.11	0.11
N	935	935	935	934	934	934

*St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01*

Additionally, I re-run the above models using the categorical variable for technology use(from zero to 3) and dropping some control variables and I have reported the results in appendix. I also run the same specifications of table 7 and 8 considering the use of the three practices on plots cultivated with crops other than oil palm. Results for these are reported and briefly discussed in appendix A.1.

4.2. Results from the Heckman's Model

Women Dietary Diversity

Table 9 shows the second stage of the Heckman's model for women with higher or lower levels of empowerment. The use of at least one among the practices considered on oil palm plots significantly increases the dietary diversity of women who score better in terms of empowerment in the POLS specification. For the other group of women, it seems that the use of the technology decreases the dietary diversity for the pooled specification (even not significantly), but it significantly and greatly increases the outcome in the fixed effect model.

Table 9. Heckman's second stage results for WDDS

	WDDS					
	Higher level of empowerment score			Lower level of empowerment score		
	POLS	FE	FE+T	POLS	FE	FE+T
Use of at least one technology on oil palm plots	0.275***	0.124	0.099	-0.027	0.764***	0.764***
	(0.087)	(0.172)	(0.171)	(0.141)	(0.200)	(0.200)
Time spent by women on all care work	0.051***	0.079***	0.051**	0.043**	-0.443***	-0.443***
	(0.010)	(0.021)	(0.023)	(0.017)	(0.055)	(0.055)
No. household members	0.026	0.015	0.081	-0.053	0.707***	0.707***
	(0.028)	(0.111)	(0.119)	(0.060)	(0.133)	(0.133)
Land cultivated(ha)	-0.001	-0.009	-0.017	0.001	0.114**	0.114**
	(0.005)	(0.014)	(0.015)	(0.011)	(0.050)	(0.050)
No. plots with oil palm	-0.059	-0.491**	-0.369*	0.158	-1.078***	-1.078***
	(0.090)	(0.193)	(0.194)	(0.099)	(0.140)	(0.140)
Asset Score	0.758**	0.826	0.925	1.227*	-1.034	-1.034
	(0.313)	(0.924)	(0.892)	(0.622)	(0.770)	(0.770)
No. female members	-0.079*	-0.099	-0.221	0.102	0.610	0.610
	(0.047)	(0.197)	(0.184)	(0.084)	(1.248)	(1.248)
Age of household head	-0.002	-0.102*	-0.018	0.000	-0.421***	
	(0.007)	(0.057)	(0.041)	(0.010)	(0.075)	
Education of hh head	-0.008	0.073**	0.051	0.017	-0.359***	-0.359***
	(0.011)	(0.036)	(0.037)	(0.020)	(0.030)	(0.030)
Mean age of female hh members	-0.001	-0.025	-0.011	0.010		
	(0.008)	(0.025)	(0.027)	(0.011)		
Mean edu of female hh members	0.001	0.007	-0.010	-0.022	-0.372***	-0.372***
	(0.012)	(0.041)	(0.042)	(0.021)	(0.086)	(0.086)
Residuals	-0.198	5.221***	3.246	0.181	-12.623***	-12.623***
	(0.353)	(1.935)	(1.985)	(0.302)	(2.083)	(2.083)
Time dummy			0.493***			0.842***
			(0.145)			(0.150)
Constant	2.812***	7.778**	3.331*	1.947***	9.209***	-12.499***
	(0.315)	(3.222)	(1.877)	(0.509)	(3.309)	(3.960)
F statistic	4.8	4.1	4.6	2.5	.	.
R-squared	0.07	0.17	0.20	0.15	0.97	0.97
N	745	745	745	150	150	150

St. errors in parenthesis; * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Food insecurity

Table 10 shows the second stage results for the women with higher and lower empowerment scores. In both of them, the use of at least one of the practices considered does not seem to affect household food insecurity significantly. A much more important role in reducing food insecurity is played by the time spent on care work and asset ownership, especially among women with a lower level of empowerment, as they are significant in all three specifications.

Table 10. Second stage Heckman

	FIES					
	Higher empowerment score			Lower empowerment score		
Use of at least one technology on oil palm plots	0.022	0.446	0.444	-0.016	0.142	0.142
	(0.349)	(0.546)	(0.550)	(0.140)	(0.250)	(0.250)
Time spent by women on all care work	-0.060*	-0.112	-0.112	-0.048***	-0.039*	-0.039*
	(0.036)	(0.074)	(0.075)	(0.014)	(0.023)	(0.023)
No. household members	0.188	-0.261	-0.259	0.035	0.199	0.199
	(0.163)	(0.272)	(0.281)	(0.054)	(0.166)	(0.166)
Land cultivated(ha)	0.019	0.038	0.037	0.005	0.038**	0.038**
	(0.045)	(0.055)	(0.057)	(0.006)	(0.015)	(0.015)
No. plots with oil palm	-0.146	-0.034	-0.029	0.054	0.349	0.349
	(0.378)	(0.778)	(0.913)	(0.106)	(0.243)	(0.243)
Asset Score	-4.971***	-5.140	-5.138	-3.548***	-4.161***	-4.161***
	(1.569)	(3.330)	(3.367)	(0.450)	(1.534)	(1.534)
No. female members	-0.194	0.161	0.158	-0.031	0.017	0.017
	(0.219)	(0.508)	(0.518)	(0.081)	(0.260)	(0.260)
Age of household head	0.006	0.003	0.004	0.011	-0.259***	
	(0.042)	(0.072)	(0.065)	(0.013)	(0.096)	
Education of hh head	-0.161	-0.146	-0.146	-0.035**	-0.105*	-0.105*
	(0.129)	(0.109)	(0.112)	(0.017)	(0.054)	(0.054)
Mean age of female hh members	0.004	0.061	0.061	-0.023	0.122***	0.122***
	(0.047)	(0.053)	(0.054)	(0.014)	(0.046)	(0.046)
Mean edu of female hh members	0.150			-0.010	-0.009	-0.009
	(0.131)			(0.017)	(0.066)	(0.066)
Residuals	0.334	2.879**	2.880**	-0.039	0.384	0.384
	(0.723)	(1.274)	(1.269)	(0.278)	(0.824)	(0.824)
Time dummy			0.007			0.517***
			(0.383)			(0.193)
Female-headed household				0.450		
				(0.824)		
Constant	2.884***	-0.208	-0.267	3.546***	9.964**	-3.487*
	(1.083)	(3.260)	(2.867)	(0.510)	(4.525)	(2.083)
F statistic	2.8	.	.	7.6	6.7	6.7
R-squared	0.09	0.15	0.15	0.13	0.12	0.12
N	218	218	218	679	679	679

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

4.3. Analysis considering two practices only

Since the three practices mentioned above could hide heterogeneity, with peculiar reference to intercropping, I also run the analysis considering only the use of agrochemicals or irrigation on oil palm plots. This time, the main explanatory variable is the use of at least one agricultural practice among irrigation and agrochemicals, captured through a dummy variable at the household level equal one if the household adopts at least one of the two practices or zero otherwise. Table 11 displays the number of households in the sample using and not using the practices considered on plots with oil palm. In addition to this, I also capture technology use as a count variable from 0 to 2, according to the number of practices used by each household.

Table 11. Number of households in the sample using and not using agricultural practices considered on oil palm plots.

	2017		2019		Pooled sample	
	Non-user	Users	Non-user	Users	Non-user	Users
At least one among agrochemicals and irrigation	547 (75.66)	176 (24.34)	644 (81.11)	150 (18.89)	1191 (78.51)	327 (21.49)

Percentage shares are shown in parentheses

Results considering two practices

Panel regressions

Table 12 shows results from the panel regression using the Women Dietary Diversity Score as dependent variable and as the main explanatory variable the count of practices used(from 0 to 2). Column I displays the coefficient for the use of the two agricultural practices, column II adds the women empowerment dummy, and column III shows the results of the specification with interaction effects. Then, in column IV, control variables were added to the model with the interaction terms. Columns V and VI report the coefficients for the FE model without and with time dummies, respectively. Using one of the practices under analysis on oil palm plots seems to affect the nutrition outcome positively in a significant way in all the specifications, increasing the WDDS by on average 0.44. The interaction term is significant in column V, meaning that the relationship between the use of two practices and Women Dietary Diversity Score also depends on the empowerment status. Indeed, the WDDS increases by 0.43 for the group of women scoring lower in terms of empowerment, while it increases by 3.27 for the other group.

Table 12. Regression results for the use of the agricultural practices on Woman Dietary Diversity Score (WDDS)

	WDDS					
	POLS	POLS	POLS	POLS	FE	FE+T
	I	II	III	IV	V	VI
Practices use						
1	0.462***	0.461***	0.481***	0.388***	0.427**	0.426**
	(0.085)	(0.086)	(0.097)	(0.097)	(0.176)	(0.170)
2	0.165	0.162	0.021	0.033	-0.814	-0.372
			(0.346)	(0.340)	(0.656)	(0.642)
Female empowerment(dummy)		-0.028	-0.016	0.456	0.151	0.026
		(0.088)	(0.101)	(0.335)	(0.951)	(0.920)
1.practice *1.empowerment			-0.095	-0.039	0.191	0.216
			(0.207)	(0.203)	(0.369)	(0.357)
2.practices#1.empowerment			0.925	0.984	**2.843****	1.606
			(0.878)	(0.861)	(1.395)	(1.376)
constant	3.066***	3.073***	3.070***	2.589***	5.418***	2.431
	(0.043)	(0.048)	(0.050)	(0.247)	(1.516)	(1.607)
Additional controls	No	No	No	Yes	Yes	Yes
Time dummy	No	No	No	No	No	Yes
F statistic	28.3	14.2	6.1	5.9	2.7	4.0
R-squared	0.03	0.03	0.03	0.08	0.12	0.18
N	933	933	933	932	932	932

Additional controls are: No. of household members, Land cultivated(ha), No. of plots with oil palm, Asset score, No. of female members, Age of the head, Education head, Female headed household. St.errors in parenthesis * p<0.1; ** p<0.05; *** p<0.01

Table 13 displays the results from the panel regressions with the Food Insecurity Experience Scale as dependent variable. Using one practice under analysis seems to reduce the score in the first three specifications. Female empowerment positively and significantly affects food security in columns II to IV. However, the interaction term is not significant in this case. This could mean that female empowerment plays a stronger role in reducing food insecurity regardless of households' technological status.

Table 13. Regression results for the use of the agricultural practices on Food Insecurity Experience Scale (FIES)

	FIES					
	POLS	POLS	POLS	POLS	FE	FE+T
	I	II	III	IV	V	VI
Practices use						
1	-0.581***	-0.576***	-0.730**	-0.415	0.287	0.307
	(0.152)	(0.152)	(0.358)	(0.343)	(0.608)	(0.609)
2	0.038	-0.032	-0.516	-0.633	1.972	2.161
	(0.566)	(0.563)	(1.022)	(0.974)	(1.484)	(1.510)
Female empowerment(dummy)		-0.573***	-0.632***	-0.681***	-0.455	-0.413
		(0.170)	(0.198)	(0.195)	(0.364)	(0.369)
1.practice *1.empowerment			0.188	0.111	-0.373	-0.405
			(0.395)	(0.377)	(0.660)	(0.662)
2.practices#1.empowerment			0.688	0.951	-1.485	-1.707
			(1.226)	(1.169)	(1.793)	(1.823)
Cons	1.501***	1.967***	2.016***	3.393***	0.992	0.289
	(0.077)	(0.158)	(0.179)	(0.435)	(2.224)	(2.445)
Additional controls	No	No	No	Yes	Yes	Yes
Time dummy	No	No	No	No	No	Yes
F statistic	7.3	8.7	5.3	10.7	2.1	2.0
R-squared	0.02	0.03	0.03	0.13	0.09	0.09
N	935	935	935	935	935	935

Additional controls are: No. of household members, Land cultivated(ha), No. of plots with oil palm, Asset score, No. of female members, Age of the head, Education head, Female headed household. St.errors in parenthesis * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Heckman's Model

Table 14 shows the second stage of Heckman's model for the two groups of women with different levels of empowerment score. The top of the table displays results for the women's nutrition outcome (WDDS). Using at least one of the practices considered on oil palm plots significantly increases the dietary diversity of women who score better in terms of empowerment in all three specifications. The results are insignificant for women with a lower level of empowerment.

The bottom part of table 14 shows results from Heckman's second stage for household food insecurity. The use of at least one of the practices considered significantly reduces FIES for women with a lower empowerment score only in the POLS specification.

Table 14. Heckman's second stage results for WDDS and FIES

	WDDS					
	High level of empowerment			Low level of empowerment		
	POLS	FE	FE+T	POLS	FE	FE+T
Use of at least one practice	0.453***	0.478**	0.399**	0.156	-0.697	-0.697
	(0.101)	(0.188)	(0.198)	(0.203)	(3.532)	(3.343)
Constant	3.142***	8.758**	2.201	1.798***	15.598	15.991
	(0.248)	(4.212)	(2.134)	(0.501)	(26.875)	(100.206)
Time dummy	No	No	Yes	No	No	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.04	0.12	0.20	0.10	0.70	0.70
N	745	745	745	150	150	150
	FIES					
	High level of empowerment			Low level of empowerment		
	POLS	FE	FE+T	POLS	FE	FE+T
Use of at least one practice	-0.123	0.006	0.025	-0.343***	-0.059	-0.059
	(0.402)	(0.539)	(0.535)	(0.126)	(0.266)	(0.250)
Constant	2.396**	-2.549	-1.945	3.342***	6.933*	1.920
	(1.136)	(7.758)	(2.532)	(0.528)	(4.207)	(1.534)
Time dummy	No	No	Yes	No	No	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.08	0.10	0.10	0.12	0.10	0.10
N	218	218	218	679	679	679

Additional controls are: No. of household members, Land cultivated(ha), No. of plots with oil palm, Asset score, No. of female members, Age of the head, Education head, Female headed household. St.errors in parenthesis * p<0.1; ** p<0.05; *** p<0.01

Overall, it is possible to say that the empowerment status plays a mediating role in the relationship between technology use and the two outcomes. The Heckman model for WDDS confirms my initial hypothesis that women with higher levels of empowerment could increase their WDDS using agricultural technology. Food insecurity seems to be reduced by the use of technologies in households where women score worse in terms of empowerment, meaning that, facing the trade-off between their nutrition and household food security and having less resources that they can manage, they privilege the latter.

5. Conclusion and policy implications

Agricultural technologies and practices could positively impact food security and nutrition in Sub-Saharan Africa. Women could be affected by these positive consequences of technologies or could be excluded depending on their position within the household and their bargaining power. Using panel data on oil palm growers in Ghana from the Agricultural Policy Research in Africa (APRA) consortium, this essay investigated the consequences of using agricultural technology. The aim was to obtain new insights on food security and nutrition, with a particular focus on women and their empowerment status. Using a fixed effects model and interaction terms, along with a Heckman's model, I investigated the mediating role of female empowerment for the nexus between technology on the one hand, and food security and women's nutrition outcomes on the other. Overall, findings show that the use of agricultural practices and female empowerment interact somehow, even if differently in the cases considered. Indeed, results for the use of the three practices are mixed. Despite an improvement in the WDDS due to the practices considered, women empowerment per se does not have significant effect. The Heckman model shows an increase in women's dietary diversity for both groups of women, confirming a lower importance of female empowerment in mediating the relationship. Instead, household food insecurity seems to be reduced by the use of agricultural practices and female empowerment. However, the Heckman model does not show any significant effect of agricultural practices on household food insecurity for women at both empowerment levels.

One possible explanation for the mixed results obtained above could be the heterogeneity in the use of technologies under analysis. Therefore, I performed the analysis excluding intercropping (section 4.3) and considering the agrochemicals and intercropping separately (in appendix). Irrigation was not considered by itself due to the low number of observations. The main results for the use of agrochemicals highlight the importance of using this practice on women's dietary diversity, and even to a lesser extent on household food security. This is true especially for women who score better in terms of empowerment and have more control over household resources. Findings for intercropping are mixed, with the empirical models considered providing different results.

Results considering only two practices show that women's dietary diversity increases due to the use of these agricultural techniques. They also show that female empowerment mediates this relationship as the impact is positive for the group of women who score better in terms of empowerment. However, the other group of empowerment status seems to have a better outcome in terms of household food security.

Overall, it can be noticed that the most consistent and robust results are those related to empowerment and women's dietary diversity while the ones about household food security are less strong. Further development of the analysis will therefore focus on that outcome.

These results mean that providing access to technology is particularly relevant for women's nutrition. Nevertheless, this is not enough, and policy interventions to increase female empowerment play an essential role in improving female nutrition.

This essay presents some limitations. Data used are not nationally representative but characterize a specific context, as only two Ghanaian districts were considered. Additionally, the two waves are close in time to one another, and this could represent a barrier to understanding the real effect on women's nutrition, an aspect that takes more time to evolve and improve. Indeed, this could be reflected in the results obtained through the fixed effect specifications, which often are not significant. In addition, with the availability of data on children's nutrition, more solid results could have been shown and justified, as it is common for women to prioritize children's diet quality, overshadowing their nutrition.

The study has some implications relevant to policymaking. It highlights the importance of adequately promoting the technologies considered for household food security and women's nutrition. Combined with this, strengthening female empowerment and women's bargaining power within the household is key. This could be improved by including women in agricultural training - together with men - and providing them with inputs they can manage independently.
Future research should focus on other technologies and other contexts. To make results stronger, it would be helpful to replicate the analysis using nationally representative data or perform RCTs in similar locations for external validity.

Essay 2

Technology adoption constraints and Laser Land Leveling: Evidence from Karnataka, India[5]

Abstract

Climate-smart agriculture can address many of the challenges faced by agriculture in semi-arid areas. However, in many developing countries, the adoption and use of this kind of technologies is still low. Knowledge constraints represent a critical barrier to adoption; hence, an effective extension system is key. In India, extension programs are characterized by partnerships involving both the public sector, the private sector and NGOs. The latest approaches take advantage of mass media and video-based extension services. In this essay, I assess the role of extension services on the adoption of laser land leveling among 604 households in the Indian state of Karnataka. Laser land leveling is a modern way for leveling fields using a laser machine; it also brings environmental, economic and social benefits. Using propensity score matching, I find that having at least one visit at the extension center (Raita Samparka Kendra, RSK) or received by RSK officials increases the likelihood of using LLL. Furthermore, a causal mediation analysis reveals that after explaining the advantages of the technology and its cost, farmers develop a perception about the affordability of laser land leveling that mediates the treatment effects of the extension service on laser land leveling adoption. Another mechanism that could mediate this relationship investigated in the essay is the increase in farmers' welfare, proxied by household expenditure.

Keywords: Climate-smart agriculture, Extension services, Mediation analysis

[5] Data available at: https://doi.org/10.7910/DVN/5094DW. Harvard Dataverse. Version 1.

1. Introduction

Climate-smart agriculture can address many of the challenges faced by agriculture in semi-arid areas. Despite their benefits, the adoption and use of many climate-smart agricultural technologies in many developing countries is still low. There are three main categories of barriers that could hinder adoption. Firstly, small-farmer households could lack information about the technology and its use. Secondly, they cannot afford the initial investment and face difficulties paying for labor or inputs needed for the technology to work. Finally, they could be risk-averse and be worried about the time delay between the investment for the technology and returns.

This essay concerns the Indian state of Karnataka, where 13.74 million people are employed in the agricultural sector (Census 2011, 2021). Most of the cultivated area in the state is under rainfed cultivation, and the presence of monsoon is essential for good agricultural production. This analysis focus on the Raichur District, located in the north-eastern dry zone of the state. The district has faced severe problems due to the declining rainfall since 2014, especially in 2018 (Pal *et al.*, 2020). Climate-smart agriculture could be an important mean to overcome these problems. To promote this type of agriculture, extension programs could foster and spread knowledge about the existence of this type of technology, informing farmers on how to use it and how to receive credit or liquidity needed to start using it. In India, extension programs are characterized by public-private partnerships also involving NGOs. Lately, many programs have taken advantage of mass media and video-based extension services (De Janvry, Macours and Sadoulet, 2016).

The climate-smart technology considered in this essay is laser land leveling (LLL), a modern method to level fields using laser-guided leveling machinery (Jat *et al.*, 2006). LLL allows improved agronomic, better soil and crop management practices, and benefits at the environmental, productivity and social level. Despite these advantages, laser land leveling is not a widespread farming practice in developing countries and additional investigations analyzing factors that influence the adoption of this technology are needed. Indeed, focusing on this technology can provide helpful insight into dealing with challenges existing in semi-arid regions.

In this essay, I analyze the role of extension centers in spreading knowledge about technology. To understand to what extent and how extension services favor the diffusion of an innovative agricultural practice it is important to take into account the role of related knowledge and affordability of the technique under analysis. Using a sample of 604 farmers and cross-sectional data collected by the SAR (South Asia Regional office) division of IFPRI between November 2018 and March 2019, after paddy harvest in the state of Karnataka, I examined the effect of extension services on the use of laser land leveling. In addition to that, I also investigate the role of farmer's attitude toward the technology under analysis and farmers' welfare in mediating the nexus between receiving extension and using laser land leveling. Rogers (1983) provides the theoretical framework guiding this analysis: in what he defined the *innovation-decision process* he highlighted the stages of adoption decisions going from the phase in which an individual recognizes the existence of an innovation to the one where she decides to adopt it. The first phase is strongly related to the dissemination of information; hence, to the role of extension services offered to farmers. In the process, the individual develops beliefs and expectations related to the innovation during the phase that Rogers called "persuasion". In this essay, this stage will be considered as a channel of transmission through which the extension service could have an impact on the decision to adopt.

Investigating the access to extension programs that foster the spreading of information about how to increase productivity and profitability among farmers is not a new issue in the literature. The latest extension methodologies include video interventions and field days showing a positive effect of an increase in knowledge and information on adoption (Wollni and Andersson, 2014; Van Campenhout *et al.*, 2017; Hörner *et al.*, 2019; Barrett *et al.*, 2021; Emerick and Dar, 2021). However, few studies deal with the use of laser land leveling and its benefits (Pal *et al.*, 2020). Shaping farmers' perception of the technology is another crucial issue in the literature as it was observed to be an important determinant of technology adoption (Asfaw *et al.*, 2011).

Empirically, I use the abovementioned data in a regression context to examine the effect of using an extension service on the adoption of laser land leveling. Then, I estimate the ATT with propensity score matching to control for selection bias. Additionally, I first examine the importance of farmers' perception of the technology, particularly its affordability, as a driver for adoption using causal mediation analysis. Secondly, I investigate the role of farmers' welfare in mediating the relationship between the extension service and the laser land leveling adoption. In this way, I want to provide additional evidence about the determinants of laser land leveling adoption and the relevant role of extension programs in spreading technologies. Furthermore, I examine empirically the farmers' perception about the technology, an issue that is not new in the theoretical literature but not enough considered in empirical studies.

The remainder of the essay is organized as follows. Section 2 reviews the literature on elements that affect adoption and explains the background. Section 3 depicts the theoretical framework and the identification strategy; section 4 presents data and descriptive statistics; section 5 the empirical strategy and section 6 results. Section 7 concludes.

2. Literature review and background

2.1. Literature

The adoption of enhanced technologies - such as disease-resistant and climate-adjusted seeds - and techniques for conserving natural resources can critically affect the sustainable growth of the agricultural sector and the reduction of poverty in rural areas (Mottaleb, 2018). Among the factors that affect the adoption of a particular innovation, it is possible to find its relevance and compatibility with environmental and farming conditions, markets' support for that technology, how extension programs introduce it, and so on (CIMMYT, 1993).

Despite the positive effects of technologies, the adoption of innovative practices by small farmers is low and not complete due to different reasons that can be summarized in three categories: low awareness about the benefits of the new technology or lack of information, high risk aversion and high transaction costs of inputs and liquidity in general (De Janvry, Macours and Sadoulet, 2016).

Farmers often lack the proper knowledge about the technology and how to use it. They also have to wait until the harvesting period to see concrete results, which usually happens months after planting (i.e. in their decision to adopt, they consider the technology's discount rate). Lastly, they are often credit constrained or do not have enough savings to invest in new agricultural innovations.

Beshir *et al.* (2012) provide a comprehensive overview of the determinants of the probability of adoption and intensity of use of inorganic fertilizer in Ethiopia, finding that extension and credit services positively impact adoption. In addition, farmers' characteristics such as age, education, non-farm income, gender and farm land size play an important role in enhancing fertilizer adoption. Elements such as distance to markets and infrastructure are essential since they facilitate information and reduce transportation costs.

Lambrecht *et al.* (2014) analyze the adoption of mineral fertilizer in Eastern DR Congo modeling technology as a three-step process made of awareness, try-out and finally adoption. In this context, education and social capital affect the first step (i.e., awareness) while extension positively influences the second step (i.e., try-out). Lastly, continued adoption seems more affected by capital constraints rather than extension programs' involvement.

Contribution to technology adoption: knowledge

Knowledge can be different things: from being informed and aware of the existence of a technology, to being capable, i.e., having gained capabilities and learned how to use it. A solution to the lack of knowledge (in all its above-mentioned definitions) is promoting extension programs: they allow farmers to obtain information about innovations and technologies, but they also provide farmers with trainings to use them. Strictly speaking, agricultural extension aims to disseminate information to increase production and profitability (Rivera, Qamar and Van Crowder, 2001).

Hörner *et al.* (2019) investigate the effect of a decentralized extension program and a video intervention on the adoption of integrated soil fertility management (ISFM) in Ethiopia, finding that both treatments (extension only and extension plus the video) increase the knowledge and the adoption of the practices included in the ISFM package. Wollni and Andersson (2014) examine various explanations for adoption decisions, particularly the availability of information in the farmer's neighborhood and the perceived positive external effects of the innovation. They found that when farmers have greater availability of information in the neighborhood, they are more likely to adopt sustainable agricultural technologies. Focusing on the determinants of the intensity of technology adoption conditional on overcoming seed access constraints in Ethiopia, Asfaw *et al.*(2011) find that knowledge of existing varieties and perception about the characteristics of the improved ones are some of the main determinants for the adoption of technologies. David, Mukandala and Mafuru (2002) analyze the importance of seed availability for the adoption of new crop varieties finding that one of the main elements that lead to low adoption is the failure in promoting the existence of improved seeds variety among farmers, which also limited their access to this kind of seeds.

But extension services are essential in providing farmers with capabilities to use agricultural technologies and practices, i.e., through training. Barrett *et al.*(2021) analyze the results of a large-scale, multi-year randomized controlled trial evaluation of a system of rice intensification (SRI) in Bangladesh, finding that SRI training has a large and positive impact on farmers' propensity to adopt. Emerick and Dar (2021) investigate the role of farmer field days as means of knowledge transmission: during these days, farmers can meet, learn about new technologies and how to use them. They are cost-effective, and they greatly impact adoption, especially for the poorer ones.

Awareness can be increased through extension, but that does not automatically lead to better practice and higher production (Van Campenhout *et al.*, 2017). Knowledge about the existence of a specific technology and its potential returns are two different matters. While the former can be freely observable, the latter is easy to hide, especially in poorly integrated markets where it can create an advantage and an incentive to keep it away from others. Van Campenhout *et al.* (2017) investigate the difference between the two issues. A distinction between information about the technology and about its profitability can help understand the heterogeneous impacts of various learning channels on adoption and their effectiveness. Hence, this can be useful to design effective extension services with the aim and ability to broadly educate people and not only to train them on several techniques. However, according to their findings, providing technical information and information on returns of a certain technology only raise awareness but not the actual adoption, probably because farmers are also constrained by other factors like land, labor and cash (Van Campenhout *et al.*, 2017). Setting a model of biases in farmer decision making, Duflo, Kremer and Robinson (2011) show that if Kenyan farmers are offered just after harvest

(when they have money) with small, time-limited discounts on fertilizer this could induce sizeable changes in fertilizer use. This policy can yield higher welfare than heavy subsidies for fertilizer and it was noted that offering free delivery to farmers early in the season increases fertilizer use by 47 to 70 percent.
Besides extension programs, a significant role in technology adoption and dissemination of innovations in a developing context is played by social networks and communication channels among farmers, which can help them improve their agricultural production and well-being. Especially among peers, interpersonal channels affect individuals' decisions. Previous analyses show that people evaluate an innovation based on subjective valuations conveyed by other individuals who have previously adopted it rather than on scientific studies (Rogers, 1983). Several studies that dealt with this specific issue fostered local evidence in developing countries (Bandiera and Rasul, 2006; Matuschke and Qaim, 2009; Conley and Udry, 2010; Benyishay and Mobarak, 2013; Maertens and Barrett, 2013; Muange, Schwarze and Qaim, 2014; Beaman *et al.*, 2018).

This essay contributes to enhancing the relative understanding of the determinants of technology adoption and in particular the role of knowledge related to a technology through extension. Furthermore, it considers the interaction between this specific constraint and the liquidity constraint, an important element in shaping farmers' perception of the technology. In fact, after farmers acknowledge the existence of the technology, they could develop an expectation based on the cost of obtaining the machine required to carry out laser land leveling.

2.2. Study area

In Karnataka, the population reaches about 61 million people; among them, 13.74 million are employed in the agricultural sector (Census 2011, 2021). In order to improve productivity and production, the Department of Agriculture tried to ensure timely availability of critical inputs such as seeds, fertilizers, agrochemicals and technology transfer in general through various schemes and programs that include demonstrations to obtain the maximum outputs from the natural resources available (Government of Karnataka, 2019).
Most of the cultivated area in the state is under rainfed cultivation and the presence of monsoon is essential for good agricultural production. Failures in the monsoon were registered and led to a smaller amount of rainfall between June and September 2018 (the southwest monsoon period), with 4% less than the usual amount. The same happened during the northeast monsoon period (October-December), with a deficit in rainfall of 49%. The average area under crops grown in the three seasons (Kharif, Rabi,

summer) is 102.80 lakh[6] ha. After the failure of monsoons, the area covered by crops declined and food grain production was less than the targeted one (Government of Karnataka, 2019). In 2011-12, the net area sown in Karnataka was 9,941,399 ha, which represents 52.2% of the total geographical area (Directorate of economics and statistics, 2015).

This analysis focus on the Raichur District, located in the north-eastern dry zone of the state (Pal *et al.*, 2020).

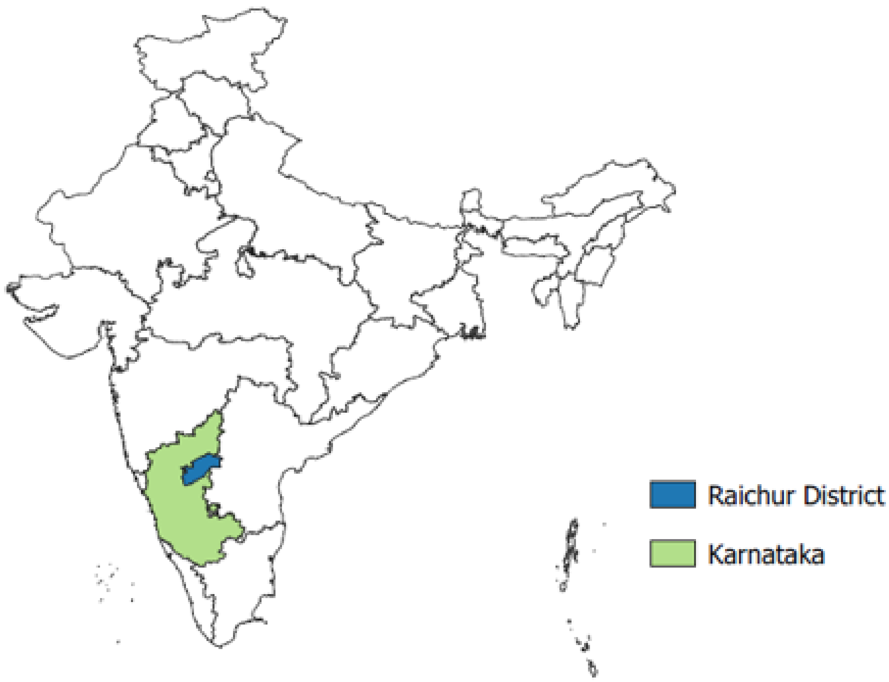


Figure 1- Map of the State and District under analysis. Source: own elaboration with Qgis.

In Census 2011, the last one carried out, the population of Raichur District was 1,928,812 (964,511 male and 964,301 female). The average literacy rate in the district was 75.12% (83.10% for males and 67.10% for females). Most of the population (74.58%) lived in rural areas where the sex ratio is 1004 females per 1000 males. The literacy rate in rural areas is 54.11% (66.01% for males and 42.37% for females) (Census 2011, 2021).

In 2013 net land sown in the district was 91,490 hectares (University of Agricultural Science Bangalore, 2015). In 2011-12 the district had the largest net area irrigated and the highest gross cropped area irrigated by canals in the state of Karnataka (Directorate of economics and statistics, 2015). The second source of irrigation in the district was tube wells and wells used to irrigate 10,213 hectares of land (University of Agricultural Science Bangalore, 2015).

[6] In the Indian system, a lakh is equal to one hundred thousand.

However, the district has faced severe problems due to the declining rainfall since 2014, especially in 2018 (Pal *et al.*, 2020).
The Raichur district was selected by a consortium of CGIAR institutions led by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), agriculture universities and the Indian Council of Agricultural Research (ICAR), having the aim to conduct pilot tests of some innovative technologies in the agricultural sector (Pal *et al.*, 2020).

Extension system in India

For many years, in the post-independence India, the extension system was guided by the public sector(Nandi and Swamikannu, 2019). It still plays a relevant role at the central level with the Indian Council of Agricultural Research (ICAR) but, starting from the 2012-2017 Indian five-year plan, the main coordinating agent in charge of implementing extension schemes became a decentralized and multi-stakeholder agency called Agricultural Technology Management Agency (ATMA). It involves farm interest groups, NGOs, the private sector and public officials. In fact, in recent years, a rise in private sector involvement was noticed, leading to public-private partnerships(De Janvry, Macours and Sadoulet, 2016). Around 13% of Indian farmers get not only seeds, agrochemicals and farm machinery, but also information from input dealers. However, they often complain that they promote their products rather than providing clear information; for this reason, the Government of India started training inputs dealers with the latest technical knowledge and certifying them as qualified Input Dealers (Nandi and Swamikannu, 2019). Furthermore, many NGOs working in the country encouraged an additional connection between the extension system and farmers, fostering self-help groups and farmer-based organizations also using mass media or video-based extension services (De Janvry, Macours and Sadoulet, 2016). Their extension models are efficient but often lack of capacity and scale. Indeed, in the country there are good practices at the local level that could have a greater impact if scaled at large. Many states promote farmers producers organizations as key in strengthening extension activities, allowing farmers to reduce the cost of cultivation, increasing profitability and reducing transaction costs. Another potential tool to link value chain is ICTs (mobile phones, internet and mass media) but scalable interventions have not emerged yet in the country (Nandi and Swamikannu, 2019).

In 2007 the Indian Government introduced the National Food Security Mission to include small, marginal and women farmers, which should represent at least 33% of contact farmers (De Janvry, Macours and Sadoulet, 2016). However, on average in 2012 it was estimated that extension services only reached less than 7% of Indian farmers (Nandi and Swamikannu, 2019).

With the 2012-2017 five-year plan, the extension system is made by extension education and extension training. Both the central and state governments fund agricultural research and extension and the expenditure has increased from ₹31,073 million in 2000-01 to ₹61,552 million 2014-15. Around 82% of total budget allocation is funded by state governments, with variations across states.

2.3. Land Leveling

Land leveling is essential to carry out good agronomic, soil and crop management practices (Rickman, 2002). The main benefit is that it can improve the uniform application of water, allowing improved nutrient-water interaction; thus, it can stabilize paddy yields (Jat *et al.*, 2006).

Traditional methods employ animals or small tractors and are labor-intensive, time-consuming and potentially expensive. Furthermore, a lot of water is wasted, and the required precision and smoothness of land surface are not always met (Rickman, 2002; Jat *et al.*, 2006).

A modern practice increasingly used also in developing countries is the so-called "Laser Land Leveling" (LLL), which uses laser-guided leveling machinery as laser-equipped drag buckets (Jat *et al.*, 2006). Briefly, this method requires plowing moist soil before and after land leveling, starting from the center of the field outwards. Then, a topographic field survey is performed, often using lasers. Lastly, the field is leveled. If all the operations are well performed, land can be re-leveled after 8-10 years and only minor land smoothing due to field operations and weather conditions is needed (Rickman, 2002).

Benefits of land leveling can be at the same time at the environmental, productivity and social level. Concerning the former, LLL saves irrigation water and soil, reduces the use of nutrients and water-soluble agrochemicals and the consumption of fossil fuel for several on-farm operations. Concerning productivity, the greater accuracy achieved translates into a larger part of the field under cultivation and thus greater yields thanks to a better distribution of nutrients farm. This method also allows an improvement of water coverage, reducing weeds and allowing better weed control. Besides reducing the time spent on manually weeding, the time dedicated to planting and crop management declines too. Moreover, other crop establishment options such as zero tillage, raised bed planting, and surface seeding face a significant improvement. At the social level, this technique can also represent an opportunity for employment for rural youth and a larger income for farmers (Jat *et al.*, 2006).

Indeed, a barrier to adopting LLL is its high initial cost due to the use of machineries such as a laser transmitter and a receiver, an electrical control panel and a twin solenoid hydraulic control valve. This high initial cost also depends on the topography and the shape of the fields. Besides, this technique needs skilled workers to set and adjust the laser setting (Rickman, 2002).

In India, this method is a recent resource-conservation technology initiative, and despite several direct and indirect benefits derived from it, it is yet to become a widespread farming practice in developing contexts (Jat *et al.*, 2006). For all the reasons mentioned above, studies investigating factors that could affect the adoption of this technology are needed.

3. Theoretical model and identification strategy

One of the first and more meaningful contributions related to adoption models is the one by Rogers (1983), where he describes the pathway of adoption using what he called the *innovation-decision process*. This process consists of five steps and goes from the phase in which the individuals acknowledge the existence of new technologies and how to use them (i.e., *knowledge*) to the step of *confirmation,* when they decide to perpetuate the use of those technologies. In between, the second step happens when individuals develop beliefs about the technology (i.e., *persuasion*). Later, they decide whether to adopt (or reject) it (step called *decision*) and lastly, the phase of *implementation* occurs (Rogers, 1983). The figure below shows this process.

Figure 2. Innovation-decision process by Rogers (1983)

The theoretical framework mentioned above will be considered in this research, with a particular focus on the first three steps of the process. This research aims to understand the link between extension and the adoption of a climate-smart agricultural innovation in the Raichur district of the Indian state of Karnataka: Laser Land Leveling (LLL), a water-saving technology for rice fields that requires the use of some machines to be performed. After analyzing this nexus, the focus of the analysis will be extended, trying to explain which mechanisms mediate the agricultural extension system and the adoption of climate-smart technologies. Among several mechanisms that link this relationship, two are of interest for this analysis: small farmers' attitude toward the innovation (and its complementary inputs), with a particular reference to its affordability; and variation in farmers' welfare, particularly in household's expenditure.

Concerning the former mechanism, in the literature, other authors developed models specifically on how attitude and perception are formed (Maertens, Michelson and Nourani, 2020) and, in turn, how they could impact technology adoption. Since extension services, when broadly identified, could also include the provision of the technology and additional resources as credit and liquidity, they could affect the cognitive process determining farmers' attitude towards innovation (Au and Enderwick, 2000). They could have the potential to positively persuade farmers to change their individual attitudes (Angst and Agarwal, 2009).

Starting from the reasonings above, I want to find evidence of whether the information obtained at Raita Samparka Kendra (RSK) – a center that provides knowledge about agricultural activities, credit, inputs and facilities – not only affect the final LLL adoption directly but it is also expected to influence the farmers' beliefs about the LLL technology and their awareness about constraints to its adoption. Indeed, training could provide farmers with important information about the costs and benefits of technology adoption (Vishwanath, 2009). In turn, this affects the actual adoption. This process is described in the figure below.

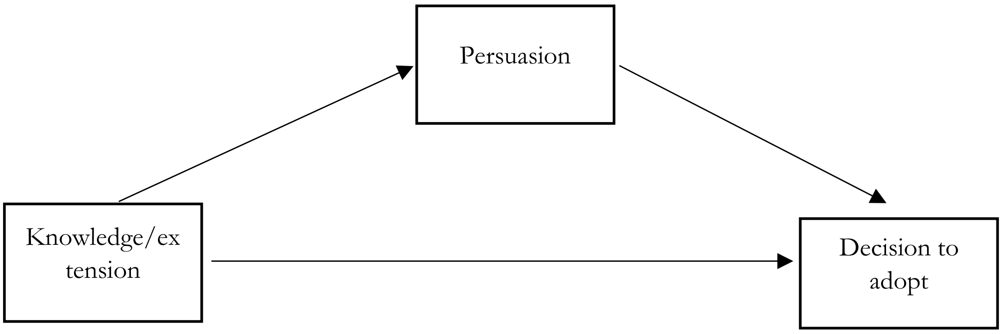


Figure 3. Conceptual nexus considering persuasion as mediating variable.

In addition, I identify variations in farmers' welfare - and in particular, household expenditure - as another mechanism that mediates visiting the extension center and adoption. Indeed, if a broader definition of extension program is considered, diversification of income opportunities should be included to support income generation and employment opportunities for rural poor (Rivera and Qamar, 2003). A complete and pro-poor extension program should offer a wider range of services, not only focusing on increasing production but also on sustainable livelihoods in an extensive sense, depending on the context considered (Farrington *et al.*, 2002). The literature on this finds evidence supporting the positive relationship, with various forms of extension programs increasing farm households' income and per capita expenditure, reducing poverty (Dercon *et al.*, 2009; Benin *et al.*, 2011; Davis *et al.*, 2012; Imai, Hasan and Porreca, 2015). Increases in farmers' welfare, in turn, can remove the constraints to adoption related to credit or liquidity and reduce farmers' risk aversion towards technology adoption.

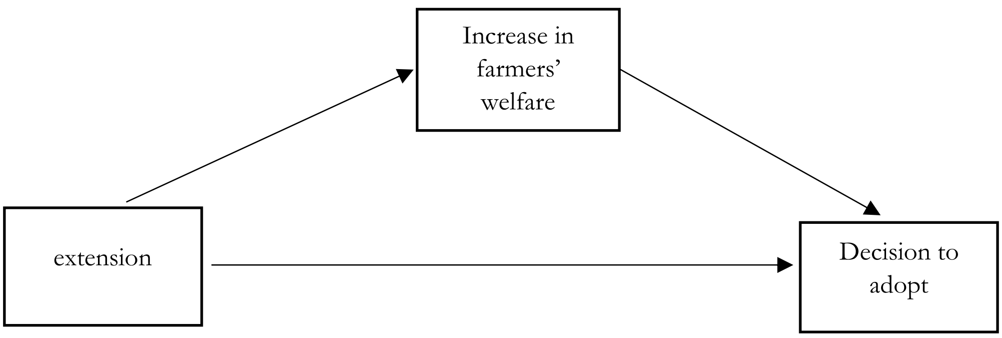


Figure 4. Conceptual nexus considering persuasion as mediating variable.

4. Data and Descriptive Statistics

4.1. Dataset and main variables

Using a survey conducted in the Raichur district of Karnataka, the analysis considers data on 604 households collected by the SAR (South Asia Regional office) division of IFPRI between November 2018 and March 2019, after paddy harvest. Among the responders, 275 were non-adopters of LLL and 329 were adopter farmers. The group of adopters includes farmers that owned a LLL machine and farmers that rented an LLL machine, while the group of non-adopters consists of neighbor farmers with land near the laser-leveled plot that grew paddy in the same season. Experts from the State Agriculture University, Raichur, scientists from the International Maize and Wheat Improvement Center (CIMMYT) and ICRISAT were consulted for purposely select adopter farmers.

Information collected included general and geographical characteristics of the respondents, if they owned or rented LLL machines, the area under crop cultivation, crop yield, farm income, cost of cultivation, assets ownership, sources of income, household characteristics, and major constraints that farmers face in adopting LLL (Pal *et al.*, 2020).

Main variables

Explanatory variable: knowledge about the technology

My interest lies in the role of knowledge about the technology in its adoption. Since I have information about the number of visits done by farm households to the RSK (an extension center) and the number of visits received by RSK officials in the year previous to the survey, it is possible to create a dummy variable equal to one if the household had at least visited the RSK center (or received visit on their field by RSK officials) once.

Dependent variable: Laser Land Leveling adoption

The dependent variable is the adoption of Laser Land Leveling (LLL), proxied by a binary variable equal to one if farmers adopt it or zero otherwise. The expected relationship is positive as it is likely that people visiting more often the RSK – hence, receiving more information about the technology – are more aware of how it works, resulting in a more mindful use of LLL.

Mediator 1: perception about machine renting

Following the model by Rogers (1983), I consider the persuasion stage as a mediator between the step called "knowledge" and the step of "decision" (i.e., the adoption). Persuasion occurs when farmers develop a favorable or unfavorable attitude toward the technology. Farmers need information about the technology before adopting it to reduce uncertainty related to the consequences of their decision to adopt.

They want to consider all the costs that they should bear to adopt the technology and the expected benefits. Previous research recommended widening the range of variables used in studies on adoption, including farmers' perception of new technology (Mwangi and Kariuki, 2015).

For all the reasons mentioned above, the mediator between extension and LLL use is proxied by a variable indicating how much farmers believe that renting the machine needed to use that technology is a constraint to its adoption. In one of their works, De Janvry *et al.* (2016) explained the lack of adoption not only coming from the demand and supply side but also from mediating factors as credit and insurance constraints. Furthermore, the persuasion channel is an element considered by more than one theoretical model, as explained in the section about the identification strategy. Table 1 shows the sample distribution of the mediating variable when farmers are in the treatment group (T=1: visiting the RSK center or receiving visits from RSK officials at least once in the last year) and in the control group (T=0).

Table 1. Sample distribution for the mediator "Farmers' perception about the cost of LLL"

	T=0	*T=1*
Don't Know	70(29.17)	53(14.56)
Not very relevant	7(2.92)	24(6.59)
Moderately relevant	17(7.08)	31(8.52)
Very highly relevant	146(60.83)	256(70.33)

Note: In the first column, the table reports the answer to the question: "How relevant is "Rent of Machines is very high" as reason for not adopting LLL?"

Percentage share in parentheses.

T=1 if visits to the extension center>=1, T=0 if visits to the extension center=0

Mediator 2: Increase in farmers' welfare

Visiting extension centers could provide farmers with inputs able to increase their productivity and with new employment opportunities that in turn raise their welfare. Farmer households' welfare could be proxied by household expenditure in the last year. The analysis will use (the log of) household monthly expenditure. The figure below shows the kernel density for the households' expenditure for people visiting at least once the extension center (blue line) and people that did not visit the extension center at all (red line). The majority of people for which T=0 (red line) shows lower household expenditure as the peak of the distribution comes earlier than the blue line. Household expenditure levels for the group represented by the red line are more concentrated in the lower part of the graph. In contrast, household expenditure levels are uniform and slightly higher for the group represented by the blue line (T=1).

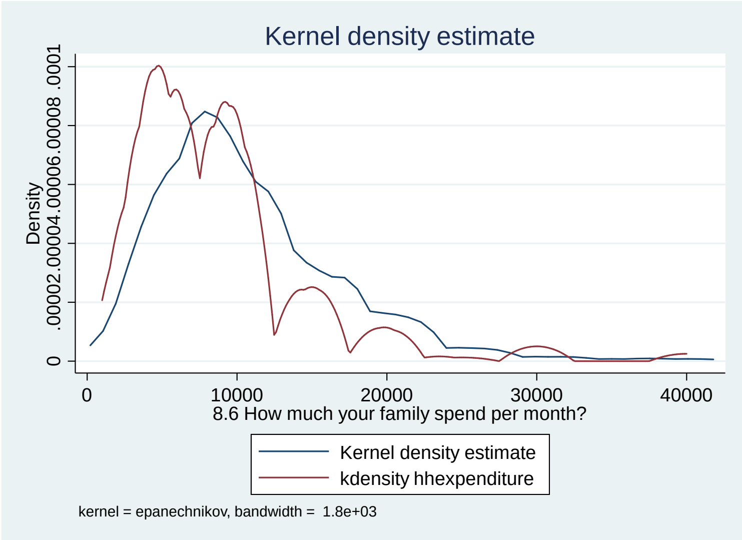


Figure 5. Kernel density of households' expenditure for treated(blue) and non-treated (red)

Table 2 shows the main variables employed in the analysis. On average, households in the sample visited (or received visits from) RSK slightly more than twice in the previous year, and 60% of the sample visited or received visits from RSK officials at least once. In the sample, 54% of households used LLL (owned or rented).

Table 2. Summary statistics on the main variables

	Mean	*Stand. Dev.*	*Min*	*Max*
Visits done at RSK and received by RSK officials	2.27	2.38	0	10
At least one visit to the RSK center	0.60	0.49	0	1
User of LLL technology or not (1 "Yes",0 "No)	0.54	0.50	0	1
N	**604**			

Table 3 shows the sample distribution of the outcome variable when the treatment variable is equal to one (at least one visit to RSK center or received by RSK officials in the previous year) or zero (no visit to the RSK center or received by RSK officials in the previous year).

Table 3. Sample distribution of the outcome variable

	T=0	*T=1*
No. of Non-Adopter households	129(53.75)	146(40.11)
No. of Adopter households	111(46.25)	218(59.89)
Total	240	364

Note: Percentage share in parentheses
T=0 refers to households with zero visits to the RSK center or received by RSK officials in the previous year
T=1 refers to households with one or more visits to the RSK center or received by RSK officials in the previous year

4.2. Descriptive statistics

Table 4 shows some sociodemographic and economic characteristics of the households included in the sample. Households are composed on average by six members, among them 2.45 are men and 2 of them are employed in farming activities. In the average household, female members are 2.37 but only 1.41 of them work in agriculture. Finally, children below 14 years in the average household are 2. The highest level of education is on average the primary one. The majority of households live in areas located from 6 to 10 km away from the RSK.

Land owned and land under irrigation has on average a semi-medium size (between 2 and 4 hectares). About 48% of households sampled own tractors and the same percentage owns irrigation pump sets. The mean wage per day for men is 322 INR, while it is almost half (177 INR) for women. Lastly, the average household has access to the lower range of loans (0-500000 INR) and spends 9718 INR per month.

Table 4. Descriptive statistics

	Count	***Mean***	***Stand. Dev.***	***Min***	***Max***
Highest Level of Education (1 illiterate, 2 primary, 3 secondary, 4 higher secondary)	604	2.31	1.18	1	5
How many family members are there in your family?	604	5.75	2.35	1	10
No. of Male	604	2.45	1.29	1	8
No. of Female	604	2.37	1.36	0	8
No. of Child (Below 14 years)	395	2.09	1.88	0	9
How many adult male members are engaged with farming related activities?	594	1.84	1.05	1	6
How many adult female members are engaged with farming related activities?	337	1.41	1.24	0	6
Land ownership classification (1 marginal (<1 ha), 2 small (1-2 ha), 3 semi-medium (2-4 ha), 4 medium (4-10 ha), 5 large (>10 ha))	604	3.27	1.29	1	5

Land under irrigation classification (1 marginal (<1 ha), 2 small (1-2 ha), 3 semi-medium (2-4 ha), 4 medium (4-10 ha), 5 large (>10 ha))	604	3.23	1.32	1	5
Does your family own tractors (1 yes, 0 no)?	604	0.48	0.50	0	1
Does your family own irrigation pump-sets or not (1 yes, 0 no)?	604	0.48	0.50	0	1
Does your family own livestock (1 yes, 0 no)?	604	0.61	0.49	0	1
How much crop loan you have availed? (INR) (0 no loan, 1 0-500000, 2 500000-1000000, 3 >1000000)	604	0.97	0.85	0	3
What is the wage per day for labour? (Male)	582	322.20	91.70	0	2020
What is the wage per day for labour? (Female)	580	176.52	39.24	0	400
How much your family spend per month?	598	9718.23	6137.97	500	40000

5. Empirical Framework

The econometric analysis will be carried out using cross-sectional data. With the data described in the previous section, I firstly perform a probit regression to find the Intention-to-treat (ITT) effect; then, a propensity score matching and a causal mediation analysis will be carried out.

This research aims to estimate the relationship between extension and the adoption of the climate-smart agricultural innovation mentioned above and to understand if specific factors could mediate this relationship. The first mediator considered is the small farmers' attitude toward the innovation (and its complementary inputs). In particular, the perception about renting the machine will be analyzed. A second mediator considered in the analysis is farmer's welfare, namely monthly household expenditure.

5.1. Estimation strategy for ITT and ATT

In order to assess the effect of extension on ISFM adoption, I estimate a probit regression as follow:

$$Y_i = \alpha + \beta\, T_i + \lambda X_i + \varepsilon_i \quad (1)$$

where Y_i denotes the outcome variable for household i. T_i is a dummy variable indicating whether the farm household i visited (or received visits from) the RSK center at least once during the last 12 months. X_i is the vector of control variables related to household's demographic and economic characteristics: level of education, number of household members, number of male and female household members, distance to the RSK center, land owned and under irrigation, whether they own tractor, pumpset or livestock, loan availability and the log of monthly household expenditure. εi is the error term. Standard errors are robust. This equation identifies the intention-to-treat, measuring the average effect of being assigned to the treatment.

Since visiting the center is not randomized, I have to consider that people who visit the center could be different from those who do not. Thus, I need to use a quasi-experimental method to estimate the average treatment effect on the treated (ATT) by propensity score matching (PSM).

The objective of PSM is to identify farmers who did not visited the RSK center the previous year (T=0, the control group) who are like the farmers that visited the RSK center at least once (T=1, the treatment group) in all the relevant observable characteristics. That is to say that the only difference between the two groups is the participation in the extension program. In this way, I can generate the average treatment effect for the treated (ATT). The aim of PSM is to balance the observed distribution of covariates across the two groups; then, a balancing test could help to understand if the difference between the groups in the matched sample has been eliminated or not after matching. The main limitation of PSM is that it cannot account for selection on unobservable variables.

The first step with PSM is to create a propensity score P(X). Rosenbaum and Rubin (1983) defined P(X) as the conditional probability of receiving the treatment (at least one visit to the RSK center or received by the RSK officials) given a set of background (observed) covariates:

$$P(X) = Pr(D = 1|X) = E(D|X)$$

where D is a dummy indicating the treatment and X the vector of household's observed demographic and economic characteristics mentioned above.

With this approach, the difference in the average outcome of treated and control groups (i.e. the baseline, those who did not visited the extension center) can be attributed to the extension service under the assumption that selection into extension is based on observable factors alone.

Propensity score matching is implemented through a Probit regression, one nearest neighbor - i.e., an individual from the control group is chosen as a matching partner for an individual in the treatment group that is the closest in terms of propensity score - with caliper 0.01 and with replacement.

Since I use the nearest-neighbor matching method (NN-1), the ATT is computed as follow:

$$\widehat{ATT} = \frac{1}{N1}\sum\nolimits_{i=I}\{Y_i - Y_j\}$$

Where Y_i and Y_j are the outcomes for treated and control households, respectively. If none of the control units is within the chosen caliper of the treated unit *i*, then *i* is left unmatched.

This equation gives the average treatment impact under the conditional independence (i.e., conditional on X, the outcomes are independent of treatment) and the overlap assumption (i.e., for each X, there are both treated and control units).

5.2. Causal Inference Approach to Mediation Analysis

From its early approaches (see appendix A2 for more details), mediation analysis is an helpful tool to elicit the mechanisms – how and why – through which an independent variable affects an outcome (Baron and Kenny, 1986), disentangling total effect into a direct effect - from the treatment to the outcome - and an indirect effect, where other variables (called mediators) play a role as transmission channels that explain the main relationship.

Imai, Keele, Tingley and Yamamoto (2011) showed that the previous approaches to mediation analysis are not the most appropriate method to identify and analyze causal mechanisms as their assumptions are not testable and appropriate. They propose to use the counterfactual approach to control for the potential heterogeneity. Among the approaches raised to deal with the limitation of the Baron and Kenny model, it is possible to find the one by Hicks and Tingley (2011). Following their strategy, I denote $Y_i(t, m)$ the potential outcome with the treatment equal to *t* and the mediator equal to *m*. The observed outcome is instead indicated as $Y_i(T_i, M_i(T_i))$ where *T* indicates the treatment status and *M(T)* the level of the mediator under the observed treatment status. I am interested in the computation of how much of the treatment variable is transmitted by the mediating variable to the outcome variable. Indirect and direct effects can be defined respectively as

$$\delta_i(t) \equiv Y_i\{t, M_i(1)\} - Y_i\{t, M_i(0)\} \tag{3}$$

and

$$\zeta_i(t) \equiv Y_i\{1, M_i(t)\} - Y_i\{0, M_i(t)\} \tag{4}$$

for each unit *i* and treatment *t* =[0,1].

Equation 3 provides a causal quantity equal to the change in the dependent variable that corresponds to a variation in the mediator from $M_i(0)$; i.e. the value of the mediator under the control condition, to $M_i(1)$; i.e. the value observed under the treatment condition, holding the treatment status at *t* (Hicks and Tingley, 2011). Equation 4, indicating the direct effects, holds constant the mediator and considers the relationship between the independent and the dependent variables along with all the other factors that could affect it (Hicks and Tingley, 2011).

I am interested in the average of the mediation effect, called the average causal mediation effect (ACME) and the average direct effect (ADE). The former can be indicated as $\overline{\delta_i}(t) \equiv E[Y_i\{t, M_i(1)\} - Y_i\{t, M_i(0)\}]$ and the latter as $\bar{\zeta_i}(t) \equiv E[Y_i\{1, M_i(t)\} - Y_i\{0, M_i(t)\}]$ (Hicks and Tingley, 2011).

Since my outcome variable is binary, the product of coefficients obtained (*ab*) does not correspond to the ACME (Imai, Keele and Tingley, 2010).

A crucial assumption when dealing with mediation analysis is sequential ignorability (SI), and it is defined by Imai, Keele and Yamamoto (2010) as

$$\{Y_i(t', m), M_i(t)\} \perp T_i | X_i = x,$$
$$Y_i(t', m) \perp M_i(t) | T_i = t, X_i = x$$

With

$$Pr(T_i = t | M_i = m\, X_i = x) > 0$$

for $t = 0{,}1$ and all $x \in$ X and $m \in$ M.

This assumption implies that the treatment is independent of all potential values of the outcome and mediating variable (given the pre-treatment variables) but also that, given the treatment and the pre-treatment covariates, the observed mediator is independent of all potential outcomes (Imai, Keele and Tingley, 2010).

A problem that affects the estimation procedure in this study concerns the use of cross-sectional data. This kind of data deals with an issue related to the temporal ordering of variables in the causal chain of mediation. Due to this nature, correlations in the estimation of a mediation effect could exist and this could damage the causation inference. The existence of these correlations does not provide clear information about the directionality of the relationship between variables (Fairchild and Mcdaniel, 2017). Another problem is that T could be endogenous; if this is the case, the causal effect of the treatment on the mediator and the outcome and the causal effect of the mediator on the outcome cannot be clearly identified. A strategy to solve this issue is to combine the instrumental variable approach with the causal mediation analysis. This approach could provide correctly specified causal relationships (Dippel *et al.*, 2020); however, with the data available, it is impossible to find a strong instrument such that both the treatment and the mediating variables are instrumented simultaneously.

6. Results and Discussion

In this section, I firstly present and discuss ITT results related to the effect of extension services on LLL adoption. Then, results from the PSM are displayed and commented. Lastly, I examine the contribution of the rent of the machine for laser land leveling and farmers' welfare as potential transmission channels to adoption.

6.1. Laser Land Leveling Adoption: ITT

Table 5 displays the ITT effect on the LLL adoption decision, obtained from a Probit specification, without control variables in column I and with controls in column II.

Table 5. Results of the probit regression

	Adoption of LLL	
	(1)	(2)
At least on visit to/from RSK	0.135***	0.079**
	(0.040)	(0.039)
Education		-0.013
		(0.017)
No of HH members		0.001
		(0.014)
No. of male members		-0.037*
		(0.020)
No. of female members		-0.024
		(0.021)
Distance from RSK		0.080***
		(0.023)
Land owned		-0.012
		(0.038)
Land under irrigation		0.111***
		(0.036)
Tractor ownership		-0.048
		(0.046)
Pumpset ownership		0.096**
		(0.039)
Livestock ownership		0.087**
		(0.040)
Loan availability		0.013
		(0.023)
HH expenditure(ln)		0.058
		(0.036)
(Pseudo) R-squared	0.013	0.1215
N	**604**	**598**

Note: Robust standard errors in parenthesis; * $p<0.1$; ** $p<0.05$; *** $p<0.01$

The average marginal effects of the Probit coefficients indicate a positive and statistically significant ITT effect of the treatment on the adoption of LLL. Households that visited the RSK center or received visits from its officials in the previous year are 7.9 percentage points more likely than control group households to adopt LLL.

6.2. Laser Land Leveling Adoption: Propensity score matching

Table 6 shows the difference in mean values of variables across treated and non-treated groups (columns 1-3). Significant differences are related to land owned, land under irrigation, ownership of tractors, loan availability and household expenditure. Columns 4 and 5 report the first stage results of the PSM estimation (probit). Only household expenditure seems to significantly predict the treatment (visit done to RSK or received from RSK's officials).

Table 6. Pre-matching descriptive statistics of household characteristics and the first stage of PSM estimation

	T=1 (mean)	T=0 (mean)	Differences (1) - (2) t-values	Propensity score (Probit) Coeff	St. err
Household characteristics	(1)	(2)	(3)	(4)	(5)
Education	2.38	2.21	-0.17	0.007	0.048
No of HH members	5.78	5.71	-0.07	-0.028	0.041
No of male members	2.47	2.42	-0.05	0.010	0.060
No of female members	2.40	2.32	-0.08	-0.002	0.059
Distance from RSK	0.87	0.95	0.07	-0.061	0.064
Land owned	3.49	2.95	-0.54***	0.116	0.096
Land under irrigation	3.43	2.91	-0.52***	0.029	0.094
Tractor ownership	0.54	0.40	-0.14***	0.050	0.125
Pumpset ownership	0.49	0.47	-0.02	-0.102	0.115
Livestock ownership	0.63	0.57	-0.06	0.106	0.113
Loan availability	1.07	0.83	-0.24***	0.114	0.073
HH expenditure(ln)	9.09	8.88	-0.20***	0.234**	0.101

Note: Column 4 reports first stage coefficients from a probit regression. Robust standard errors are presented in column 5. ***p<0.01; **p<0.05; *p<0.10

Table 7 presents post-matching statistics: columns 1 and 2 show the post-matching means of the two groups, column 3 the percent reduction in bias and column 4 the t-values on the post-matching sample. Differences between the two groups after matching are not significant anymore.

Table 7. Covariate balance-individual t-test

	T=1 (mean)	T=0 (mean)	% Reduction bias	Differences (1)-(2) t-values
Household characteristics	(1)	(2)	(3)	(4)
Education	2.393	2.356	78.0	0.43
No of HH members	5.754	5.975	-336	-1.25
No of male members	2.480	2.613	-118.7	-1.39
No of female members	2.398	2.427	61.5	-0.28
Distance from RSK	0.881	0.915	54.9	-0.53
Land owned	3.477	3.446	94.1	0.34
Land under irrigation	3.432	3.418	97.3	0.15
Tractor ownership	0.537	0.557	85.9	-0.53
Pumpset ownership	0.483	0.534	-169.8	-1.35
Livestock ownership	0.632	0.613	68.7	0.54
Loan availability	1.071	1.093	90.9	-0.34
HH expenditure(ln)	9.084	9.148	68.3	-1.59

***p<0.01; **p<0.05; *p<0.10.

An additional test for the matching quality can be a comparison of the pseudo R-squared in pre e post matching sample as suggested by Sianesi (2004). A lower value of pseudo R-squared in the post-matching sample compared with pre-matching indicates a higher quality of matching. Table 8 presents this result and shows that the post-matching pseudo R-squared is lower (0.01) than the pre-matching pseudo R-squared (0.05), indicating that treated and non-treated households are quite similar. In column 2 a likelihood ratio test of the joint significance is reported. It shows that after matching it becomes insignificant (p-value=0.672 in column 3) suggesting again that the quality of matching is good.

Table 8. Pseudo R^2 and likelihood ratio test (LR χ^2)

	Pseudo-R^2	LR χ^2	$p>\chi^2$
	(1)	(2)	(3)
Unmatched	0.048	38.35	0.000
Matched	0.010	9.36	0.672

Graphically, figure 7 shows the overlap in the propensity score among treated and non-treated groups using a caliper of 0.01. Only observations on common support will be included in the matching process, while off-support observations are not considered in the analysis. The visual analysis of the density distribution of propensity score in the figure indicates sufficient overlap, satisfying the overlap condition of the PSM.

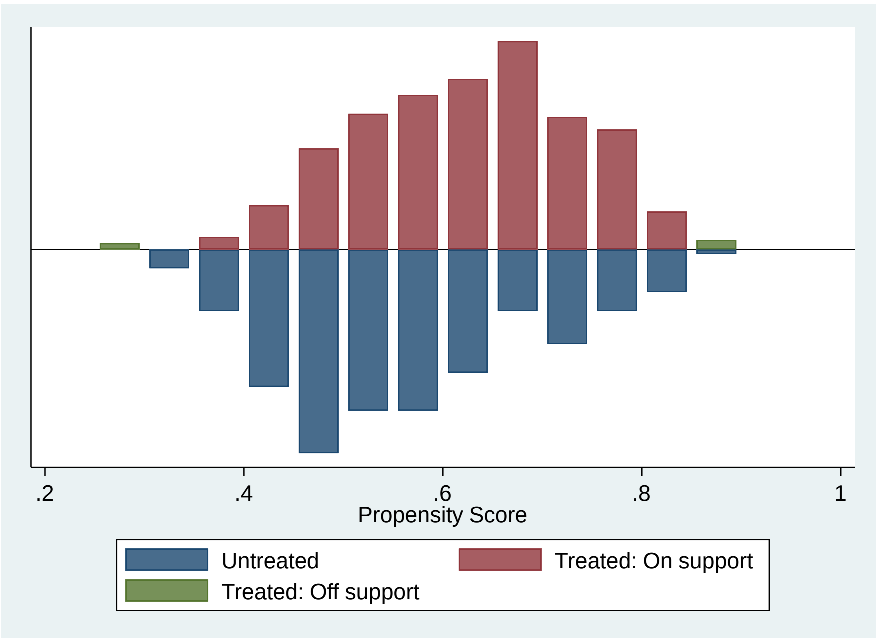


Figure 7. Distribution of propensity score

Figure 8 displays the imbalance in terms of standardized percentage differences for each covariate using a dot chart. It reports information both before (dots) and after (crosses) matching. The chart shows that crosses are closer to the zero line, meaning that the standardized % bias is reduced after matching.

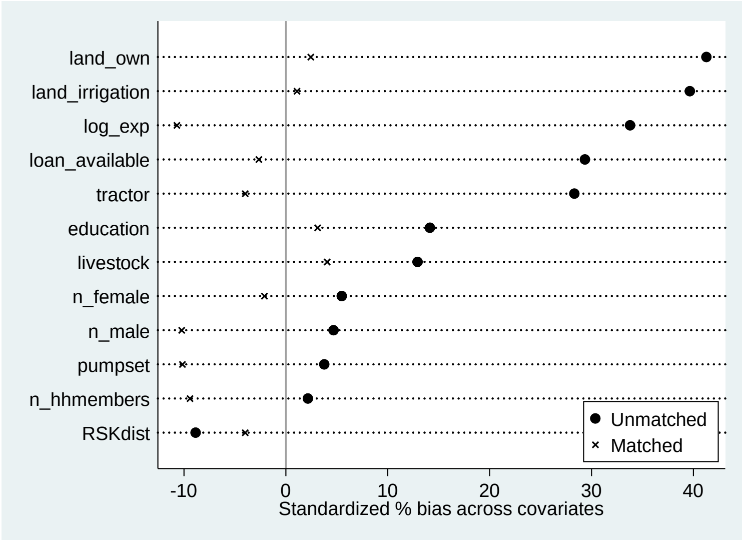


Figure 8. Pre and Post matching standardized % bias

Lastly, the table below reports the ATT, i.e., the difference in mean of the treatment group *vs.* the control group, for the LLL use outcome. Visiting RSK (or receiving visits from its officials) leads to an increase in the use of LLL of almost 13 percentage points.

Table 9. Average treatment effect PSM

	PSM(NN1)
Visits to RSK (ATT)	0.129**
	(0.054)

***p<0.01; **p<0.05; *p<0.10.

Robustness check:

The results above should be interpreted cautiously as propensity score matching is able to correct for bias due to observable variables and not for the ones due to unobservable characteristics, as they are not available. Indeed, the main assumption of matching methods is conditional independence. As sensitivity analysis, I employ the bounding approach proposed by Rosenbaum (2002): it does not test the assumption itself, but it is helpful in determining how strongly the unobservables must influence to make the estimated results null. If the results turn out to be very sensitive, alternative estimation strategies must be considered. To this aim, I used the Mhbounds package in Stata developed by Becker and Caliendo (2007). Table 10 displays the results of the sensitivity analysis. Let Q_{mh}^{+} be the Mantel-Haenszel statistic assuming that I have an overestimation of treatment effect and Q_{mh}^{-} be the Mantel-Haenszel statistic with the assumption of an underestimation of treatment effects. When Γ=1, the bounds are equal to the base scenario of no hidden bias. Since in table 10 Q_{mh} statistics are similar, this indicates a significant treatment effect. The Q_{mh}^{+} test statistic adjusts the MH statistics downward for the case of positive unobserved selection (i.e., those more likely to adopt LLL tend to visit more often the extension centre given that they have the same X vector as individuals in the comparison group, leading to an upward bias in the estimated effects). On the opposite, the Q^{-}_{mh} test statistic adjusts the MH statistic downward for the case of negative unobserved selection. In the case under analysis, since who is most likely to visit the RSK center has also a higher probability of using LLL, the estimated treatment effects likely overestimate the true effect. Hence, Q_{mh} (in the table =2.334) is too high and must be adjusted downwards. For this reason, I look at columns 1 and 3 in the table below and I check until what value of Γ Q^{+}_{mh} is still significant. The largest value of Γ for which there is no change to inference is 1.2. This means that for a pair of matched individuals, the treated one is 1.2 times as likely to receive the treatment because of unobserved pre-treatment differences that are positively correlated with the outcome.

Table 10. Sensitivity Analysis: Rosenbaum bounds

	Mantel and Haenszel (1959) bounds for variable LLL use			
	Q^{+}_{mh}	Q^{-}_{mh}	p^{+}_{mh}	p^{-}_{mh}
Γ	(1)	(2)	(3)	(4)
1	2.334	2.334	0.010	0.010
1.05	2.090	2.583	0.018	0.005
1.1	1.855	2.819	0.032	0.002
1.15	1.632	3.045	0.051	0.001
1.2	1.418	3.263	0.078	0.006
1.25	1.213	3.471	0.113	0.000
1.3	1.016	3.672	0.155	0.000
1.35	0.827	3.867	0.204	0.000
1.4	0.645	4.054	0.260	0.000
1.45	0.469	4.236	0.319	0.000
1.5	0.300	4.412	0.383	0.000

Γ: odds of differential assignment due to unobserved factors; Q^{+}_{mh} : Mantel-Haenszel statistic (assumption: overestimation of treatment effect); Q^{-}_{mh} : Mantel-Haenszel statistic (assumption: underestimation of treatment effect); p^{+}_{mh} : significance level (assumption: overestimation of treatment effect); p^{-}_{mh} : significance level (assumption: underestimation of treatment effect)

6.3. Mediation analysis

After performing PSM, I also computed the quantities of interest (ACME, ADE and average total effect) and summary statistics as confidence intervals to understand whether perception about the rent of machine for LLL could mediate the relationship between extension and LLL adoption. Panel A of table 11 displays coefficient estimates including the perception variable as controls in a Probit regression with robust standard errors (column 1 and 2). It suggests a positive and significant effect of both the treatment and the perception variable on LLL adoption (column 1). However, adding all the other household's characteristics the coefficient for the visits to the RSK center becomes insignificant, while the one related to the farmers' perception about the rent of machine for LLL remains significant but slightly reduced in magnitude. Column 3 and 4 shows the coefficient of the Probit regression, considering the second mediator as a covariate in the regression. Without additional control variables (column 3), it is possible to see a significant impact of the treatment (at 1% level) and of monthly household expenditure (at 5%) on LLL adoption. Adding the other controls, visiting the RSK center remain significant but only at the 5% level whereas household expenditure becomes insignificant. Panel B reports the estimated ACME, ADE and total effect of the treatment on LLL adoption, computed using the first mediator (M1: persuasion) and robust standard errors. Instead, panel C reports the same quantities of interest as panel B, but this time estimated using the second mediator (M2: increase in farmers' welfare), again with robust standard errors.

Table 11. Quantities of interest from mediation analysis

	Use of LLL			
Panel A. Coefficients estimates	(1)	(2)	(3)	(4)
At least one visit to RSK	0.075**	0.032	0.117***	0.073**
	(0.036)	(0.036)	(0.041)	(0.039)
Perception about the rent of machine for LLL	0.170***	0.152***		
	(0.009)	(0.010)		
Household expenditure(log)			0.078**	0.051
			(0.033)	(0.036)
(Pseudo) R-squared	0.159	0.224		
Additional controls	No	Yes	No	Yes
	604	598	598	598

Panel B. ACME and ADE Estimates of treatment (M1)		
	(1)	(2)
ACME	0.062***	0.041**
	(0.020)	(0.016)
ADE	0.076**	0.029
	(0.038)	(0.035)
Total effect	0.138***	0.071*
	(0.043)	(0.040)
Share of the treatment effect explained by the mediator	44.65%	54.23%
Additional controls	No	Yes
Observations	604	598

Panel C. ACME and ADE Estimates of treatment (M2)		
	(1)	(2)
ACME	0.016**	0.006
	(0.008)	(0.005)
ADE	0.118***	0. 074**
	(0.042)	(0.038)
Total effect	0.1345***	0.080**
	(0.042)	(0.038)
Share of the treatment effect explained by the mediator	12.18%	6.80%
Additional controls	No	Yes
Observations	598	598

Panel A: Average Marginal Effect (AME) of the Probit specification with machine rent as control variable; robust standard errors in parenthesis.

Panel B: ACME stands for average causal mediation effect, ADE for average direct effect. Mediator equation with OLS specification and outcome equation with Probit specification. Mediating variable (M1) is farmers' perception. Additional controls are the education of the household head, number of total household members, number of male and female members, distance from the RSK center, land owned, land under irrigation, tractor ownership, pumpset ownership, livestock ownership, amount of crop loan available, household expenditure.

Panel C: ACME stands for average causal mediation effect, ADE for average direct effect. Mediator equation with OLS specification and outcome equation with Probit specification. Mediating variable (M2) is farmers' welfare. Additional controls are the education of the household head, number of total household members, number of male and female members, distance from the RSK center, land owned, land under irrigation, tractor ownership, pumpset ownership, livestock ownership, amount of crop loan available.

Robust standard errors in parenthesis, ***p<0.01, **p<0.05, *p<0.10.

The results in panel B tell us that the perception about the rent to be paid for the required machine acts as a mediator between the extension at the RSK center and the adoption of LLL technology. Adding the control variables, the total effect is still significant at 10%; however, the direct effect is no longer significant. On average about 54% of the total effect of the treatment on LLL adoption was explained by the indirect effect through the attitude towards the complementary input needed to use the technology (column 2 of panel B). Figure 9 displays the quantities of interest graphically with their confidence intervals (at 90%).

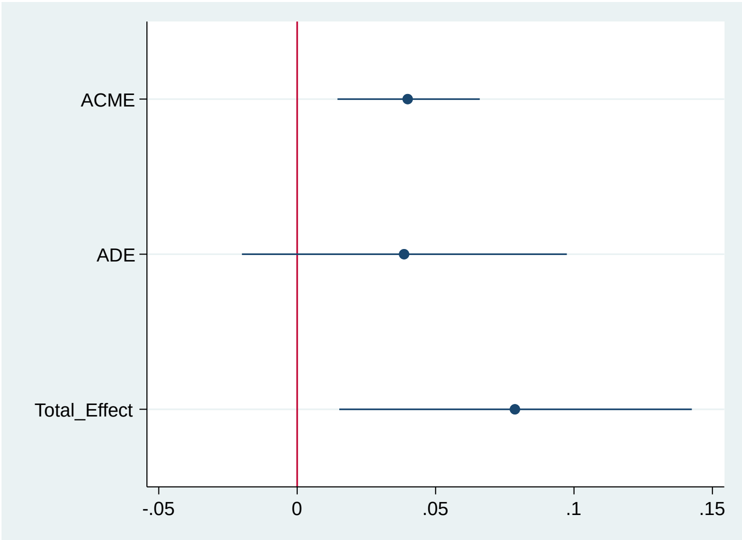


Figure 9. Graphical representation of the quantities of interest (M_1) with control variables and confident interval =90%

Panel C presents the estimated ACME and ADE of the treatment for the second mediator under analysis (log of household expenditure). Only around 8% of the treatment effect of visiting the RSK center seems to be explained by variations in farmers' welfare. The ACME is significant at 5% in column 1; however, adding controls, it turns out to be insignificant. The figure below shows the quantities of interest graphically for the second mediator with their confidence interval (95%).

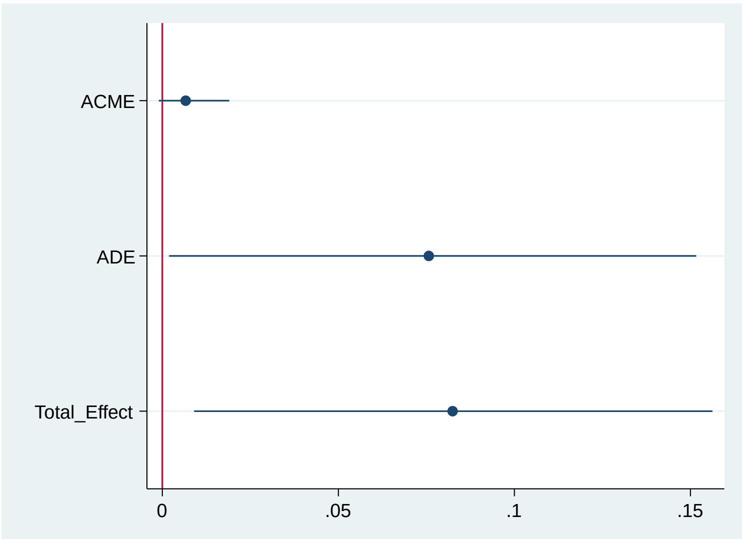


Figure 10. Graphical representation of the quantities of interest (M_2) with control variables and confident interval= 95%

Sensitivity Analysis

In order to check whether the results are robust to violation of the sequential ignorability assumption, I performed a sensitivity analysis[7].

This analysis is based on the correlation between the errors terms of the mediator and outcome models in eq. 1 and 2 (that is denoted as ρ), and it provides the value of ρ that makes the ACME equal to zero. Non-zero values of ρ imply a departure from the SI assumption (Imai, Keele and Tingley, 2010).

However, the interpretation of the magnitude of the correlation coefficient ρ can be tricky and an alternative approach is to interpret the ACME as a function of the R^2. This gives information about the importance of a confounder in explaining the mediator or outcome variable. In this case, the relationship between the ACME and R^2 parameters can be defined as the product of the R^2 parameters for the mediator and outcome variables[9] $R_M^{*2}R_Y^{*2}$ (Hicks and Tingley, 2011). In this way, interpretation is more straightforward since it allows to understand the role of potential omitted variables in terms of their explanatory power (Imai, Keele and Tingley, 2010).

Table 12. Sensitivity results for the two mediators

Sensitivity results		
	M1	**M2**
ρ at which ACME=0	0.400	0.100
$R_M^{*2}R_Y^{*2}$ at which ACME=0	0.160	0.010
$\tilde{R}_M^2\tilde{R}_Y^2$ at which ACME=0	0.087	0.006

95% confidence interval

The results of the test, displayed in table 12, show that in order to have the point estimate of the ACME equal to zero, ρ (i.e., the correlation between the two error terms) related to the first mediator should be 0.4 while for the second it should be 0.1. In other words, the sensitivity analysis tells us how large should ρ be for the causal mediation effect to disappear (Imai, Keele and Tingley, 2010).

Focusing on the first mediator and interpreting the ACME as a function of R^2, the proportion of residual variance in mediator and outcome explained by a potential omitted variable ($R_M^{*2}R_Y^{*2}$) is 0.16 while the proportion of total variance in mediator and outcome explained by a potential omitted variable ($\tilde{R}_M^2\tilde{R}_Y^2$) is 0.087. Focusing on the second one, the proportion of residual variance in mediator and outcome explained by a potential omitted variable ($R_M^{*2}R_Y^{*2}$) is 0.010 while the proportion of total variance in mediator and outcome explained by a potential omitted variable ($\tilde{R}_M^2\tilde{R}_Y^2$) is 0.006.

[7]The sensitivity of the causal mediation results is checked by using the medsens command in Stata developed by Hicks and Tingley (2011).

[9] When the mediator or outcome are binary variables, the pseudo-R^2 is used (Hicks and Tingley, 2011)

From figure 11 and 12 it is also possible to see the value of ACME when ρ is equal to zero for the two mediators. Furthermore, the grey areas depict the 95% confidence interval for the mediation effects and the line represents the estimated average mediation effect at each value of ρ (Imai, Keele and Tingley, 2010).

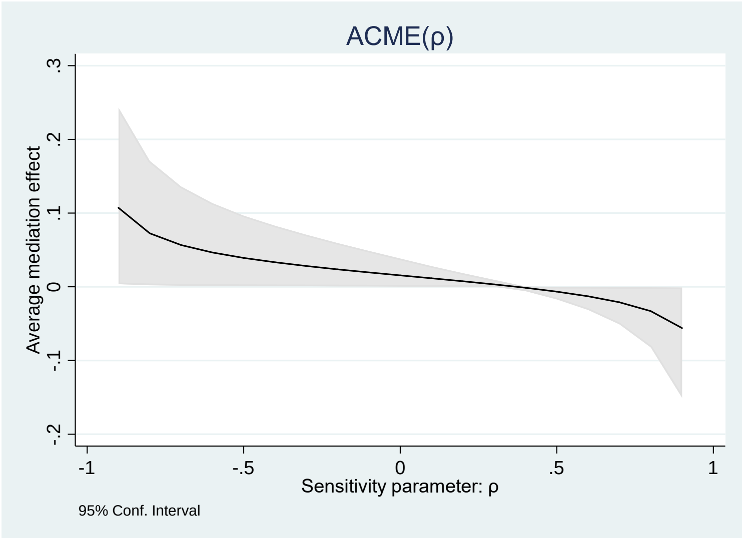


Figure 11. M_1: Average causal mediation effect as a function of ρ (degree of violation of the SI assumption)

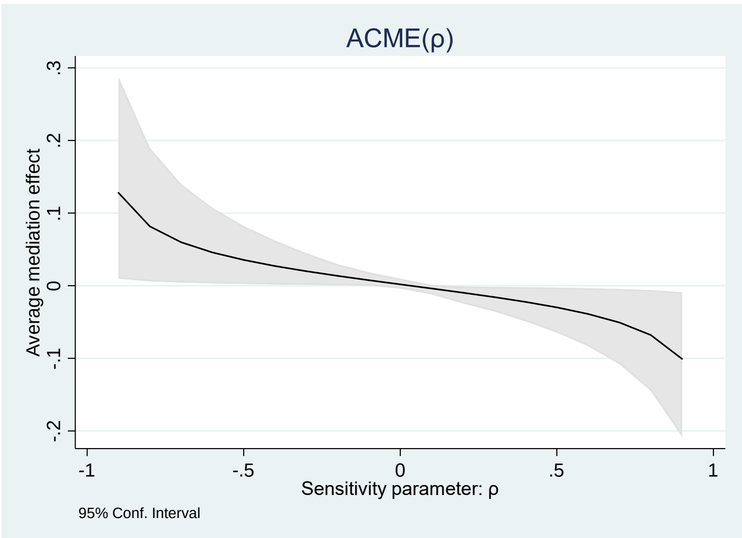


Figure 12. M_2: Average causal mediation effect as a function of ρ (degree of violation of the SI assumption)

7. Summary and Concluding Remarks

Previous literature showed that three main mechanisms could influence technology adoption and use: there could be a lack of knowledge about its existence and how to use it correctly; or credits and liquidity constraints could hinder and discourage the adoption and use of technologies; lastly, time delay between investment and return on yields could be problematic for risk-averse farmers. In this essay, I have focused mainly on the former mechanism, including the second one just as a possible component in shaping farmers' perception that could mediate the relationship between extension services and laser land leveling adoption. To increase the spread of knowledge about a certain technology, an intervention expanding the access to extension centers (and a proper selection among the neediest farmers) could benefit them. If, instead, the problem is related to credit constraints, the extension should include a component of credit, informing farmers how to access it or promoting microcredit schemes.

This essay investigated the effect of an extension service on the adoption and use of LLL in the state of Karnataka, India. Laser Land Leveling can be included among the climate-smart technologies that can be useful in adapting to climate variability thanks to more efficient use of water, its contribution in reducing the cost of cultivation, and minimizing the risk of losing crop yield and income for farmers.

The analysis results provide evidence that visiting the extension centers has a positive and statistically significant (at 10%) ITT effect on the adoption and use of laser land leveling. Also, results obtained by performing a PSM - to address the concern of selection bias - enhance that evidence.

Additionally, since Pal et al. (2020) identified among the constraints to laser land leveling adoption and use elements related to the machine needed to carry out this kind of land leveling, the essay focuses also on the farmers' perception about the rent for the machine required as a mediator for the relationship under analysis. The analysis shows that it acts as a mediator with around 54% of the total effect that seems to be explained by the indirect effect through this farmers' perception. Furthermore, I considered as an additional mediator farmers' welfare, proxied by monthly household expenditure. Indeed, visiting and extension center more often could provide farmers with information and tools able to increase their welfare; in turn, this additional income obtained by the household could be invested into technology adoption. However, this variable seems to explain less than 7% of the total effect, and the average causal mediation effect does not seem to be significant. This result confirms the fact that income is a control variable and not a mediator.

This essay presents some limitations. The availability of cross-sectional data could lead to a problem related to the temporal ordering of variables in the mediation approach, damaging causal inference. Another problem is that the treatment could be endogenous in this empirical setting. Trying to solve this, I first performed a propensity score matching that confirmed the results obtained with the Probit regression. Furthermore, endogeneity could be an issue also considering the treatment and the mediator in the causal mediation analysis. An instrumental variable mediation approach could be used to control for this, but an instrument strong enough could not be identified in the dataset available. Lastly, another problem that may arise in this analysis is the violation of the stable unit treatment assumption (SUTVA).

In a context like the one considered in this analysis, it could be likely that the potential outcome for any unit varies with the treatment assigned to other units (Imbens and Rubin, 2015).

The study has some implications relevant to policymaking. Firstly, it underlines that it is necessary to foster extension programs to increase awareness and thus the adoption and use of the technology under analysis. Secondly, strengthening financial options for farmers is another relevant issue. A common and parallel debate in the literature is whether to target transfers to farmers who are more likely to take up the technology or the one in need, and additional studies should contribute to this. Future research should also focus on other factors that could hinder the use and adoption of laser land leveling, but also how information about climate change could shape it. Lastly, to enhance external validity, it would be good to run RCTs in the area and other locations with similar characteristics (semi-arid regions) to enhance external validity.

Essay 3

Market access and agrochemical use in Nigeria

Abstract

Market access represents an essential driver of inclusion for small farmers. In recent years, policymakers have focused their attention on smallholder farmers' participation in markets to stimulate rural development and poverty, but also as a mean to promote agricultural technologies and practices. However, insufficient liquidity and limited access to credit, insufficient knowledge about the technology or the agricultural practice, and farmers' risk aversion represent three significant barriers to their adoption. This essay delves into the intricate dynamics between market access and technological adoption, with a specific focus on understanding the mediating role played by the three proposed constraints. Using the four waves of the LSMS-ISA for Nigeria, I firstly identify the local governmental areas (LGAs) that can be classified as hot spots and cold spots for the main crops grown in the country, i.e., cereals, cassava, or tubers. Whether a household lives in a hot spot LGA or not will be used as a proxy for market access in the analysis, together with whether it sells on the market or not and in what position (only locally or to the main market). Then, I employ instrumental variables mediation analysis to account for non-random selection and possible simultaneity between market access and the use of agrochemicals. Confirming previous literature, my results show a positive correlation between selling on the market and the outcome variable, and this is confirmed also by the instrumental variable mediation. The most important outcome emerging from this essay is that the primary transmission channel that explains the relationship seems to be the possibility to access to credit.

1. Introduction

Low productivity due to inefficient use of modern agricultural technologies - such as chemical fertilizers and agrochemicals - characterizes the agricultural sector in many developing countries. The primary constraints to adoption detected from previous literature include limited access to credit, insufficient knowledge about the existence of the technology or the agricultural practices, and farmers' risk aversion. Technology adoption decisions are also linked to farmers' market participation and it is impossible to ignore that the two issues are somehow interdependent (Mekonnen, 2017). Market access represents a relevant driver of inclusion for small farmers. Being on the market could positively reduce the three main barriers to adopting agricultural technologies and practices for farmers. At the same time, the use of agricultural technologies could increase productivity, generating surplus products and allowing farmers to sell more to the main markets.

In the literature, Ciarli *et al.* (2018) developed an analytical framework to understand how innovation and inclusion (defined over several dimensions including market access) are linked both in a linear fashion and dynamically. Saha and Ciarli (2018) analysed it empirically at the macro level. However, they leave the integration of feedback from inclusion to innovation for future research. Thus, I proceed in this direction focusing on inclusion and innovation at the micro level. Being market access an important component of inclusion, I will narrow the definition focusing only on that dimension.

To what extent and through which transmission channel does market access - chosen as a proxy for inclusion - affect the adoption and the use of agricultural technologies? If it is no surprise that a strong association between market access and technology exists, more complicated is the identification of the direction of causality due to feedback and endogeneity biases - discussed in greater detail in section 3.2 - that dampen the causal analysis. This essay examines the facets of this linkage and tries to provide a comprehensive picture. The empirical analysis is focused on Nigeria as it offers an extensive panel dataset covering almost ten years. Furthermore, the country is an important case for external validity because of the challenges that its agricultural sector faces - such as climate change, poor distribution of inputs and limited access to the market - and that are shared by several African countries. When considering commercialization in an empirical analysis it is essential to take into consideration geography. For this reason, I include in the analysis a novel way to detect clusters where commercialization levels of the main crops grown in the country are higher, that following Getis and Ord (1992) and Kondo (2016), will be called hot spots. This method is based on the idea that the spatial association may be locally heterogeneous and exploits information on latitude and longitude available in the dataset. As previous empirical literature is scarce and heterogenous in terms of the conclusions reached about the nexus under analysis, and do not consider the geographical structure involved in this, further research can provide more insight into this issue.

The main contribution of this essay to the study of smallholder farmers, their engagement in commercialization, and their consequent uptake of agricultural practices as agrochemicals is methodological. In particular, I introduce the use of a new method, seldomly found in development economics literature, to detect commercialization hot spots based on the Getis and Ord statistic (Getis and Ord, 1992; Kondo, 2016). Lastly, being in a hot spot is used as a treatment - together with other definitions of market access - in an instrumental variable mediation approach. To this aim, I employ the method by Dippel, Ferrara and Heblich (2020), including separately as mediators the three factors identified in the literature as main constraints to technology adoption and a fourth one identified through the principal component analysis of the others.

The remainder of this essay is organized as follows. Section 2 reviews the literature on technology adoption and market access; the theoretical background and the identification strategy. Section 3 presents the data and discusses some summary statistics. In section 4, the empirical framework is presented. In section 5, the empirical results are displayed and discussed. Section 6 concludes.

2. Literature review and background

2.1 Literature

Previous literature relevant to my analysis includes a first strand of literature related to the direct relationship between market access and technology use; a second one investigating the impact of market access on the barriers to technology adoption; and a third one related to role of these constraints on technology adoption. Here below I report the main studies in detail. The aim of this essay is to enrich the existing literature, combining these three strands of the literature.

2.1.1. Commercialization and technology adoption

In addition to the elements presented above, market conditions represent another critical factor that could affect the adoption of a particular innovation (CIMMYT, 1993). I dedicate a separate paragraph to this, given the importance of this strand of literature in this essay. Burkitbayeva, Janssen and Swinnen (2020) analyze the role of value chains and foreign direct investment (FDI) in farm-level technology adoption using panel data from representative farm surveys in 2008 and 2015 in the dairy sector in the Punjab, India. Using fixed-effects models and a linear probability model with fixed-effects, they find that the role of vertical coordination in value chains in stimulating technology adoption among traditional and poor dairy farmers seems to be minor, both for domestic and for FDI companies. In his paper, Porteous (2020) tries to understand how trade costs affect the incentives for technology adoption; how do trade costs alter the potential effects of widespread technology adoption (a Green Revolution); and how do trade costs affect the impact and cost of input subsidies, i.e., the principal policy that governments have used to promote adoption. The article evaluates two alternative approaches to promote technology adoption: lowering trade costs and subsidizing fertilizer. While trade cost reduction shifts production towards the most productive regions, subsidies lead to larger increases in fertilizer use. Greater adoption lowers local food prices under existing high trade costs but only increases farmer incomes when trade costs are low. Awotide, Karimov and Diagne (2016) assess the determinants of the intensity of adoption of Improved Rice Varieties (IRVs) and the effect of market participation on farmers' welfare in Nigeria using the Tobit and Heckman two-stage models, respectively. The sample consists of cross-sectional data from 600 rice farmers selected randomly from three notable rice-producing States in Nigeria. Results suggest that any increase in the farmers' welfare is conditional on the farmer's probability of participating in the rice output markets. Minten, Randrianarison and Swinnen (2009) study the case of small farmers in Madagascar and their involvement in the global supply chain. These farmers can benefit from integration into global value chains, and the authors find that one of the benefits of contracting, in that specific context, is that processing firms teach farmers how to make compost combined with chemical fertilizer. Most farmers state that the contract with firms changed how they cultivate other off-season crops, use compost on their fields, and more weeding after signing the contract. However, this is not the case for rice, as only a small minority of farmers claim to have changed their cultivation methods. Devaux et al. (2009) focus on the participatory market chain approach, a way to bring small-scale potato producers together with market agents and agricultural service providers in the case of the Papa Andina network in the Andes. Their analysis reveals that this market approach encourages interactions among agents involved and helps to stimulate innovation. Shiferaw et al. (2015) show that market access significantly increases the probability of a farmer having access to improved seeds in Uganda, highlighting the importance of low-cost transport systems in promoting linkages input and output markets. Maggio and Sitko (2019) examine how small farmers adapt their farm practices in response to receiving seasonal forecasts in Zambia, focusing on the role of private grain buyers in mediating the relationship. In addition to the importance of receiving seasonal forecast information, they also highlight an increase in the probability that a farmer implements the adaptive farm management practices considered as the number of private grain buyers in the farmers' village increases. This means that the dissemination of weather information and the agricultural market development are crucial and integrated elements in adopting practices useful for farmers' adaptive responses.

There is, however, limited evidence about whether the nexus between market access and agricultural technologies is mediated by the three constraints that hinder the adoption.

As I will better explain in section 2.3, the relationship between technology use and commercialization also occurs in the opposite direction. Here below few studies that analyze the impact of technology on commercialization. Asfaw *et al.* (2011) examine farmers' decision to adopt agricultural technologies and the causal impact on their integration into the output market using a cross-sectional sample of 700 farmers in Ethiopia. Using the treatment effect model, regressions based on propensity score and matching techniques, they find that adopting improved agricultural technologies plays a significant role. This reflects that technology increases productivity, which translates into higher output market integration among rural households. Using cross-sectional data collected in 2016 in rural Timor-Leste and an instrumental variable approach, Akter *et al.* (2021) find a significant role of high-yielding maize varieties as a driver of small farmers' market participation, operating through an increase in maize productivity able to generate a marketable surplus. Mosha *et al.* (2021) examine the System of Rice Intensification (SRI) and a group of SRI-trained farmers in the Mngeta division, Kilombero district in the Morogoro region, Tanzania. They use a production function model to determine whether implementing SRI management practices could influence paddy yields and a fractional logistic model to evaluate the nexus between SRI interventions and rice commercialization. The estimated Rice Commercialization Index (RCI) for the group of SRI-trained farmers is higher than the non-trained counterpart. Also, productivity has a significant and positive effect on rice commercialization, highlighting the positive impact of innovation due to SRI on commercialization. Mekonnen (2017) analyzes the impact of agricultural technologies on small farmers' output market participation with data collected by the World Bank between 2010 and 2012 in Ethiopia. Using endogenous treatment effect and sample selection to account for the self-selection bias in technology adoption and market participation, the author finds that the use of improved agricultural inputs - high-yielding varieties and chemical fertilizers, both used jointly and separately - affects farm households' marketable surplus production, increasing markets participation of farmers.

2.1.2.Nexus market access- determinants of technology adoption

This strand of the literature is the least developed. In the literature only few studies investigated the linkage between market participation and the three factors hindering technology adoption(lack of knowledge, lack of liquidity or credit and risk aversion). Therefore, there is still the need for more research to understand how increasing farmers' access to deeper output markets may increase their knowledge about the technology, or reduce risk, or improve farmers profits and welfare reducing their liquidity constraints, while triggering technology adoption (Bridle *et al.*, 2019).

Among the literature about the impact of market access on farmers' income - it is possible to find Bozzoli and Brück (2009), who find that market participation of farm households in Northern Mozambique has a positive effect on their welfare, suggesting the creation of policies that offer marketing opportunities. Rao and Qaim (2011) analysed the impacts of supermarket channel participation in Kenya, founding that it leads to improvements in household income.
Other authors focused on the linkage between market access and risk aversion or knowledge. Volatility in prices by markets in different region and seasons - for instance, due to an influx of output that could collapse prices - increasing farmers' risk aversion in Sub-Saharan countries(Bridle *et al.*, 2019).
In the case of Papa Andina network a participatory market chain approach where producers were engaged together with market agents and agricultural service providers aiming to share market knowledge and develop new business opportunities.

2.1.3. Determinants of technology adoption

Despite the positive effects of agricultural technologies, the adoption of innovative practices by small farmers is low and not complete due to different reasons that can be summarized in three categories: low awareness about the benefits of the new technology or lack of information, high risk aversion and high transaction costs of inputs and liquidity in general (De Janvry, Macours and Sadoulet, 2016). Wollni and Andersson (2014) examine various explanations for adoption decisions, particularly the availability of information in the farmer's neighborhood and the perceived positive external effects of the innovation. They found that when farmers have greater availability of information in the neighborhood, they are more likely to adopt sustainable agricultural technologies. Barrett *et al.* (2021) analyze the results of a large-scale, multi-year randomized controlled trial evaluation of a system of rice intensification (SRI) in Bangladesh, finding that SRI training has a large and positive impact on farmers' propensity to adopt. Emerick and Dar (2021) investigate the role of farmer field days as means of knowledge transmission: during these days, farmers can meet, learn about new technologies and how to use them. They are cost-effective and significantly impact adoption, especially for the poorer ones. Focusing on the determinants of the intensity of technology adoption conditional on overcoming seed access constraints in Ethiopia, Asfaw *et al.* (2011) find that knowledge of existing varieties and perception about the characteristics of the improved ones are some of the main determinants for the adoption of technologies. Awareness can be increased through extension (Hörner *et al.*, 2019), but that does not automatically lead to better practice and higher production (Van Campenhout *et al.*, 2017). Knowledge about the existence of a specific technology and its potential returns are two different matters. Van Campenhout *et al.* (2017) investigate the difference between the two issues finding that providing technical information and information on returns of a particular technology raises awareness but not the actual adoption, probably because farmers are also constrained by other factors (Van Campenhout *et al.*, 2017).

Another mechanism that can explain the low rate of technology adoption is risk aversion with a smaller expected utility of profits over time. Dercon and Christiaensen (2011) focus on risk avoidance, i.e., the ability of households to take on new production technologies and bear the risk of potential poor harvests due to shocks that could have consequences on their welfare. They analyzed fertilizer adoption in Ethiopia, finding that it is dampened not only by ex-ante credit constraints but also by the potential low consumption outcomes in case of harvest failures. Kebede et al. (1990) investigate the impact of farmers' risk attitude on adopting some technologies as part of a post-drought recovery project in Ethiopia. The results showed that the degree of risk aversion is significant and negatively affects the adoption of the practices considered in the areas under analysis. Another source of uncertainty is that many technological decisions demand investment in more points over time: firstly, farmers have to invest when they decide to adopt (take-up of the technology); then, the technology could require several subsequent investments to be implemented and used. The risk is that farmers abandon the technology if, after the take-up, they consider it not worth continuing to use the technology given the new information acquired about subsequent investments needed (De Janvry, Macours and Sadoulet, 2016). Jack *et al.* (2016) focus on this problem in the context of agroforestry in Zambia, carrying out an experiment, discovering that farmers are responsive to incentives offered but also that they are not able to identify the pay-off from adoption when they have to decide whether to adopt or not. In addition, farmers could change their minds over time and abandon the technology when they believe it does not provide the expected benefits; hence, when uncertainty for farmers is high, the authors proposed to reward follow-through instead of giving subsidies for taking up (Jack *et al.*, 2016).

Lastly, even when information is not the primary constraint to technology adoption, other elements, such as inefficiency in credit markets and difficulty accessing complementary inputs, could prevent farmers from adopting. If access to credit is limited and farmers cannot save or pay high-interest rates for informal lending, they may not have enough cash to make the proper investments in technology adoption (Bridle *et al.*, 2019). Croppenstedt, Demeke and Meschi (2003) provide empirical evidence of the role of constraints on farmer adoption of technologies, underling the role of credit and subsidies as particularly relevant for policy-making in Ethiopia. They suggest a policy that increases the availability of credit for these households and the creation of subsidies for fertilizer adoption to improve the nutrient imbalance observed in the country. Diiro and Sam (2015) investigate whether households in rural Uganda use their non-farm earnings to invest in improved maize seed technologies. The analysis reveals that this kind of earnings represents a relevant source of capital for farmers who cannot access credit markets or borrow the capital needed to use the technology. Moser and Barrett (2006) develop a technology adoption model with specific attention to high-yielding low external input rice production in Madagascar and focus on farm households living in an environment of incomplete financial and land markets. They found that seasonal liquidity constraints hinder adoption by poorer households.

The literature above mentioned provide specific results for each strand, but this essay is the first to try to provide a comprehensive picture of these elements. To fill this gap, I use panel data collected by the LSMS-isa for Nigeria in four rounds between 2010 and 2018.

2.2. The Nigerian Context

Nigeria is a federation of 36 autonomous states and the Federal Capital Territory. The country also includes 774 local government areas (The World Bank, 2022). The war against Boko Haram and other terrorist groups in the northeast since 2011 characterizes the political and security landscape. In addition, many cases of banditry and kidnapping in the north-west and part of the southwest happened in recent years. Lastly, in the southeastern part of the country separatist agitations represent an issue.

The total Nigerian population in 2021 was around 211 million people. In 2018, 83 million of them lived below the poverty line. With Nigeria's population growth (2.5% annually) continuing to outpace poverty reduction, the number of Nigerians living in extreme poverty is expected to rise by 7.7 million between 2019 and 2024. Almost 100 million people lived in rural areas in 2021 (The World Bank, 2022).

The Nigerian GDP growth was 3.6%, and the agricultural sector accounted for around 23% of the total GDP in 2021 (FAO, 2022; The World Bank, 2022). The sector also accounted for 65% of employment in 2016 (The World Bank, 2016). Despite its contribution to the Nigerian economy, the agricultural sector faces several challenges. These include poor land tenure systems, low irrigation levels, climate change, low technology adoption, generally poor distribution of inputs, and limited access to the market(FAO, 2022). To address these issues, the Government recently implemented several programs aiming to increase agricultural productivity, reduce food import, and increase commodity crop exports. Major crops grown in the country are maize, cassava, sorghum, yam, bean, millet and rice, as shown by the figure below.

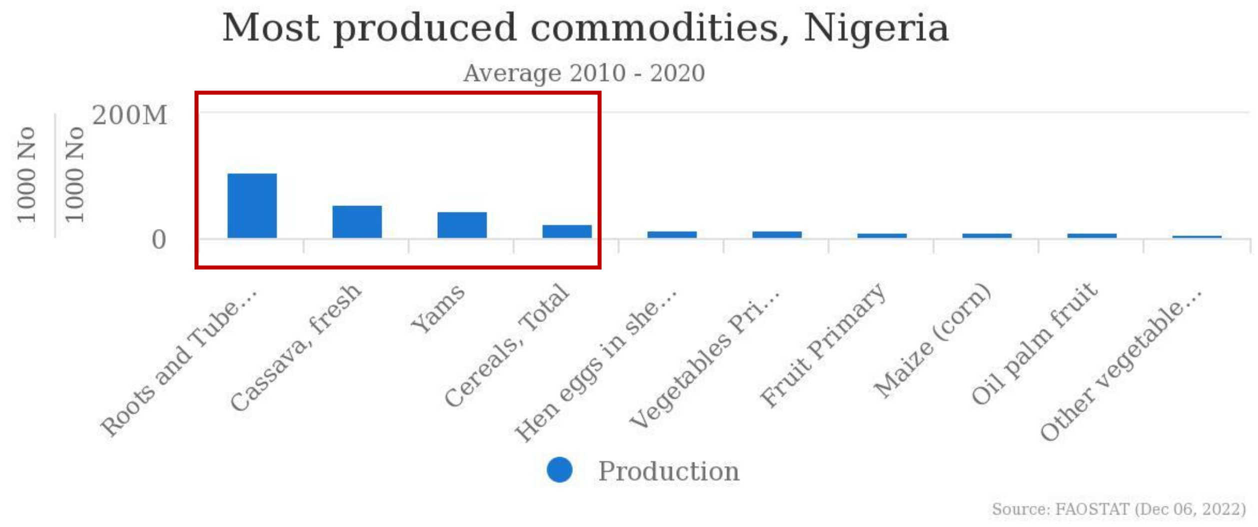


Figure 1. Most Produced Commodities, Nigeria. Source: FAOSTAT[10]

Nigeria's cassava production amounted to 59 million tons in 2017, making the country the world's largest producer, with around 20% of global production. Improved varieties and production techniques could play a relevant role in increasing cassava production (FAO, 2022). Nigeria is also Africa's largest rice producer and among the top 15 producers globally. The Government of Nigeria planned to make the country self-sufficient in rice production by 2018, but the target was never reached, and around half of the country's demand is still met by imported rice, mainly from Thailand and India (International Trade Administration, 2021). Cereals and tubers are particularly important as over 15% of the population does not have access to diverse diets and relies on those types of crops for their nutrition (Robinson *et al.*, 2014).

Given the increasing population, adapting new technology and innovations is critical in ensuring food security and nutrition for all (FAO, 2022). In 2016 the Nigerian Government launched the Agriculture Promotion Policy (APP), which was replaced by the National Agricultural Technology and Innovation Plan" (NATIP) in 2020. The aim is to modernize the agricultural sector, attract public and private investments into technology and innovation, and promote the adoption of climate-smart practices, in line with the global food system and supply chains. Enhancing agricultural research and training systems in collaboration with the private sector to develop inputs and technology consistent with local needs is one of the plan's main pillars. Additionally, it wants to promote mechanization and access to private service centers equipped with tractors to reduce production - and post-harvest - losses and create job opportunities. The plan also encouraged digital and climate-smart agriculture to enhance the food system,

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[10] https://www.fao.org/faostat/en/#data/QCL/visualize, accessed on Dec, 6th 2022

increase biodiversity, enrich soils and promote organic farming. This could help in boosting productivity and reducing emissions. Under this pillar, the plan wants to ease access to quality agricultural inputs and promote investments in local fertilizer production and distribution.

Market development and crop value chain enhancement represent other important plan components. In particular, it focuses on the value-chain development of maize, sorghum, rice, wheat, cassava, yam and other staple and cash crops. To reduce constraints these value chains face, it recommends the active participation of local government, smallholder farmers and private investors, providing processing centers and promoting the development of clusters that link the agricultural sector with the processing sector. Since the marketing of commodities remains largely unorganized and under-developed, the government also seeks to remove inefficiencies through a multi-stakeholder approach that could improve urban market infrastructures (FMARD, 2020). However, it is also important to take in mind that promoting a market-oriented and private sector-led economy could result in smallholder farmers facing considerable additional market constraints, including poor market information, restricted access to credit and modern inputs, and high transaction costs arising from weak market integration. If this is the case, the risk is that farmers become vulnerable to economic exclusion and poverty (Olomola, 2010).

2.3. Theoretical background and identification strategy

Theoretical models in the literature on the nexus innovations-market participation

Ciarli *et al.* (2018) proposed an analytical framework to understand how innovation, inclusion are linked in a linear fashion and dynamically. Their framework builds on the literature on the determinants of innovation, which in their model is defined as the standard Oslo Manual definition of innovation of the OECD "*the implementation of a new or […] improved product (good or service), or process, a new marketing method, or a new organizational method in [manufacturing or delivery], workplace organization or external relations.*" (OECD, 2005, pp.46) and shaped by variables, actors and interactions. Pro-poor growth and equity are included in the definition of inclusion, described as the redistribution of benefits and losses so that marginalized people can reap net benefits from changes. They first consider how variations in inclusion at time t influence innovation at time $t+1$ in a linear pathway. However, they also recognize that the relation between these three elements is non-linear and subject to feedback mechanisms. Thus, the model also considers a dynamic component where feedback from structural change and inclusion in t+1 to innovation in t+2 is included. The integration of feedback from inclusion to innovation is left for future research.

Despite the fact that this is not the focus of the essay, I also report below other models investigating the relationship from technology to market participation to provide a complete overview. Barrett (2008) introduces a stylized model of farm households' market participation behavior where one of the

components is the relationship between markets and technologies. The assumption is that market access is not uniform among households as they face different transaction costs to market participation and since there could be different levels of geographic market integration into the global economy. In the model, households' production technology choices directly influence their market participation by affecting their productivity. The conceptual and empirical evidence suggests that interventions aimed at facilitating smallholder organization, at reducing the costs of intermarket commerce, and, perhaps especially, at improving poorer households' access to improved technologies and productive assets are central to stimulating smallholder market participation and escape from semi-subsistence poverty traps.
Other researchers suggest that a strategy aiming at modernization and farmers' well-being should consider these two elements together. De Janvry and Sadoulet (2019) outline a theory of change where the removal of market and government failures to achieve modernization can be approached through two contrasted and complementary initiatives. One is a "constraint removal" approach where development agents facilitate overcoming the major constraints to adoption: liquidity, risk, information, and market access. The other is an "inclusive value chain development" approach where agents in value chains (entrepreneurs, coordinating agencies, producer organizations) create incentives for smallholder modernization through contracting and vertical coordination.

Identification strategy

Ciarli *et al.* (2018) leave the integration of feedback from inclusion to innovation for future research. Inclusion is key in their theoretical framework on adoption. My identification strategy starts from Ciarli *et al.* (2018) and Saha and Ciarli (2018) and focuses on inclusion and technology use at the micro level in Nigeria. Since the model defines inclusion as a way through which benefits from technology could be redistributed toward marginalized households, I will concentrate on one of the main dimensions of inclusion considered in the model: access to the market. Market access is key in promoting small and marginalized farmers' inclusion.
Indeed, in many developing countries small farmers face barriers to participate to the market due to transaction costs. In some cases, markets do not even exist, whereas in others they are characterized by high transaction costs as small farmers are located in remote areas lacking of sufficient infrastructure and access to assets or information(Alene *et al.*, 2008).
Reducing these specific transaction costs can enhance the integration of small and less efficient producers in high-value value chains (Reardon, Barrett and Berdegue, 2009), and consequently their adoption of the agricultural technology. Small-scale producers often lack sufficient and sustained incentives to adopt productivity- or quality-enhancing technologies under current output market structures(Bridle *et al.*, 2019), that is why it is important to investigate the issue. Lastly, I define innovation as the implementation

of an existing but improved product; namely, the use of agrochemicals (either organic and inorganic fertilizers, pesticides and herbicides).

It is not possible to ignore that farmers' market participation and technology adoption decisions are somehow linked and interdependent (Mekonnen, 2017). Indeed, it seems clear that there is a sort of circularity: selling on the market - particularly in a downstream position - has positive effects on adoption thanks to the possibility of reducing the three main barriers: credit and liquidity constraints, the discount rate of technology and uncertainty, limited knowledge and information about innovations (De Janvry et al. 2016). Selling crops to the market and the positioning of farmers in the market chain (i.e., whether they sell to local or main markets) may have different impacts on these barriers to technology adoption. Downstream positions could positively affect them: it could increase and stabilize farmers' income, enabling investments in technology. Market positioning could also reduce the knowledge gap on the existence of agricultural technologies and practices. At the same time, technology positively affects access to the market through the increase in productivity, generating surplus products. This may allow farmers to sell more to the main markets, shifting towards a more downstream position in the market chain (Tesfay, 2020). Therefore, I should observe a strong association between market access and technology use, whereas identifying the direction of causality would be more problematic, and in this essay, I try to deal with that. My contribution to the literature is twofold: using national-representative panel data that covers almost a 10-year period, I first provide insights on the long-term relationship between access to markets, agricultural technology's constraints and its adoption. Secondly and more importantly, the contribution of this essay is methodological: firstly, it uses a new method, seldomly found in economical empirical applications, to detect commercialization hot spots based on the Getis and Ord statistic (Getis and Ord, 1992; Kondo, 2016) that will be used as a proxy to market access. This method is based on the idea that the spatial association may be locally heterogeneous and exploits information on latitude and longitude available in the dataset. Then, this essay tries to explain the correlation between the two main variables focusing on the determinants of adoption (measures of credit/liquidity constraints, discount rate and information constraints), considering them in an instrumental variable mediation analysis. This method combines the advantages of mediation analysis with the one of instrumental variable approach. On the one hand, it allows to disentangle total effect into a direct effect from market access to agrochemicals use and an indirect (or mediated) effect that occurs through the three transmission channels. On the other, it is able to control reverse causality thanks to the use of an instrumental variable. The figure below reports the conceptual framework that I will investigate.

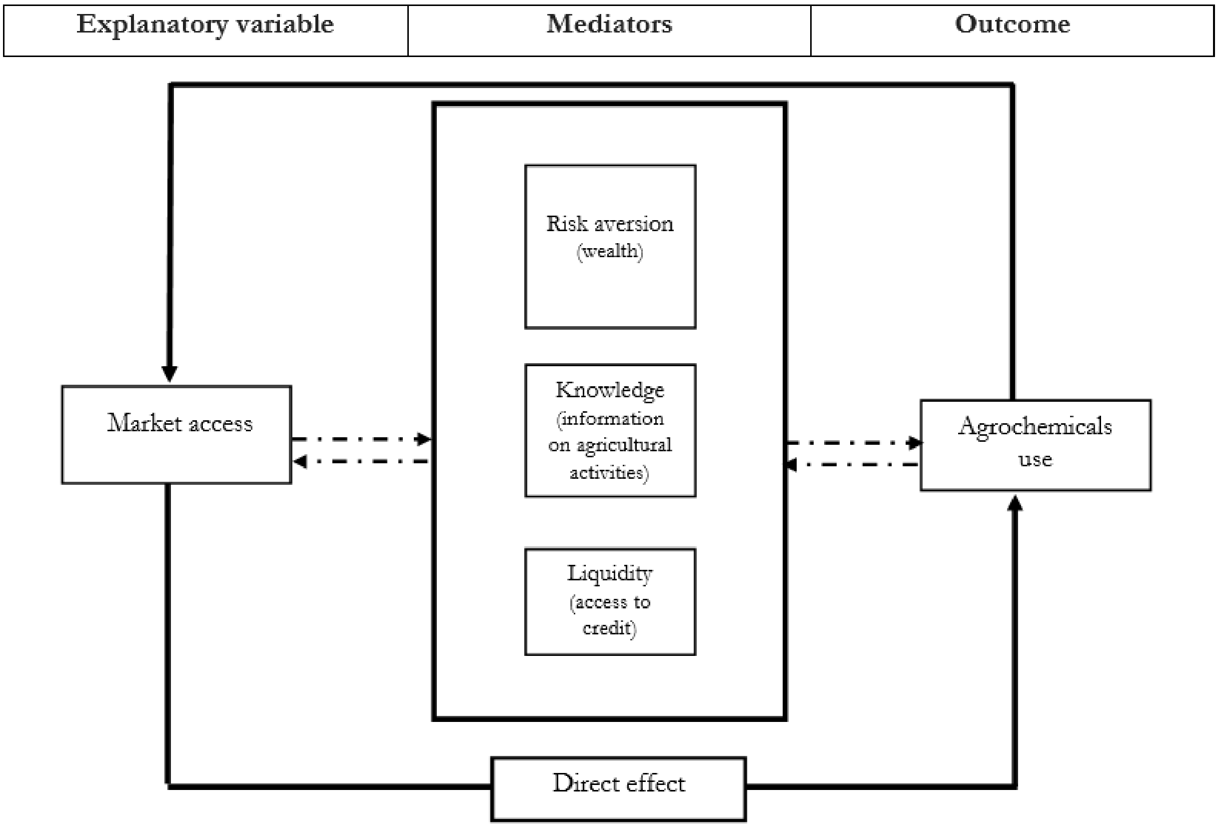

Figure 2. Conceptual framework

4. Data and Descriptive Statistics

The data used in this analysis come from the General Household Survey (GHS-Panel) fielded by the Nigeria National Bureau of Statistics (NBS) in collaboration with the LSMS teams of the World Bank. The GHS-Panel is a subsample of Nigerian households selected from the GHS core survey, an annual survey carried out in February-March on a sample of 22000 households. The panel component is implemented every two years, and the panel households are visited twice a year for each wave in the post-planting and post-harvesting periods.

Nigeria LSMS-ISA is representative at the national level and provides reliable estimates of socio-economic variables for the six zones in the country. The sample was visited four times in 2010/2011 (Wave 1), 2012/2013 (Wave 2), 2015/2016 (Wave 3), and 2018/2019 (Wave 4). Three datasets are used: household-level, agricultural, and community-level data. The survey includes modules related to agricultural activities, other household income activities, and household expenditure and consumption. Table 1 shows the number of households included in the sample under analysis for each wave and by zone.

In the general survey, all efforts were made to keep in the panel sample the same households. However, some of them could not be re-interviewed due to security concerns. For this reason, in the last wave, some new households - selected from the same sampling frame as the original GHS-Panel sample in 2010 - were added to partially refresh the sample and to maintain its integrity and representativeness. Rural areas of Borno state were entirely excluded from the refreshed sample for security reasons. Other parts of the country where conflict events were occurring were also excluded.

Table 1. Nigeria sample distribution by wave and region

Wave	**1 (2010/2011)**	**2 (2012/2013)**	**3 (2015/2016)**	**4 (2018/2019)**
Zone				
North Central	800	800	798	849
North east	800	774	644	829
North west	900	881	882	866
South east	800	779	759	839
South south	800	771	755	829
South west	900	813	781	841
Total	**5,000**	**4,818**	**4,619**	**5,053**

Table 2 below shows the sample number used for this analysis with attrition with respect to the previous wave (column 1) and the first wave (column 2). Wave 4 shows a substantial attrition rate compared to the previous wave and the first wave, while for the rest of the wave, the attrition does not represent an issue.

Table 2. Attrition between waves

		(1)	**(2)**
Wave	**N**	**Attrition wave t vs. wave t-1 (%)**	**Attrition wave t vs. wave 1 (%)**
1	5,000	-	
2	4,818	3.64	
3	4,619	5.60	7.64
4	5,053	68.51	70.92

Main variables

Technology adoption/use

The use of technology includes organic (manure) and inorganic fertilizer, pesticides and herbicides. Despite the acknowledged importance of using fertilizer and the massive subsidization, fertilizer consumption rates in Nigeria remain low (Banful, Nkonya and Oboh, 2010). I created a dummy equal to 1 if the household uses at least one among organic or inorganic fertilizers, pesticides and herbicides; equal to zero otherwise. I also report in table 4 and 5 a count variable that goes from zero (no agrochemicals use) to 4 (all the agrochemicals used) and a last dummy equal to 1 if the household uses all the agrochemical types combined on their plots. Lastly, since there could be heterogeneity in household fertilizer use, I will consider the kg and kg/ha of agrochemicals used on plots they manage.

Determinants of adoption:

Below, I describe the proxies for the three main elements that affect technology adoption and use.

a) Knowledge

Promoting information flows is a way to reduce the barrier to adoption related to insufficient knowledge about the technology and how to use it. I have created a variable that reflects the number of visits received on farmers' plots and done by farmers, allowing them to obtain information about agricultural and marketing activities. I have also created a categorical variable indicating farmers' rating of these visits. The pictures below show that most farmers rate them as very useful.

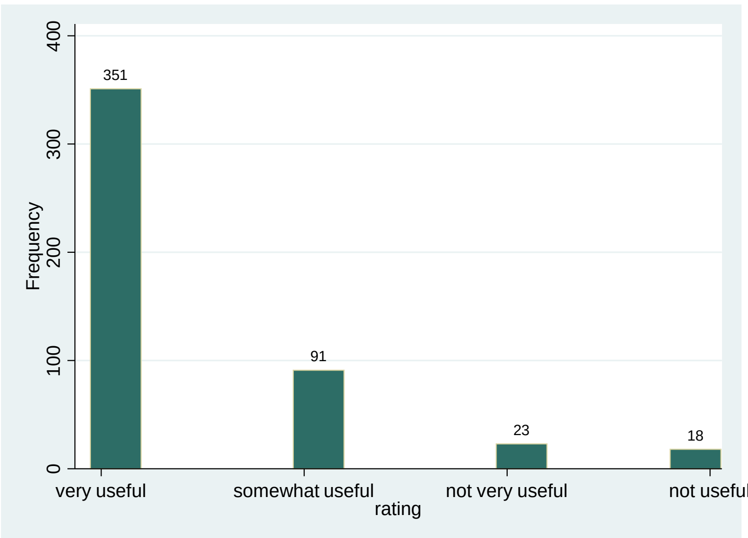

Figure 3. Rating of information received. Source: Own elaboration from LSMS-ISA for Nigeria (wave 1)

b) Risk aversion

Discount rate of technology is not easily observable, some authors use wealth and in particular stable income sources. They assume that household's unobservable discount rate is strongly associated with wealth(Moser and Barrett, 2006)[11]. Following their idea, I will use a dummy indicating whether households have savings in informal groups to proxy farmers' risk aversion.

c) Credit/liquidity

Lastly, a barrier to technology adoption and use is credit availability from formal and informal sources. I created a dummy equal to 1 if households borrowed from formal institutions.

Market access:

Another crucial variable in the analysis is farmers' positioning along the market chain. I defined market access in several ways: firstly, I created a dummy equal one for farmers that sell their crops on the market and zero if they sell only to relatives, friends, neighbors and farm gate. Secondly, similar to Montalbano, Pietrelli and Salvatici (2018), I created a dummy variable for farmers selling in an upstream position, i.e., distant from the final markets - and another for farmers selling in a downstream position, i.e., close to the final markets. Some farmers deal with multiple sales channels simultaneously. In these cases, I consider them to be in a downstream position whether at least one of the sale channels is "*main market*" or "*private company/business person*". Table 3 shows the classification of farmers according to their main buyer and the total number of farmers in upstream and downstream positions. Lastly, I created a dummy indicating whether the household lives in a LGA identified as hot spots according to the Getis-Ord statistic. This statistic allows to identify clusters in a geographic space using information on latitude and longitude. Section 5 explains how this statistic is computed. A LGA is identified as hot spot if the related z-score is above 1.96.

Table 3. (Pooled) sample of farmers by positioning on the market chain

(Panel) Farmers selling to:	
1. Relative 2. Friend/neighbor 3. At farm gate	*Off the market:* 13,103
1. Main farm/Plot 2. Roadside 3. Mobile market 4. Local market	*Upstream:* 4,887
1. Main market 2. Private trader in main market 3. Private company/business person 4. If multiple buyers, at least one is main market 5. If multiple buyers, at least one is private company/business person	*Downstream:* 1,501

[11] However, please note that not all the literature agrees on the use of this proxy (see Bellemare and Brown, 2010).

Table 4 describes the main variables used, whereas table 5 shows the summary statistics by market access and waves.

Table 4. Description of main variables

Variable	Description/Proxy
<u>Technology</u>	
Agrochemicals (dummy)	Use of at least one among organic or inorganic fertilizer, pesticides, herbicides
Agrochemicals (Count)	No. of agrochemicals used (from 0 to 4)
Agrochemicals(kg)	Kg of agrochemicals used by the household
Agrochemicals (kg/ha)	Kg of agrochemicals used per ha
<u>Determinant of adoption</u>	
Knowledge	Number of visits received/done to receive information (to extension centers, from neighbors, NGOs, agricultural cooperatives)
Credit (Dummy)	Household borrowed from institutions or informal groups or friends, relatives, money lenders
Risk/uncertainty(dummy)	HH experienced at least one climatic or security shock in the previous years
<u>Access to market</u>	
On the market (dummy)	Household sells into the market
Upstream position (dummy)	Farmers selling their crops with an upstream position (i.e., distant from the final markets);
Downstream position (dummy)	farmers selling their crops with a more downstream position (i.e., close to the final markets).
Hot spots	Household is in a hot spot LGA
Cold spots	Household is in a cold spot LGA

It is possible to notice some significant differences (t-test statistic) among the groups raising concerns of possible self-selection. A greater percentage (from 60% in wave 1 to around 75% in wave 4) of households selling on the market - both local and main market - uses agrochemicals compared to households selling only to friends and neighbors (from 25% to 30%); they use more types of agrochemicals and a larger quantity. They have greater access to credit - on average, 31% of them across the four waves borrowed money - and a bigger percentage of them stated they were affected by some shocks.

The table shows that there does not seem to be significant differences in the main variables between households in upstream and downstream positions, except for the use of agrochemicals in wave 3, where it seems to be higher for households in upstream position (75% vs. 70% for households in downstream position). A higher percentage of households in hot spots LGAs use agrochemicals compared to households in cold spots in wave 2. In wave 3 this is also shown by the significantly larger quantity of agrochemicals used by these households. They also receive more information about agricultural activities in waves 3 and 4 and access more credit in waves 2 and 3. In wave 3, a slightly higher percentage of them (4%) reported being affected by a shock in the previous year.

Table 5. Summary statistics of main variables by market access and waves

Variable	Off the Market	On the Market	Upstream	Downstream	Hot spot	Cold spot
Agrochemicals (dummy)						
Wave 1	0.251	0.602***	0.595	0.623	0.287	.34
SD	(.434)	(.490)	(.491)	(.485)	(.453)	(.478)
Obs	3532	1,468	1,131	337	550	50
Wave 2	0.256	0.665***	0.661	0.679	0.389	0.333*
SD	(.436)	(0.472)	(0.475)	(0.468)	(0.488)	(0.476)
Obs	3440	1378	1073	305	524	57
Wave 3	.282	0.740***	0.756	0.694*	0.360	0.491
SD	(.450)	(0.439)	(0.430)	(0.461)	(0.481)	(0.505)
Obs	3044	1576	1167	409	444	53
Wave 4	0.304	0.756***	0.751	0.773	0.378	0.425
SD	(.460)	(0.429)	(0.433)	(0.419)	(0.485)	(0.495)
Obs	3087	1966	1517	450	540	553
Agrochemicals (Count)						
Wave 1	0.376	0.934***	0.919	0.985	0.436	.38
SD	(.725)	(.924)	(.929)	(.908)	(.775)	.567
Obs	3532	1468	1131	337	550	50
Wave 2	0.383	1.035***	1.021	1.085	0.672	0.404
SD	(.723)	(0.912)	(0.906)	(0.935)	(0.937)	(0.623)
Obs	3440	1378	1073	305	524	57
Wave 3	0.506	1.396***	1.407	1.367	0.795	0.604
SD	(.930)	(1.144)	(1.132)	(1.179)	(1.236)	(0.716)
Obs	3044	1576	1167	409	444	53
Wave 4	0.541	1.404***	1.384	1.469	0.661	0.599
SD	(.951)	(1.113)	(1.107)	(1.135)	(1.006)	(0.820)
Obs	3087	1966	1517	450	540	553
Agrochemicals(kg)						
Wave 1	83.718	104.657**	100.419	118.862	103.196	35
SD	(196.958)	(217.587)	(207.502)	(248.243)	(257.879)	63.698
Obs	1620	1458	1123	335	297	38
Wave 2	862.245	741.452	912.950	139.515	523.276	852.376
SD	(13654.26)	(12,218.47)	(13,845.04)	(408.494)	(3774.466)	(4681.223)
Obs	1594	1371	1067	304	292	41
Wave 3	459.207	476.823	509.690	383.044	407.137	43.904*
SD	(1253.917)	(1651.126)	(1704.289)	(1487.011)	(1055.147)	(73.383)
Obs	1295	1576	1167	409	233	41
Wave 4	1775.075	2446.767	2225.9	3169.661	2128.779	150.350
SD	(23115.22)	(28909.84)	(23744.9)	(40365.71)	(22750.42)	(233.301)
Obs	938	1487	1139	348	204	235
Agrochemicals (kg/ha)						
Wave 1	453.457	408.541	370.8299	538.231	550.057	831.964
SD	(2578.648)	(3024.886)	(2066.402)	(5096.899)	(2843.327)	(2006.884)
Obs	1505	1385	1073	312	276	38
Wave 2	1592.458	1048.913	1272.203	246.340	1210.622	1915.615
SD	(15697.25)	(11528.45)	(13019.72)	(796.412)	(7936.382)	(9223.075)
Obs	1431	1291	1010	281	263	41
Wave 3	1550.72	1177.538	1255.447	946.400	1174.234	923.212
SD	(6502.182)	(7756.42)	(8685.275)	(3855.633)	(3489.604)	(2220.337)
Obs	1092	1432	1071	361	211	41
Wave 4	1119.183	1514.591	1468.684	1664.713	1289.13	606.556
SD	(8236.307)	(13031.93)	(13614.67)	(10927.53)	(9954.304)	(1496.668)
Obs	938	1486	1138	348	204	234
Knowledge						
Wave 1	3.733	4.039	3.866	4.66	4.855	7.857
SD	(6.354)	(5.011)	(4.627)	(6.209)	(6.368)	18.206
Obs	285	229	179	50	62	7
Wave 2	.583	0.583	0.639	0.386	0.873	0.244

SD	(2.916)	(2.534)	(2.728)	(1.674)	(2.891)	(1.562)
Obs	1713	1368	1065	303	307	41
Wave 3	.634	0.510	0.521	0.479	1.113	0.073*
SD	(2.184)	(2.144)	(2.057)	(2.379)	(2.615)	(0.346)
Obs	1456	1565	1162	403	248	41
Wave 4	0.743	1.072	1.136	0.853	0.914	0.241***
SD	(3.129)	(16.129)	(18.318)	(2.293)	(2.401)	(1.318)
Obs	1826	1959	1512	448	359	498
Credit (Dummy)						
Wave 1	0.323	0.421***	0.424	0.410	0.291	.22
SD	(.468)	(.494)	(.494)	(.493)	(.455)	.418
Obs	3529	1467	1130	337	550	50
Wave 2	0.348	0.436***	0.449	0.393	0.450	0.259**
SD	(.476)	(0.496)	(0.498)	(0.489)	(0.498)	(0.442)
Obs	3369	1373	1068	305	516	54
Wave 3	0.158	0.211***	0.221	0.183	0.257	0.113*
SD	(.365)	(0.409)	(0.415)	(0.388)	(0.438)	(0.320)
Obs	3035	1575	1166	409	443	53
Wave 4	0.145	0.165*	0.164	0.171	0.191	0.175
SD	(.352)	(0.372)	(0.370)	(0.377)	(0.394)	(0.381)
Obs	3086	1966	1517	450	539	553
Shocks (dummy)						
Wave 1	0.073	0.141***	0.141	0.142	0.084	.06
SD	(.260)	(.348)	(.348)	(.350)	(.277)	.240
Obs	3532	1468	1131	337	550	50
Wave 2	0.122	.179***	.183	.163	.149	.105
SD	(.326)	(.383)	(.386)	(.371)	(.356)	(.310)
Obs	3440	1378	1073	305	524	57
Wave 3	0.080	0.088***	0.090	0.081	0.043	0*
SD	(.271)	(0.283)	(0.286)	(0.273)	(0.203)	(0)
Obs	3044	1576	1167	409	444	53
Wave 4	0.110	0.220***	0.222	0.211	0.113	0.141
SD	(.313)	(0.414)	(0.416)	(0.409)	(0.317)	(0.348)
Obs	3087	1966	1517	450	540	553

Descriptive statistics

Table 6 describes additional variables relevant to the analysis for the pooled sample and by wave. In the pooled sample, one can observe that on average, household heads are 51 years old; among them, 12% have not completed any educational level, 22% the primary school, and 33.7% the secondary school or above. About 83% of the households are headed by a man, and most household heads are in monogamous marriage (58%), while 18% are in polygamous marriage. On average, 15% are widowed, and a minority is in an informal union, separated, divorced, or never married. The mean household size is 6. Households manage on average 8 ha of land, but most of them are small farmers that manage less than 5 ha (95%)

Sampled households' average expenditure for non-food items (per household member) in the pooled sample was 7110.289 Naira - approximately, $16 - in the post-planting survey, while in the post-harvest survey, the same indicator is on average equal to 8707.583 Naira (approx. $19). Concerning the food consumption per household member in the seven days previous to the survey, households spent on average around 1000 Naira (approximately $2.2) both in the post-planting and post-harvest surveys. The asset score is very low in the pooled sample.

Table 6. Additional summary statistics by waves

Variable	**Panel**	**Wave 1**	**Wave 2**	**Wave 3**	**Wave 4**
Age	50.889 (15.119)	49.440 (15.231)	51.703 (14.937)	52.924 (14.578)	49.738 (15.398)
Education level (Highest qualification attained by the household head)					
None (dummy)	0.118 (0.322)	0.111 (0.314)	0.112 (0.315)	0.120 (0.325)	0.129 (0.335)
Primary (dummy)	0.217 (0.412)	0.227 (0.419)	0.204 (0.403)	0.216 (0.411)	0.219 (0.414)
Secondary or above (dummy)	0.338 (0.473)	0.314 (0.464)	0.303 (0.460)	0.330 (0.470)	0.404 (0.491)
Other(dummy)	0.014 (0.116)	0.021 (0.143)	0.023 (0.149)	0.006 (0.075)	0.005 (0.072)
Gender (1=male)	0.825 (0.380)	0.849 (0.359)	0.845 (0.362)	0.801 (0.399)	0.805 (0.396)
Monogamous marriage (dummy)	.583 (0.493)	0.608 (0.488)	0.597 (0.491)	0.562 (0.496)	0.565 (0.496)
Polygamous marriage (dummy)	0.178 (0.383)	0.184 (0.388)	0.161 (0.367)	0.184 (0.388)	0.183 (0.386)
Informal union (dummy)	0.002 (0.047)	0.004 (0.060)	0.002 (0.043)	0.001 (0.025)	0.003 (0.051)
Separated or divorced(dummy)	0.033 (0.178)	0.033 (0.178)	0.030 (0.169)	0.034 (0.180)	0.035 (0.185)
Widowed(dummy)	0. 149 (0.356)	0. 126 (0.332)	0.132 (0.338)	0.181 (0.385)	0.159 (0.366)
Never married(dummy)	0.040 (0.197)	0.043 (0.203)	0.031 (0.174)	0.032 (0.128)	0.054 (0.226)
Household size	6. 187 (3.456)	5.522 (3.102)	6.203 (3.248)	6.982 (3.532)	6.103 (3.750)
Non-food expenditure annual (per household member, Naira) PP	7110.289 (168288)	4017.698 (9993.904)	10321.2 (339174.4)	5041.894 (21718.56)	9045.061 (26186.62)

Non-food expenditure annual (per household member, Naira) PH	8707.583 (128853.7)	11234.36 (252194.4)	6164.734 (24646.38)	5271.744 (16020.52)	11838.28 (36983.82)
Food consumption annual (per household member, Naira) PP	1050.339 (1722.497)	781.311 (688.227)	779.494 (832.716)	826.736 (907.579)	1767.063 (2959.337)
Food consumption annual (per household member, Naira) PH	1031.74 (1258.453)	1031.47 (1134.633)	801.109 (931.760)	780.5185 (809.062)	1481.67 (1758.964)
Land size	8.092 (230.569)	1.068 (2.304)	0.883 (1.354)	0.852 (1.325)	24.422 (417.29)
Small Scale Farm (SSF, dummy)	0.950 (0.218)	0.965 (0.184)	0.983 (0.129)	0.983 (0.128)	0.888 (0.316)
Medium Scale Farm (MSF, dummy)	0.044 (0.204)	0.035 (0.184)	0.017 (0.129)	0.017 (0.128)	0.091 (0.287)
Assets Score	0.075 (0.074)	0.542 (0.286)	0.061 (0.054)	0.080 (0.073)	0.124 (0.097)

5. Empirical strategy

After defining hot spot and cold spot LGAs, I analyze the impact of market access on technology use. Using the hot spots obtained, I create a household-level indicator variable equal to one if the household lives in an LGA identified as being part of the hot spot and zero otherwise. This will be an additional proxy of market access used in the analysis.

Before focusing on the indirect effect of market access through the three main channels affecting the relationship, I will run some regression to understand whether market access has a direct effect on the outcome (agrochemicals use) and on the three mediators. Indeed, an important assumption of the mediation analysis is that the treatment should have an impact on the mediator, that in turn should have an impact on the outcome. For this reason, I'll firstly run some preliminary panel regressions.

The analysis also focuses on the transmission channels from the market access to agrochemicals use. Based on the identification strategy outlined above, I identify three mediators. Since both the treatment and the mediators could be endogenous and reverse causality is an issue, I first performed the instrumental variable mediation developed by Dippel, Ferrara and Heblich (2020), considering the three mediators in three separate specifications. I will include in the analysis as treatment variables a dummy indicating whether households sell crops on the (local or main) market and a second one indicating whether a household is located in a hot spot. The use of the IV approach to sort reverse causality will be better explained in section 5.2.1.

Additionally, I run a structural equation model considering the second dummy as treatment and trying to incorporate all three mediators together (in appendix). In section 6, some meaningful results are reported.

5.1. Hot spots and cold spots identification

I first identify commercialization hot spots and cold spots using spatial identification. To detect these groups of spatially contiguous areas, I use the method developed by Getis and Ord (1992) following Kondo (2016). Spatial autocorrelation is becoming a relevant concept in the literature about how socioeconomic activities are distributed in space. This concept comprises global spatial autocorrelation (Moran's *I)* and local spatial correlation. The method used in this essay, the statistic *Getis–Ord G*i* (*d*), is embedded in the latter strand and is based on the idea that the spatial association may be locally heterogeneous, even if a global spatial autocorrelation is not observed.

The *Getis–Ord G*i (d)* statistic allows to identify clusters in a geographic space using information on latitude and longitude. This statistic for a given variable *xi* for district *i* (in the case of Nigeria, for Local Governmental Area - LGA) is calculated as:

$$G_i^*(d) = \frac{\sum_{j=1}^{N} w_{ij}(d) x_j}{\sum_{j=1}^{N} x_j}$$

Where N is the number of LGAs and $w_{ij}(d)$ denotes the ij^{th} element of the spatial weight matrix with ones for all links identified as being within a threshold distance *d* while other links are zero:

$$w_{ij}(d) = \begin{cases} 1, & if\ d_{ij} < d, \quad for\ all\ i,j \\ 0, & otherwise \end{cases}$$

The numerator of the *Getis–Ord G*i (d)* statistic is the local sum of the variable *x* within a circle of d radius from the base point (for example, centroid) of LGA *i*, and the denominator is the total sum of variable *x* for all the LGAs. Hence, hot spots and cold spots are identified as spatial outliers.

To compute this statistic in Stata, I used the command *getisord* (Kondo, 2016) using geographic information on the latitude and longitude. It calculates the great-circle distance between locations by using the simplified version of the Vincenty (1975) formula - which considers that the shape of Earth is not a perfect sphere. It allows for visualization if the shape file is available as it can be combined with the *spmap* command, which displays regional data in a map. The command also endogenously builds the spatial weight matrix, and I used a binary spatial weight matrix considering a threshold distance of 50 km. This identification is interesting as it also allows to investigate which specific characteristics characterize hot spots in order to promote them in cold spots (for instance, also through techniques of qualitative analysis).

Table 7 displays the results of the hot spot analysis using indicators related to crop sales. In particular, I considered maize, sorghum, millet, cassava, cereals (combining maize, sorghum, millet and rice) and main crops (maize, sorghum, millet, rice, cassava and tubers) sold (mean at the LGAs level) for each wave. These crops were selected as they are key for the country's agriculture. Related maps are shown in the appendix section. For cereals (maize, rice, millet and sorghum) sales, the hot spot LGAs are 19 in waves 1 and 2, 18 in wave 3, and 11 in wave 4. For maize sales, I identified 16 hot spot LGAs in wave 1 and 17 in the other waves; for sorghum 11 in waves 1 and 3, 12 in wave 2, and 8 in wave 4; for millet 4 hot spots are identified in wave 1, 6 in wave 2, 4 in waves 3 and 4; for cassava 10 in wave 1, 8 in wave 2 and 3, 4 in wave 4; lastly, considering main crops (which include cereals, cassava and other tubers) I identified 14 hot spot LGAs in wave 1, 15 in wave 2, 12 in wave 3 and 18 in wave 4. Greater variations in wave 4 could be because the sample has been partially refreshed as a consequence of difficulties in accessing some areas due to security reasons.

Table 7: Getis-Ord G∗ i (d) Test for Spatial Clustering (LGA level)

Indicator (mean values)	z<=-2.58	-2.58<z<=-1.96	-1.96<z<1.96	1.96<=z<2.58	2.58<=z
Cereal sold					
Wave 1 (obs=331)	0	12	300	6	13
Wave 2 (obs=341)	0	15	307	7	12
Wave 3 (obs=339)	0	14	307	7	11
Wave 4 (obs=292)	16	21	224	6	5
Maize sold					
Wave 1 (obs= 264)	0	5	243	2	14
Wave 2 (obs=273)	0	5	251	2	15
Wave 3 (obs=274)	0	6	251	4	13
Wave 4 (obs=247)	24	14	192	6	11
Sorghum sold					
Wave 1 (obs=138)	0	0	127	8	3
Wave 2 (obs=142)	0	0	130	9	3
Wave 3 (obs=139)	0	0	128	8	3
Wave 4 (obs=115)	0	2	105	4	4
Millet sold					
Wave 1 (obs=95)	0	0	91	2	2
Wave 2 (obs=95)	0	1	88	3	3
Wave 3 (obs=92)	0	0	88	2	2
Wave 4 (obs=62)	0	0	58	2	2
Cassava sold					
Wave 1 (obs=177)	0	0	166	6	4
Wave 2 (obs=182)	0	0	174	4	4
Wave 3 (obs=181)	0	0	173	4	4
Wave 4 (obs=159)	0	0	155	0	4

Main crops sold					
Wave 1 (obs=350)	0	0	336	4	10
Wave 2 (obs=361)	0	0	346	5	10
Wave 3 (obs=359)	0	3	344	2	10
Wave 4 (obs=316)	0	0	298	6	12

Note: Getis-Ord G∗ i (d) test for local spatial independence in a 50km radius with a binary spatial weight matrix. Local spatial independence is given when the z-score on the corresponding test statistic lies within $-1.96 < z < 1.96$. Spatial clusters of unusually low/high variable values (cold/hot spots) are found for LGAs with z-scores of $z \leq -1.96$ (cold spots) and $1.96 \leq z$ (hot spots). The number of LGAs in each z-score bin is provided in the columns of the table. Each LGA is identified by the latitude and longitude of its centroid. "Cereals" include maize, sorghum, millet and rice; "Main crops" include maize, sorghum, millet, cassava, rice and tubers.

Table 8 shows the sample distribution of households in hot spots and cold spots for each indicator considered and by wave.

Table 8. Nigeria sample distribution by hot spots and cold spots and by wave

Wave	**1 (2010/2011)**	**2 (2012/2013)**	**3 (2015/2016)**	**4 (2018/2019)**	**Total**
Hotspots					
Maize	190	196	164	217	**767**
Sorghum	130	148	121	100	**499**
Millet	50	70	48	60	**228**
Cassava	160	110	108	64	**442**
Cereals	220	215	165	176	**776**
Main crops	180	173	145	249	**747**
Cold spots					
Maize	50	47	53	513	**663**
Sorghum	0	0	0	40	**40**
Millet	0	10	0	0	**10**
Cassava	0	0	0	0	**0**
Cereals	130	154	137	506	**927**
Main crops	0	0	26	0	**26**

5.2. Mediation analysis

5.2.1 Instrumental variable mediation analysis

The classical mediation approach defined by Baron and Kenny (1986) investigates the effect of a treatment X on the outcome Y going "through" the mediator M. However, Baron and Kenny's approach does not allow the identification of causal mechanisms due to inappropriate and untestable assumptions (Imai *et al.*, 2011). Hence, other approaches were developed to unpack the transmission mechanisms where a treatment and a mediator jointly cause an outcome of interest. The aim is to disentangle the total effect of treatment T on outcome Y into two components. The first one is the direct effect, namely the causal effect that the treatment has on the outcome when the distribution of the mediator is held constant;

the second one is the indirect effect of the treatment on the outcome, which operates through the impact that the treatment has on an intermediate outcome, i.e., the mediator (Dippel, Ferrara and Heblich, 2020). However, these approaches assume the treatment to be randomly assigned, an assumption that does not hold here. In this analysis, the treatment is potentially endogenous to both the mediator and the outcome; the same can be said for the mediator with respect to the outcome. In some cases, it could be the case that the mediator is endogenous due to some post-treatment confounders. In other cases, the treatment is not exogenous even after controlling for pre-treatment covariates. In this case, one or more instruments can be used to control for these sources of endogeneity (Imai, Tingley and Yamamoto, 2013; Frölich and Huber, 2017; Dippel, Ferrara and Heblich, 2020; Celli, 2022). However, since I are dealing with three potentially endogenous mediators, more than a single strong instrument would be necessary; and this could be challenging (Otter *et al.*, 2018; Celli, 2022). In addition, the standard IV framework is not suitable for identifying the causal effect of the mediator on the outcome of interest (Dippel *et al.*, 2020).

To overcome this problem, Dippel *et al.* (2020) propose a new identification strategy imposing causal relationships among unobserved variables using a single instrument[12]. This approach allows for unpacking the treatment effect from a standard IV regression into the direct and indirect effects of potentially endogenous treatment and mediator variables without needing an additional instrument for the mediator. In this way, the big advantage is that a single IV is enough to identify both effects. Furthermore, to provide tests for weak identification, the command *ivmediate* reports the F statistic by Kleibergen and Paap (2006). The mediation effect is reported as a percentage of the total effect, and it is simply the indirect effect divided by the total effect multiplied by 100 (Dippel, Ferrara and Heblich, 2020). This instrumental variable-mediation analysis method was developed to use a single mediator; hence, I will analyze each of the three mediators separately. In this case, mediators not included will only have an additive effect on the outcome rather than being a transmission channel. In this way, I can test which of the three factors has the strongest power in explaining the indirect effect. Trying to capture the mediating effect of all the three elements, I also use principal component analysis to identify principal components from these mediators that will be used as a fourth specification.

5.2.2. Structural equation model

The IV mediation approach is useful as it allows the use of a single instrument. However, it does not permit to consider the three mediators together. Aiming at a complete understanding of the relationship among the variables under analysis, I also run a structural equation model (SEM) that includes all the three determinants of adoption (credit/liquidity constraints, discount rate, and information constraints) simultaneously (see in appendix).

[12] In stata the command is ivmediate

6. Results

In this essay, I will perform several regressions and many specifications, obtaining different results. Among them, the more interesting could be summarized as follow. Confirming previous literature, the results presented here highlight the importance of selling to the markets for small farmers. In addition, they also underline the role of obtaining credit from formal institutions as the main transmission channel that could facilitate the relationship between market access and agrochemical use.

M1: risk aversion

Table 9 shows the results from the IV mediation analysis for the mediator risk aversion. The instrument is the distance from the border in columns 2 and 3 and the log of the distance to the border in columns 1 and 4. Other instrumental variables were tested but results are not reported since the Kleibergen-Paap F-statistics for the two first stages were far below the threshold defined by Dippel et al. (2020) - i.e., 30. Both the total and the indirect effect show significant coefficients in column 1,2 and 4. Living in a hot spot LGA increases the use of agrochemicals by about 1.42, whereas being in an upstream position decreases the use by 2.6. The F statistic is around the threshold defined by Dippel et al. (2020) - i.e., 30- in column 4 while it is much lower for the first stage one in column 1 to 3. The mediated effect in column 4 explains 98% of the total effect.

Table 9. Impact of market access on agrochemical use (M=risk aversion)

	(1)	(2)	(3)	(4)
	Agrochemicals use			
Total effect	-4.195**	-2.583***	5.009	1.421***
	(2.124)	(0.962)	(3.129)	(.384)
Direct effect	0.060	0.059	-0.038	.033
	(0.063)	(0.044)	(0.048)	(.055)
Indirect (or mediated effect)	-4.25*	-2.642**	5.047	1.388***
	(2.367)	(1.123)	(3.317)	(.493)
Observations	1180	1163	1163	1180
Mediator	Risk (wealth: savings in informal groups)	Risk (wealth: savings in informal groups)	Risk (wealth: savings in informal groups)	Risk (wealth: savings in informal groups)
Treatment	On the market	Upstream	Downstream	Hotspot
Instrument	Distance to the border(ln)	Distance to the border	Distance to the border	Distance to the border(ln)
Kleibergen-Paap F-statistic for excluded instruments in first stage one (T on Z)	4.438	8.365	2.713	26.025
Kleibergen-Paap F-statistic for excluded instruments in first stage two (M on Z|T)	30.388	38.832	39.698	37.315
Mediation effect as a percentage of the total effect (%)	101.45	102.27	100.76	97.71

Note: Results from the IV mediation analysis are reported. The dependent variable is the use of agrochemicals. Control variables include the number of visits to receive information on agricultural activities, whether households borrowed money, the quantity of main crops sold, time to the closest city, household size, and ha of land managed. Standard errors are reported in parentheses.
***p<0.01, ** p<0.05, * p<0.1.

Placebo tests to check the validity of the instrumental variables

To provide indirect empirical evidence in favor of the validity of the instruments mentioned above, I run some placebo tests in table 10a and 10b. Firstly, I run a reduced form regression of the mediator controlling for the instrument and other covariates (number of visits to obtain information on agricultural activities, access to credit, the quantity of main crops sold in kg, time to reach the closest city in minutes[13], household size and land size) on overall, treated and control group sample. The expectation is that the coefficient for the instrument is significant for the treated group but not for the control group. Secondly, I separately estimate a reduced form model of the final outcome for overall, treated, and control groups to test exclusion restriction. Again, the expectation is that the coefficient of the instrument for the control group should not be significant, as the only way the instrument affects the outcome is through the treatment.

Table 10a. Placebo tests for the instrument used in column 4 of table 9

	(1)	(2)	(3)	(4)	(5)	(6)
	Risk aversion			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance in km to Nearest Border Crossing(ln)	0.286***	0.220	0.326***	-0.106***	0.023	-0.131***
	(0.060)	(0.169)	(0.069)	(0.021)	(0.050)	(0.025)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,180	207	973	1,181	207	974

Note: Average marginal effects from probit regression of risk aversion (columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Unfortunately, the results in the table above do not confirm the validity of the instrument. Indeed, the impact of the instrumental variable is significant also for the untreated sample in columns 3 and 6. Conversely, its effect on the treated sample is not significant (column 2 and 5). On the opposite, table 10b confirm the validity of the instrument used in column 1 of table 9.

[13] Weiss et al. (2015) developed and validate a map that quantifies travel time to cities for 2015 at a spatial resolution of approximately one by one kilometre by integrating ten global-scale surfaces that characterize factors affecting human movement rates and 13,840 high-density urban centres within an established geospatial-modelling framework.

Table 10b. Placebo tests for the instrument used in column 1 of table 9

	(1)	(2)	(3)	(4)	(5)	(6)
	Risk aversion			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance to the border(ln)	0.286 ***	0.304***	0.073	-0.106***	-0.120***	-0.026
	(0.060)	(0.065)	(0.183)	(0.021)	(0.023)	(0.055)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,180	1,068	112	1,180	1,069	112

Note: Average marginal effects from probit regression of risk aversion (columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Mediator 2: Knowledge

Table 11 reports results from the IV mediation analysis for the mediator knowledge. This time, the instruments considered are the (ln) distance of each household (in km) to the Nearest Border Crossing, the (ln) distance to the Capital of the State and dummy indicating whether the distance to the market is lower than 1 km.

Column 4 shows that living in a hot spot increases the use of agrochemicals by 1.35. This effect can be decomposed into a negative direct effect of -0.2 and an indirect effect of 1.23. the indirect effect explains 92% of total effect. However, the F statistic for the first stage two is very low, suggesting interpreting these results cautiously.

Table 11. Impact of market access on agrochemical use (M=knowledge)

	(1)	(2)	(3)	(4)
	Agrochemicals use			
Total effect	-2.324**	-0.716**	-3.237	1.349***
	(1.177)	(0.347)	(3.338)	(.314)
Direct effect	0.191*	0.007	-0.002	-.204**
	(0.110)	(0.074)	(0.042)	(.098)
Indirect (or mediated effect)	-3.421	-0.669	-4.026	1.232**
	(3.421)	(0.995)	(4.285)	(.653)
Observations	1180	1164	1164	1181
Treatment	On the market	Upstream	Downstream	Hotspot
Mediator	Knowledge	Knowledge	Knowledge	Knowledge
Instrument	Distance to the border(ln)	Distance to the Capital of the State(ln)	Distance to the market<1km	Distance to the border(ln)
Kleibergen-Paap F-statistic for excluded instruments in first stage one (T on Z)	12.615	25.502	1.865	66.610

Kleibergen-Paap F-statistic for excluded instruments in first stage two (M on Z|T)	9.359	1.006	18.133	8.166
Mediation effect as a percentage of the total effect (%)	147.20	93.26	124.36	91.29

Note: Results from the IV mediation analysis are reported. The dependent variable in columns 1-3 is the use of agrochemicals(dummy), and in column 4, the quantity of agrochemicals used (ln). Control variables include an indicator for self-reported experience of climates or safety shocks, whether households borrowed money, the quantity of main crops sold, time to the closest main city, household size, and ha of land managed. Standard errors reported in parentheses. ***p<0.01, ** p<0.05, * p<0.1.

Placebo tests to check the validity of the instruments

As for the previous mediator, I run a placebo test to provide indirect empirical evidence in favor of the exclusion restriction and relevance of the abovementioned instrument.

Table 12a considers the treatment and the instrument used in column 1 of table 11. As expected, the coefficient of the instrument is significant both in the intermediate and final models for the treated group and the whole sample but not for the control group. These test results provide indirect support for the validity of the exclusion restriction. However, I have to take in minds that the Kleibergen-Paap F-statistic is lower than the one expected.

Tables 12b, 12c and 12d report the results of the placebo tests for the same instrument considering the treatments used respectively in columns 2, 3, and 4 of table 11. In these cases, they do not support the instrument's validity.

Table 12a. Placebo tests for the instrument used in column 1 of table 11

	(1)	(2)	(3)	(4)	(5)	(6)
	Knowledge			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance in km to Nearest Border Crossing (ln)	-0.388***	-0.315***	-0.886	-0.111***	-0.109***	-0.033
	(0.129)	(0.106)	(0.829)	(0.018)	(0.023)	(0.053)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,180	1,068	112	2,046	1,068	112

Note: Results from linear regression of risk aversion (columns 1-3) and average marginal effect from probit regression for agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12b. Placebo tests for the instrument used in column 2 of table 11

	(1)	(2)	(3)	(4)	(5)	(6)
	Knowledge			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance in km to the Capital of the State(ln)	0.072	0.110	-0.045	0.036***	0.025*	0.069***
	(0.078)	(0.094)	(0.147)	(0.011)	(0.014)	(0.022)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,180	808	355	2,046	1,394	605

Note: Average marginal effects from probit regression of risk aversion (columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12c. Placebo tests for the instrument used in column 3 of table 11

	(1)	(2)	(3)	(4)	(5)	(6)
	Knowledge			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance to the market<1km	-0.821***	-0.852***	-0.361	-0.006	-0.011	0.020
	(0.222)	(0.224)	(0.323)	(0.021)	(0.025)	(0.039)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,180	808	355	2,046	1,394	605

Note: Average marginal effects from probit regression of risk aversion (columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12d. Placebo tests for the instrument used in column 4 of table 11

	(1)	(2)	(3)	(4)	(5)	(6)
	Knowledge			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance in km to Nearest Border Crossing(ln)	-0.392***	0.150	-0.404***	-0.111***	0.032	-0.130***
	(0.128)	(0.462)	(0.142)	(0.017)	(0.049)	(0.025)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1181	207	974	2047	307	974

Note: Average marginal effects from probit regression of risk aversion (columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

M3: Liquidity/credit

Table 13 reports the results from the IV mediation analysis for the mediator liquidity. The instruments used are the distance to the Capital (column 1-3) and a dummy equal to one if the distance to the market is less than 1 km (column 4). In column 2 and 3, the total effect is significant, highlighting a reduction in the use of agrochemicals for households in upstream position (i.e., far from the main market) and an increase for those in downstream position (i.e., closer to the main market). The indirect effect is also significant, explaining respectively 117.97% and 96.75% of the total effect. The F statistics in column 2 and 3 are around or above 30, giving a clue for the validity of the instrument used.

Table 13. Impact of market access on agrochemical use (M=credit)

	(1)	(2)	(3)	(4)
	Agrochemicals use			
Total effect	-1.072	-.512*	.899*	.344
	(.685)	(.299)	(.484)	(.336)
Direct effect	.012	.009	-.013	-.075
	(.063)	(.030)	(.034)	(.047)
Indirect (or mediated effect)	-1.670*	-.605*	.870*	.746*
	(1.011)	(.332)	(.510)	(.404)
Observations	1181	1164	1164	1181
Treatment	On the market	Upstream	Downstream	Hot spots
Mediator	Credit	Credit	Credit	Credit
Instrument	Distance to Capital	Distance to the Capital(ln)	Distance to Capital(ln)	Distance to the market<1km
Kleibergen-Paap F-statistic for excluded instruments in first stage one (T on Z)	24.507	48.571	24.039	30.026
Kleibergen-Paap F-statistic for excluded instruments in first stage two (M on Z|T)	17.026	43.371	43.220	24.665
Mediation effect as a percentage of the total effect (%)	155.71	117.97	96.75	216.92

Note: Results from the IV mediation analysis are reported. The dependent variable in columns 1-3 is the use of agrochemicals(dummy), and in column 4, the quantity of agrochemicals used (ln). Control variables include an indicator for self-reported experience of climates or safety shocks, number of visits to the extension center, quantity of main crops sold, time to the closest main city, household size, and ha of land managed. Standard errors reported in parentheses. ***p<0.01, ** p<0.05, * p<0.1.

Placebo tests to check the validity of the instruments

As for the previous mediator, I run some placebo tests to provide indirect empirical evidence in favor of the instrument's validity in table 14a, 14b, 14c, 14d. However, also in this case, the placebo tests performed do not confirm the insight provided by the Kleibergen Paap F statistics in table 13.

Table 14a. Placebo tests for the instrument used in column 1 of table 13

	(1)	(2)	(3)	(4)	(5)	(6)
	Liquidity			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance in km to Capital of State	-0.027***	-0.031***	0.028	-0.007	0.026*	0.027
	(0.009)	(0.009)	(0.026)	(0.007)	(0.014)	(0.047)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,181	1,069	112	2,888	1,069	112

Note: Average marginal effects from probit regression of liquidity(columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14b. Placebo tests for the instrument used in column 2 of table 13

	(1)	(2)	(3)	(4)	(5)	(6)
	Liquidity			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance in km to Capital of State(ln)	-0.027***	-0.027***	-0.032**	-0.007	0.026*	-0.055**
	(0.009)	(0.010)	(0.016)	(0.007)	(0.016)	(0.025)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,181	809	355	2,888	809	355

Note: Average marginal effects from probit regression of liquidity (columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14c. Placebo tests for the instrument used in column 3 of table 13

	(1)	(2)	(3)	(4)	(5)	(6)
	Liquidity			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance in km to Capital of State(ln)	-0.027***	-0.050***	-0.022**	-0.007	0.061**	0.029*
	(0.009)	(0.018)	(0.010)	(0.007)	(0.029)	(0.015)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,181	260	904	2,888	260	904

Note: Average marginal effects from probit regression of liquidity(columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14d. Placebo tests for the instrument used in column 4 of table 13

	(1)	(2)	(3)	(4)	(5)	(6)
	Liquidity			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance to the market<1 km	0.076***	0.005	0.098***	-0.086***	-0.002	-0.122***
	(0.021)	(0.030)	(0.025)	(0.019)	(0.060)	(0.031)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,181	207	974	2,888	207	974

Note: Average marginal effects from probit regression of liquidity(columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

From the tables above the following conclusion can be drawn. Considering as explanatory variable whether a household lives in a hot spot LGA is correlated to a higher use of agrochemicals and this relationship is mediated through a reduction in risk aversion (column 4, table 9) and improved knowledge (column 4, table 11). Credit constraints is an important transmission channel when considering as independent variable the position along the market chain (column 2 and 3, table 13).

M4: PCA of the three mediators

Trying to consider the three mediators together and given that the instrumental variable mediation by Dippel et al. (2020) allows for a single mediator only, I use PCA to identify the principal components from the three already mentioned mediators. Table 15 reports the results of the IV mediation analysis for the mediator created through the PCA. The instrument used is a dummy equal to one if the distance from the households to the market is less than 1 km, zero otherwise. For the total effect, living in a hot spot LGA increases the use of agrochemicals by 0.99. The direct effect is not significant, while the indirect effect is 0.6 and explains around the 60% of total effect.

Table 15. Impact of market access on agrochemical use (M=PCA)

	(1)
	Agrochemicals use
Total effect	0.991***
	(0.347)
Direct effect	0.001
	(0.045)
Indirect (or mediated effect)	0.597**
	(0.278)
Observations	1880
Treatment	Hot spots
Mediator	PCA of the previous three
Instrument	Distance HH-market<1km
Kleibergen-Paap F-statistic for excluded instruments in first stage one (T on Z)	23.631
Kleibergen-Paap F-statistic for excluded instruments in first stage two (M on Z|T)	43.323
Mediation effect as a percentage of the total effect (%)	60.24

Note: Results from the IV mediation analysis are reported. Control variables include an indicator for self-reported experience of climates or safety shocks, number of visits to the extension center, quantity of main crops sold, time to the closest main city, household size, and ha of land managed. Standard errors reported in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Placebo tests to check the validity of the instrument

As previously done, I run some placebo tests. Even though the F statistic is above the customary level of 10 (even if below 30, the threshold required by Dippel et al., 2020), the results in table 16 do not confirm the relevance and the exclusion restriction.

Table 16. Placebo tests for the instrument used in table 15

	(1)	(2)	(3)	(4)	(5)	(6)
	PCA mediators			Agrochemical use		
	Full sample	T=1	T=0	Full sample	T=1	T=0
Distance market<1 km	0.125***	0.088	0.135***	-.009	0.043	-.026
	(0.029)	(0.064)	(0.032)	(.016)	(0.042)	(0.017)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,180	207	973	3,758	486	3,272

Note: Average marginal effects from probit regression of risk aversion (columns 1-3) and agrochemicals use (columns 4-6) indices are reported, controlling for the instrument and other covariates that include the number of visits to obtain information on agricultural activities, access to credit, quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

7. Summary and Concluding Remarks

In this essay, I investigated the effect of inclusion - defined as market access - on the adoption of agricultural technologies, namely agrochemicals use. To do so, I used panel data from the Nigerian GHS survey for a period of time covering almost ten years. The theoretical framework starts from Ciarli *et al.* (2018), who proposed an analytical framework to understand how innovation and inclusion are linked in a linear fashion and dynamically. They consider how variations in structural change and inclusion at time *t* influence innovation at time *t+1* in a linear pathway. However, they also recognize that the relation between these three elements is non-linear and subject to feedback mechanisms. Despite that, they leave the investigation on the link from inclusion to innovation for future research. This essay builds on it and investigates the nexus between inclusion and innovation, focusing on market access as a proxy for inclusion and agrochemicals use as a proxy for innovation (i.e., the implementation of an improved product or process). Among the transmission channels that characterize this nexus, the main barriers to technology adoption identified in the literature are mainly of three types: credit and liquidity constraints, the discount rate of technology and its uncertainty, and limited knowledge and information about technology (De Janvry et al. 2016). Thus, the essay also focuses on the role of these three main barriers to technology adoption, including them in the analysis as potential transmission channels through which market access could affect agrochemical use. Theoretically, it is reasonable to think that market access could indeed alleviate the three issues, allowing farmers to adopt and use agrochemicals, and I will investigate this.

Market access was defined in more than a single way in the essay: firstly, as a simple dummy variable indicating whether households sell on the market or not. Secondly, it includes the position along the value chain, as farmers could sell their crops locally (i.e., in an upstream position) or to the main market or to private business (i.e., in a downstream position). Lastly, I create another dummy indicating whether a household is located in a hot spot LGA for selling crops, based on a spatial identification through the Getis and Ord statistic, a method still rarely used in economic applications. Agrochemical use is defined in the analysis as a dummy variable.

Being able to sell on the market can impact the barriers to adoption and the use of a technology. The same is true considering in which position farmers are along the value chain and whether they live in a hot spot LGA. Furthermore, it is not possible to ignore that farmers' market participation and technology adoption decisions are somehow linked and interdependent (Mekonnen, 2017). Hence, endogeneity characterizes the framework outlined. To deal with that, I performed an instrumental variable mediation analysis (and a SEM in appendix) to understand the impact of market access on technology. Considering a mediator at the time, I employed the instrumental variable mediation developed by Dippel et al. (2020). Traditional IV framework is usually used to identify unbiased impact based on observational data, but it is not enough to unpack the black box of causality and provide information on the causal impact when the treatment and the mediator jointly contribute to causing an outcome.

In this essay, I performed several regressions and specifications, but what emerge clearly is that participating in the markets improve the use of agrochemicals, confirming previous literature. More importantly, from the instrumental variable mediation analysis emerge that the main transmission channels between positioning along the market chain (upstream or downstream) and agrochemicals use seems to be the access to credit. In Nigeria only one third of rural adults are banked compared to the two third in urban areas. Thus, the country needs to expand the access points in rural areas. Some progresses were noticed in recent years, but they are still far from the targeted one. For instance, credit was offered to only the 3% (against 40% targeted). Efforts are also needed to promote the financial inclusion for marginalized groups such as women, young people and rural dwellers (Central Bank of Nigeria, 2020). On the opposite, when considering whether a household lives in a hot spot LGA, reduction in risk aversion and improvements in knowledge seem to be the main transmission channels explaining the relationship between market access and agrochemical use.

The essay presents some limitations. The main one, as discussed above, concerns the instrumental variables taken into consideration, which are not always strictly exogenous and relevant. Despite the instrumental variable mediation approach allows to overcome econometric issues as endogeneity, simultaneity and selection bias, the choice of weak instruments can harm the causal analysis presented. Thus, further studies should be devoted to the research of stronger and exogenous instrumental variables. Additionally, wave 4 presents a high percentage of attrition rate. Running the most significant regressions using only the first three waves, results remain similar. However, results presented should be interpreted with caution.

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Appendices

A.1- Essay 1: Panel regressions considering plots with crops other than oil palm

Among other crops cultivated by the households in the area, it is possible to find, among other minor crops, the ones reported in table A1. Table A2 displays the sample using and not using agricultural practices on plots with crops other than oil palm.

Table A1. Number of other crops other than oil palm cultivated on farmers' plots

	2017	**2019**	**Pooled sample**
Cassava	397(19.93)	427 (19.28)	824 (19.59)
Cocoa	227 (11.40)	277 (12.51)	504 (11.98)
Plantain	167 (8.38)	176 (7.95)	343 (8.15)
Coconut	70 (3.51)	72 (3.25)	142 (3.38)
Maize	31 (1.56)	69 (3.12)	100 (2.38)
Okra	43 (2.16)	30 (1.35)	73 (1.74)
Pepper	44 (2.21)	29 (1.31)	73 (1.74)
Tomato	40 (2.01)	31 (1.40)	71 (1.69)

Percentage share in parenthesis

Table A2. Number of households in the sample using and not using agricultural practices considered <u>on plots with crops other than oil palm.</u>

	2017		2019		Pooled sample	
	Non-user	Users	Non-user	Users	Non-user	Users
At least one of the three practices	168	555	295	499	463	1054
	(23.24)	(76.76)	(37.15)	(62.85)	(30.52)	(69.48)
Intercropping	208	515	342	452	550	967
	(28.77)	(71.23)	(43.07)	(56.93)	(36.26)	(63.74)
Irrigation	546	177	696	98	1242	275
	(75.38)	(24.62)	(87.41)	(12.59)	(81.67)	(18.33)
Agrochemicals	388	335	593	201	981	536
	(53.67)	(46.33)	(74.69)	(25.31)	(64.67)	(35.33)

Percentage shares are shown in parentheses

Table A3 shows the questions used to create the Food Insecurity Experience Scale(FIES).

Table A3. Questions used to create FIES

N.	Question
1	During the past 12 months, was there a time when you or others in your household worried about not having enough food to eat because of a lack of money or other resources?
2	During the past 12 months, was there a time when you or others in your household were unable to eat healthy and nutritious food because of a lack of money or other resources?
3	During the past 12 months, was there a time when you or others in your household ate only a few kinds of foods because of a lack of money or other resources?
4	During the past 12 months, was there a time when you or others in your household had to skip a meal because there was not enough money or other resources to get food?
5	During the past 12 months, was there a time when you or others in your household ate less than you thought you should because of a lack of money or other resources?
6	During the past 12 months, was there a time when your household ran out of food because of a lack of money or other resources?
7	During the past 12 months, was there a time when you or others in your household were hungry but did not eat because there was not enough money or other resources?
8	During the past 12 months, was there a time when you or others in your household went without eating for a whole day because of a lack of money or other resources?

Source: APRA questionnaire, based on Cafiero, Viviani and Nord, 2018

Table A4 displays the results for a different version of table 7 using the categorical variable for technology use (from zero to 3) and dropping some control variables: No. of household members, No. of plots with oil palm, age and education of household head.

Table A4. Regression results for the combined use of technologies on oil palm plots on WDDS

	WDDS					
	POLS	POLS	POLS	POLS	FE	FE-time dummy
Use of agricultural practices (categorical)	0.251***	0.250***	0.294***	0.275***	0.143	0.0987
	(0.0758)	(0.0759)	(0.0870)	(0.0849)	(0.169)	(0.162)
Female empowerment		-0.0345	0.0663	0.521	0.347	0.138
		(0.0885)	(0.132)	(0.343)	(0.971)	(0.933)
1 use of practices#1.fememp			-0.182	-0.210	0.0538	0.161
			(0.178)	(0.174)	(0.368)	(0.353)
Land cultivated(ha)				-0.00281	-0.0294*	-0.0301*
				(0.00447)	(0.0167)	(0.0161)
Asset score				0.870***	0.581	1.149
				(0.258)	(0.785)	(0.762)
No. of female members				-0.0303	0.100	-0.0190
				(0.0289)	(0.127)	(0.124)
Female headed household				-0.315	-0.308	0.171
				(0.325)	(1.072)	(1.034)
Time spent on care work				0.0519***	0.0517***	0.0298**
				(0.00776)	(0.0141)	(0.0142)
Time dummy						0.507***
						(0.101)
Const	3.041***	3.049***	3.024***	2.415***	2.523***	2.477***
	(0.0576)	(0.0618)	(0.0666)	(0.147)	(0.468)	(0.449)
N	933	933	933	932	932	932
R-squared	0.012	0.012	0.013	0.070	0.064	0.140

st.errors in parenthesis, * p<0.1; ** p<0.05; *** p<0.01

Table A5 shows the results for the use of the three practices considered on plots with crops other than oil palm for the Women Dietary Diversity Score. The use of one practice seems to reduce the women dietary diversity score significantly. However, using two practices seems to increase the WDDS (except in the last specification) by around 0.58(column V). Female empowerment and the interaction terms are not significant.

Table A5. Regression results for the use of three practices on plots with other crops on WDDS

	WDDS					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of one practice	-0.218***	-0.222***	-0.211**	-0.155	-0.394**	-0.408**
	(0.083)	(0.083)	(0.096)	(0.100)	(0.198)	(0.190)
Use of two practices	0.422***	0.421***	0.443***	0.507***	0.582**	0.404
	(0.114)	(0.114)	(0.133)	(0.144)	(0.281)	(0.273)
Use of three practices	-0.224**	-0.223**	-0.212*	-0.130	-0.425	-0.371
	(0.103)	(0.103)	(0.122)	(0.163)	(0.306)	(0.295)
Female empowerment		-0.098	-0.064	0.553	-0.350	-0.316
		(0.078)	(0.144)	(0.354)	(0.983)	(0.945)
1 practice#1.fememp			-0.042	-0.132	0.329	0.265
			(0.191)	(0.201)	(0.410)	(0.395)
2.practices#1.fememp			-0.084	-0.005	0.409	0.324
			(0.259)	(0.280)	(0.503)	(0.484)
3.practices#1.fememp			-0.038	0.019	0.684	0.450
			(0.231)	(0.327)	(0.619)	(0.597)
No. of household members				0.029	0.006	0.122
				(0.026)	(0.103)	(0.102)
Land cultivated(ha)				-0.004	-0.025	-0.026
				(0.005)	(0.017)	(0.016)
No. of plots with oil palm				0.095	-0.252	-0.169
				(0.067)	(0.194)	(0.187)
Asset score				0.742***	1.234	1.529**
				(0.273)	(0.776)	(0.748)
No. of female members				-0.039	0.052	-0.126
				(0.041)	(0.158)	(0.156)
Age of the head				-0.002	-0.032	0.006
				(0.003)	(0.023)	(0.023)
Education head				-0.007	-0.011	0.003
				(0.009)	(0.026)	(0.025)
Female headed household				-0.478	-0.430	0.343
				(0.333)	(1.106)	(1.074)
Time dummy						0.527***
						(0.108)
Constant	3.188***	3.215***	3.205***	2.969***	5.145***	2.309
	(0.064)	(0.067)	(0.075)	(0.260)	(1.504)	(1.557)
F statistic	13.4	10.4	6.0	3.5	2.3	3.8
R-squared	0.03	0.04	0.04	0.05	0.11	0.18
N	1128	1128	1128	933	933	933

St.errors in parenthesis, * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table A6 shows the results for the combined use of the practices considered on plots with crops other than oil palm for the outcome Food Insecurity Experience Scale. In the fixed effect models the use of two practices has a positive and significant (at 5% level in column V and 10% in column VI) effect on food insecurity, reducing the food insecurity experience scale. Female empowerment has the same and even more significant effect in all the specifications. The interaction terms are positive and significant for all three practices in the fixed effect models. For instance, using one practice seems to decrease the FIES for the group of women who score lower in terms of empowerment by 0.956, while for the other group, it seems there is an increase in the Food Insecurity Experience Scale by 0.54(-0.956+1.496=0.54).

Also here, an increase in the asset score and the head's education seem to reduce food insecurity in a significant way.

Table A6. Regression results for the use of technologies on plots with other crops on FIES

	FIES					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of one practice	0.505***	0.499***	0.267	0.098	-0.956	-0.986
	(0.156)	(0.156)	(0.377)	(0.345)	(0.613)	(0.616)
Use of two practices	0.003	0.003	-0.827	-0.574	-1.644*	-1.671**
	(0.215)	(0.215)	(0.529)	(0.486)	(0.836)	(0.838)
Use of three practices	0.496**	0.507***	-0.160	-0.230	-0.982	-0.984
	(0.195)	(0.195)	(0.508)	(0.537)	(0.949)	(0.950)
Use of one practice	0.505***	0.499***	0.267	0.098	-0.956	-0.986
	(0.156)	(0.156)	(0.377)	(0.345)	(0.613)	(0.616)
Female empowerment		-0.380**	-0.747**	-0.998***	-1.810***	-1.801***
		(0.171)	(0.325)	(0.300)	(0.591)	(0.592)
1 practice#1.fememp			0.276	0.407	1.496**	1.528**
			(0.414)	(0.379)	(0.660)	(0.663)
2.practices#1.fememp			0.993*	0.916*	1.998**	1.985**
			(0.579)	(0.531)	(0.917)	(0.918)
3.practices#1.fememp			0.785	0.594	1.697*	1.701*
			(0.551)	(0.597)	(1.002)	(1.003)
No. of household members				0.092**	0.224	0.246
				(0.044)	(0.150)	(0.154)
Land cultivated(ha)				0.002	0.029	0.029
				(0.008)	(0.024)	(0.024)
No. of plots with oil palm				-0.070	0.334	0.348
				(0.114)	(0.283)	(0.284)
Asset score				-3.349***	-3.597***	-3.549***
				(0.463)	(1.140)	(1.144)
No. of female members				-0.142**	-0.102	-0.138
				(0.068)	(0.229)	(0.236)
Age of the head				-0.000	0.011	0.018
				(0.005)	(0.033)	(0.035)
Education head				-0.036**	-0.075*	-0.073*
				(0.015)	(0.039)	(0.039)
Female headed household				0.451**	-0.700	-0.574
				(0.179)	(0.826)	(0.851)
Time dummy						0.104
						(0.165)
Constant	1.203***	1.520***	1.827***	3.352***	2.681	2.173
	(0.121)	(0.187)	(0.297)	(0.499)	(2.230)	(2.374)
F statistic	5.0	5.0	3.4	9.8	2.3	2.2
R-squared	0.01	0.02	0.02	0.14	0.11	0.11
N	1130	1130	1130	935	935	935

St.errors in parenthesis, * p<0.1; ** p<0.05; *** p<0.01

Overall, it is possible to notice a significant reduction in food insecurity (but mixed results for women's dietary diversity) considering the use of the technologies under analysis on plots cultivated with other crops. This could be explained by the fact that farmers - investing in agricultural practices for oil palm - can also use the same practices on these other crops, increasing the yields of food crops. However, they could not have enough money available (before harvesting oil palm) to buy different food on the market such as meat, milk and so on, which could explain the mixed results for women's dietary diversity.

Considering female farmers' empowerment, what can be noticed in all cases is that empowering women significantly reduces household food insecurity, but it does not significantly impact women's dietary diversity.

<u>Heckman model with three practices: first stages</u>

Outcome: Women Dietary Diversity

Table A7 shows the relationship between the abovementioned instruments and female empowerment (column 1) and between the instruments and the dependent variable WDDS (column 2). The variables considered significantly predict female empowerment with a joint F-statistic equal to 76.4. At the same time, they do not significantly predict the outcome; thus, they can be used as the Z vector in the probit equation in the first stage.

Table A7. Test of the instruments

	Female empowerment	WDDS
At least one plot used by the household came from the woman's clan or inheritance from the woman's family	0.074 ***	0.029
	(0.028)	(0.078)
Female-headed household	0.427***	-0.116
	(0.030)	(0.081)
Constant	0.521***	3.134***
	(0.014)	(0.044)
F statistic	126.4	1.0
R-squared	0.14	0.00
N	1,514	1,128

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Table A8 displays the results of the first stage, showing that female empowerment is significantly affected by being in a female-headed household. Other variables that affect empowerment, even if with a coefficient that is almost zero and significant only at 10%, are the time women spend on all care work, the education of the household head, and the average education level of female members in the household.

Table A8. First stage Heckman model

	Female empowerment
At least one plot used by the household came from the woman's clan or inheritance from the woman's family	-0.029
	(0.024)
Female-headed household	0.340***
	(0.067)
Time spent by women on all care work	0.004*
	(0.002)
No. household members	0.005
	(0.007)
Land cultivated(ha)	0.002
	(0.001)
Asset Score	0.054
	(0.077)
No. female members	-0.014
	(0.011)
Age of household head	-0.000
	(0.002)
Education of hh head	0.005*
	(0.003)
Mean age of female hh members	0.002
	(0.002)
Mean education of female hh members	0.006**
	(0.003)
N	1084

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Outcome: Food Insecurity Experience Scale

Concerning food insecurity, I used a slightly different Z vector. Table A9 shows a test of the two instruments. They significantly predict female empowerment but not the Food Insecurity Experience Scale.

Table A9. Test for instrument

	Female empowerment	FIES
At least one plot used by the household came from the woman's clan or inheritance from woman's family	0.261***	0.205
	(0.027)	(0.140)
Death of a child in the household in the past ten years	0.076***	-0.197
	(0.029)	(0.151)
_cons	0.156***	1.485***
	(0.016)	(0.084)
F statistic	51.5	1.8
R-squared	0.08	0.00
N	1130	1130

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

The first stage of the Heckman model (table A10) shows that the level of female empowerment seems to be significantly increased by whether the woman's clan allocated at least one of the plots used by the household, the number of female members, the average age of female members in the household and their average level of education. On the opposite, it seems to be significantly reduced by the time spent by the household on all care work, the number of total household members, land cultivated, assets owned, the age and education of the household head.

Table A10. First stage Heckman

	Female empowerment
At least one plot used by the household came from the woman's clan or inheritance from woman's family	0.099***
	(0.017)
Death of a child in the household in the past ten years	0.018
	(0.020)
Time spent by women on all care work	-0.004**
	(0.002)
No. household members	-0.037***
	(0.006)
Land cultivated(ha)	-0.004***
	(0.001)
Asset Score	-0.279***
	(0.066)
No. female members	0.042***
	(0.009)
Age of household head	-0.016***
	(0.001)
Education of hh head	-0.026***
	(0.002)
Mean age of female hh members	0.021***
	(0.001)
Mean edu of female hh members	0.020***
	(0.003)
N	1084

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

<u>Single practice: Agrochemicals only</u>

Panel regressions considering plots with oil palm

<u>Women Dietary Diversity</u>

Since women could cover specific tasks in the oil palm sector, I also analyzed some of the practices by themselves. Here below, I report the results for the use of agrochemicals only. Table A11 shows the results of the POLS, fixed effect model and fixed effect model with time dummies. The use of agrochemicals seems to significantly increase the dietary diversity for women in all the specifications. However, female empowerment and the interaction term do not seem to have any significant effect.

Table A11. Regression results for agrochemicals use on oil palm plots (WDDS)

	WDDS					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of agrochemicals	0.531***	0.527***	0.545***	0.461***	0.518***	0.540***
	(0.083)	(0.083)	(0.094)	(0.099)	(0.182)	(0.173)
Female empowerment		-0.063	-0.048	0.523	-0.032	-0.076
		(0.078)	(0.086)	(0.341)	(0.965)	(0.916)
Interaction term			-0.082	-0.112	0.273	0.175
			(0.201)	(0.208)	(0.372)	(0.353)
No. household members				0.026	-0.016	0.129
				(0.026)	(0.102)	(0.100)
Land cultivated(ha)				-0.004	-0.028*	-0.031*
				(0.005)	(0.017)	(0.016)
No. Plots with oil palm				0.081	-0.219	-0.137
				(0.067)	(0.186)	(0.177)
Asset Score				0.643**	1.196	1.564**
				(0.275)	(0.783)	(0.746)
No. female members				-0.032	0.055	-0.164
				(0.041)	(0.159)	(0.156)
Age of household head				-0.002	-0.037	0.009
				(0.003)	(0.022)	(0.023)
Education of hh head				-0.007	-0.020	-0.004
				(0.009)	(0.026)	(0.025)
Female-headed household				-0.458	-0.435	0.485
				(0.333)	(1.109)	(1.065)
Time dummy						0.596***
						(0.105)
Constant	3.001***	3.018***	3.014***	2.844***	5.230***	1.860
	(0.038)	(0.043)	(0.044)	(0.247)	(1.470)	(1.517)
F statistic	40.9	20.8	13.9	3.7	2.2	4.9
R-squared	0.04	0.04	0.04	0.04	0.08	0.17
N	1128	1128	1128	933	933	933

St. errors in parenthesis; * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Food insecurity

Table A12 shows that the Food Insecurity Experience Scale decreases significantly in the first three specifications, but seems to increase when considering the fixed-effect models (even if, in this case, coefficients are not significant). Female empowerment significantly decreases food insecurity but only in the POLS specifications.

Table A12. Regression results for agrochemicals use on oil palm plots (FIES)

	FIES					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of agrochemicals	-0.723***	-0.738***	-0.682*	-0.435	0.510	0.542
	(0.156)	(0.156)	(0.362)	(0.331)	(0.572)	(0.575)
Female empowerment		-0.414**	-0.397**	-0.683***	-0.428	-0.396
		(0.171)	(0.196)	(0.195)	(0.362)	(0.367)

Interaction term			-0.069	0.152	-0.628	-0.667
			(0.402)	(0.367)	(0.629)	(0.634)
No. household members				0.089**	0.215	0.235
				(0.044)	(0.149)	(0.154)
Land cultivated(ha)				0.006	0.033	0.032
				(0.008)	(0.024)	(0.024)
No. plots with oil palm				-0.059	0.275	0.287
				(0.114)	(0.271)	(0.272)
Asset Score				-3.304***	-3.478***	-3.435***
				(0.465)	(1.148)	(1.152)
No. female members				-0.128*	-0.095	-0.128
				(0.068)	(0.230)	(0.239)
Age of household head				-0.002	0.017	0.024
				(0.005)	(0.033)	(0.035)
Education of hh head				-0.036**	-0.073*	-0.072*
				(0.015)	(0.039)	(0.039)
Female headed household				0.440**	-0.771	-0.659
				(0.178)	(0.823)	(0.849)
Time dummy						0.088
						(0.164)
Constant	1.652***	2.000***	1.986***	3.392***	1.392	0.898
	(0.072)	(0.160)	(0.179)	(0.435)	(2.148)	(2.338)
F statistic	21.4	13.7	9.1	12.5	2.4	2.2
R-squared	0.02	0.02	0.02	0.13	0.08	0.09
N	1130	1130	1130	935	935	935

St.errors in parenthesis; * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Heckman's Model for agrochemicals use

Table A13 shows the coefficient related to the variable included in the Z vector of the Heckman's first stage equation, a vector of variable(s) influencing female empowerment but not the outcome of the main model. As can be noticed below, having received at least one plot from the woman's clan or inherited it from the woman's family significantly predict female empowerment but not the food insecurity experience scale.

Table A13. Test of the instrument

	Female empowerment	FIES
At least one plot used by the household came from the woman's clan or inheritance from woman's family	0.195***	0.195
	(0.028)	(0.140)
Constant	0.576***	1.441***
	(0.014)	(0.077)
F statistic	47.6	1.9
R-squared	0.03	0.00
N	1,514	1,130

St. errors in parenthesis; * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A14 shows the results of the selection equation of the Heckman model.

Table A14- First stage results

	Female empowerment
At least one plot used by the household came from the woman's clan or inheritance from woman's family	0.007
	(0.024)
Time spent by women on all care work	0.003
	(0.002)
No. household members	-0.007
	(0.007)
Land cultivated(ha)	0.001
	(0.001)
Asset Score	-0.006
	(0.080)
No. female members	-0.004
	(0.011)
Age of household head	-0.004***
	(0.002)
Education of hh head	-0.003
	(0.003)
Mean age of female hh members	0.008***
	(0.002)
Mean edu of female hh members	0.008***
	(0.003)
N	1,084

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Table A15 shows the results of the second stage of the Heckman model for the outcome Women Dietary Diversity Score. The Z vector is the same as the one used in the previous case. The use of agrochemicals seems to significantly increase the diversity of women's diets for the group of women who score better in terms of empowerment but not for the other one.

Table A15. Second-stage regression results for agrochemicals use only (WDDS)

	WDDS					
	Higher empowerment score			Lower empowerment score		
	POLS	FE	FE+T	POLS	FE	FE+T
Use of agrochemicals on oil palm plots	0.451***	0.492**	0.492***	0.046	-0.122	-0.122
	(0.097)	(0.195)	(0.189)	(0.175)	(0.479)	(0.479)
Time spent by women on all care work	0.050***	0.069***	0.042*	0.040**	-0.300***	-0.300***
	(0.010)	(0.020)	(0.022)	(0.017)	(0.076)	(0.076)
No. household members	0.028	0.039	0.110	-0.052	1.243***	1.243***
	(0.028)	(0.111)	(0.118)	(0.061)	(0.318)	(0.318)
Land cultivated(ha)	-0.003	-0.014	-0.022	0.000	0.197**	0.197**
	(0.005)	(0.013)	(0.014)	(0.011)	(0.085)	(0.085)
No. plots with oil palm	-0.011	-0.431**	-0.301	0.157	-1.036***	-1.036***
	(0.090)	(0.180)	(0.184)	(0.099)	(0.207)	(0.207)
Asset Score	0.579*	1.319	1.398	1.157*	2.173*	2.173*
	(0.305)	(0.926)	(0.888)	(0.624)	(1.218)	(1.218)
No. female members	-0.080*	-0.127	-0.263	0.104	-0.583	-0.583
	(0.047)	(0.189)	(0.180)	(0.086)	(1.517)	(1.517)
Age of household head	-0.000	-0.097*	-0.014	0.001	-0.139	

	(0.007)	(0.053)	(0.034)	(0.010)	(0.109)	
Education of hh head	-0.009	0.064*	0.040	0.016	-0.331***	-0.331***
	(0.010)	(0.035)	(0.036)	(0.020)	(0.073)	(0.073)
Mean age of female hh members	-0.003	-0.028	-0.011	0.008		
	(0.007)	(0.023)	(0.021)	(0.011)		
Mean edu of female hh members	-0.000	-0.012	-0.026	-0.026	-0.217*	-0.217*
	(0.012)	(0.040)	(0.040)	(0.021)	(0.115)	(0.115)
Residuals	-0.180	4.549**	2.729	0.042	-4.038	-4.038
	(0.348)	(1.841)	(1.847)	(0.292)	(2.589)	(2.589)
Time dummy			0.506***			0.277
			(0.135)			(0.218)
Constant	2.865***	7.746**	3.154**	1.850***	3.851	-3.302
	(0.303)	(2.997)	(1.449)	(0.498)	(4.597)	(5.228)
F statistic	5.6	5.2	5.9	2.4	.	.
R-squared	0.08	0.19	0.23	0.15	0.88	0.88
N	745	745	745	150	150	150

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Food insecurity

Table A16 displays the results of the Heckman model's main equation for only agrochemicals use, and considers FIES as dependent variable. For women scoring better in terms of empowerment, it seems that the use of agrochemicals on oil palm plots reduces food insecurity significantly at 10% (POLS specification only), while no significant impact seems to occur to the group of disempowered women.

Table A16. Second stage results of the Heckman model (agrochemicals use only)

	FIES					
	Higher empowerment score			Lower empowerment score		
	POLS	FE	FE+T	POLS	FE	FE+T
Use of agrochemicals on oil palm plots	-0.273*	-0.133	-0.134	0.057	1.930	1.930
	(0.144)	(0.265)	(0.266)	(0.379)	(3.522)	(3.522)
Time spent by women on all care work	-0.048*	-0.007	-0.010	0.014	-0.396	-0.396
	(0.025)	(0.067)	(0.069)	(0.118)	(2.425)	(2.425)
No. household members	0.058	0.148	0.160	-0.106	1.458	1.458
	(0.061)	(0.178)	(0.188)	(0.276)	(7.261)	(7.261)
Land cultivated(ha)	0.009	0.045*	0.044*	0.004	0.545	0.545
	(0.010)	(0.023)	(0.024)	(0.050)	(1.487)	(1.487)
No. plots with oil palm	-0.024	0.113	0.130	0.074	0.354	0.354
	(0.127)	(0.293)	(0.311)	(0.181)	(1.861)	(1.861)
Asset Score	-3.440***	-3.295***	-3.273**	-5.563***	-3.359	-3.359
	(0.475)	(1.265)	(1.280)	(1.035)	(14.655)	(14.655)
No. female members	-0.040	-0.009	-0.029	-0.242	-14.100	-14.100
	(0.085)	(0.290)	(0.302)	(0.219)	(14.740)	(14.740)
Age of household head	-0.005	-0.017	-0.008	-0.048	0.274	
	(0.025)	(0.077)	(0.080)	(0.161)	(1.570)	
Education of hh head	-0.050**	-0.065	-0.066	-0.046	-0.117	-0.117
	(0.023)	(0.077)	(0.077)	(0.100)	(0.954)	(0.954)
Mean age of female hh members	0.005	0.034	0.036	0.062		
	(0.042)	(0.118)	(0.119)	(0.282)		
Mean edu of female hh members	0.018	0.082	0.079	0.066	-0.918	-0.918
	(0.051)	(0.164)	(0.164)	(0.305)	(6.068)	(6.068)
Residuals	0.068	4.650	4.431	3.874	-40.814	-40.814
	(3.806)	(11.136)	(11.246)	(10.448)	(191.029)	(191.029)
Time dummy			0.060			-0.548
			(0.217)			(3.141)

Constant	3.019	-0.585	-1.075	10.325	-38.924	-24.780
	(1.857)	(6.045)	(5.882)	(11.572)	(246.443)	(315.180)
F statistic	8.9	1.8	1.7	5.0	.	.
R-squared	0.12	0.06	0.06	0.22	0.41	0.41
N	746	746	746	151	151	151

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Plots with crops other than oil palm

Table A17 shows the results of the regressions considering the use of agrochemicals on plots with all the other crops except oil palm. It can be noticed that the use of agrochemicals seems to significantly improve the dietary diversity for women in all the specifications. Results for female empowerment and the interaction term are instead not significant.

Table A17. Regression results for agrochemicals use only and WDDS for plots with crops other than oil palm

	WDDS					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of agrochemicals	0.207***	0.205***	0.195**	0.267***	0.412*	0.358*
	(0.071)	(0.071)	(0.081)	(0.097)	(0.210)	(0.201)
Female empowerment		-0.084	-0.098	0.471	0.061	0.062
		(0.079)	(0.099)	(0.344)	(0.974)	(0.933)
Interaction term			0.039	0.122	0.448	0.227
			(0.164)	(0.202)	(0.389)	(0.375)
No. household members				0.031	-0.014	0.115
				(0.026)	(0.103)	(0.102)
Land cultivated(ha)				-0.005	-0.024	-0.026
				(0.005)	(0.017)	(0.016)
No. plots with oil palm				0.101	-0.147	-0.088
				(0.068)	(0.191)	(0.184)
Asset Score				0.764***	1.291	1.577**
				(0.275)	(0.789)	(0.757)
No. female members				-0.036	0.077	-0.116
				(0.041)	(0.160)	(0.157)
Age of household head				-0.002	-0.038*	0.004
				(0.003)	(0.023)	(0.023)
Education of hh head				-0.007	-0.019	-0.002
				(0.009)	(0.027)	(0.026)
Female headed household				-0.442	-0.570	0.271
				(0.335)	(1.117)	(1.082)
Time dummy						0.558***
						(0.108)
Constant	3.034***	3.056***	3.060***	2.809***	5.077***	1.994
	(0.043)	(0.048)	(0.051)	(0.251)	(1.488)	(1.545)
F statistic	8.6	4.9	3.3	2.5	1.8	4.0
R-squared	0.01	0.01	0.01	0.03	0.07	0.15
N	1128	1128	1128	933	933	933

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Table A18 shows the results for food insecurity. The use of agrochemicals does not seem to significantly impact food insecurity in all the specifications. Female empowerment seems to have a significant and negative impact on food insecurity, increasing it but only in the second and third specifications. However, adding control variables in the fourth, fifth and sixth specifications, coefficients become insignificant.

Table A18. Regression results for agrochemicals use only (FIES)

	FIES					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of agrochemicals	-0.137	-0.121	-0.120	-0.057	0.083	0.073
	(0.132)	(0.131)	(0.151)	(0.164)	(0.306)	(0.307)
Female empowerment		0.732***	0.732***	-0.119	0.775	0.775
		(0.146)	(0.183)	(0.581)	(1.420)	(1.421)
Interaction term			-0.001	0.194	-0.067	-0.108
			(0.304)	(0.342)	(0.567)	(0.571)
No. household members				0.085*	0.209	0.232
				(0.044)	(0.150)	(0.155)
Land cultivated(ha)				0.003	0.031	0.031
				(0.008)	(0.024)	(0.024)
No. plots with oil palm				-0.023	0.312	0.323
				(0.116)	(0.279)	(0.280)
Asset Score				-3.536***	-3.433***	-3.379***
				(0.466)	(1.149)	(1.154)
No. female members				-0.123*	-0.114	-0.150
				(0.069)	(0.233)	(0.240)
Age of household head				-0.001	0.008	0.016
				(0.005)	(0.033)	(0.035)
Education of hh head				-0.044***	-0.089**	-0.086**
				(0.015)	(0.039)	(0.039)
Female headed household				0.296	-1.906	-1.750
				(0.567)	(1.628)	(1.649)
Time dummy						0.104
						(0.165)
_cons	1.552***	1.360***	1.360***	2.947***	1.734	1.163
	(0.081)	(0.089)	(0.094)	(0.425)	(2.168)	(2.353)
F statistic	1.1	13.1	8.7	10.7	2.0	1.8
R-squared	0.00	0.02	0.02	0.11	0.07	0.07
N	1130	1130	1130	935	935	935

St.errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Single practice: Intercropping

Panel regressions considering plots with oil palm

Women Dietary Diversity

Table A19 displays the results of the panel regressions considering intercropping only. The use of intercropping on oil palm plots seems to significantly increases the Women Dietary Diversity Score in the POLS specifications but not in the fixed effects models. The fact that the latter models do not provide significant results could be due to the short period of time between the two waves considered, while variations in the dietary diversity could take more time. Results for female empowerment and the interaction term are not significant.

Table A19. Regression results for intercropping use only (WDDS)

	WDDS					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of intercropping	0.277***	0.275***	0.289***	0.237***	0.170	0.093
	(0.071)	(0.071)	(0.082)	(0.088)	(0.194)	(0.185)
Female empowerment		-0.082	-0.061	0.540	0.237	0.111
		(0.079)	(0.097)	(0.349)	(0.996)	(0.948)
Interaction term			-0.060	-0.138	-0.010	0.074
			(0.166)	(0.178)	(0.370)	(0.353)
No. household members				0.027	-0.048	0.093
				(0.026)	(0.105)	(0.104)
Land cultivated(ha)				-0.002	-0.022	-0.024
				(0.005)	(0.017)	(0.016)
No. plots with oil palm				0.044	-0.280	-0.189
				(0.069)	(0.193)	(0.184)
Asset Score				0.921***	1.082	1.456*
				(0.277)	(0.797)	(0.761)
No. female members				-0.034	0.122	-0.094
				(0.041)	(0.162)	(0.159)
Age of household head				-0.003	-0.039*	0.006
				(0.003)	(0.023)	(0.023)
Education of hh head				-0.005	-0.010	0.007
				(0.009)	(0.027)	(0.026)
Female-headed household				-0.415	-0.601	0.327
				(0.336)	(1.134)	(1.092)
Time dummy						0.596***
						(0.108)
_cons	3.014***	3.035***	3.030***	2.796***	5.400***	2.092
	(0.043)	(0.047)	(0.050)	(0.252)	(1.511)	(1.558)
F statistic	15.0	8.1	5.4	2.1	1.0	3.5
R-squared	0.01	0.01	0.01	0.02	0.04	0.13
N	1128	1128	1128	933	933	933

St.errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Table A20 shows the results of the same regressions used so far, considering the impact of intercropping on household food insecurity. Intercropping on oil palm plots does not seem to affect food insecurity significantly. However, the coefficients for female empowerment show a positive and significant effect providing evidence of a reduction in the household food insecurity experience scale (from 0.92 in the POLS specification to 1.28 in the fixed effect model). This confirms the results from previous studies that highlighted female empowerment's role in reducing household food insecurity. The interaction term is positive and significant in the last three columns, meaning that the relationship between the use of intercropping and FIES also depends on the empowerment status.

Table A20. Regression results for intercropping use only (FIES)

	FIES					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of intercropping	-0.048	-0.088	-0.280	-0.432	-0.778	-0.798
	(0.134)	(0.135)	(0.315)	(0.293)	(0.513)	(0.515)

Female empowerment		-0.397**	-0.507**	-0.924***	-1.293***	-1.283***
		(0.174)	(0.237)	(0.237)	(0.454)	(0.455)
Interaction term			0.236	0.591*	1.283**	1.300**
			(0.348)	(0.325)	(0.543)	(0.545)
No. household members				0.085*	0.227	0.247
				(0.044)	(0.147)	(0.151)
Land cultivated(ha)				0.003	0.033	0.032
				(0.008)	(0.024)	(0.024)
No. plots with oil palm				-0.066	0.224	0.237
				(0.115)	(0.272)	(0.273)
Asset Score				-3.436***	-3.534***	-3.488***
				(0.463)	(1.131)	(1.136)
No. female members				-0.125*	-0.106	-0.137
				(0.068)	(0.226)	(0.234)
Age of household head				-0.001	0.012	0.018
				(0.005)	(0.033)	(0.035)
Education of hh head				-0.037**	-0.079**	-0.077**
				(0.015)	(0.039)	(0.039)
Female-headed household				0.404**	-0.603	-0.497
				(0.178)	(0.817)	(0.844)
Time dummy						0.084
						(0.161)
Cons	1.517***	1.863***	1.958***	3.565v	2.320	1.873
	(0.080)	(0.171)	(0.221)	(0.460)	(2.165)	(2.332)
F statistic	0.1	2.7	1.9	12.4	3.0	2.7
R-squared	0.00	0.00	0.01	0.13	0.10	0.10
N	1130	1,130	1130	935	935	935

St.errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

<u>Heckman model</u>

The Z vectors used in this case (for both outcomes) are the same as the ones used before. Table A21 shows the results of the main equation of the Heckman model, where it can be noticed a positive and significant effect of the use of intercropping on dietary diversity for the group of women who score better in terms of empowerment (only in the POLS specification, where intercropping increases the Women Dietary Diversity Score by 0.228).

Table A21. Heckman's second stage results (WDDS)

	WDDS					
	Higher empowered score			Lower empowered score		
	POLS	FE	FE+T	POLS	FE	FE+T
Use of intercropping on oil palm plots	0.228***	0.267	0.186	0.132	0.025	0.025
	(0.087)	(0.195)	(0.197)	(0.137)	(0.405)	(0.405)
Time spent by women on all care work	0.054***	0.052**	0.030	0.055***	-0.197***	-0.197***
	(0.011)	(0.021)	(0.021)	(0.016)	(0.063)	(0.063)
No. household members	0.022	-0.031	0.065	-0.067	1.227***	1.227***
	(0.028)	(0.104)	(0.115)	(0.060)	(0.344)	(0.344)
Land cultivated(ha)	0.000	-0.019	-0.024*	0.005	0.180	0.180
	(0.005)	(0.013)	(0.014)	(0.010)	(0.112)	(0.112)
No. plots with oil palm	-0.066	-0.585***	-0.416**	0.146	-1.020***	-1.020***

	(0.090)	(0.201)	(0.211)	(0.093)	(0.206)	(0.206)
Asset Score	0.807**	0.579	0.812	1.232**	3.616**	3.616**
	(0.316)	(0.925)	(0.885)	(0.616)	(1.386)	(1.386)
No. female members	-0.083*	0.029	-0.157	0.069	-0.533	-0.533
	(0.047)	(0.183)	(0.186)	(0.083)	(2.326)	(2.326)
Age of household head	-0.005	-0.058	0.020	-0.016	-0.103	
	(0.008)	(0.050)	(0.029)	(0.012)	(0.103)	
Education of hh head	-0.010	0.058	0.042	0.012	-0.299***	-0.299***
	(0.011)	(0.040)	(0.040)	(0.020)	(0.087)	(0.087)
Mean age of female hh members	0.004	-0.061**	-0.034	0.037**		
	(0.010)	(0.031)	(0.024)	(0.016)		
Mean edu of female hh members	0.008	-0.031	-0.038	0.008	-0.110	-0.110
	(0.015)	(0.046)	(0.045)	(0.024)	(0.115)	(0.115)
Residuals	0.212	0.667	-0.036	1.234***	0.579	0.579
	(0.748)	(1.847)	(1.733)	(0.406)	(4.073)	(4.073)
Time dummy			0.557***			0.205
			(0.133)			(0.206)
Cons	2.684***	8.978***	3.615**	3.038***	6.505	1.206
	(0.456)	(2.942)	(1.459)	(0.636)	(6.464)	(8.245)
F statistic	4.5	3.2	5.3	3.6	.	.
R-squared	0.07	0.15	0.20	0.17	0.85	0.85
N	745	745	745	150	150	150

St. errors in parenthesis; * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table A22 displays the results for the second stage equation considering household food insecurity as outcome. The use of intercropping seems to increase food insecurity significantly in the fixed effect models for women scoring better in terms of empowerment, while I do not obtain any significant results for the other group.

Table A22. Heckman's second stage results (FIES)

	FIES					
	Higher empowerment score			Lower empowerment score		
	POLS	FE	FE+T	POLS	FE	FE+T
Use of intercropping on oil palm plots	0.186	0.541**	0.540**	-0.453	-1.842	-1.842
	(0.148)	(0.259)	(0.262)	(0.319)	(1.465)	(1.465)
Time spent by women on all care work	-0.051**	-0.006	-0.006	0.018	-0.129	-0.129
	(0.025)	(0.068)	(0.070)	(0.122)	(2.094)	(2.094)
No. household members	0.064	0.161	0.162	-0.131	1.791	1.791
	(0.061)	(0.176)	(0.187)	(0.281)	(6.629)	(6.629)
Land cultivated(ha)	0.005	0.041*	0.041*	0.004	1.010	1.010
	(0.010)	(0.023)	(0.023)	(0.052)	(1.001)	(1.001)
No. plots with oil palm	-0.050	0.013	0.014	0.100	-0.584	-0.584
	(0.130)	(0.291)	(0.314)	(0.178)	(1.518)	(1.518)
Asset Score	-3.460***	-3.290***	-3.289***	-5.664***	-9.640	-9.640
	(0.477)	(1.236)	(1.255)	(0.976)	(7.370)	(7.370)
No. female members	-0.041	-0.066	-0.067	-0.199	-23.472***	-23.472***
	(0.086)	(0.281)	(0.292)	(0.221)	(6.410)	(6.410)
Age of household head	-0.001	-0.023	-0.023	-0.047	0.426	
	(0.025)	(0.074)	(0.076)	(0.164)	(0.937)	

Education of hh head	-0.048**	-0.068	-0.068	-0.044	-0.284	-0.284
	(0.023)	(0.076)	(0.076)	(0.102)	(0.787)	(0.787)
Mean age of female hh members	0.001	0.035	0.035	0.061		
	(0.042)	(0.116)	(0.116)	(0.288)		
Mean edu of female hh members	0.011	0.088	0.088	0.065	-0.613	-0.613
	(0.052)	(0.164)	(0.166)	(0.311)	(5.637)	(5.637)
Residuals	-0.316	4.616	4.606	3.864	-39.470	-39.470
	(3.845)	(11.220)	(11.333)	(10.647)	(187.739)	(187.739)
Time dummy			0.003			-0.852
			(0.215)			(1.875)
_cons	3.080	-0.287	-0.311	10.586	-21.599	0.409
	(1.873)	(6.114)	(5.938)	(11.762)	(241.820)	(282.493)
F statistic	8.7	2.2	2.0	5.8	.	.
R-squared	0.12	0.07	0.07	0.23	0.45	0.45
N	746	746	746	151	151	151

St. errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Use of intercropping on plots with crops different than oil palm

Table A23 shows the panel regression results considering intercropping on plots cultivated with crops different than oil palm. The use of intercropping seems to reduce the Women Dietary Diversity Score in all the specifications. Female empowerment does not seem to affect the outcome significantly, but the interaction term is positive and significant at 5% in the fixed effect model (column V). The WDDS is expected to decrease by 0.305 for the group of women who score lower in terms of empowerment, whereas it seems to increase by 0.371 (-0.305+0.676=0.371) for the other group.

Table A23. Regression results for intercropping use only (WDDS)

	WDDS					
	POLS	POLS	POLS	POLS	FE	FE+time dummy
Use of intercropping	-0.162**	-0.161**	-0.141*	-0.062	-0.305*	-0.341**
	(0.073)	(0.073)	(0.084)	(0.091)	(0.175)	(0.166)
Female empowerment		-0.086	-0.032	0.560	-0.273	-0.268
		(0.079)	(0.138)	(0.359)	(1.006)	(0.956)
Interaction term			-0.081	-0.074	0.676*	0.565
			(0.168)	(0.184)	(0.372)	(0.354)
No. household members				0.025	-0.077	0.072
				(0.026)	(0.104)	(0.103)
Land cultivated(ha)				0.000	-0.016	-0.019
				(0.005)	(0.017)	(0.016)
No. plots with oil palm				0.076	-0.273	-0.188
				(0.068)	(0.189)	(0.181)
Asset Score				0.808***	1.062	1.453*
				(0.278)	(0.791)	(0.755)
No. female members				-0.027	0.124	-0.096
				(0.041)	(0.160)	(0.157)
Age of household head				-0.003	-0.044*	0.001
				(0.003)	(0.023)	(0.023)
Education of hh head				-0.005	-0.011	0.004
				(0.009)	(0.027)	(0.026)
Female headed household				-0.448	-0.633	0.285
				(0.338)	(1.128)	(1.084)
Time dummy						0.601***
						(0.107)
Cons	3.220***	3.241***	3.228***	2.949***	6.054***	2.685*

	(0.059)	(0.062)	(0.068)	(0.260)	(1.520)	(1.565)
F statistic	5.0	3.1	2.1	1.5	1.3	3.9
R-squared	0.00	0.01	0.01	0.02	0.05	0.14
N	1128	1128	1128	933	933	933

St.errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Results for the use of the same practice on plots with crops other than oil palm on food insecurity are reported in table A24. In the fixed effect models, intercropping seems to reduce household food security significantly, and female empowerment has the same effect in all the specifications considered. The interaction term is positive and significant, and it seems to suggest that female empowerment plays a role in mediating the relationship between intercropping and the FIES.

Table A24. Regression results for intercropping use only (FIES)

	FIES					
	POLS	POLS	POLS	POLS	FE	FE+T
Use of intercropping	0.367***	0.366***	-0.224	-0.325	-1.532***	-1.553***
	(0.135)	(0.135)	(0.332)	(0.306)	(0.540)	(0.542)
Female empowerment		-0.381**	-0.850***	-1.071***	-2.057***	-2.048***
		(0.172)	(0.296)	(0.272)	(0.541)	(0.542)
Interaction term			0.707*	0.711**	1.991***	2.007***
			(0.363)	(0.336)	(0.581)	(0.583)
No. household members				0.091**	0.254*	0.275*
				(0.044)	(0.146)	(0.150)
Land cultivated(ha)				0.001	0.027	0.026
				(0.008)	(0.024)	(0.024)
No. plots with oil palm				-0.062	0.291	0.304
				(0.114)	(0.265)	(0.267)
Asset Score				-3.409***	-3.663***	-3.611***
				(0.462)	(1.117)	(1.122)
No. female members				-0.140**	-0.128	-0.162
				(0.068)	(0.224)	(0.232)
Age of household head				0.000	0.013	0.019
				(0.005)	(0.032)	(0.034)
Education of hh head				-0.038**	-0.074*	-0.072*
				(0.015)	(0.038)	(0.038)
Female headed household				0.398**	-0.852	-0.740
				(0.178)	(0.808)	(0.834)
Time dummy						0.089
						(0.160)
Cons	1.258***	1.576***	1.968***	3.514***	2.930	2.459
	(0.110)	(0.181)	(0.270)	(0.481)	(2.176)	(2.336)
F statistic	7.4	6.2	5.4	12.9	3.5	3.2
R-squared	0.01	0.01	0.01	0.13	0.12	0.12
N	1130	1130	1130	935	935	935

St.errors in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

A.2- Essay 2: Mediation analysis: the early approaches

Baron and Kenny and the SEM approach

The simple mediation model (Baron & Kenny, 1986) consists of two steps. Firstly, the mediator (M) is regressed on the explanatory variable (X) to check whether the latter is a significant predictor of the mediator. Secondly, the dependent variable (Y) is regressed on the mediator and on the explanatory variable to confirm that the mediator is a significant predictor of the dependent variable. The path that goes from the independent variable to the dependent variable describes the direct effect, whereas the one that links the two variables through the mediator represents the indirect effect (Hayes, 2017).

The main equations of the simple mediation analysis describe the diagram in Figure 6 and are the following eq. (1) and (2):

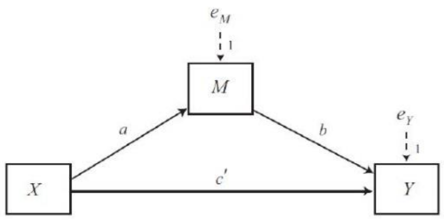


Figure A1. Statistical diagram of the simple mediation model (Hayes, 2017)

$$M = i_1 + aX + e_M \quad (1)$$

$$Y = i_2 + c'X + bM + e_Y \quad (2)$$

where c' estimates the direct effect of X (i.e., extension) on Y (i.e., adoption of LLL) mediated by M (i.e., rent of the machine), whereas the indirect effect in the simple mediation model is usually computed as the product of a and b.

In order to be considered a mediator, a variable must be significantly affected by changes in the independent variable, and it must significantly influence changes in the dependent variable. Lastly, the existence of a mediator should make the previously significant relationship between X and Y no more significant, reducing its magnitude: if the path c is equal to zero, I are dealing with a dominant mediator; if it is only reduced, it could be the case of a multiple mediator model (Baron and Kenny, 1986)

Since X and M are causally related, this could result in multicollinearity in the last equation; thus, one must pay attention to the significance and magnitude of coefficients. A way to test the indirect effect obtained by the mediation analysis was provided by Sobel (1982).

Two other assumptions are needed (Baron and Kenny, 1986):

- No measurement errors should exist in the mediator: this could underestimate the mediator's effect and overestimate the independent variable's effect on the outcomes. A solution to control for this issue is to use a multiple indicator approach and estimate mediation paths by latent-variable structural modelling methods;
- The dependent variable does not causally affect the mediator (Baron and Kenny, 1986).

Advantages of the B&K model

The main advantage of this model is that it can elicit the mechanisms – how and why – through which the independent variable affects the outcome, which is the main interest of the mediation analysis (Baron and Kenny, 1986). Indeed, simply adding the mediator as a simple predictor to the regression will not give us information about the mechanism that links the independent variable to the outcome. Instead, it will provide only an "additive effect" where I analyze the effect of the explanatory plus the mediator on the outcome. This is useful, but mediation goes a step further, providing more insightful information (Jose, 2013).
Another advantage of using SEM instead of OLS regression is the possibility to employ it to estimate latent variable models or models that combine observed and latent variables. If the observed variables are not reliable and the predictors contain measurement errors, a solution can be to use a combination of a structural model and a latent variable measurement model using SEM to reduce the errors due to random measurement errors (Hayes, 2013).
Compared to other methods such as ANOVA, mediation analysis could provide a more robust test of mediational hypothesis, as discussed in Fiske, Kenny and Taylor (1982).
According to Baron and Kenny (1986), using the structural modelling approach is a good option because it was developed to analyze non-experimental data. It is also a better approach than ANOVA since all the relevant paths are tested, and none are omitted as it happens with ANOVA. Furthermore, measurement errors and feedbacks can be included in the model (Baron and Kenny, 1986).

Limitations of the B&K model

It is important to note that the simple mediation model by Baron and Kenny suffers from many limitations, and in recent years many criticisms arose, leading researchers to develop new tools to deal with more complex situations.
Firstly, some researchers, as Fritz and Mackinnon (2007), argued that the simple mediation model is the lowest in power and that the use of the Sobel test is lower in power compared to other tests such as the bootstrap test (Hayes, 2009; Zhao, Lynch and Chen, 2010). Another limitation is the fact that it is not based on a quantification of the intervening effect, but this effect is logically inferred following a set of

hypothesis tests: if *a* (i.e., the coefficient for X in a model predicting M) and *b* (i.e., the coefficient in a model prediction of Y from M) are *both* significantly different from zero, also the indirect effect is considered in the same way by this approach. However, in social science the aim is to quantify the effects and then to test the hypothesis or to create interval estimates for their magnitude. Furthermore, there is the possibility that an indirect effect could be different from zero even if one of the two coefficients is not (Hayes, 2009).

The SEM approach is not the most appropriate method to identify and analyze causal mechanisms. In fact, the structural equation model assumptions are not appropriate and testable. The traditional exogeneity assumptions can be sufficient for identifying the average treatment effect but not enough for the identification of causal mechanisms. Furthermore, in the Baron and Kenny's approach it is necessary to control for several pre and post-treatment covariates that can confound the relationship between the variables under investigation and bring different results depending on the covariates included (Imai *et al.*, 2011).

A relevant advantage of the counterfactual notation is that potential heterogeneity is not a problem. Furthermore, it is unnecessary to specify the functional form of the parameters and the relations among variables, and the existence of non-linearities and interactions cannot harm the analysis (Imai *et al.*, 2011; Kenny, 2018).

In order to cite some of the works done following this approach, I can mention Pearl (2012) and Imai, Keele and Tingley (2010).

In the causal approach, counterfactuals or potential outcomes are used. It is possible to denote $Y_i(1)$ as the potential outcome for person *i* on Y for whom X=1 and $Y_i(0)$ for X=0, whereas the averages of these potential outcomes are denoted as E[Y(0)] and E[Y(1)]. Furthermore, the assumptions are similar to the one previously stated; however, they are sufficient but not necessary (Kenny, 2018):

1. *No unmeasured confounding of the X-Y relationship* – namely, any variable that causally affects the treatment and the outcome must be included in the model;

2. *No unmeasured confounding of the relationship between M and Y* – namely, the model must include any variable that causes the mediator and the outcome;

3. *No unmeasured confounding of the X-M relationship* – namely, any variable that causes the treatment and the mediator must be included in the model;

4. *The treatment variable must not cause any known confounder of the relationship between the mediator and the outcome.*

Dealing with causal inference, this model talks about Controlled Direct Effect (CDE), Natural Direct Effect (NDE) and Natural Indirect Effect (NIE). The sum of the NDE and the NIE forms the total effects (Kenny, 2018).

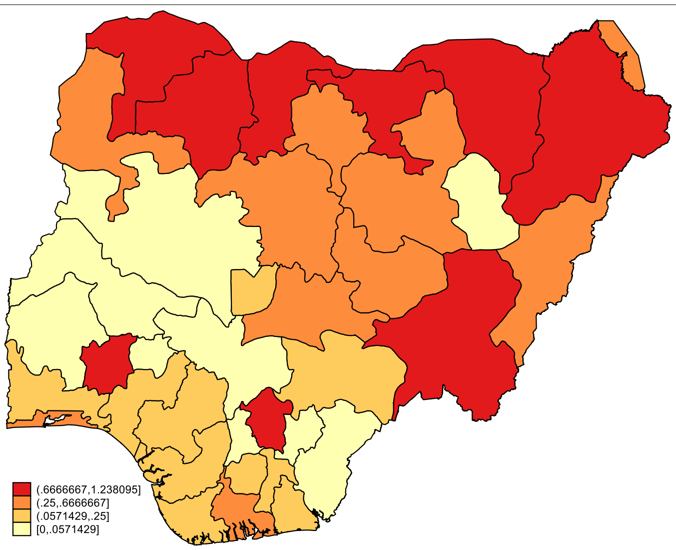
In the case in which the effect of the treatment does not change for different levels of the mediator, CDE and NDE coincide and the NIE is simply the difference between them. On the opposite, and more often, CDE will change as the mediator changes; thus, CDE and NDE will be different (VanderWeele, 2015). If the model is linear and the assumptions are met, the CDE and NDE would be equal to what Baron and Kenny called *c'* (the path from X to Y) and the NIE would equal *ab* (Kenny, 2018).

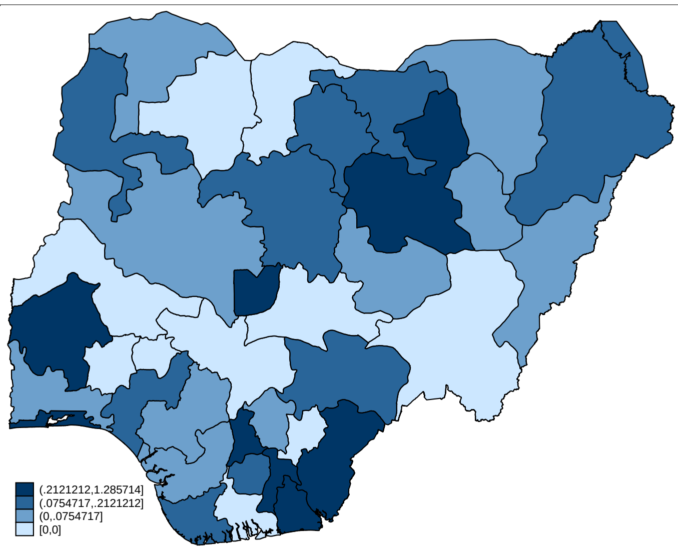
A.3- Essay 3: Average number of shocks at the state level reported by the sampled households

Figure A1 displays the average number of climatic shocks for each state (panel A) and the average number of shocks related to thefts of crops or other properties, robbery, and kidnapping (panel B).

Shocks related to climate change, such as flooding or poor rains, seem to be more reported in the Northern part of the country, whereas shocks related to security seemed to hit households in the South.

Panel A. Average number of shocks related to climate (average number per state)	Panel B. Average number of shocks related to security (average number per state)





Source: own elaboration from LSMS-ISAdataset (wave 1)

Figure A1. Average number of shocks reported by Nigerian states

Hot spots and cold spots for main crops grown in Nigeria

Maize

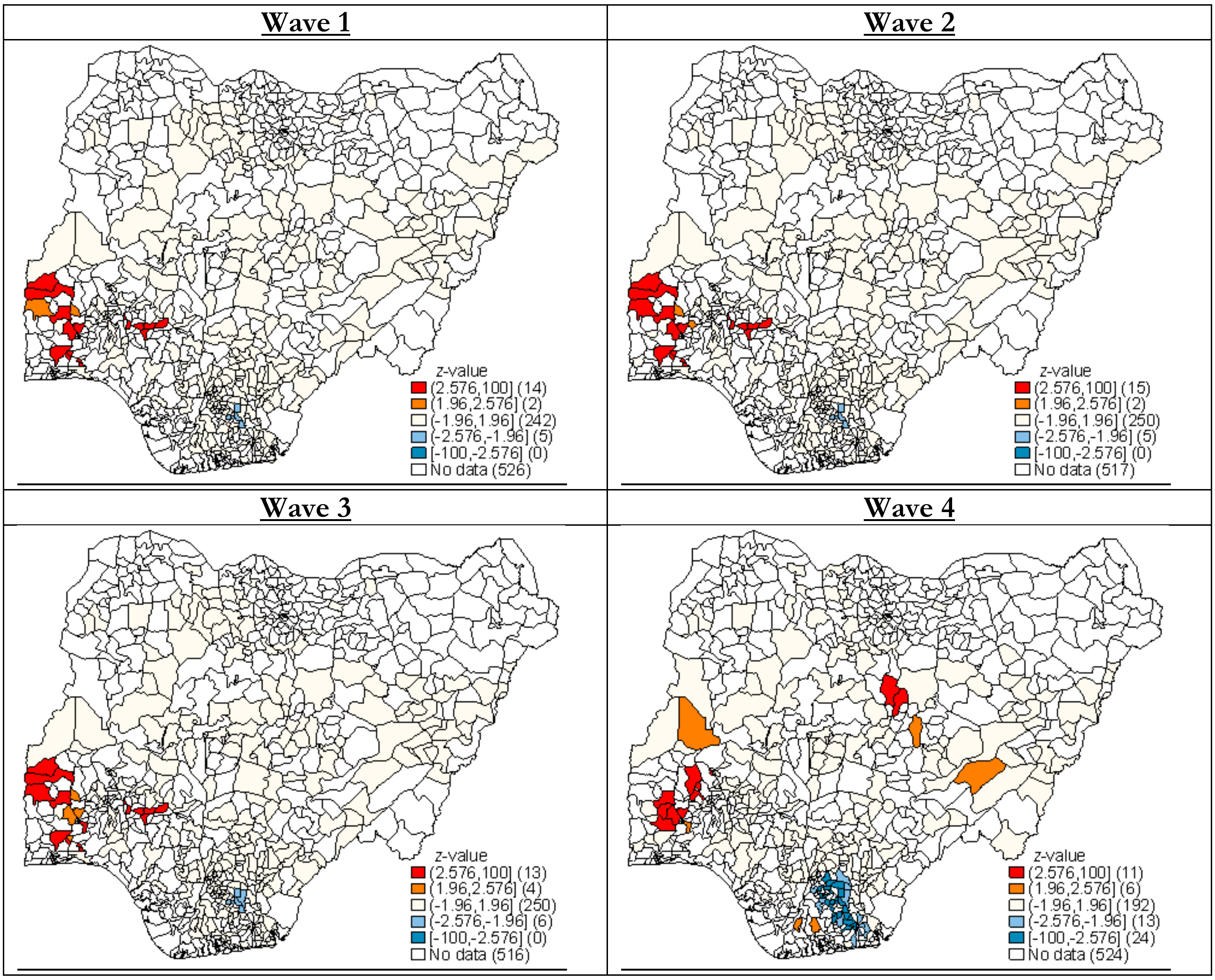
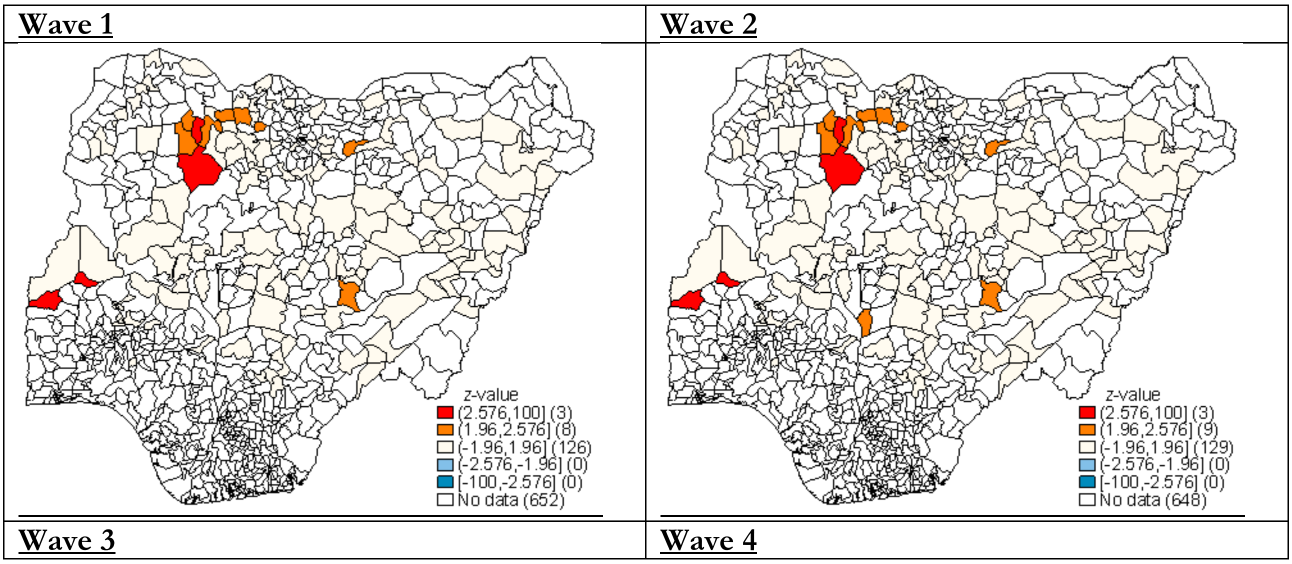


Figure A2. Hot spots and cold spots LGA for maize

Sorghum



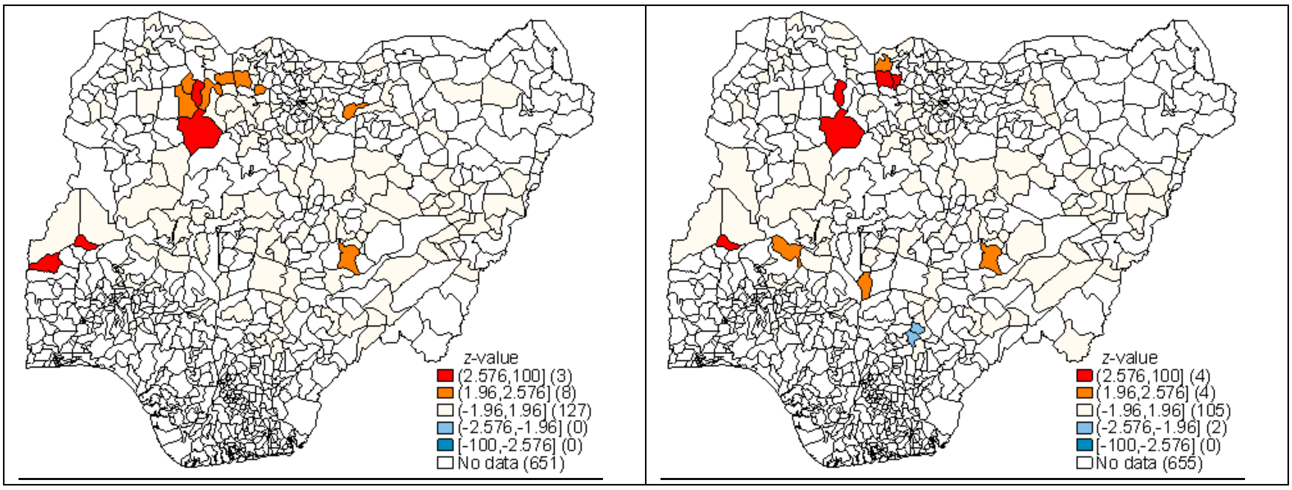


Figure A3. Hot spots and cold spots LGA for sorghum

Cassava

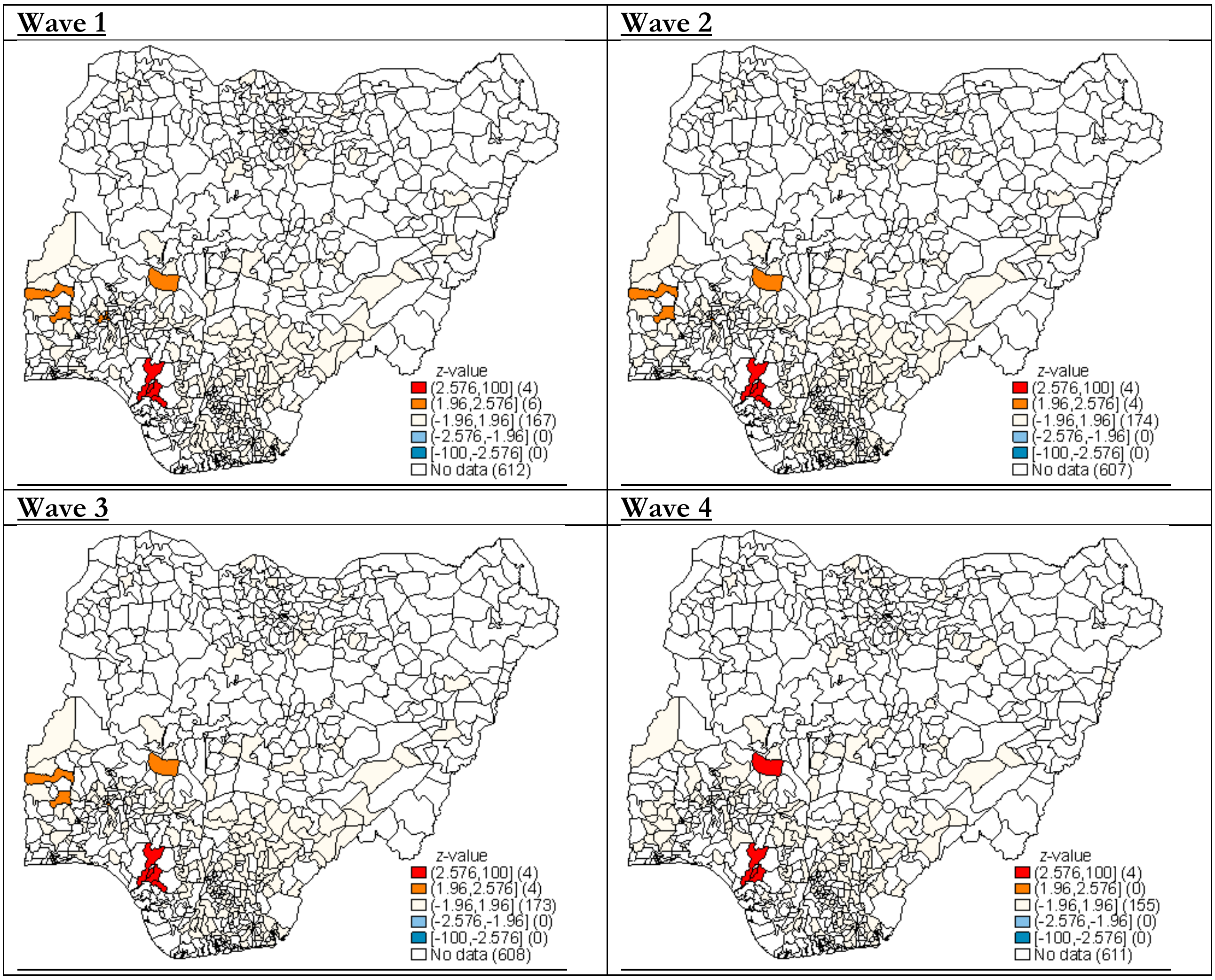
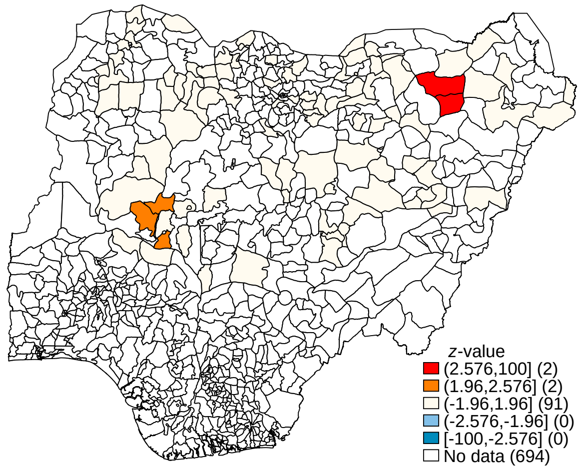


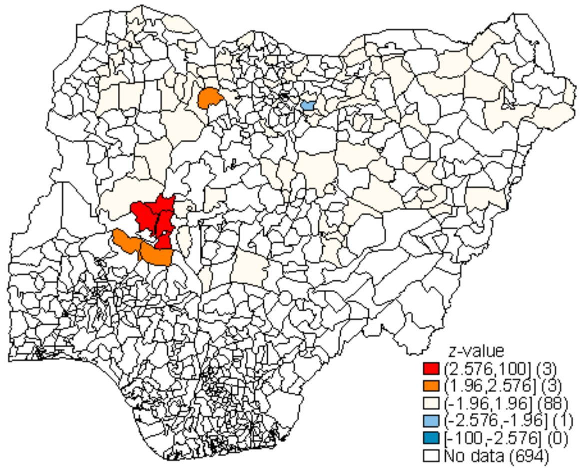
Figure A3. Hot spots and cold spots LGA for sorghum

Millet

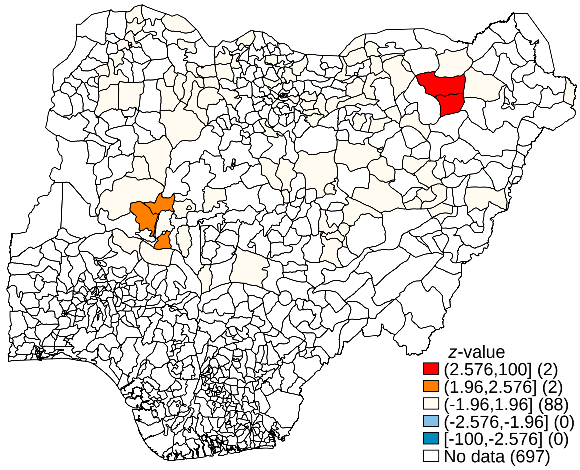
Wave 1



Wave 2



Wave 3



Wave 4

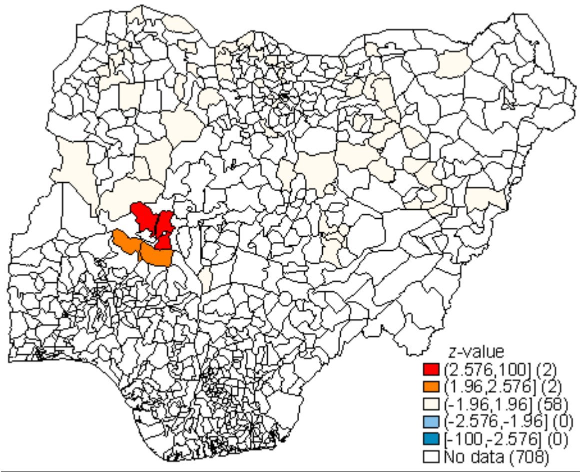
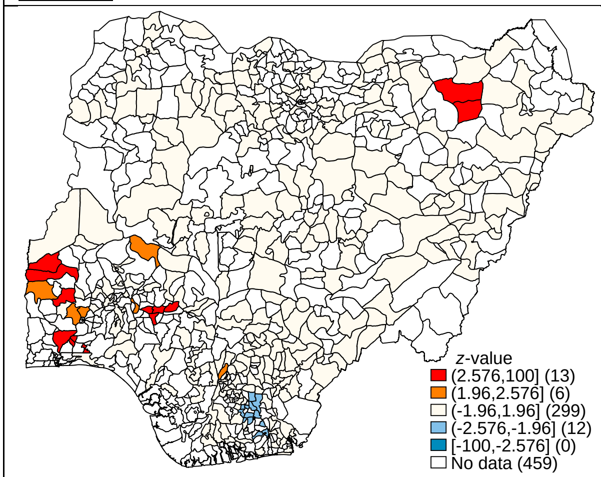


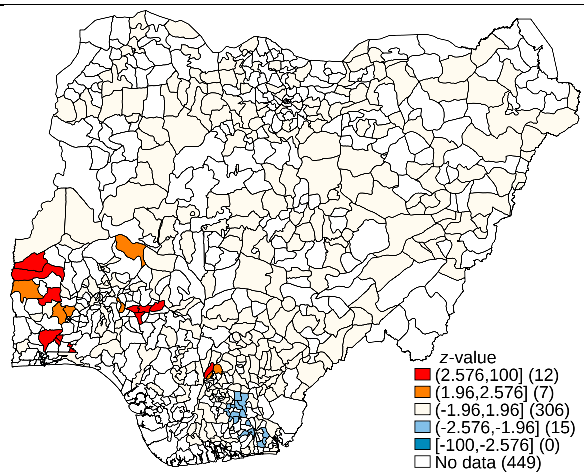
Figure A4. Hot spots and cold spots LGA for millet

Cereals(maize, sorghum, millet, rice)

Wave 1



Wave 2



Wave 3

Wave 4

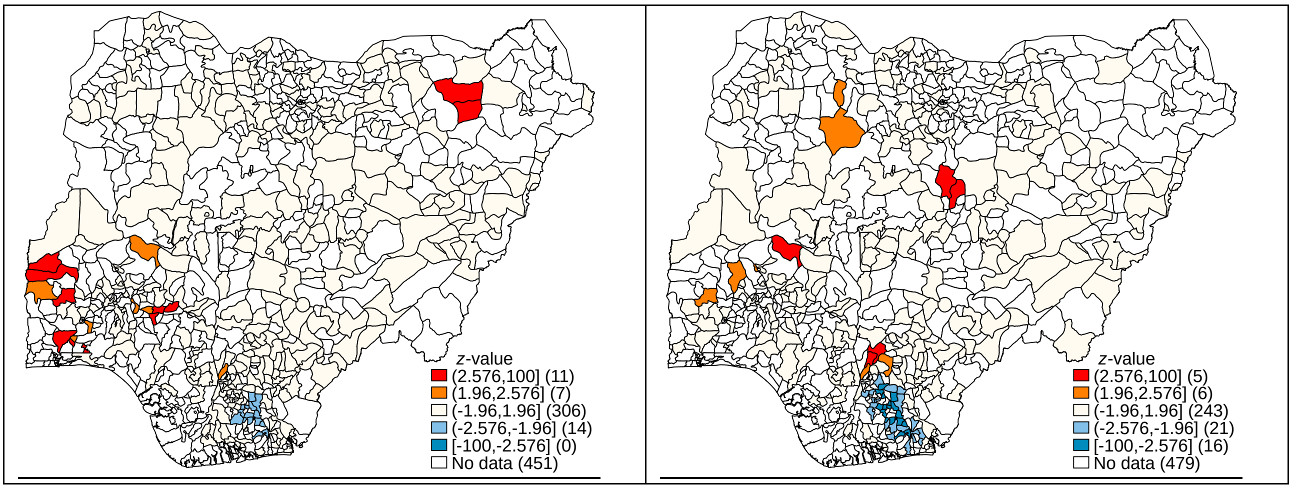


Figure A5. Hot spots and cold spots LGA for cereals

Main crops(Cereal and tubers)

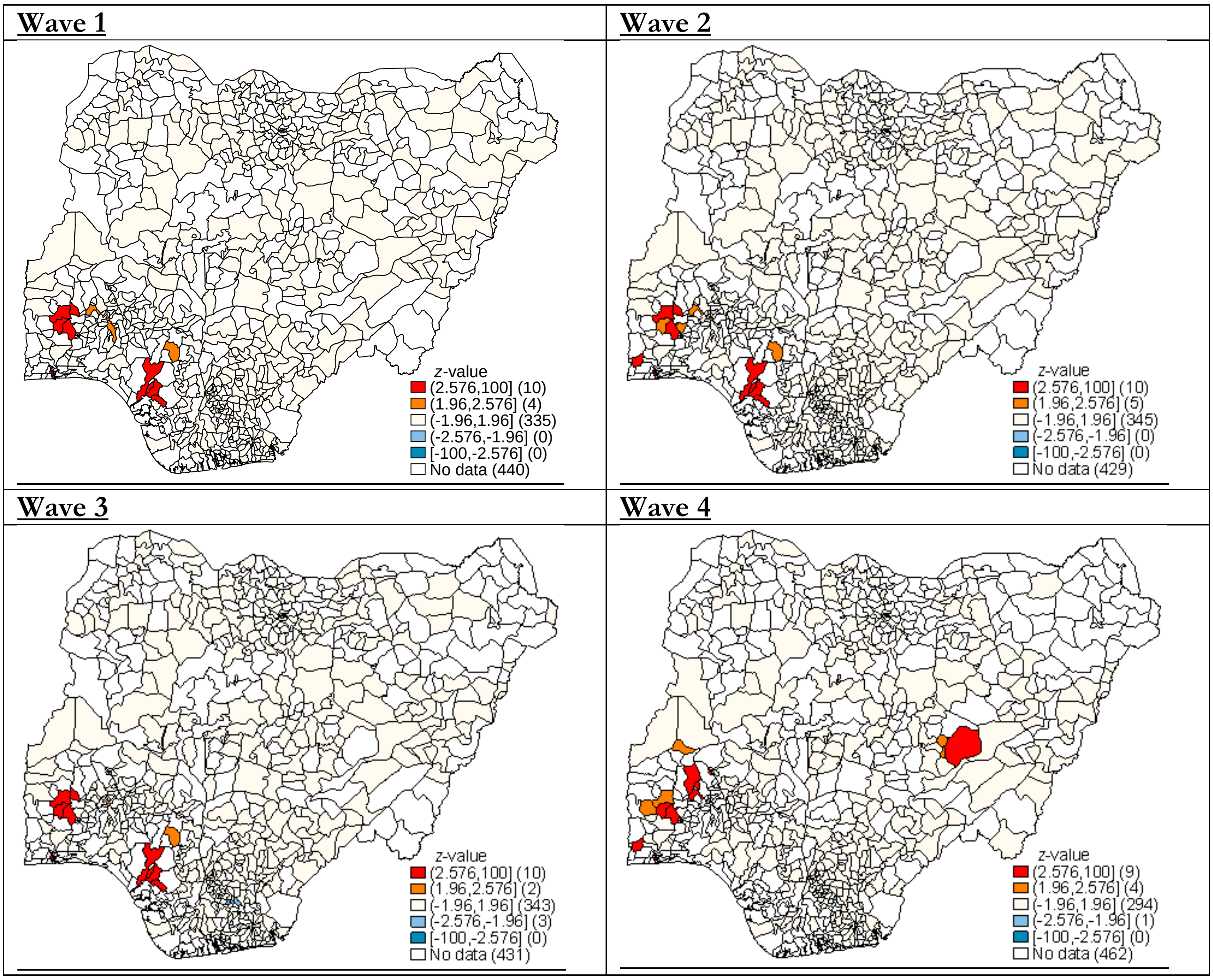


Figure A6. Hot spots and cold spots LGA for main crops

Panel regressions

1. Market access and the three mediators

To test whether market access has an association with the three mediators considered (as requested by the mediation analysis) I report the results of some pooled panel probit regressions (column 1 without controls and column 2 with controls reported below the tables). In column 3 I report the coefficient for the IV regression using as instrument the distance (in km) from the market.

Mediator: credit from formal institutions

Results are quite mixed. Concerning the POLS specification, selling on the market seems to increase households' access to credit by 2 percentage points on average (table A1, column 2); being in an upstream or downstream position only affect access to credit in column 1 of table A2 and A3. Living in a hot spot significantly affects the dependent variable under consideration but the coefficients show opposite direction(table A4). The instrument selected displays a high F-statistics but the IV approach (column 3) makes the coefficients insignificant.

Table A1. Results of POLS and IV

	(1)	(2)	(3)IV
		Access to credit	
On the market	-0.002	0.020**	0.160
	(0.006)	(0.009)	(0.136)
Controls	No	Yes	Yes
IV	-	-	Distance to the market
F-stat	-	-	34.48
Observations	11,310	2,884	2,884

Marginal effects. Control variables: shock, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * p<0.1; ** p<0.05; *** p<0.01

Table A2. Results of POLS and IV

	(1)	(2)	(3) IV
		Access to credit	
Upstream	-0.023**	-0.021	.008
	(0.010)	(0.014)	(0.233)
Controls	No	Yes	Yes
IV	-	-	Dist. Market
F-stat	-	-	26.27
Observations	3,826	1,540	1,540

Marginal effects. Control variables: shock, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * p<0.1; ** p<0.05; *** p<0.01

Table A3. Results of POLS and IV

	(1)	(2)	(3) IV
		Access to credit	
Downstream	0.034***	0.016	-0.006
	(0.011)	(0.015)	(0.178)
Controls	No	Yes	Yes
IV	-	-	Dist. Market
F-stat	-	-	26.27
Observations	3,826	1,540	1,540

Marginal effects. Control variables: shock, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table A4. Results of POLS and IV

	(1)	(2)	(3) IV
		Access to credit	
Hot spot	0.030***	-0.027*	0.137
	(0.009)	(0.016)	(0.111)
Controls	No	Yes	Yes
IV	-	-	Dist. Market
F-stat	-	-	34.64
Observations	11,310	2,884	2,884

Marginal effects. Control variables: shock, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

<u>Mediator: knowledge</u>

Living in a hot spot significantly increases the average number of opportunities to receive information about agricultural activities (by around 0.47) in all the three specifications considered (table A5).

Table A5. Results of POLS and IV

	(1)	(2)	(3) IV
		Knowledge	
On the market	-0.037	-0.048	-0.0479
	(0.059)	(0.089)	(0.0903)
Controls	No	Yes	Yes
IV	-	-	Dist. market
F-stat	-	-	7.43
Observations	10,399	2,884	2,884

Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, asset score. Robust standard errors. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table A6. Results of POLS and IV

	(1)	(2)	(3) IV
		Knowledge	
Upstream	-0.089	0.100	0.100
	(0.089)	(0.131)	(0.111)
Controls	No	Yes	Yes
IV	-	-	Dist. market
F-stat	-	-	5.48
Observations	5,528	1,540	1,540

Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A7. Results of POLS and IV

	(1)	(2)	(3) IV
		Knowledge	
Downstream	-0.054	-0.224	-1.011
	(0.098)	(0.151)	(1.872)
Controls	No	Yes	Yes
IV	-	-	Dist mark
F-stat	-	-	5.15
Observations	5,528	1,540	1,540

Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A8. Results of POLS and IV

	(1)	(2)	(3) IV
		Knowledge	
Hot spot	0.406***	0.470***	0.471***
	(0.107)	(0.161)	(0.175)
Controls	No	Yes	Yes
IV	-	-	Dist market
F-stat	-	-	7.54
Observations	10,399	2,884	2,884

Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Mediator: Risk

Selling on the market - both local and main market - and living in a hot spot has a significant and positive effect on the possibility for households to have savings in informal groups, reducing their risk aversion. This is consistent in all the specifications considered (even if the magnitude of the coefficients increases a lot in the IV specification). Also selling in a downstream position - closer to the main market - seems to have the same effect (table A11), but the coefficient is no more significant in the IV specification.

Table A9. Results of POLS and IV

	(1)	(2)	(3) IV
		Risk	
On the market	0.242***	0.267***	0.777***
	(0.025)	(0.059)	(0.269)
Controls	No	Yes	Yes
IV	-	-	
F-stat	-	-	40.98
Observations	19,386	2,884	2,884

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A10. Results of POLS and IV

	(1)	(2)	(3) IV
		Risk	
Upstream	-0.090**	-0.010	-1.92**
	(0.042)	(0.094)	(0.961)
Controls	No	Yes	Yes
IV	-	-	Dist. Market
F-stat	-	-	4.46
Observations	6,913	1,540	1,540

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A11. Results of POLS and IV

	(1)	(2)	(3) IV
		Risk	
Downstream	0.161***	0.207*	1.539
	(0.046)	(0.109)	(0.575)
Controls	No	Yes	Yes
IV	-	-	Dist. market
F-stat	-	-	10.71
Observations	6,913	1,540	1,540

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A12. Results of POLS and IV

	(1)	(2)	(3) IV
		Risk	
Hot spot	0.260***	0.414***	0.688***
	(0.042)	(0.105)	(0.205)
Controls	No	Yes	Yes
IV	-	-	Dist.
F-stat	-	-	60.44
Observations	19,386	2,884	2,884

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

2. Market access on the use agrochemicals

Selling on the market significantly increases the use of agrochemicals in all the specifications (table A13), increasing it by 11 percentage points.

Table A13. Results of POLS and IV

	(1)	(2)	(3) IV
		Agrochemicals	
On the market	0.289***	0.112***	0.111***
	(0.007)	(0.017)	(0.017)
Controls	No	Yes	Yes
Instrumental var.	-	-	Distance to the market
F-stat	-	-	21.42
Observations	19,489	2,884	2,884

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A14. Results of POLS and IV

	(1)	(2)	(3) IV
		Agrochemicals	
Upstream	0.011	0.000	1.949
	(0.012)	(0.026)	(1.048)
Controls	No	Yes	Yes
Instrumental var.	-	-	Distance to the market
F-stat	-	-	2.37
Observations	6,927	1,540	1,540

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A15. Results of POLS and IV

	(1)	(2)	(3) IV
		Agrochemicals	
Downstream	-0.002	-0.001	-1.484**
	(0.013)	(0.030)	(0.616)
Controls	No	Yes	Yes
Instrumental var.	-	-	Distance to the market
F-stat	-	-	3.88
Observations	6,927	1,540	1,540

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A16. Results of POLS and IV

	(1)	(2)	(3) IV
		Agrochemicals	
Hot spot	-0.062***	0.045	-.284
	(0.013)	(0.032)	(0.220)
Controls	No	Yes	Yes
Instrumental var.	-	-	Distance to the market
F-stat	-	-	14.68
Observations	19,489	2,884	2,884

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

3. Market access on the use agrochemicals

An additional visit to obtain information on agricultural activities seems to increase the probability of using agrochemicals by 1.8 percentage points (table A17, column 2). Table A18 shows that having borrowed money from formal institutions increases the probability of using agrochemicals by 6.4 percentage points (column 2). Again, the coefficient is no more significant in the IV specification. Table A19 show contrasting results: in column one having savings in informal groups seems to increase the use of agrochemicals by 4 percentage points; however, adding controls and in the IV specification, the coefficient turns to have a negative impact, reducing the use of agrochemicals by around 6 percentage points.

Table A17. Results of POLS and IV

	(1)	(2)	(3) IV
		Agrochemicals	
Knowledge	0.009***	0.018***	0.210
	(0.002)	(0.005)	(0.145)
Controls	No	Yes	Yes
IV	-	-	Mobile phone
F-stat	-	-	9.17
Observations	10,399	2,884	2,879

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A18. Results of POLS and IV

	(1)	(2)	(3) IV
		Agrochemicals	
Credit	0.001	0.064**	0.351
	(0.013)	(0.030)	(0.764)
Controls	No	Yes	Yes
IV	-	-	Financial institution in the community
F-stat	-	-	18.22
Observations	11,310	2,884	2,871

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A19. Results of POLS and IV

	(1)	(2)	(3) IV
		Agrochemicals	
Risk (sav. Inf)	0.042***	-0.059***	-0.055***
	(0.006)	(0.019)	(0.019)
Controls	No	Yes	Yes
IV	-	-	Annual precipitation
F-stat	-	-	18.42
Observations	19,386	2,884	2,924

Marginal effects. Control variables: shock, access to credit from formal institutions, access to credit from informal sources, savings in informal groups, savings in formal institutions, time to closest city, number of household members, land size, number of visits to obtain information about agricultural activities, asset score. Robust standard errors. * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Structural equation model

The IV mediation approach is useful as it allows the use of a single instrument. However, it does not permit to consider the three mediators together. Aiming at a complete understanding of the relationship among the variables under analysis, I also run a structural equation model (SEM) that includes all the three determinants of adoption (credit/liquidity constraints, discount rate, and information constraints) simultaneously. SEMs are employed to measure the causal effect and are usually employed to statistically model and test complex phenomena, especially when longitudinal data are available. They allow researchers to decompose the total effect into direct and indirect effects. SEMs are not unrelated to statistical models such as ANOVA, multiple regression analysis, and principal factor analysis; they can be described as, at least in part, a generalization, integration, and extension of these models. In addition, SEMs allow to better specify the relations between more than one dependent variable and for the fact that a variable could be both an independent and a dependent variable (Hoyle, 2012).

Frölich and Huber (2017) suggested that confoundings in treatment and mediator can be addressed using instrumental variables (Ohrnberger *et al.*, 2020). Hence, I first compute the household fixed effect of the variables of interest to account for the longitudinal structure of the data, and then I run the following structural equation model:

$$\left.\begin{array}{c}
Knowledge: Y_1 = \alpha_h + \beta_1 Market\ access_{ht} + \beta_2 Z_2 + \beta_3 X + \varepsilon_{ht} \\
Risk: Y_2 = \alpha_h + \beta_4 Market\ access_{ht} + \beta_5 Z_3 + \beta_6 X + \varepsilon_{ht} \\
Liquidity: Y_3 = \alpha_h + \beta_7 Market\ access_{ht} + \beta_8 Z_4 + \beta_9 X + \varepsilon_{ht} \\
Market\ Access: Y_4 = \alpha_h + \beta_{10} Z_1 + \beta_{11} X + \varepsilon_{ht} \\
Tech: Y_5 = \alpha_h + \beta_{13} Y_{4,ht} + \beta_{14} Y_{3,ht} + \beta_{15} Y_{2,ht} + \beta_{16} Y_{1,ht} + \beta_{17} X + \varepsilon_{ht}
\end{array}\right\}$$

where X indicates other covariates and Z indicates the instrumental variables.

Figure A7 shows the complete framework where all the three mediators are included. The picture also incorporates the four instrumental variables used following the approach suggested by Frölich and Huber (2017), which will be tested later on. Household fixed effects have been used to control for unobserved time-invariant heterogeneity among households in running the model over the longitudinal sample. Following previous literature, I identify as instrumental variable for the explanatory variable the (ln) distance from the household to the market; for the first mediator, the use of mobile phone; for the second, the presence of the financial institution in the community; and for the third mediator, the (ln) annual amount of rainfall in the area.

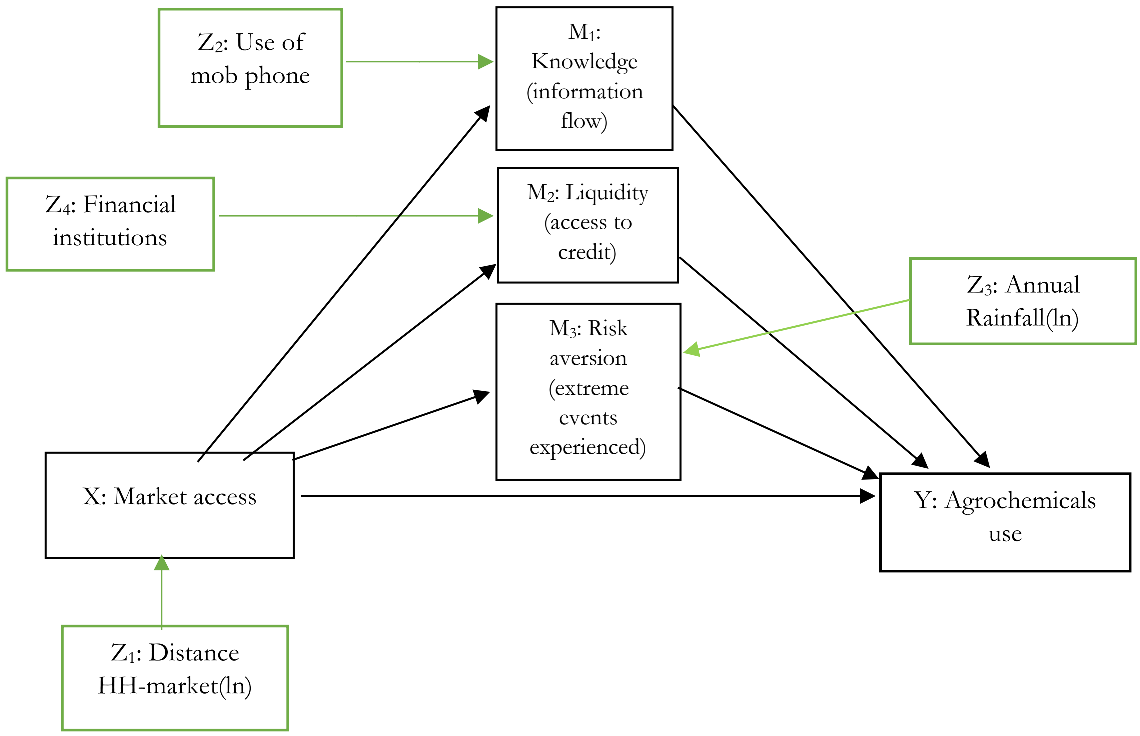


Figure A7. SEM with instrumental variables

Table A20 reports the estimates of direct, indirect, and total effects. Only some direct effects can be significantly found in the framework under analysis, which do not confirm the evidence shown above. Household size seems to directly negatively affect the information flow and access to credit, while it seems to positively affect market access - namely, selling on the market. Risk aversion is negatively affected by rainfall and positively affected by the time to reach the nearest city. Looking at the outcome model, market access seems to improve the use of agrochemicals significantly. Access to credit decreases the use of agrochemicals (significant at 5%), and household size and land size increase agrochemicals use.

Table A20. Direct, indirect and total effects of the model

	Direct effect	Indirect effect	Total effect
	Std. coef.	Std. coef.	Std. coef.
M1: Knowledge			
Market access (selling at the market)	.012	-	.012
mobile phone	-.027	-	-.027
Crops sold	.009	-.000	.009
Time to city	.001	-.000	.001
Household size	-.048**	-.001	-.046**
Land size	.002	-.000	.001

Distance HH-market	-	.000	.000
T: Market access (selling at the market)			
Crops sold	-.003	-	-.003
Time to city	-.028	-	-.028
Household size	.116***	-	.116***
Land size	-.021	-	-.021
Distance HH-market	-.008	-	.008
M2: Liquidity			
Market access (selling at the market)	-.005	-	-.005
Crops sold	.001	.000	.001
Time to city	-.001	.000	-.001
Household size	-.163***	-.001	-.164***
Land size	-.000	.000	-.000
Financial institutions	.001	-	.000
Distance HH-market	-	-.000	-.000
M3: Risk aversion			
Market access (selling at the market)	.007	-	.008
Crops sold	-.007	-.000	-.007
Time to city	.040**	-.000	.039**
Household size	.024	-.001	.025
Land size	-.004	-.000	-.004
Rainfall	-.034*	-	-.034*
Distance HH-market	-	.000	.000
Agrochemicals use			
Knowledge	-.005	-	-.005
Market access (selling at the market)	.130***	.000	.130***
Liquidity	-.038**	-	-.038**
Risk aversion	-008	-	.008
mobile phone	-	.000	.000
Crops sold	-.009	-.001	-.010
Time to city	-.010	-.003	-.013
Household size	.067***	.022***	.089***
Land size	.070***	.003	.067***
Financial institutions	-	-.000	-.000
Rainfall	-	.000	.000
Distance HH-market	-	.001	.001

Note: *** p<0.01, ** p<0.05, * p<0.1.

As explained in the previous subsection, I run some placebo tests to statistically test the relevance and the exclusion restriction of the instruments used. Some issues arise. Firstly, as shown in the table below, instruments are correlated even if not at a higher level. This is against the assumption of independence between them required by Frölich and Huber (2017).

Table A21. Correlation among instruments used in the SEM

	Distance HH-market(ln)	Mobile phone	Rainfall	Financial institutions
Distance HH-market(ln)	1.000			
Mobile phone	-0.048	1.000		
Rainfall	-0.092	0.112	1.000	
Financial institutions	-0.080	0.165	0.019	1.000

As expected, the instrument "distance from household's location to the market" affects the outcome of interest for the overall sample and the treated group but not for the untreated (Table A22). However, it does not seem to affect market access, defined here as whether the household sells crops on any market. Table A23, table A24, and table A25 test the other instruments for the three mediators. Again, the results are not the ones expected; thus, further studies will be necessary to find proper instrumental variables.

Table A22. Placebo test for Z1

	(1)	(2)	(3)	(4)
	Market access	Agrochemical use		
	Full sample	Full sample	T=1	T=0
Distance HH-market(ln)	0.007	-.043***	-.049***	-.000
	(0.005)	(0.009)	(0.009)	(0.032)
Control variables	Yes	Yes	Yes	Yes
Observations	3758	3758	3433	325

Note: Average marginal effects from probit regression of market access (column 1) and agrochemicals use (columns 2-4) indices are reported, controlling for the instrument and other covariates that include quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A23. Placebo test for Z2

	(1)	(2)	(3)	(4)
	Knowledge	Agrochemical use		
	Full sample	Full sample	T=1	T=0
Mobile phone	-0.077	0.028	0.086***	-0.062*
	(0.184)	(0.023)	(0.033)	(0.034)
Control variables	Yes	Yes	Yes	Yes
Observations	2885	3747	1331	2416

Note: Results from linear regression of knowledge (column 1) and average marginal effects from probit regression of agrochemicals use (columns 2-4) indices are reported, controlling for the instrument and other covariates that include quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A24. Placebo test for Z3

	(1)	(2)	(3)	(4)
	Risk aversion	Agrochemical use		
	Full sample	Full sample	T=1	T=0
Annual rainfall	-0.106***	-0.430***	-0.335***	-0.445***
	(0.018)	(0.021)	(0.045)	(0.024)
Control variables	Yes	Yes	Yes	Yes
Observations	3758	3758	647	3111

Note: Average marginal effects from probit regression of risk aversion (column 1) and agrochemicals use (columns 2-4) indices are reported, controlling for the instrument and other covariates that include quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A25. Placebo test for Z4

	(1)	(2)	(3)	(4)
	Access to credit	Agrochemical use		
	Full sample	Full sample	T=1	T=0
Financial institutions	-0.000	-0.016	-0.108**	0.024
	(0.025)	(0.026)	(0.046)	(0.031)
Control variables	Yes	Yes	Yes	Yes
Observations	3733	3734	1053	2680

Note: Average marginal effects from probit regression of access to credit (column 1) and agrochemicals use (columns 2-4) indices are reported, controlling for the instrument and other covariates that include quantities of main crops sold in kg, time to reach the closest city in minutes, household size and land size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.