MARKET PARTICIPATION, INNOVATION ADOPTION AND POVERTY IN RURAL GHANA

Grazia Pacillo

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Department of Economics

University of Sussex

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Declaration

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.

Signature

University of Sussex

Degree of Doctor of Philosophy in Economics

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SUMMARY

Agricultural commercialisation via increased market participation and innovation adoption has been widely argued to reduce poverty. However, empirical evidence suggests that both of these are persistently low in developing countries. Recent analyses suggest that different types of transaction costs and social capital may influence both market access and innovation adoption decisions.

This thesis investigates these two factors in agricultural commercialisation and poverty reduction. Using data from three GLSS survey rounds, Chapter 1 investigates the determinants of the decision to sell as well as the decision of how much to sell, focusing on the role of transaction costs. The empirical analysis is carried out at household level and for a specific crop (maize). A Heckman two-step model is used to control for self-selection into market participation, using measures of fixed transaction costs as identifier variables. The overall results, although generally consistent with previous literature, show an unexpected positive relationship between remoteness and market participation, which might reflect peculiarities of Ghanaian crop marketing systems.

Chapter 3 investigates the relationship between social capital and innovation using primary data on 305 Ghanaian farmers collected during field work in 2012 (described in Chapter 2). The chapter analyses innovation (the decision to adopt, its timing and intensity) at crop level, focusing on a non-traditional cash crop, exotic varieties of mango. The analysis investigates the role of different types of social capital, both in disaggregated and aggregated forms. The results suggest that social capital should not be overlooked in the innovation process, supporting recent evidence that there exists a positive relationship between the "know-who" and adoption dynamics.

Finally, Chapter 4 investigates the impact of innovation adoption on objective and subjective measures of poverty. Matching techniques are used to estimate the Average Treatment Effect on the Treated, using primary data. The results show that adoption does not impact objective poverty but it does have a significant positive impact on self-perceived poverty status.

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ACDI/VOCA	Agricultural Cooperative Development International and Volunteers in Overseas Cooperative Assistance
ADRA	Adventist Development and Relief Agency
EDAIF	Export Development and Agricultural Investment Fund
EU TRAQUE	EU Trade Related Assistance and Quality Enabling Programme
FAGE	Federation of Association of Ghanaian Exporters
FSML	Farm Management Services Limited
GhC	New Ghana Cedis
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit Gmb
GLSS	Ghana Living Standard Survey
HCI	Household Commercialisation Index
HECK	Heckman
HEII	Horticulture Exports Industry Initiative
ILO	International Labour Organisation
ITFC	Integrated Tamale Fruit Company
IV	Identifier Variable
MNL	Multinomial logit
MOAP	Market-Oriented Agriculture Programme
MOFA	Ministry of Food & Agriculture - Ghana
MCA	Multiple Correspondence Analysis
NGO	Non-governmental organisation
OLS	Ordinary Least Squares
OMOA	Organic Mango Outgrowers Associations
PCA	Principal Component Analysis
SNV	Netherlands Development Organisation
TIPCEE	The Trade and Investment Program for a Competitive Export Economy
UNIDO	United Nations Industrial Development Organisation
UK-DFID	UK-Department For International Development
UNICEF	United Nations Children Fund
USAID	United States Agency for International Development

INTRODUCTION

For most of the last three decades, Ghana has been considered the star economy in West Africa (Coulombe and Wodon, 2007). Sustained GDP growth and adoption of important economic reforms since the early 1980s have made Ghana one of the richest economies in Sub-Saharan Africa (IFPRI, 2012; Figure 1).

Notwithstanding the fast and high economic growth, which has led to a reduction in agriculture's share of GDP (Figure 2), agriculture remains the dominant sector of the economy. The major contribution to the agricultural sector is provided by the export of traditional cash crops, such as cocoa. The process of economic transformation occurred in the past decades has considerably reduced the dependence of the Ghanaian agricultural sector from cocoa exports. As Figure 3 shows, from a peak of about 45%, the contribution of cocoa trade to the total value of exports is currently at its historical minimum level (about 10%). Hence, since the early 2000s, international donors and national government have heavily supported agricultural commercialisation in a wider variety of crops including both food and non-traditional cash crops.

Figure 1 GDP growth, % (WB)

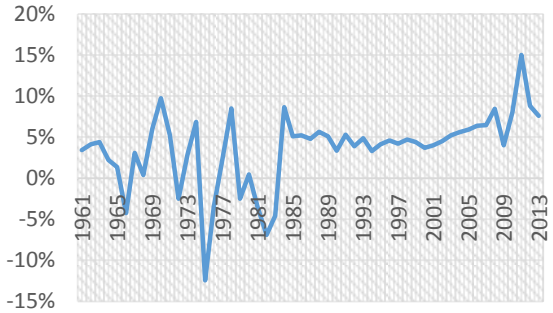


Figure 2 Agriculture, % GDP (WB)

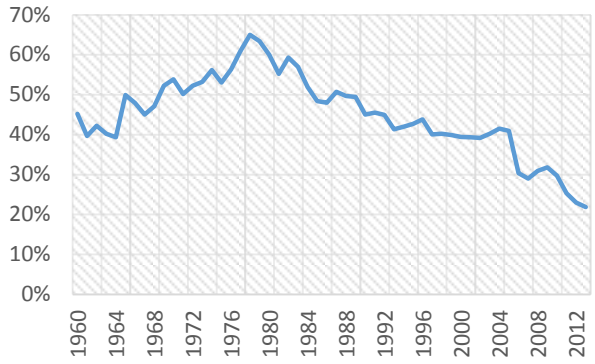
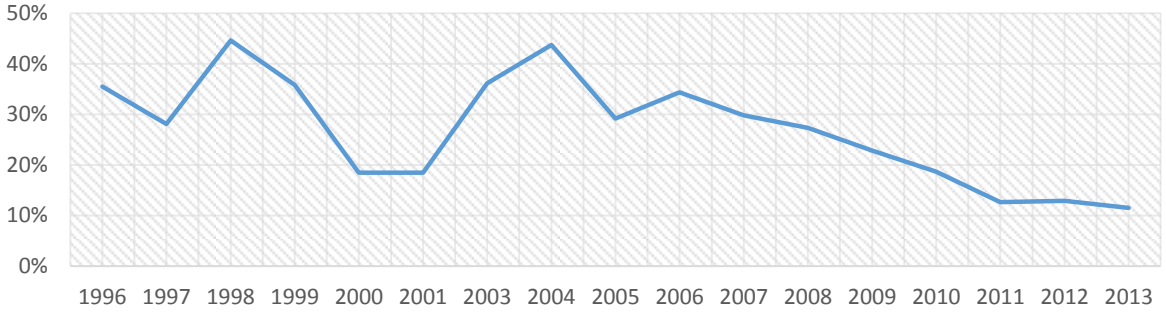


Figure 3 Cocoa Trade, % (UNCOMTRADE)

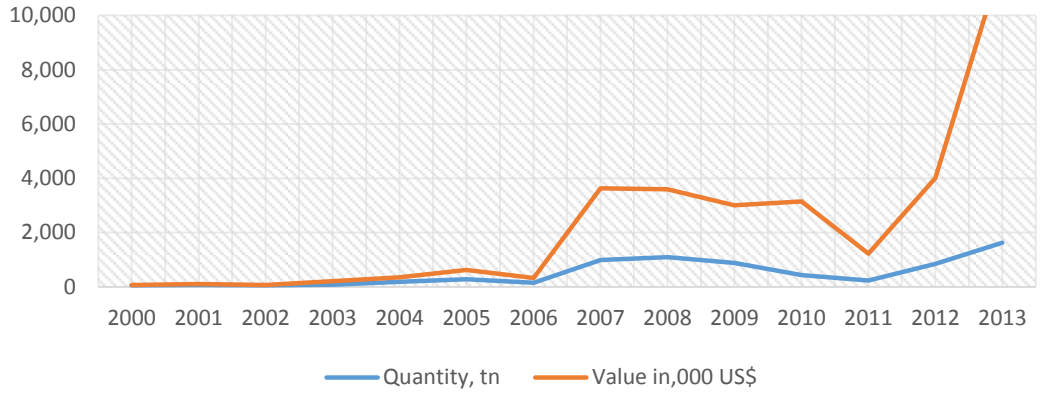


In 2008, the Ghana Export Horticulture Cluster Strategic Profile Study (Jaeger, 2008) set up a systematic national framework for these developments. The study recognises the importance of supporting agricultural commercialisation and fostering the development of a wider agricultural crop portfolio, with a specific focus on horticultural crops.

Within the main objective of increasing agricultural commercialisation, two priorities were identified: increase farmers' market participation and support more innovation adoption. Higher farmers' commercialisation via market participation is believed to be effective in fostering agricultural development and reducing poverty (Christiaensen and Demery, 2007; Ravallion and Chen, 2007). Similarly, innovation adoption, whether in the form of inputs or new marketable products, is believed to enhance agricultural productivity and farmers' economic returns, which might impact agricultural poverty (Minot and Roy, 2007).

Exotic varieties of mango, such as Kent and Keitt, are one of the target crops supported by recent government and donor initiatives. In the past decade both the production and the export of these varieties of mango have increased considerably as a result of the sustained national and international support. Figure 4 shows that the value and quantity of exports towards European Union, the main Ghanaian export partner, have considerably increased since the mid-2000s.

Figure 4 Mango trade with EU (EUROSTAT)



Although positive developments in the non-traditional cash crops sector constitute an important accomplishment of these initiatives, the notable effort by international donors and national government in fostering nationwide agricultural commercialisation via

market participation and product innovation adoption rates have not been as successful (Asmah, 2011). Numerous studies have pointed out that Ghanaian agriculture is still suffering from low levels of farmers' commercialisation, low adoption of innovations, poor communication and transport infrastructure, and rainfed irrigation systems (e.g. IFPRI, 2012; Lay and Schuler 2007).

The literature on market participation and innovation adoption provides important insights into what hinders farmers' decision to increase their level of commercialisation, via market participation and innovation adoption. Aside from classical determinants, such as asset endowments and wealth, the more recent literature gives stronger attention to the role of transaction costs and social capital in the processes of market participation and innovation adoption (Key et al., 2000; Bandiera and Rasul, 2006).

I follow these latest developments in the literature to explain why farmers in rural Ghana are still facing difficulties in accessing the market and in adopting product innovation. I explicitly focus on the supply side of agricultural commercialisation, namely output markets, and as such input markets are out of the scope of this analysis. This is partly driven by data constraints as input data are relatively limited in the GLSS while crop level data are much more detailed as far as the type of crops investigated, their production and marketing values are concerned. Moreover, the analysis of innovation adoption only covers product innovation (new crops) and not processes.

More specifically, Chapter 1 investigates what factors affecting market participation in Ghana. The analysis covers both the decision to sell or not to sell as well as the extent of this market participation, i.e. the extent of commercialisation. I use data from three rounds of the Ghana Living Standard Survey (GLSS4, GLSS5, GLSS6). I model the decision to sell using a probit model and then I explore commercialisation with a Heckman two step model to control for self-selection into market participation. Following the conceptual framework set out by Key et al. (2000) and Alene et al. (2008), I investigate the role of transaction costs in market participation decisions. Both fixed and proportional transaction costs are evaluated, using standard measures such as ownership of communication and transport assets for fixed transaction costs, and measures of distances for proportional transaction costs. The analysis covers both the household level and the crop level decision, with the latter focused on one of the most common staple crops in Ghana, maize. The advantage of carrying out a crop level

analysis is to unveil the different role that transaction costs might have in relation to food crops market participation decisions, which are commonly characterised by relatively higher transaction costs compared to cash crops. In addition, the crop level analysis allows the use of crop level data regarding the choice of marketing channels, available in the GLSS. The results of these analyses suggest that transaction costs play a relevant role in the farmers' decision to participate in the market and how much to participate. More specifically, access to information via communication and transport assets, which are commonly used as measures of fixed transaction costs, are found to be positively associated with market participation. Amongst measure of proportional transaction costs, a positive association between remoteness and market participation is observed. This result, although contrasting with previous empirical evidence, might reflect the peculiar nature of the marketing system in rural Ghana. As Zanello et al. (2014) and Martey et al. (2012) point out, long term relationships between producers and traders that have evolved in contexts of remoteness as well as strong social networks play a considerable role in reducing transaction costs, including those measured by remoteness, especially in rural remote areas of Ghana.

GLSS data do not provide detailed information on the role social networks on market participation and adoption of product innovation, and the sample size of farmers growing non-traditional cash crops is relatively small. This represents a serious limitation for studies of non-traditional cash crops which have been highlighted in recent years by the Ghana Horticultural Cluster Strategy study (Jaeger, 2008) as being important strategic goals for Ghanaian agriculture and poverty reduction targets. In order to investigate the role that social capital exerts on agricultural commercialisation via product innovation, I collected primary data in three regions of Ghana during the summer of 2012. Chapter 2 provides details on design and implementation phases of the data collection exercise. With financial support from GIZ, I spent about three months collecting data on the adoption of exotic varieties of mango. I surveyed both adopters and non-adopters in Northern, Brong-Ahafo and Eastern regions. The total sample is composed of 305 farmers, 196 adopters and 109 non-adopters, of which about 60% are very small farmers (with three or less acres of land). The field work experience provided me with a much better understanding of the major constraints related to the adoption of exotic mango, and, at the same time, enriched me with better insights on

how to deal with field work related challenges. This knowledge and experience constitute, for me, invaluable personal resources for future fieldwork activities.

Using the data collected during the field work, I investigate, in Chapter 3, the role of social capital in the adoption of product innovation, exotic varieties of mango, following the seminal works by Bandiera and Rasul (2006) and van Rijn et al. (2012). The analysis aims to understand what the main factors that affect farmers' decision to innovate are, and also describes the reasons why some farmers innovate earlier and more intensively than others, with a focus on social capital factors. Social capital is included in both its aggregated, as composite indexes, and disaggregated forms, and it covers its three main components: structural bridging, structural bonding and cognitive. The results are consistent with previous empirical evidence in supporting the relevance of social capital, especially in the form of social networks, in fostering the adoption of product innovation. The findings also show that different change agents might be relevant in the decision to adopt earlier or more intensively than others. For example, the results suggest that while development agencies accelerate the time of adoption, NGOs are more relevant in the decision to adopt more intensively. On the other hand, the results tend to support the idea that both farmers' organisations and Ministry of Agriculture extension officers tend to delay the time of adoption.

Finally, Chapter 4 evaluates the main assumption that adopting product innovation, such as exotic varieties of mango, has an effect on farmers' well-being. The rationale for the widespread support of the adoption of exotic varieties of mango has been its potential in reducing poverty. I question this rationale using both objective and subjective measures of poverty, collected during the field work. The objective measure of poverty is based on the estimation of an asset index using principal component analysis. The subjective measure of poverty is based on the "Economic Ladder" question which asks farmers to locate their economic status on a step from 1 to 9 relative to other people in the village. The empirical analysis makes use of matching techniques in an attempt to identify a counterfactual. The estimations of the Average Treatment Effect on the Treated show that the adoption of exotic varieties of mango has indeed had a positive effect on farmers' well-being. However, this effect is almost exclusively observed for subjective poverty. Hence, the effect of adoption on poverty defined using the asset index is often not significant, suggesting that adopters are not better endowed or able to accumulate

assets more than non-adopters. I explore these results further comparing early and late adopters, respectively, to non-adopters, and also examine cultivation and marketing differences between poor and non-poor mango farmers, which suggest that early adopters benefited more than late adopters and that poor mango farmers do struggle in accessing positive returns from mango adoption compared to non-poor mango farmers. Conversely, the results support the idea that mango farmers do feel less poor than non-mango farmers. The expectation of future positive returns and the awareness that innovation might have benefited themselves or other adopters in the past might have made adopters perceive their economic status in a more optimistic way.

The last part of this thesis is the conclusion. This section summarises the most important insights from the analyses and it provides some policy recommendations.

CHAPTER 1

Determinants of market participation in Ghana: an analysis of three rounds of the Ghana Living Standard Survey

Introduction

When we talk about market participation, we usually think about it as a simple, almost natural process by which an individual sells or buys goods or services in exchange for cash income. From boot sales of unused furniture in Western countries to petty trade of fruits in the streets of rural Ghana, market activities occur and look like the smoothest of any economic transaction. However, the reality in rural areas in developing countries is that access to markets is, instead, a very complicated process, and related risks and costs constantly hinder participation of those farmers whose endowments do not match market demands.

Notwithstanding the effort of both development agencies and national governments in "getting the price and market right", farmers in developing countries still experience enormous difficulties in accessing formal market channels. Barrett (2008) reports that, across 16 studies, 9 African countries and a period of about twenty years, market participation rates among smallholder farmers vary by country and market type but they overall remain pretty low, from a minimum of 22% to a maximum of just above 40%.

In Ghana, market participation rates also vary by type of crops, farm characteristics and location. For food producers, such as maize growers, it ranges from a minimum of 31% among very small farmers (less than one hectare) located in the savannah agro-ecological zones, to a maximum of 70% among farmers with four to five hectares of land located in coastal agro-ecological zones (Ghana Statistical Services, 2007; Musah et al., 2014; Martey et al., 2012; Brempong et al., 2013).

The extent of market participation, often defined as degree of agricultural commercialisation, is generally observed to be quite low in Ghana. In 2007, the Ghana Statistical Service estimated that less than half of the produce was sold in the market. In a recent analysis on maize growers in Upper West and Upper East regions, Musah et al.

(2014) show that, although about 50% of the maize farmers do participate in the market, only 24% of the produce is actually sold, compared to the national average of about 33%. Martey et al. (2012) show that the degree of farmers' commercialisation in Central region varies depending on the crop marketed. For example, while 53% of the produce is sold by maize growers, about 72% of the produce is, instead, sold among cassava producers, suggesting a considerably higher degree of marketability of this staple crop compared to the national average. Moving away from the major staple crops, Brempong et al. (2013) show that higher marketability can be observed also for horticultural crops, such as tomatoes or pineapples. They estimate that about 64% of the horticultural produce is sold on average in Brong-Ahafo and Eastern regions[1].

Several studies have tried to identify the major facilitators and inhibitors of market participation and its extent and, more recently, a strand of the literature embedded the notion of transaction costs in the market participation framework. Transaction costs are often approximated with those measurable factors that are thought to mitigate fixed costs (ownership of communication and transport equipment) or explain proportional costs, as, for example, distance to market.

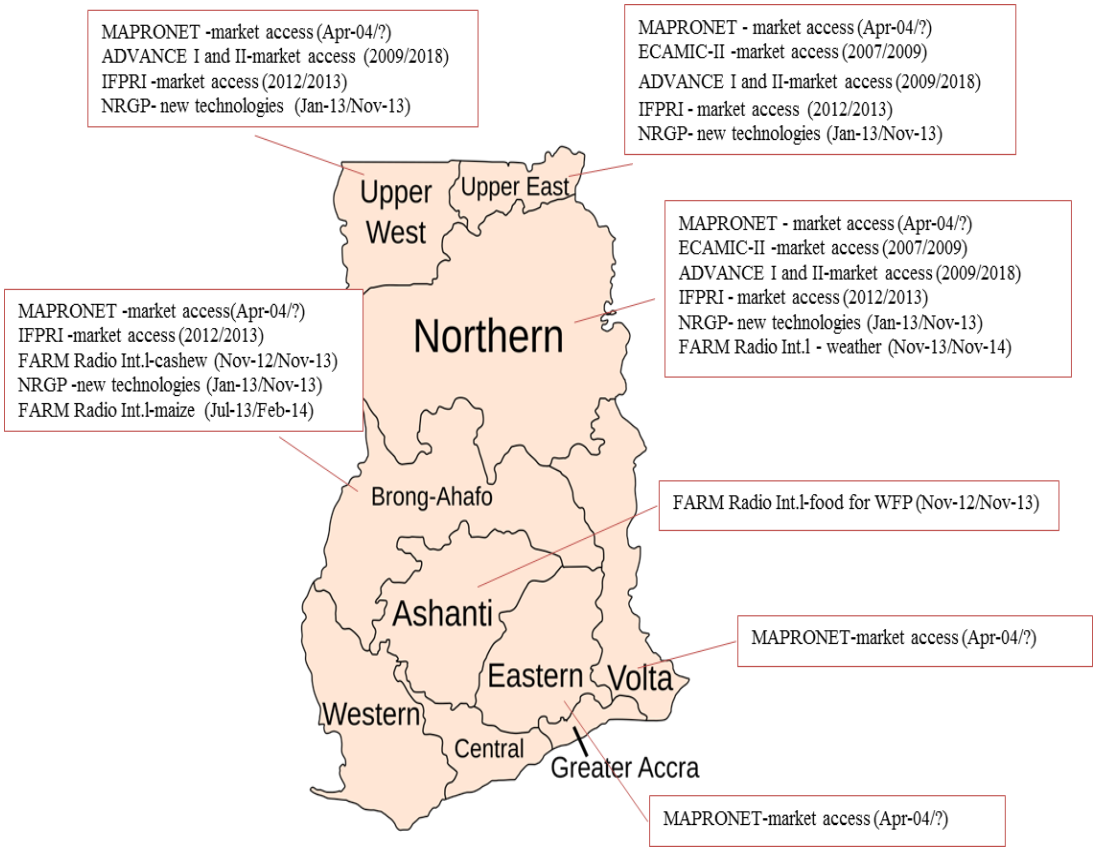
In Ghana, there has been an intense work in the past decade by development agencies and government towards the reduction of transaction costs related to market participation. Communication assets, such as radios and mobiles phones are, indeed, becoming important vehicles of marketing information[2]. In addition, several other projects have been working on disseminating market information and improving market infrastructure to facilitate agricultural commercialisation (Figure 1)[3].

[1] These two regions are considered among the most commercialised in the country and as such could provide an overestimation of the rates.

[2] For example, Farm Radio International currently runs a project in Brong-Ahafo and Ashanti regions started in 2012 for maize and cashew producers, while Radio ADA disseminates price information in the Greater Accra and Eastern regions.

[3] One important project aiming to increase market participation through the use of mobiles has been supported by the International Finance Corporation of the World Bank that specifically invested in the private mobile phone company, called Esoko, to extend its SMS-based mobile phone service to include weather information and prices, among other ad-hoc marketing service (World Bank, 2011). Currently, Esoko provides push SMS, a voice help line, extension service and weather information in all the local Ghanaian languages. Information on prices are collected regularly from 60 markets nationwide and disseminated to their subscribers for free, for a basic bundle, and for a small fee in the case of more ad-hoc services. The size of their coverage in Ghana is not clear although they have been cooperating with NGOs since 2007, with the program SEND, and with IFPRI and IFAD for the dissemination of information in the Northern region since 2011. In addition, cocoa and pineapple farmers are claimed to have been part of the platform in the past four/five years.

Figure 1 Dissemination on market information in Ghana



This paper aims to analyse the major determinants of agricultural commercialisation via market participation in Ghana, with a specific focus on the role of transaction costs, usually measured by transport and communication assets ownership and households' location. I use a sample of 14,736 rural farming households drawn from three rounds of the Ghanaian Living Standard Surveys (GLSS 4, GLSS 5 and GLSS 6). The analysis aims to investigate market participation with regards to the decision to sell or not (the discrete decision of market participation) and the decision of how much to sell (the continuous decision of the extent of market participation, i.e. commercialisation). Thus, this paper studies market participation as a two-step decision process whereby self-selection confounding effects will be taken into account, using the Heckman two-step approach.

The analysis investigates, first, the determinants of market participation and its extent, commercialisation at aggregate level, i.e. household level, as measures of transaction costs are only available at household and village levels in the GLSS data. Then, the

analysis turns the focus on one of the most important staples grown in Ghana, i.e. maize. The advantage of carrying out the analysis for a specific crop is that different effects of different types of transaction costs can be observed more clearly, as they can have specific crop related relevance. For example, food crops are normally associated with lower barriers to market participation because of the low quality and quantity requirements, but they are also claimed to have higher transaction costs, due to search costs, uncertainty related to quality and quantity and the need for the buyer to engage in frequent quality inspections (Boughton et al., 2007). GLSS data do not provide detailed information on single market transactions for the majority of the crops produced in the sample. However, information on preferred sale outlets for a selection of crops is available. Using these data, I investigate the decision of maize market participation using a multinomial logit model, which compares non-participation to participation in two different outlets: farm gate and market trader.

This study aims to identify associations, and not causality, between commonly identified inhibitors and facilitators of market participation. It contributes to the market participation literature as it provides insights on the role of transaction costs in relation to the rural Ghanaian context using the latest secondary data available, which has, to my knowledge, not been done in the past. Also, the two levels of aggregation of the analysis carried out only using secondary data, available to government and development practitioners, contributes in providing an overall, household level, picture of the determinants of market participation but it also describes them in the context of one of the most important crop in Ghana, maize.

The next sections are organised as follows. Section 1 summarises the market participation literature; Section 2 describes the conceptual framework of market participation under transaction costs; Section 3 presents the main descriptive statistics of the sample; Section 4 describes the empirical model and Section 5 and 6 present and discuss the results at household and crop level, respectively. Finally, Section 7 summarises the main results and draws the conclusions of the analysis.

Section 1. A brief literature review

The puzzling evidence that market participation rates remain persistently low especially among poorer and more remote farmers in Africa has motivated numerous scholars in the investigation of potential facilitators and inhibitors of access to markets. The literature covers both crops with high and low marketability, such as cash crops and food crops. Compared to cash crops, staple crops are usually associated with low market barriers to entry, high transaction costs and relatively low return per unit of production or low value for weight (Goetz, 1992; Makhura et al., 2001; Alene et al., 2008; Omiti et al., 2009; Bougthon et al., 2007; Longhurst and Lipton, 1989).

Aside from location related inhibitors, poverty, assets and low adoption of technologies are among the main household's characteristics that could hinder market participation. Several studies have shown that better endowed farmers find it easier to access markets because they can use their assets (and the disposable income generated by the use of these assets) as collateral for the purchase of productivity enhancing technology (improved seeds, machinery etc.). Better endowed farmers can also divert factors of production away from staples towards higher return cash crops, as they are able to secure food needs via market purchases. Assets, especially farm assets and land, are found to be strongly associated with market participation and its extent (de Janvry et al., 1991; Fafchamps, 1992). Barrett (2008) shows that in Mozambique the probability to participate increases substantially for farmers with a land size bigger than four hectares. Several other studies censor their sample based on the size of the land cultivated. Key et al. (2000), in their study of Mexican corn producers, for example, only select farmers with more than 10 hectares because any lower land endowment is deemed to be strongly associated with self-sufficiency production. Brempong et al. (2013) show that land and labour productivity are important determinants of tomato market participation and its extent in two regions in Ghana, while, in addition to land productivity, access to savings facilitates market access in the pineapple sector. Similarly, Musah et al. (2014) and Martey et al. (2012) find that both farm size and wealth are significant predictors of both market participation and its extent among staple producers in the both Northern and Central Ghana.

Conversely, previous works show that other common sources of wealth, such as livestock ownership, access to credit and off-farm income, may act as market participation inhibitors, because of substitution effects with crop cash income. The expected negative association between market participation and, for example, livestock ownership and off-farm activities, may derive from the rational choice between crop farming and alternative livelihood activities. Although producing crops and selling some of the produce, some households might be running alternative economic activities as their main source of livelihood and, as such, the decision to participate in the crop market and how much to participate could be negatively affected when the household prefers relying on these alternative livelihood activities, instead. Moreover, livestock are commonly used as collateral in periods of income shortage and they act as a "walking bank" in substitution of other income sources (Bellemare and Barrett, 2006). Similarly, access to credit might be negatively associated with market participation as it can provide an alternative source of disposable income to secure food access and investments in farming productivity (Alene et al., 2008).

On the other hand, studies also show that the role of these inhibitors might change with the type of crops under scrutiny. In fact, some studies show that access to credit might, instead, foster market participation in the case of food crops, as it can be used for investments in higher yielding varieties, longer cycle crops, seasonal inputs and improved technology, which in turns may facilitate market participation (Barrett, 2008, Musah et al., 2014). The same case is found for off-farm income in the maize and cassava market participation by Martey et al. (2012) in Central Ghana. There is also evidence that the association between higher food crops productivity, market participation and cash crops production may be explained by the fact that often farmers use credit and inputs obtained through cash crops contracts, also for staple production processes (Barrett, 2008).

Another important inhibitor of market participation is the gender of the farm manager or household head. Some authors, such as Cunningham et al. (2008), argue that men are likely to sell more due to their *acumen* in bargaining and in negotiating and enforcing contracts. Also, there is a general consensus on the idea that there exists a set of "gender discriminated" crops whereby women are traditionally more involved in the production of staple or petty tradable crops, while men usually manage cash crops productions,

which have a higher marketable scope than food crops (e.g. Zamasiya et al., 2014). Although this is generally true, recent developments have shown that, through market cooperatives and access to higher value chains, as in the case of rice and shea-butter in the Northern region of Ghana, this agricultural gender divide might be evolving with time, towards a more equal distribution of production and marketing opportunities (Zanello et al., 2014).

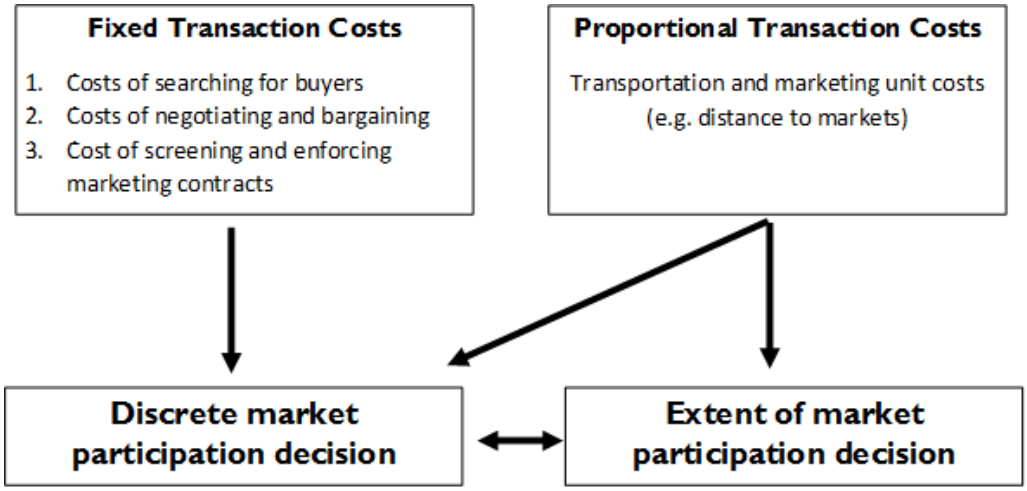
Despite the relevance of determinants described so far, a relatively recent literature strand focuses on the role of market related transaction costs. Several authors claim that the first set of constraints that farmers experience in accessing markets are risks and uncertainties related to prices and potential buyers, in presence of segmented or isolated markets, as it is in the case of rural areas. These uncertainties translate in transaction costs that could hinder market participation. In fact, due to the imperfect spatial price transmission, imperfect competition and asymmetric information, farmers may face multiple equilibria scenarios where also self-sufficiency might be an optimal choice, which could explain the low market participation intensity especially in rural areas (Fafchamps, 2004; Barrett, 1995).

Transaction costs are not a new concept in economic theory as they have been introduced in the literature by Coase back in 1937. They are usually described as "unobservable and observable costs associated with the exchange of goods and services" (Jagwe et al., 2010). The role of transaction costs in the market participation literature had largely been overlooked until the work of Goetz in 1992 and Key et al. in 2000. Since then, several authors have empirically and theoretically demonstrated that transaction costs matter in the explanation of why farmers have difficulties in accessing the market. They also explain how different costs affect in different ways the decision to enter the market and the extent of that participation, i.e. commercialisation.

More specifically, two types of transaction costs have been identified in the past literature: fixed costs and proportional costs. The former include the costs of searching for buyers, of negotiating and bargaining as well as of screening and enforcing marketing contracts. Proportional transaction costs, on the other hand, are defined as transportation and marketing unit costs, and as such are proportional to the extent of market participation. Fixed costs, which are mainly related to access to market information, are claimed to affect only the decision to sell or not, while proportional

costs are deemed to affect both the decision to entry as well as the decision of how much to sell (Figure 2).

Figure 2 Market participation and transaction costs



While households, crop and location specific determinants of market participation are generally easily quantifiable through household's surveys, it is commonly known that transaction costs are, instead, very difficult to measure for economic analysis for several reasons. First, if transaction costs are too high, market transactions do not occur and as such the analysis itself becomes not feasible. Second, when farmers do not have access to transportation or communication intermediaries these costs are very difficult to estimate. Even in the case when intermediaries exist, quantifying the cost of the time spent by farmers in marketing activities is extremely challenging (Key et al., 2000). As a consequence, transaction costs enter the empirical analysis through those observable factors that explain (e.g. distances to markets) or mitigate them (ownership of transport and communication equipment, age, level of education, etc.) (Alene et al., 2008).

The evidence of the effect of fixed transaction costs, measured as the cost of accessing market information, is often not consistent across the literature. For example, age is usually associated with higher risk aversion and lower propensity to adopt new technology and as such it is found to be negatively associated with market participation (Alene et al., 2008; Adeoti et al., 2014; Musah et al., 2014; Makhura et al., 2001). However, other studies found an opposite association of age with market participation, as, for example, in the case of maize farmers in Nigeria (Adenegan et al., 2012) and among cotton farmers under contract farming in South Africa (Randela et al., 2008). These studies suggest that older farmers would sell more often and more of their output

to offset their increasing physical inability to produce their own crops. Also, older farmers might be more experienced in farming activities and this could increase their ability to participate in the market (Adenegan et al., 2012).

Moreover, while education, ownership of radio and bicycles are found to facilitate market participation, via access to market information (Martey et al., 2012), the differential relevance that these costs might have in influencing market participation and/or its extent is not always clear. There is evidence that these fixed transaction costs may affect both the decision to sell or not and the decision of how much to sell. Heltberg and Tarp (2002) and Boughton et al. (2007), for example, both show that ownership of transport equipment (bicycle and motorcycle) increase both market participation and level of commercialisation among food producers in Mozambique. Similarly, Sibiza et al. (2010) show that, in Central and Northern Mozambique, for maize farmers ownership of a radio only affects the value of sales (i.e. extent of market participation), while it is associated with both market participation and its extent, in the case of cotton farmers. Alene et al. (2008), on the other hand, find a significant association only between these fixed transaction costs and market participation, and not its extent, among maize farmers in Kenya.

Proportional transaction costs, often measured as distances to markets, to extension officers, or to motorable roads are generally found strongly and negatively associated with both the intensive and extensive margins of market participation (e.g. Alene et al., 2008; Martey et al., 2014; Makhura et al., 2011). The direction of this association, however, can depend on the marketing systems of the area under analysis. For example, while, theoretically, a higher transaction cost (and a lower market participation and its extent) is expected with longer distances, Zamasiya et al. (2014) find that the extent of market participation increases the further away farmers are from the market. They argue that, because relatively lower prices are usually offered in sale outlets which are further away from the main markets, farmers might be pushed to reach distant markets where higher prices, and so higher value of sales, could be obtained. Zanello et al. (2014), on the other hand, argue that the majority of market transactions in Northern Ghana occur at farm gate or through personal relationship with market trader, especially in remote rural areas. Following this argument, even in remote areas farmers are able to participate in the market as they will be regularly visited by traders and therefore

remoteness to markets might not necessarily represent proportional transaction costs in the market participation decision in these contexts. In remote areas farmers may, indeed, rely on good social capital relationship when there is a certainty that a buyer will eventually turn up. These relationships are found to play a facilitating role in market participation in Ghana, especially in the Northern and Central regions among food crops producers (Zanello et al., 2014; Martey et al., 2014).

Section 2. A model of market participation in the presence of transaction costs

2.1 Conceptual framework

The conceptual framework draws from past literature and in particular from Barrett (2008), Key et al. (2000) and Alene et al. (2008). They use a non-separable agricultural static model where a hypothetical households, *i*, maximises its utility, defined over a consumption of a vector of agricultural commodities, y^c for c = 1,. . . ,C, and a Hicksian composite of other tradables, *x*, subject to its budget and crop level production technology constraints. The cash budget constraint vector includes access to substitutes of crop cash income (such as livestock, credit and non-farm income, W_i). In addition, the household faces private (A_i) and public assets constraints (G_i), a parametric market price for each crop ($p^m{}_i$) and a vector of proportional transaction costs, τ_{pi}, and fixed transaction costs, τ_{fi}[4]. The optimization problem can then be written as follows:

$$Max\ U(y_i^c,\ x_i) \tag{1}$$

where y_i^crepresents the consumption of a vector of agricultural commodities *c* and x_i is a vector of other tradables. The optimization problem is subject to:

1) The cash budget constraint:

$$p^x x_i + \sum_{c=1}^{C} M_i^{cb} p^{c*} y_i^c = \sum_{c=1}^{c} M_i^{cs} * p^{c*} f^c(A_i^c, G_i) + W_i \tag{2}$$

where $p^x x_i$ is the value of other tradables bought; M_i^{cb} is equal to 1 if the household buys any commodity, and 0 otherwise; p^{c*} is the price paid for commodity *c* and y_i^c is the quantity bought; M_i^{cs} equals to 1 if the household sells any commodity, and 0 otherwise; p^{c*} is the sale price of the commodity; which is function of private, A_i^c, and public assets, G_i^c; W_i is the access to substitutes of crop cash income. The left hand side represents household's consumption and the right hand side represents total revenues from sales of own produced, which is function of private, A_i^c, and public assets, G_i^c, and earnings from substitutes of crop cash income, W_i.

[4] Barrett (2008) also includes total value of sales in the conceptual framework. However, in the empirical analysis of this chapter, this variable is not included for endogeneity issues with the second stage of the Household Commercialisation Index as described below. As a consequence I am omitting this variable from any of the equations discussed here.

2) The non-tradables' availability constraints:

$$A_i = \sum_{c=1}^{C} A_i^c, \text{ subject to} \quad (3)$$

$$\left(1 - M_i^{cb}\right) y_i^c \leq f^c(A_i^c, G_i) \forall\ c = 1, \dots, c$$

where A_i represents the vector of private assets (e.g. land) that is allocated for the production of crops, *c*.

3) The parametric price, adjusted by the presence of variable transaction costs:

$$p^{c*} = (p^{cm} - \tau_{pi})\ if\ M_i^{cs} = 1 \quad (4)$$

$$p^{c*} = (p^{cm} + \tau_{pi})\ if\ M_i^{cb} = 1 \quad (5)$$

so that *proportional* transaction costs, τ_{pi}, decrease the price received in a sale transactions and increases the price paid in a purchase transactions.

4) The presence of fixed transaction costs:

$$\tau_{fi} \int_{0\ if\ M_i^{cs}=0}^{>0\ if\ M_i^{cs}=1} \quad (6)$$

such that they can only be observed if market participation occurs and they do not affect the extensive margins of participation, i.e. the amount of sales.

The optimization problem can be re-written as follows:

$$Max\ U(y_i^c, x_i) =$$

$$U\left(p^x x_i + \sum_{c=1}^{C} M_i^{cb}\left(p^{cm} + \tau_{pi}\right) y_i^c - \left[\sum_{c=1}^{c} M_i^{cs} * (p^{cm} - \tau_{pi}) + \sum_{c=1}^{c} M_i^{cs} \tau_{fi}\right]\right) \quad (7)$$

From (8), the decision to participate, M_i^{cs}, and the extent of participation in the market, Q^{cs}, can then be written as follows:

$$M_i^{cs} = f(A_i, G_i, W_i, p^{cm}, \tau_{pi}, \tau_{fi}) \quad (8)$$

$$Q^{cs} = f(A_i, G_i, W_i, p^{cm}, \tau_{pi}) \quad (9)$$

2.2 Empirical model

The empirical model follows the conceptual framework described above. Both the decision to participate and the decision of the extent of this participation are investigated. The household level decision to participate in the market can be expressed as follows:

$$M_i^s = \beta_0 + \beta_1 A_i + \beta_2 G_i + \beta_3 W_i + \beta_4 \tau_{fi} + \beta_5 \tau_{pi} + \beta_6 r + \beta_7 y + \mu_i \quad (10)$$

Where M_i^s is equal to 1 if the household i participated in the market in the survey year and 0 otherwise; A_i, is a vector of household's characteristics and private assets; G_i is a vector of public assets; W_i is access to non-crop cash income; τ_{fi} and τ_{pi} are vectors of fixed and proportional transaction costs, respectively; r are regional dummies, y are year dummies; μ_i is the error term[5].

While the decision of the extent of market participation i.e. commercialisation, will be estimated using the following specification:

$$HCI_i = \beta_0 + \beta_1 A_i + \beta_2 G_i + \beta_3 W_i + \beta_6 \tau_{pi} + \beta_5 r + \beta_6 y + \mu_i \quad (11)$$

HCI_i is the Household Commercialisation Index (0-100) which is calculated as the ratio of total value of sales to total value of production for household i (see paragraphs below).

The goal of equation (10) is to estimate the binary decision to participate in the market. On the other hand, equation (11) is used to estimate the decision of how much to participate. The main difference between the two equations is the inclusion of proportional (τ_{pi}) and fixed (τ_{fi}) transaction costs in the right hand side as explanatory variables. Following the literature, the decision of how much to sell (11) is not function of fixed transaction cost. Nonetheless, considering the often contrasting empirical findings on their role in explaining the extent of market participation, the effect of fixed transaction costs on the level of commercialisation remains, to my view, an empirical question.

[5] The vector of prices is not included either in the equation (11) or (12) because prices, although collected in the GLSS, were not available in the datasets used for this analysis. Also, due to the cross sectional nature of the data, including prices could have created serious additional problems of endogeneity and reverse causality. Farmers in this analysis are assumed to be price takers. Prices mostly vary by location, type of crop and time. Including controls for these indicators could approximate for the omission of price information.

The data

The data I use are drawn from three rounds of the Ghanaian Living Standard Survey. The data cover three survey years: 1998/1999 (GLSS 4); 2005/2006 (GLSS 5) and 2012/2013 (GLSS 6). To my knowledge no other previous analysis has been done using the latest GLSS survey for the analysis of determinants of market participation. GLSSs are nationally representative independent cross sectional surveys collected by the Ghana Statistical Service in collaboration with the World Bank, UK-DFID, UNICEF and ILO. The surveys collected detailed information on demographic characteristics of respondents and all aspects of living conditions including health, education, housing, household income, consumption and expenditure, credit, assets and savings, prices and employment.

From the total sample of 31,457 households (5,998 households in GLSS 4, 8,687 households in GLSS 5 and 16,772 households in GLSS 6), my sample is only composed of rural farming households for which data on crop level production and sales as well as community level information are not missing. Rural households are defined as those households that are located in rural areas as identified by the surveys. A farming household is, instead, defined as such if the main activity of any member of the household is farming on their own land[6].

The final sample is composed of 14,736 households, 3,117 households from GLSS 4; 4,172 from GLSS 5 and 7,447 households from GLSS 6, which corresponds to 47% of the total number of households and 81% of the rural households of the pooled sample of the three rounds of GLSS.

[6] This definition of farming households could be considered too broad as some households, although producing and possibly selling their produce, may not consider themselves "farmers" as they are predominantly engaged in other livelihood activities. In order to ascertain the degree by which this definition affects the results, I also estimate the empirical models of market participation and its extent using a more restrictive definition of farming household. More specifically, I run the analysis for the sub-sample of households whose agricultural income is bigger than 20% of the total income. Although this threshold is arbitrary, it seems reasonable to assume that it could at least provide insights on the differences that a more restrictive definition would make on the final results. The full estimations are attached in the Appendix 1.1. The results are overall consistent with the model presented in this paper, especially with regards to the transaction costs variables. However, some differences can be pointed out. First, the selection coefficients in the Heckman models are never significant suggesting that selection biases are less relevant for this group of farmers. Second, higher education and access to non-farm income is found positively associated with the extent of market participation suggesting a complementary role between education and alternative cash income with the market participation decisions. Finally, farm size and land ownership matters more for this group of farmers as they are found to be positive and significantly associated with the decision to sell or not to sell. However, using measures of income in the context of developing countries is often criticised because of the high degree of measurement error involved. Accordingly, these results might be affected by an a priori measurement error that informed the selection of the sub-sample of households. As a consequence, I think that the main model based on the entire sample of rural farming households could provide a better framework for the analysis.

The dependent variables

Market participation

The definition of market participation I use for this analysis only captures the "sale" transactions of any type of crop and, as such, a household is defined as market participant if it engaged in the sale of any of its crops in any market outlet during the 12 months preceding the time of each survey. On the other hand, a household is defined as non-market participant if it did not engage in any sale transaction during the same period.

The extent of market participation (commercialisation)

While market participation identifies the *discrete* decision to sell or not to sell, commercialisation reflects the decision on the *extent* of the market participation. The measure of commercialisation that I am going to use follows Govereh et al. (1999) and Strasberg et al. (1999) who created a simple Household Commercialisation Index which is based on total value of sales and total value of production and it is formally expressed as the ratio of total value of sales TS_i to total value of production TQ_i at household level, expressed in percentages:

$$HCI_i = \frac{TS_i}{TQ_i} * 100, \qquad 0 < HCI_i < 100 \qquad (12)^7$$

Different measures of commercialisation have been proposed in the literature. Some studies focus on the degree of farm and crop specialization, as proxies for a more or less commercialised farming system (Bezabih and Sarr, 2012; Kasem and Thapa, 2011). There have also been attempts to formalise the measure of commercialisation into indexes. First, von Braun et al. (1994) suggest the use of three indexes: the proportion

[7] Some authors apply a lower cut-off to the HCI or equivalent measures of commercialisation in a way to distinguish between "occasional" market participation and "real" commercialisation. Although in the main specification I do not apply any cut-off which could increase distortions by reducing my sample size, I also run a sensitivity check estimation using the 25th percentile of the HCI as lower cut-off in the estimation of the determinants of commercialisation. The full results are attached in the Appendix 1 and they show consistent results with the main model regarding the main variables of interest, transaction costs. However, some differences can be pointed out. First, land ownership becomes significant in the decision to sell or not to sell. Second, in the analysis of the extent of market participation, gender of the head of the household loses relevance as also farm size. In addition to the main determinants observed in the main models, higher education and food only production are positively associated with the extent of market participation while access to credit and distance to the extension officer are negatively associated. Another discrepancy with the main estimations, is the insignificance of the lambda coefficient which suggests that, for this group of farmers, selection bias is less relevant when controlling for the selected observable characteristics. Also, the sign of the lambda changes direction. If significant, that would have meant that the unobservables that determines market participation are negatively associated with the unobservables that affect the extent of commercialisation.

of output sold and input bought from the market to the total value of agriculture production; the ratio of value of goods and services acquired through market's transactions to total household's income; ratio of value of goods and services acquired by cash transaction to the total household's income. Similarly and more recently, Gabre Madhin et al. (2007) use four approaches to measure household's commercialisation (sales to output ratio, sales to income ratio, net absolute market position and income diversification) which includes measures of the degree of specialization of the agricultural production.

The HCI index (calculated as in (12)) has been preferred for its simplicity and because it fits better the purpose of the analysis which only focuses on the "sale" side of the output market transactions at household level. Other measures of commercialisation, described above, extend the breath of the analysis to the demand side of market participation in trying to understand what the determinants of the choice to be a net buyer or seller are, most of the time at crop level. Other measures, instead, capture production constraints and demand for inputs which do not fit the objective of this analysis. My main investigation aims to investigate the decision to *sell* and *how much to sell* in *aggregate* for *all* the crops and for one staple crop (maize) produced by *the entire household*. Hence, the choice of HCI.

The explanatory variables

The explanatory variables were chosen following the past literature and they are listed in Table 1. The role of fixed transaction costs is going to be estimated through the effect of four observable household characteristics: age, education and ownership of transport and communication equipment. They are expected to affect only the discrete choice of whether to participate or not. Age is expected to have an ambiguous effect on market participation: it could reduce the probability to participate, due to risk aversion and lower propensity to innovate issues, or it could increase the probability because of the increasing needs for cash income with age and because it could capture longer farming experience. Education, on the other hand, is expected to have a positive effect on market participation via the improved capability in interpreting and using market information, and as such reducing fixed transaction costs (Makhura et al., 2001).

The ownership of radio is expected to mitigate the costs of accessing markets in my sample, due to the increase of radio marketing information services in the past decade.

Finally, the ownership of a bicycle is also expected to mitigate fixed costs of accessing the market. However, as Alene et al. (2008) have pointed out, bicycles may also serve as facilitators in the decision of how much to sell as they could be used not only to physically reach the market for gathering information but also for transporting crops to the market itself. Hence, especially for this variable, the empirical question on whether it should be considered linked to fixed or proportional cost is particularly relevant.

Proportional transactions costs are included in the form of distances to periodic market and extension officer. These distances are expected to affect negatively both the decision to participate in the market and the extent of the participation. Following Alene et al. (2008), I convert the continuous variables (expressed in km) in dummy variables to avoid threshold effects. Hence, each distance explanatory variable equal to 1 if the distance is larger than the median value and 0 otherwise.

The main variable of interest in this group is distance to market. The expected effect, although usually negative, is not that clear in studies of the Ghanaian context. As several authors have pointed out, marketing transactions very often occurs at farm gate or in the village of residence (e.g. Zanello et al., 2014). Qualitative studies have also shown that the role of intermediaries or "market women", even more nowadays with the diffusion of mobile phones, is quite strong and widespread across the country (Burrell, 2014). It is, indeed, very common that traders travel to communities and farms to buy crops and sell them at the periodic markets or to other traders. Long lasting relationship and social ties with these market traders may increase the ability to sell more or at a better rate when farmers are further away from the main markets. Also, the price differential between local, assumed rural and remote, and further away markets, assumed more urban and dynamic, could justify a positive relationship between distance to market and the extent of market participation, i.e. value of sales (Zamasiya et al., 2014).

Aside from variables expected to explain or mitigate transaction costs, other explanatory variables include: gender of the head of the household (capturing gender differences in marketing choices), farm labour, farm size and land ownership (as proxies of wealth),

substitutes of cash crop income (livestock, access to credit, access to non-farm income) and measures of crop diversification (food only production) [8].

Table 1 Explanatory variables

	Description	Expected sign	Expected relevance for*:
Fixed transaction costs			
Age head	Age of household head in years	-/+	MP
Primary or lower education	Dummy variable equal to 1 if the highest level of education of household's head is primary (some or all); 0 if household's head has no education.	+	MP
Secondary or higher education	Dummy variable equal to 1 if the highest level of education of household's head is higher than primary; 0 if household's head has lower education levels.	+	MP
Ownership of radio	Dummy variable equal to 1 if household owns a radio; 0 otherwise	+	MP
Ownership of bicycle	Dummy variable equal to 1 if household owns a bicycle; 0 otherwise	+	MP
Proportional transaction costs			
Distance to nearest periodic market	Community level variable, dummy variable equal to 1 if distance is bigger than the median value of distance in Km; 0 otherwise.	-/+	MP and CI
Distance to nearest extension officer	Community level variable, dummy variable equal to 1 if distance is bigger than the median value of distance in Km; 0 otherwise.	-	MP and CI
Other explanatory variables			
Male head	Dummy variable equal to 1 if household's head is a man; 0 otherwise	+	MP and CI
Farm labour	Number of household's member working on own farm	+	MP and CI
Farm size	Hectares	+	MP and CI
Land ownership	Dummy variable equal to 1 if household owns any land; 0 otherwise	+	MP and CI
Livestock	Number of livestock owned	-	MP and CI
Access to non-farm income	Dummy variable equal to 1 if household had access to non-farm income; 0 otherwise	-	MP and CI
Access to credit	Dummy variable equal to 1 if household had access to credit; 0 otherwise	-/+	MP and CI
Food only production	Dummy variable equal to 1 if household produced only food crops; 0 otherwise	-	MP and CI
Processing	Dummy variable equal to 1 if household processes any food or fish; 0 otherwise	-/+	MP and CI

*MP=market participation (0/1); CI=commercialisation (0-100)

[8] The choice of the explanatory variables for the analysis of the discrete choice of market participation has been taken simultaneously with the choice of the variables that are relevant in the decision of the extent of market participation. This resulted, for example, in the exclusion of total value of production or prices which would have been endogenous in the analysis of the extent of market participation. The simultaneous choice of the explanatory variables has been driven not only by the nature of the econometric model used, Heckman two step, whereby the omission in the second stage would have meant treating these variables as instrument for selection bias, but also by the uncertainty on whether these two marketing decision are taken simultaneously or sequentially.

Section 3. Market participation in GLSS 4, 5 and 6

Farmers in the sample participate quite actively in the market. On average about 77-78% of the sample sold any output in the market during 12 months preceding the survey periods across all rounds of GLSS. These rates are much higher than what previous studies have observed. However, this result is somehow expected as, differently from previous analysis, the market participation definition used here is much broader, including any crop produced and sold by anyone in the household. When differentiating by type of crops, the data show, in line with the expectations, that market participation rates are lower for staple crops than for cash crops, such as cocoa (Figure 2).

Figure 2 Market participation rates, selected crops

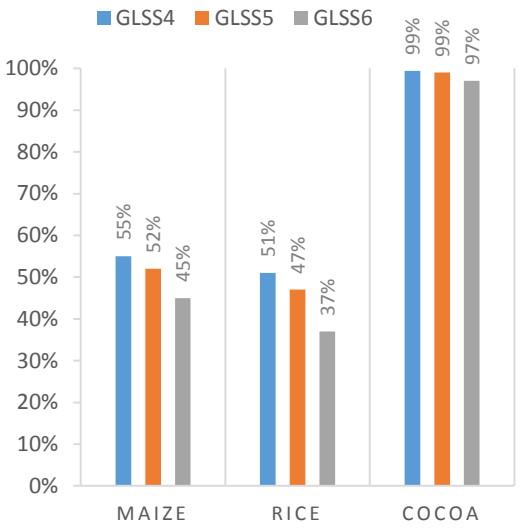


Figure 3 Market participation rates, by agro-ecological zone

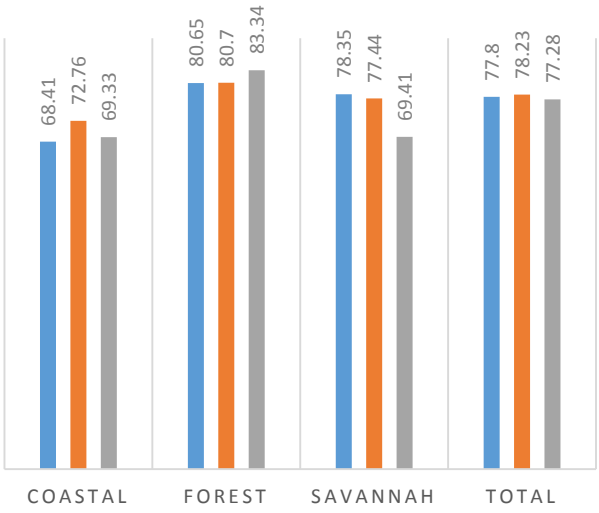
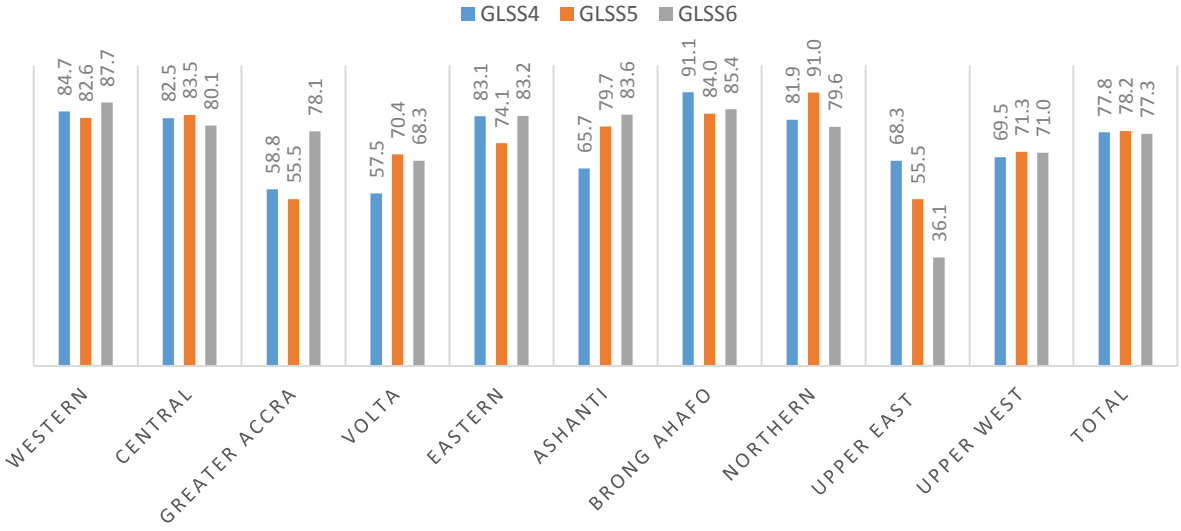
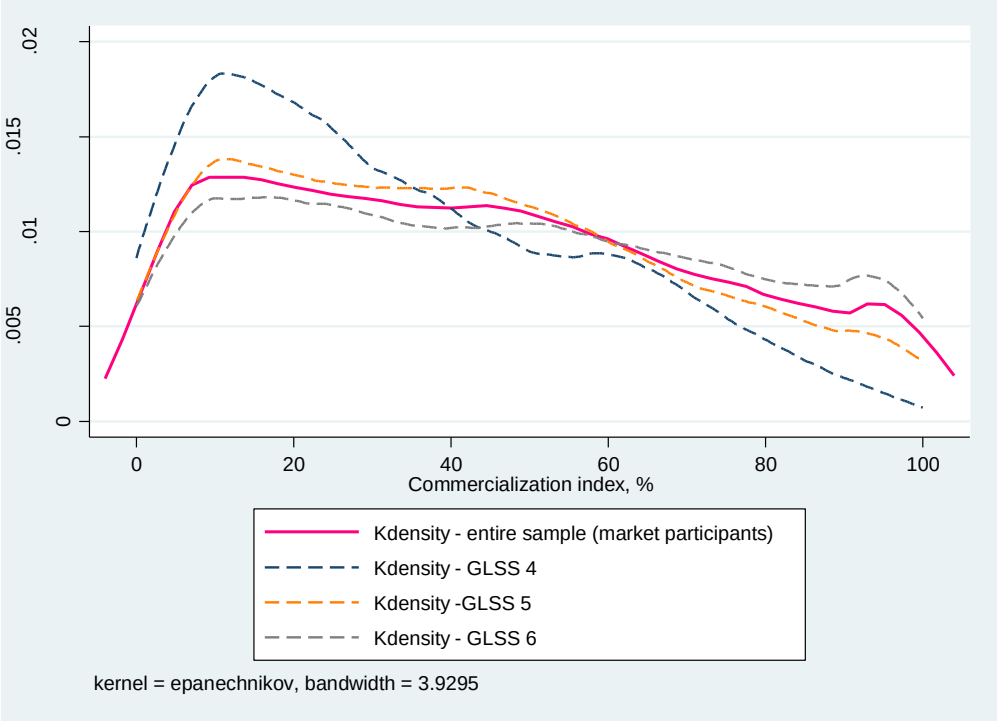


Figure 4 Market participation rates, by region



Across location and time, market participation rates appear quite similar and stable, although some regional differences can be pointed out. Overall, the highest market participation rates can be observed in the Brong-Ahafo and Northern regions and in forest agro-ecological zones, where, however, a decline from 1998 to 2013 can be noticed. Conversely, in other regions, such as Greater Accra, Eastern and Ashanti market participation rates have increased through time (Figure 3, Figure 4), maybe due to their closeness and better connection to the main shipping, packaging and marketing facilities developed in the past years in the Tema harbour, in Accra. Finally, the lowest market participation rates are observed in the Upper East region, with a minimum of 36% during 2012/2013. The rates have been declining since 1998/99 when the average market participation rate was about 68%, possibly due to the occurrence of serious agricultural stressors since 2004 (ASIS, 2014)[9]. Figure 5 shows the distribution of the Household Commercialisation Index. The figure shows that, differently from the trend of market participation rates observed above (Figure 4), the extent of market participation among market participants has increased through time (from 35% in GLSS4 to 39% in GLSS 5 and 46% in GLSS 6).

Figure 5 Household Commercialisation Index, market participants



[9] A detailed discussion of these results can be found in the Appendix 1.3.

The location disaggregated distribution in Figure 6 confirms this trend[10]. Hence, the *extent* of market participation, i.e. commercialisation, is observed to have increased steadily from 1998/99, both within regions and agro-ecological zones.

Figure 6 Commercialisation index, by region and agro-ecological zones

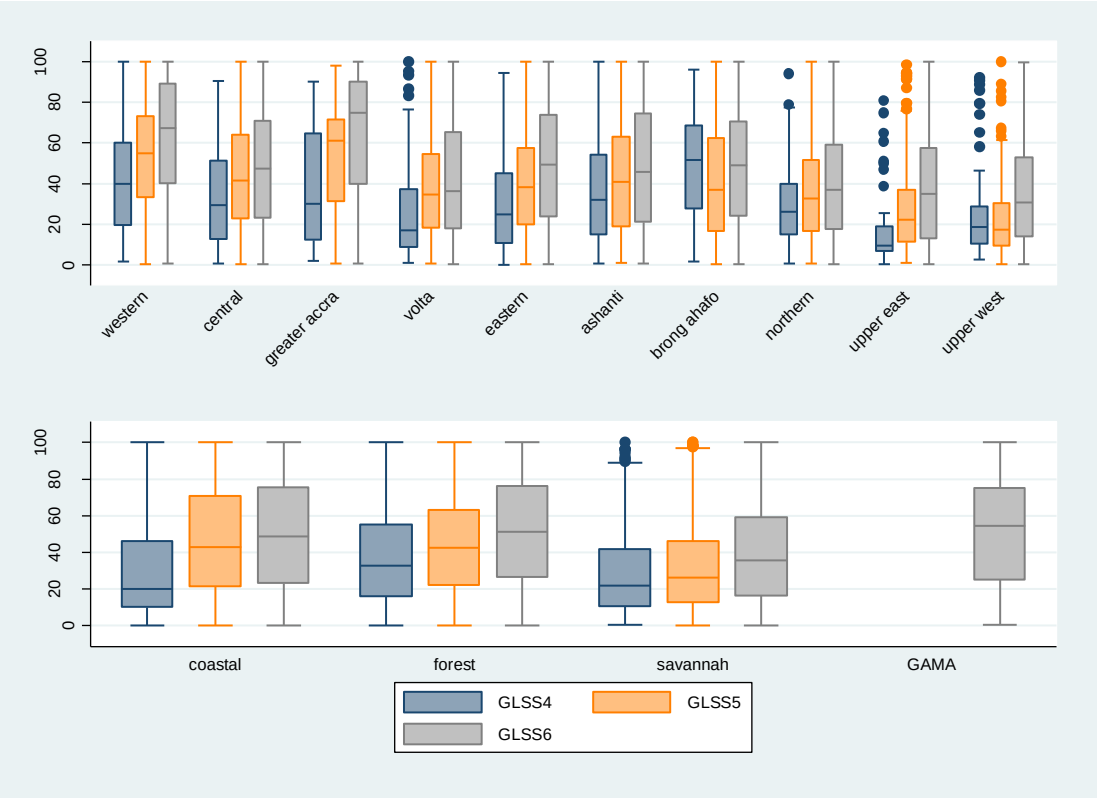


Table 2 presents some summary statistics of selected household and community level characteristics that have been used in the literature to explain market participation behaviours. The data show that market participants are mainly men, not necessarily older or better educated than non-market participants. Similarly, household size does not seem to differ that much across market participation status and time. On the other hand, farm labour, defined as the number of household's members working on their own farm, is consistently higher for market participants.

Farm size is usually bigger for sellers (i.e. market participants), which could explain why more household's members are engaged in farming activities on their own farm, but it is only significantly different from non-market participants at aggregate level and

[10] Only GLSS6 reports observation for the agro-ecological zone GAMA, Greater Accra Municipality. This is why the figure only has GLSS 6 data.

for the period 2005/06. However, the size of the farm owned as well as land ownership are both significantly higher across the three surveys.

A higher degree of production diversification is observed for market participants, who are less often food only producers. No significant difference is, instead, observed about processing activities. Market participants do not seem to be engaged in processing activities more or less than non-market participants.

Similarly, the access to substitutes for crop cash income, such as livestock, credit and non-farm income is observed to be not significantly different for market participants, aside from the access to credit which is consistently higher compared to non-market participants.

Among measures of fixed transaction costs, the summary statistics show that market participants own more commonly communication and transport assets, such as radio and bicycle, which could suggest that farmers who participate in the market may be facing lower costs in accessing market information.

As for proportional transaction costs, or transportation and marketing per unit costs, the statistics show an unclear pattern, as market participants are located generally further away from periodic markets than non-market participants. Figure 7 shows the distribution of the distance to the periodic market for non-market participants and market participants and it also seem to suggest that, over the pooled sample, market participants are located further away from a periodic market. This distance seems to increase with time, as the major differences between market participants and non-participants can be observed for the last round of GLSS (2012/13; in grey in Figure 7).

This unexpected association between remoteness and market participation could cover a simple location effect and if so a disaggregation at regional level should be able to identify a consistent trend across time of different regions. However, Figure 8 which disaggregates the distance to the market by region and by GLSS round, does not show a clear pattern across regions that could explain the positive correlation between remoteness and market participation.

Table 2 Selected descriptive statistics

		Total			GLSS4			GLSS5			GLSS6		
		NMP[1] Mean	MP[2] Mean	P-value	NMP[1] Mean	MP[2] Mean	P-value	NMP[1] Mean	MP[2] Mean	P-value	NMP[1] Mean	MP[2] Mean	P-value
Male head	(0/1)	0.66	0.80	0.000***	0.72	0.81	0.001***	0.65	0.80	0.000***	0.71	0.82	0.000***
Age head	Years	47.87	46.74	0.013**	45.21	44.44	0.699	48.16	46.47	0.025**	47.05	47.63	0.299
Primary or lower education	(0/1)	0.22	0.28	0.000***	0.36	0.37	0.123	0.22	0.28	0.001***	0.25	0.27	0.183
Secondary or higher education	(0/1)	0.14	0.12	0.965	0.04	0.10	0.746	0.07	0.05	0.055*	0.34	0.36	0.142
HH size	#	4.54	5.03	0.000***	5.39	5.60	0.862	4.33	4.86	0.000***	5.13	5.61	0.002***
Farm labour[3]	#	1.66	2.08	0.000***	1.34	1.52	0.163	1.72	2.20	0.000***	1.47	1.68	0.140
Farm size	Ha	4.75	5.72	0.597	1.53	3.79	0.000***	5.65	6.29	0.854	2.18	3.85	0.000***
Farm size owned	Ha	0.19	0.92	0.000***	0.25	0.99	0.038**	0.18	0.94	0.001***	0.23	0.86	0.003***
Land ownership	(0/1)	0.60	0.65	0.373	0.29	0.44	0.000***	0.59	0.66	0.013**	0.62	0.63	0.085*
Food only producer	(0/1)	0.56	0.31	0.000***	0.56	0.27	0.000***	0.54	0.30	0.000***	0.62	0.33	0.000***
Processing	(0/1)	0.33	0.34	0.489	0.82	0.81	0.692	0.19	0.23	0.059*	0.72	0.68	0.822
Livestock	#	12.97	13.24	0.771	11.06	5.23	0.467	7.73	10.84	0.000***	12.28	21.19	0.263
Access to non-farm income	(0/1)	0.47	0.39	0.000***	0.98	0.98	0.474	0.43	0.38	0.028**	0.61	0.44	0.000***
Credit	(0/1)	0.31	0.37	0.000***	0.37	0.45	0.176	0.25	0.33	0.001***	0.48	0.53	0.001***
Radio	(0/1)	0.62	0.74	0.000***	0.51	0.61	0.007***	0.65	0.77	0.000***	0.54	0.63	0.000***
Bicycle	(0/1)	0.30	0.34	0.077*	0.23	0.27	0.429	0.28	0.34	0.005***	0.35	0.33	0.576
Distance to periodic market	Km, community	6.13	6.99	0.003***	15.08	12.48	0.751	5.63	5.91	0.621	7.52	10.56	0.000***
Daily market	(0/1), community	0.17	0.14	0.199	0.17	0.20	0.832	0.18	0.14	0.158	0.15	0.11	0.798
Distance to extension officer	Km, community	9.30	8.58	0.568	15.85	17.25	0.936	8.93	8.05	0.380	10.35	10.34	0.684
N		3,736	11,000		743	2,374		986	3,186		2,007	5,440	

[1]NMP=Non market participants
[2]MP=Market participants
[3]N. household's members working on own farm

Figure 7 Distance to periodic market, km

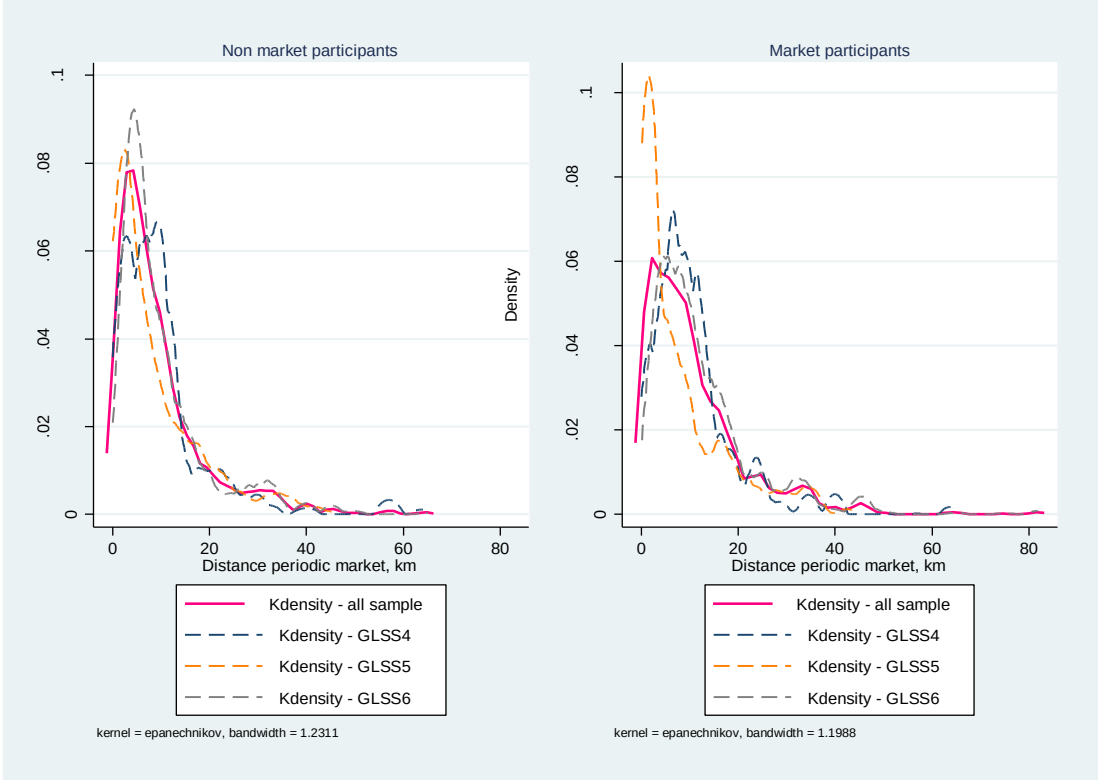
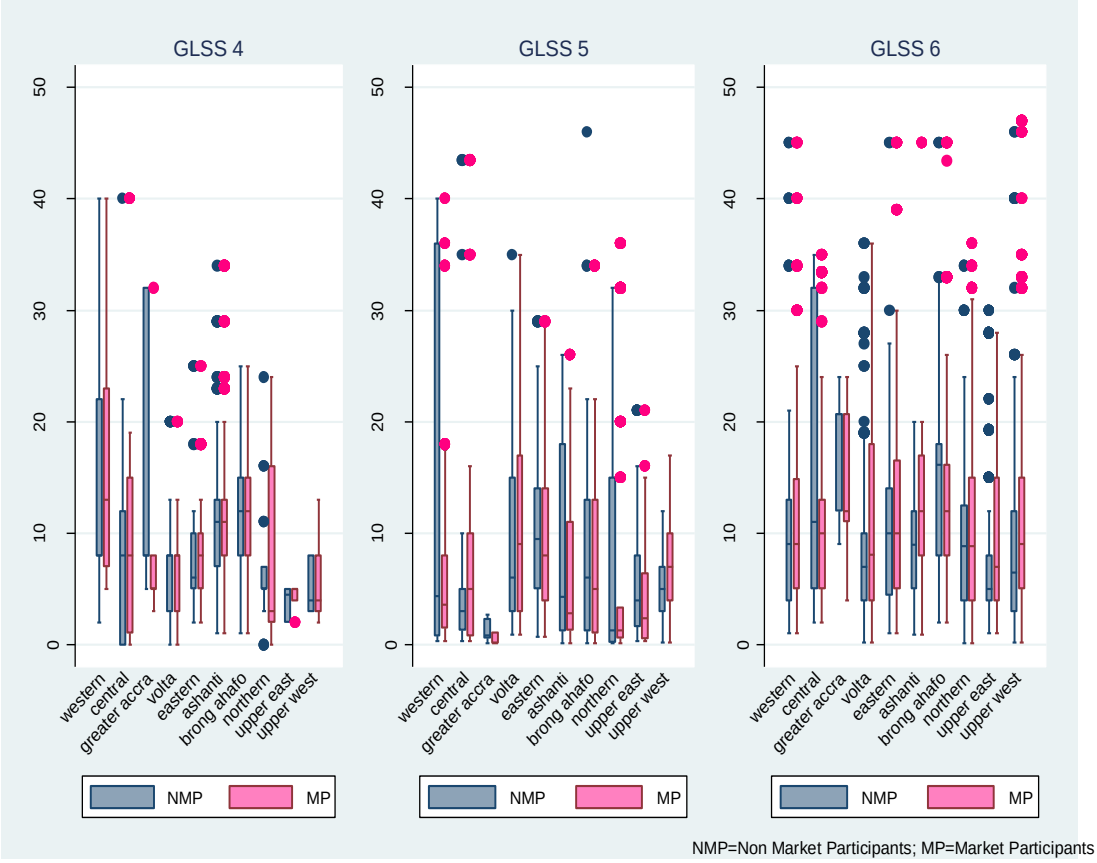


Figure 8 Distance to periodic market, by region



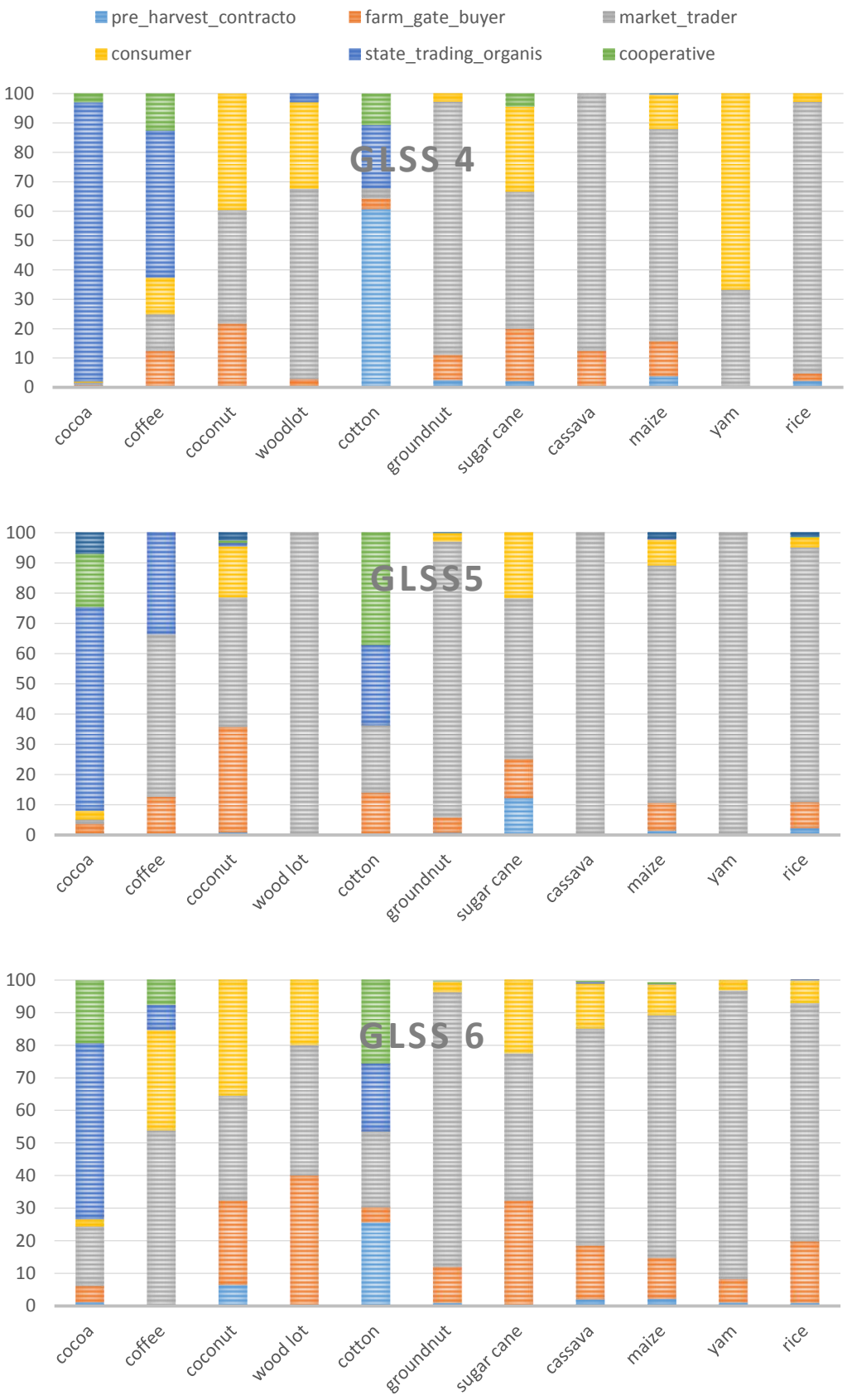
Aside from location drivers, one other reason why a positive association between remoteness and market participation is observed can simply be that the periodic market, whose distance is reported in the surveys, is not the preferred location of market transactions for the farmers included in the sample, who, maybe, sell their produce at the local market, within the community of residence. However, even in this case, comparing the existence of daily markets in communities where market participants and non-participants are located does not provide useful insights. Hence, the summary statistics in Table 2 show that the presence of daily markets in the community does not differ between communities where seller and non-seller are located and, as such, it does not help in explaining this unexpected association.

Another possible explanation of this odd relationship may be embedded in the traditional Ghanaian specific marketing systems. As suggested by previous studies of the Ghanaian marketing systems (e.g. Zanello et al., 2014) it may be possible that, also in my sample, market transactions do not occur in what is commonly identified as "market" (neither periodic nor daily) but they instead occur at the farm gate or via market traders who collect directly from the community of residence of the supplier[11].

Figure 9 summarizes the distribution at crop level of the preferred sale outlets and it shows that, indeed, the most common sale outlets since the first round of the three surveys are market traders and farm gate buyers, for the majority of the crops. Cocoa is the only crop that stands out among all the other crops as it is mainly sold to state managed trading organisations. Direct sales transactions to consumers are only rarely chosen as preferred outlet and their relevance in the overall marketing systems is found to decrease with time. On the other hand, the graphs also show that intermediaries, such as market traders, often dominating the sale transactions of staple crops, whereas pre-harvest contractors are more common for cash crops.

[11] Although GLSS questionnaires do not allow for a direct comparison of type of markets (periodic and daily markets) and main sale outlets, a question in the agricultural production distinguishes between the following main sale outlets: pre-harvest contractor, farm gate buyer, market trader, consumer, state trade organisation and other sale outlets.

Figure 9 Preferred sale outlet-GLSS4, 5, 6



Section 4. Econometric models

Following past literature, the preferred econometric models for the analysis of market participation and its extent are probit for the discrete choice of selling or not and Heckman two step for the decision of how much to sell (i.e. commercialisation or extent of market participation). While the choice of the probit model is quite straightforward in the case of bivariate analysis, the choice of the Heckman model has been driven by one of the main limitations of the market participation analysis: self-selection or selection bias. In the analysis of market participation, selection bias refers to the very likely scenario that farmers who are market participants might be systematically different from non-market participants and this difference necessarily affects the extent of their participation, which is null in the case when farmers decide to not participate and cannot be observed.

OLS produces biased and inconsistent estimates in presence of selection biases and, as such, cannot be used. In alternative to OLS, other models have been used in the literature, such as and double-hurdle approaches based on Tobit models, Heckman, and, sometimes, switching endogenous regressions.

The Heckman two-step model is normally preferred to these other approaches as it allows for fewer restrictions than other models require. More specifically, compared to other MLE models, it relaxes the joint normality distribution of the error assumptions, which makes model such as Tobit type 1 less preferable to Heckman. In addition, Tobit models in the case of market participation would assume that "zero" values of the commercialisation level associated with "non-participation" are the result of a rational choice, i.e. non-participant farmers decide to sell "zero" in the market. Moreover, using a Tobit model in the analysis of the extent of market participation would mean assuming that transaction costs and other determinants affect in the same way and direction both the discrete decision to sell or not sell ("zero") and the extent of market participation. Furthermore, as the decision to participate or not is only addressed in this analysis in a dichotomous fashion, Heckman models can be also preferred to endogenous switching regressions, which is often related to the investigation of

alternative non-independent marketing regimes choices[12]. Finally, following Alene et al. (2008), the two step procedure within the Heckman approach also allows the investigation of the role that transaction costs play in non-participation, on the discrete decision to participate and on its extent[13].

Notwithstanding its advantages, one main difficulty in using the Heckman models is the identification of exclusion factors that are deemed to affect the variable of interest only through the selection equation. Selection biases can derive from observables and unobservable factors. Unobservable factors are likely to affect this analysis as more motivated, more dynamic and more able farmers could self-select into market participation. It is well known that the choice of factors that could effectively capture the selection on unobservable is as complicated and as fundamental as finding a good instrument variable in any econometric analysis. Nonetheless, in the analysis of market participation, the conceptual framework predicts that fixed transaction costs, such as age, education and ownership of transportation and communication assets, should affect only the discrete decision to participate in the market and not the decision on its extent, i.e. commercialisation. As a consequence, those observable factors that are thought to efficiently proxy for often unobservable fixed costs have been considered in the past literature as valid candidate of identifier variables (IV) in the selection model[14].

Aside from the selection bias, problems of endogeneity are deemed to affect this analysis. The main variables that are more likely to be endogenous are the following: access to credit, access to non-farm income and crop portfolio choices. It is highly likely that there could be reverse causality between market participation and these variables. A higher access to credit, for example, might have been caused by the decision to

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[12] For example, Goetz (1992) analyse the determinants of three regimes: being a net buyer, being a net seller or being autarchic. In this paper I assume that there is a dichotomous decision and as such I keep my identification strategy as simple as possible.

[13] In order to validate my main results I have also estimated a Craggit – double hurdle model and a Tobit model. The results are shown in Appendix 1.5. The results of the first tier of the double hurdle model (market participation) are perfectly consistent with the probit estimations, while the analysis of the second tier (extent of market participation) shows that in addition to the determinants identified in the Heckman procedure, food only production and distance to extension officers become significant using this model. On the other hand, the results from the Tobit estimation show that most of the explanatory variables are significant in the analysis of the extent of market participation. These differences with my main results might be a result of the constraints described above. Nonetheless, considering the amount of similarities in these estimations and my preferred models, I believe that the choice of probit and Heckman-two step could be appropriate in this analysis.

[14] Although no official statistical test is available, one way to ascertain the relevance of the IVs in capturing selection bias, is to verify the significance of their coefficients in both the discrete and extensive decisions of market participation. If significant in the former and not in the latter model, the variable under scrutiny could be possibly considered a good instrument.

participate and its extent. If the expected positive return of market participation on living standards holds, the better economic status of market participants might have facilitated access to credit. On the other hand, market participants might have borrowed more money than non-market participants to support adoption of more marketable crops or assets as well as to face transaction costs that sales activities often require. One option to overcome this issue would be to use a lagged value of credit, two or three years before market participation and its extent are observed. However, the contemporaneous nature of the data used does not allow implementing this strategy. Another possible solution would be to use an instrument variable that would predict the effect of credit on market participation and its extent. However, the search for a valid instrument might be very difficult considering the type of data that I am using and the type of analysis that I am carrying out. It is indeed likely that all the most common variables used to instrument for credit affect or are affected by market participation as well[15].

A similar problem can be caused by the access to non-farm income and crop portfolio choices. A higher intensity of market participation could allow a higher access to non-farm income and vice-versa, via the adoption, for example, of more marketable crops. Controlling for access non- or off-farm income is part of the traditional conceptual market participation and as a consequence I will follow the literature including it in my main specification[16]. Nonetheless, in order to ascertain the degree of distortion caused by these problematic variables, I have estimated different specifications of the model of both market participation and commercialisation with and without these potential endogenous variables. The results, in the Appendix 1. 6, show that the significance, the size and the direction of the coefficients of the majority of the other covariates and especially the variable of interests, transaction costs, do not seem to be affected by their inclusion or exclusion. Thus, although acknowledging the unsolved endogeneity problems in the model I feel confident in including these variables in the final specification as their contribution to the interpretation of the effect of the variables of interests is somehow minimal.

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[15] Past studies use, for example, farm size, land ownership and other farm characteristics as instrumental variables for access to credit. These variables are most likely to be relevant in the market participation equation (Beke, 2011; Diagne and Zeller, 2001).

[16] It is probably worth mentioning that these variables are included in the model only as controls for both the analysis of market participation and its extent.

Section 5. Results

5.1 Determinants of market participation

Table 3 shows the results of the marginal effects of the probit estimation of market participation. Model (1) does not include measures of fixed transaction costs, aside from age and education. Model (2) includes all fixed transaction costs as measured by ownership of radio and bicycle and model (3) also includes proportional transaction costs. All of the specifications include regional and year dummies.

The results in Table 3 show that common determinants of market participation are also relevant in this analysis. For example, the gender of the household's head is highly significant and positively associated with market participation, supporting the argument that men are more likely to be involved in marketing activities. The availability of farm labour in the household is also positive and significant, suggesting that more people are engaged in own farming activities when the household participates in the market.

Among substitutes of crop cash income, access to non-farm income has, as expected, a negative association with the decision to participate in the market. On the other hand, livestock ownership is not significant and access to credit is positively associated with market participation, which could suggest that farmers in the sample might be using credit for activities that are not necessarily substitutes of market participation, as, for example, improvement in the production of tradable crops or producing more marketable crops. Producing only food crops is, indeed, observed to lower the probability of market participation.

Moreover, the results also show that some of those observable factors deemed to explain or mitigate proportional and fixed transaction costs are strongly associated with the decision to participate or not in the market. More specifically, fixed transaction costs, as measured by age, education, ownership of radio and bicycle, are all statistically significant at 1% confidence level. Age is negatively associated with the probability to participate, supporting the idea that older farmers are less prone to participate in market transactions, maybe because of a higher risk aversion as suggested by Alene et al. (2008). On the other hand, owning a radio or a bicycle are both positively associated with the probability to participate, and the results are consistent throughout the

specifications, suggesting that these assets lower fixed transaction costs by making it easier the access to marketing information and, thus, reducing uncertainties from market transactions[17]. Unexpectedly, education seems to affect negatively the decision to sell or not to sell. This result contrasts with previous literature where education is claimed to be a facilitator instead of an inhibitor of market participation. One of the reasons of this unexpected result may be that higher educated, instead of mitigating fixed transaction costs within agriculture activities, allows access to better remunerated non-farm activities (Gould et al., 1989).

Different measures of proportional transaction costs are found to affect market participation in a different way. While, the distance to the extension officer is negatively associated with market participation, the results show a positive association of distance to market with the decision to sell, which is inconsistent with the theoretical predictions. This result suggests that the further away from the market the higher is the probability that a household decides to sell. However, as discussed above, the inconsistency of this association might be explained looking at the specific characteristics of the Ghanaian marketing system. Hence, as Zanello et al. (2014) point out, and as explored in the descriptive analysis, it might be possible that the majority of market transactions do not occur at the periodic market, included in the model, but, instead, sales occur mostly at farm gate or through intermediaries, such as market traders. However, this should have been better supported via lack of significance of the distance to market coefficient. The positive association, instead, might be explained by the possibility that the further away farmers are, the more likely buyers would travel to their farm gate, or different marketing arrangements (e.g. pre-harvest contractors or group marketing) would be put in place, such that higher market participation could be observed.

[17] The ownership of radio and bicycle might not be exogenous to the market participation decision as farmers, for examples, might buy a bicycle to reach the market or a radio to gather market information. In addition market participation's benefits, via increase of disposable income, could by itself favour asset accumulation. Although acknowledging this limitation in the analysis, I believe that an instrumental variable approach to overcome this issue could prove quite difficult as the same factors affecting asset ownership could directly affect the decision to participate in the market. In an attempt to understand the extent at which endogeneity issues affect the final results, looking at the estimations of the models without these variables tends to suggest that that the main results do not significantly change (Table 3, p.48 model (1)).

Table 3 Determinants of market participation

Dependent variable: Market participation (0/1)		(1) Probit	(2) Probit	(3) Probit
VARIABLES		mfx[1]	mfx[1]	mfx[1]
Male head	(0/1)	**0.14*** **	**0.12*** **	**0.12*** **
		(0.01)	**(0.01)**	**(0.01)**
Age head	Years	**-0.00*** **	**-0.00*** **	**-0.00*** **
		(0.00)	(0.00)	(0.00)
Primary or lower education	(0/1)	**-0.03*** **	**-0.03*** **	**-0.03*** **
		(0.01)	(0.01)	(0.01)
Secondary or higher education	(0/1)	**-0.05*** **	**-0.05*** **	**-0.05*** **
		(0.01)	(0.01)	(0.01)
Farm labour	# member of household who work on own farm	**0.02*** **	**0.02*** **	**0.02*** **
		(0.00)	(0.00)	(0.00)
Farm size	Hectares	0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
Land ownership	(0/1)	0.00	0.00	0.00
		(0.01)	(0.01)	(0.01)
Livestock owned	#	-0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	**-0.06*** **	**-0.06*** **	**-0.06*** **
		(0.01)	(0.01)	(0.01)
Food only producer	(0/1) - 1 if household produces only food crops; 0 otherwise	**-0.21*** **	**-0.21*** **	**-0.21*** **
		(0.01)	(0.01)	(0.01)
Access to credit	(0/1)	**0.03*** **	**0.03*** **	**0.03*** **
		(0.01)	(0.01)	(0.01)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	**0.08*** **	**0.08*** **	**0.07*** **
		(0.01)	(0.01)	(0.01)
Radio	(0/1)		**0.03*** **	**0.02*** **
			(0.01)	(0.01)
Bicycle	(0/1)		**0.06*** **	**0.06*** **
			(0.01)	(0.01)
Distance to periodic market	(0/1) - 1 if distance is above the median; 0 otherwise[1]			**0.04*** **
				(0.01)
Distance to extension officer	(0/1) - 1 if distance is above the median; 0 otherwise[2]			**-0.02** **
				(0.01)
Region dummies	(0/1)	Yes	Yes	Yes
Year dummies	(0/1)	Yes	Yes	Yes
Observations		14,736	14,736	14,736
Obs.P %		75	75	75
Pred.P %		78	78	78
Pseudo/R-squared		0.127	0.131	0.132
LR chi2		2121***	2179***	2205***

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[1]Distance to market median=8km (GLSS4); 1.5 km (GLSS5); 6 km (GLSS 6)

[2]Distance to extension officer= 8km (GLSS 4); 4 km (GLSS5) 8km (GLSS 6)

5.2 Determinants of the extent of market participation

Table 4 shows the results of the OLS non-corrected and corrected for selection bias[18]. Three specifications are presented. Model 1 does not include any transactions costs, aside from age and education. Model 2 includes all fixed transaction costs and Model 3 includes also proportional transaction costs. As for the bivariate estimations in Table 3, regional and year dummies are included in all the specifications. The dependent variable is the Household Commercialisation Index (0-100), estimated as in (12). From the total sample of 14,736 households, 3,736 observations are censored as they correspond to those farmers who do not sell any of the harvest.

Three identifier variables have been used in the Heckman two step model: primary and secondary and/or higher education, and ownership of a bicycle. Following the discussion above, while education is expected to capture fixed transaction costs, the ownership of a bicycle is not found statistically significant in the estimation of household's commercialisation. As a consequence, it is plausible to argue that in the context of this analysis, transport assets, measures by the ownership of a bicycle, could approximate fixed and not proportional transaction costs. If so, it is possible that farmers in the sample do not use bicycles to transport their crops for sales transactions but, instead, this asset serves the role of a facilitator of the access to marketing information and as such affects market participation but not its extent.

Using these identifier variables, Table 4 shows that the lambda coefficient is significant in all pooled models, suggesting that the OLS uncorrected produced biased and inconsistent results. The significance of the lambda coefficients supports that idea that there exists selection bias in the estimation of market determinants and its extent. More specifically, the positive signs of the rho coefficients indicate that a positive correlation between the unobservables that affect the decision to sell as well as the decision of how much to sell, exists. Thus, in my sample market participants are not a random sample and possess unobservable or unobserved characteristics that make them more likely to be market participants, such as less risk aversion, higher ability and so on. The size of the selection bias, calculated following Gyourko and Tracy (1988) and Reilly (1991), suggests that the market participants in my sample sell from 7% points to about 4%

[18] The first stage of the Heckman estimation corresponds to the estimations reported in Table 3.

points more than a household drawn at random from the population with similar observable characteristics would be expect to have. This can be due to their higher ability to reach a higher value of their sales or to their entrepreneurial skills in managing their farming activities better. The estimation of the market participation models by survey year might provide some insights on the reasons why this type of selection bias is observed. The results, in Appendix 1.7, show that selection bias only occurs in the latest round of the GLSS[19]. The fact that farmers are not self-selected in to the market participation status in previous rounds could suggest that unobservable characteristics have been developed in the past five to six years. These unobservables, such as ability and entrepreneurial skills but also better linkages within agricultural value chains, might have been the result of the interventions of development agencies and national government projects. As shown in Figure 1 in p.18, several projects have been trying to facilitate market access. The provision of trainings, information on potential buyers and better linkages within the relevant value chains might have improved farmers' marketing ability and this could explain why a selection bias is observed.

Aside from the selection bias issue, the results show that, overall, classical determinants of commercialisation are also significant in the context of this analysis. For example, the gender of the head of the household is found positively and significantly associated with the level of household's commercialisation. The size of the effect suggests that male headed households sell 2 to 6 percentage points more than female headed households. Previous findings suggest that gender of the head of the household is a significant determinant of the extent of market participation. However, the size of this effect tends to vary quite considerably depending on the type of crop under scrutiny and the nature of the analysis. For example, while Sebatta et al. (2014) find that man headed households sell from 2 percentage points more than female headed households in the potato market in Uganda, Boughton et al. (2007) find a much bigger effect, as men headed households are found to sell 26% more maize than a female headed household.

[19] The full results, in the Appendix 1.7, show, first of all that the selection variables are never significant. Education variables did not qualify as identifier variables for GLSS 4 while only basic education did for GLSS 5. Aside from remoteness discussed below, the results also show that gender is not relevant in the marketing decision for both GLSS 5 and 6 while education is only a relevant determinant in the discrete market participation decision in GLSS 6. Moreover, the importance of farm size decreases with time as it is observed to be positively associated with both the decision to participate and its extent for the GLSS 4 but not for the two more recent surveys. Land ownership, instead, is found not positively associated with the decision to sell or not sell in the latest GLSS but it is still observed to increase the amount of sales, consistently with the main estimation and with the other two survey rounds.

However, the effect becomes not significant when cotton and tobacco market participation are analysed.

Among other classical determinants of commercialisation, Table 4 shows that farm size and land ownership are consistently positive and significant throughout the different specifications, suggesting that farmers with a bigger land are more likely to sell more harvest. This is in line with other studies of commercialisation in Ghana, as, for example, Martey et al. (2012). They found that an additional hectare of land increases the household's commercialisation in maize and cassava by 10%. Similarly, Boughton et al. (2007) find that an addition hectare of land increases the extent of maize market participation by about 20 percentage points. My results indicate that farm size has a smaller effect on commercialisation as an additional hectare of land would increase the Household Commercialisation Index by about 0.04 percentage points. A large effect is exerted by land ownership which is observed to increase the Household Commercialisation Index by about 4 percentage points. This could suggest that although farm size is an important component of the decision of how much to sell, owning land, and as a consequence avoiding the risk to share the benefits of any investments on that land, might affect more the value of sales, ceteris paribus.

Substitutes for crop cash income were expected to affect negatively the extent of market participation. In line with the expectations, the number of livestock is found negatively associated with the dependent variable, suggesting that owning more livestock reduces the amount of crop sales. However, both access to non-farm income and credit are not significant in the decision of how much to sell, which were, instead, found significant in the analysis of the discrete decision of market participation. Similarly, producing only food crops does not seem to affect the extent of market participation but only the decision to participate in the market. This finding could support the idea that food crops might foster market integration as much as the traditional more marketable cash crops. However, the effect of processing food crops is negatively associated with the level of market participation, suggesting that if the household processes any food or fish the proportion of the value of sales to the total value of production is lower compared to households who do not process crops[20].

[20] This result is in contrast with the idea that primary producers should engage in value adding activities, such as, for example, processing, in order to have access to higher sale prices. However, in the context of this analysis there is no

Moving on to the effect of transaction costs, the results show that both proportional and fixed transaction costs are relevant in the analysis of household's commercialisation. More specifically, the effect of transaction costs is observed to be strongly significant when measured by ownership of communication assets, radio, and distances to market and extension officers.

However, the observed empirical effects, aside from the coefficient for the distance to the extension officers, are not always consistent with the previous literature. The first inconsistency is the relationship between measures of fixed transaction costs and the extent of market participation. According to the theoretical framework discussed in the previous section, fixed transaction costs should not be relevant in the decision of the extent of market participation but only in the discrete choice of participation. However, the findings in Table 4 suggest that, for example, ownership of a radio is significantly associated with the Household Commercialisation Index. Although conflicting with the conceptual framework, this result might be explained by the fact that marketing information diffused via radio could possibly affect the choice of the sale outlet in favour of the one that provides a higher price, which would, if chosen, increase the value of sales ratio to the total value of production. Similarly, access to this information could increase the negotiating power of the farmers with intermediaries, such as market traders, in local market transactions and this, again, could increase the value farmers get from sales. The diffusion of marketing information via radio and other communications assets is a quite recent development in Ghana and as a consequence this argument could explain the relevance of the ownership of a radio also in the analysis of the extent of market participation.

Another unexpected result concerns, once again, one of the measures of proportional transaction costs: distance to market. Similarly to the results of the bivariate market participation analysis, (Table 3), the distance from the periodic market is found to be positively associated with the extent of market participation.

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clarity on what the processing activities really mean. This question was asked in the agricultural section of the surveys and as a consequence I believe that it mainly captures petty processing of mostly staple crops that are sold in small quantities and for low returns, as, for example, cooked rice or smoked fish. These crops are generally sold in the street by women at considerably low prices.

Table 4 Determinants of the extent of market participation

Dependent variable: Household Commercialisation Index (0-100) VARIABLES		(1) OLS Un-corr[1]	(1) OLS corr[2]	(2) OLS Un-corr[1]	(2) OLS corr[2]	(3) OLS Un-corr[1]	(3) OLS corr[2]
Male head	(0/1)	**2.19*** **	**3.21*** **	**1.68** **	**5.68*** **	**1.64** **	**3.61*** **
		(0.70)	(1.01)	(0.72)	(1.23)	(0.72)	(1.02)
Age head	Years	-0.00	-0.01	-0.00	-0.02	0.00	-0.01
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Primary or lower education	(0/1)	0.14	IV	0.08	IV	0.15	IV
		(0.66)		(0.66)		(0.66)	
Secondary or higher education	(0/1)	1.26	IV	1.15	IV	1.28	IV
		(0.85)		(0.85)		(0.85)	
Farm labour	# member of household who work on own farm	**-0.53*** **	**-0.35***	**-0.54*** **	-0.03	**-0.56*** **	-0.27
		(0.15)	(0.20)	(0.15)	(0.23)	(0.15)	(0.20)
Farm size	Hectares	**0.04** **	**0.04*** **	**0.04** **	**0.04*** **	**0.04** **	**0.04*** **
		(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Land ownership	(0/1)	**3.72*** **	**3.75*** **	**3.67*** **	**3.80*** **	**3.69*** **	**3.72*** **
		(0.54)	(0.54)	(0.54)	(0.57)	(0.54)	(0.55)
Livestock owned	#	**-0.00*** **	**-0.00***	**-0.00*** **	**-0.00***	**-0.00*** **	**-0.00***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	-0.13	-0.74	-0.20	**-1.63** **	-0.14	-1.03
		(0.58)	(0.69)	(0.58)	(0.78)	(0.59)	(0.70)
Food only producer	(0/1) - 1 if HH produces only food crops; 0 otherwise	1.09	-1.22	1.09	**-4.55** **	1.13	-1.92
		(0.71)	(1.46)	(0.71)	(1.84)	(0.71)	(1.48)
Access to credit	(0/1)	-0.45	-0.17	-0.53	0.37	-0.59	-0.04
		(0.55)	(0.57)	(0.55)	(0.61)	(0.55)	(0.57)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	**-4.35*** **	**-3.63*** **	**-4.32*** **	**-2.60*** **	**-4.35*** **	**-3.38*** **
		(0.65)	(0.75)	(0.65)	(0.85)	(0.65)	(0.76)
Radio	(0/1)			**1.75*** **	**2.26*** **	**1.75*** **	**2.17*** **
				(0.55)	(0.58)	(0.55)	(0.58)
Bicycle	(0/1)			0.47		0.49	IV
				(0.63)		(0.63)	
Distance to periodic market	(0/1) - 1 if distance is above the median; 0 otherwise[1]					**1.98*** **	**2.36*** **
						(0.54)	(0.59)
Distance to extension officer	(0/1) - 1 if distance is above the median; 0 otherwise[2]					-0.84	**-1.01***
						(0.53)	(0.55)
Lambda			**18.69*** **		**10.21** **		**7.98***
			(5.63)		(4.42)		(4.39)
Region dummies	(0/1)	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	(0/1)	Yes	Yes	Yes	Yes	Yes	Yes
Observations		11,000	14736	11,000	14736	11,000	14736
Censored obs			3736		3736		3736
R-squared		0.12		0.12		0.12	
Wald			1188***		1297***		1316***
Rho			0.654		0.381		0.302
Sigma			28.57		26.77		26.45

[1]OLS Un-corr= OLS on market participants only; not corrected for self-selection into market participation
[2]OLS corr=2nd stage of Heckman two step; corrected for self-selection into market participation
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
[1]Distance to market median=8km (GLSS4); 1.5 km (GLSS5); 6 km (GLSS 6)
[2]Distance to extension officer= 8km (GLSS 4); 4 km (GLSS5) 8km (GLSS 6)

More specifically, if the farmer is located in a village that is more distant to a periodic market, he/she would have higher ratio of value of sales to total value of production, by about 2 percentage points, on average and ceteris paribus. Among the few studies that find a positive relationship between remoteness and market participation, Zamasiya et al. (2014), find a bigger effect of remoteness in their study of soybean market participation in Zimbabwe. Their results suggest that being further away from the market increases household's commercialisation in soybean by about 4 percentage points. Aside from the similarities between this study and Zamasiya et al. (2014), a positive relationship between remoteness and market participation contradicts the theoretical expectation that remoteness should reduce the extent of sales transactions.

As mentioned above, following Alene et al. (2008) I use a dummy variable which takes the value of 1 if the farmer is located further away than the median distance observed[21]. In order to verify the robustness of these results I have also changed the specification of the distance variable (using the mean instead of the median as well as a continuous variable, Km, instead of a binary variable).

Table 5 Remoteness and market participation

		Market participation	Extent of market participation
Pooled	Median Threshold (0/1)	**0.04*** **	**2.36*** **
		(0.01)	(0.59)
Pooled	Mean Threshold (0/1)	**0.03*** **	**1.20***
		(0.01)	(0.63)
Pooled	Km	0.00	0.01
		(0.00)	(0.01)
Pooled	Km – no extreme values	**0.00***	**0.03** **
		(0.00)	(0.01)
GLSS 4	Median Threshold (0/1)	0.01	-0.73
		(0.02)	(1.12)
GLSS5	Median Threshold (0/1)	-0.01	0.01
		(0.01)	(1.09)
GLSS6	Median Threshold (0/1)	**0.08*** **	**2.55*** **
		(0.01)	(0.95)

The results, summarised in Table 5[22], show that the direction of the association between remoteness and market participation remains positive while the coefficients lose significance when distances in Km are used, possibly because of the existence of extreme values. When excluding the extreme values from the distance variables, the coefficients become significant again and remain still positive. I have also estimated the

[21] The median values of distance to market are the following: 8km (GLSS4); 1.5 km (GLSS5); 6 km (GLSS 6).
[22] The full results are reported in Appendix 1.8, 1.9 1.10 for exposition purposes.

same models but using the mean distance, instead of the median, as threshold for the definition of the distance variables. These results are pretty consistent with the main estimations, in direction and size of the associations, suggesting that a positive relationship between remoteness and market participation might really exist.

Although inconsistent with previous empirical evidence, this type of relationship could be explained looking at how marketing transaction occurs and have evolved in Ghana. As Martey et al. (2012) and Zanello et al. (2014) point out, it is very common in rural Ghana that market transaction occur via the establishment of personal relationship with buyers and traders, which could replace the need for farmers to physically reach a formal market place. Following this argument, it is plausible to argue that the further away from the market the farmers are the more they could be pushed towards the establishment of long lasting relationship with market traders or other buyers, which could favour market participation and its extent[23]. On the other hand it is also possible that distance to market might attract different buyers, as, for example, contractors, or induce farmers to engage in group marketing within farmers' organisation. As suggested by Quartey et al. (2012) sales through these alternative outlets might provide farmers access to higher sales prices.

In addition, the analysis of market participation by survey year (Table 5) suggests that remoteness was not always significant across time. More specifically, distance to markets is found not relevant in the analysis of market participation for both GLSS 4 and 5 while it becomes positively associated and significant in the latest round of GLSS. The non-significance supports the idea that farmers did not need to physically reach the market, because their preferred outlet was maybe at their door step. Moreover, the positive association observed in the most recent survey suggests once again that in the past decades the effort of development agencies and national government in linking remote farmers with buyers has had an effect in reducing the transaction cost of reaching the markets. This could also explain why, for example, the coefficients for remoteness in the previous rounds have a negative sign, although not significant.

[23] These personal relationships might translate in a stronger negotiating power with buyers. And a stronger negotiating power could allow access to a higher value for their sales, compared to what they would receive in "formal" markets where personal ties with buyers may be less common. This, as a consequence, could increase the ratio of value of sales to the value of total production as observed in this analysis.

Section 6. An analysis of maize market participation

As anticipated in the introduction, different effects of different type of transaction costs can have specific crop related relevance. Food crops, in particular, are normally associated with lower barriers for market participation compared to cash crops because of the low quality requirements. However, marketing food crops is sometimes characterised by higher transaction costs, due to higher search and enforcement costs (Boughton et al., 2007).

In this section, I investigate the decision to participate in the market and how much to participate for a subset of maize growers. Focusing on one common staple also allows the analysis of additional data available in GLSS. Hence, these surveys have collected, for a selection of crops, information on preferred sale outlets. Using these data, I analyse the decision of maize market participation using a multinomial logit model (MNL), which compares non-participation to participation in two different outlets: farm gate and market trader[24].

Maize is the most commonly produced crops all across Ghana. In the sample used for this analysis, maize market participation rates are observed to be on average 51%, i.e. about half of the maize farmers sell maize. Across the survey years, market participation rates reduced by about 10% since 1998/99. The declining trend is mainly observed in coastal and forest agro-ecological zones, which include some of the most commercialised regions in the country, such as Eastern region and Brong-Ahafo region (Figure 10). Among maize market participants, the average Maize Household Commercialisation Index is 57%, meaning that about half of the maize produce is sold. However, differently from the estimations at household level, commercialisation levels seem to be declining with time (Figure 11).

[24] Other econometric models, such as ordered probit, switching endogenous regressions or nested logit models, could have been used in this analysis. I chose the multinomial logit model for its simplicity as the aim of this analysis is mainly to validate the results of the main selection models.

Figure 10 Maize market participation

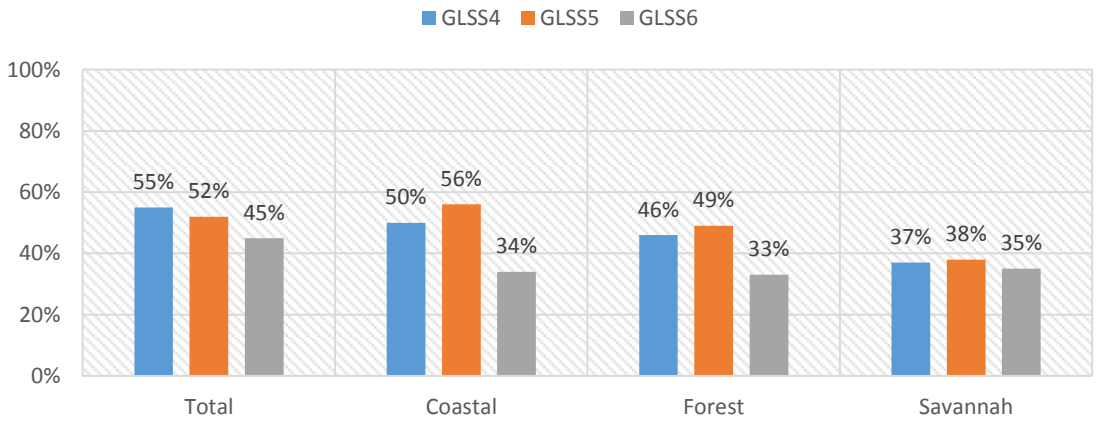


Figure 11 Household Commercialisation Index, maize market participants

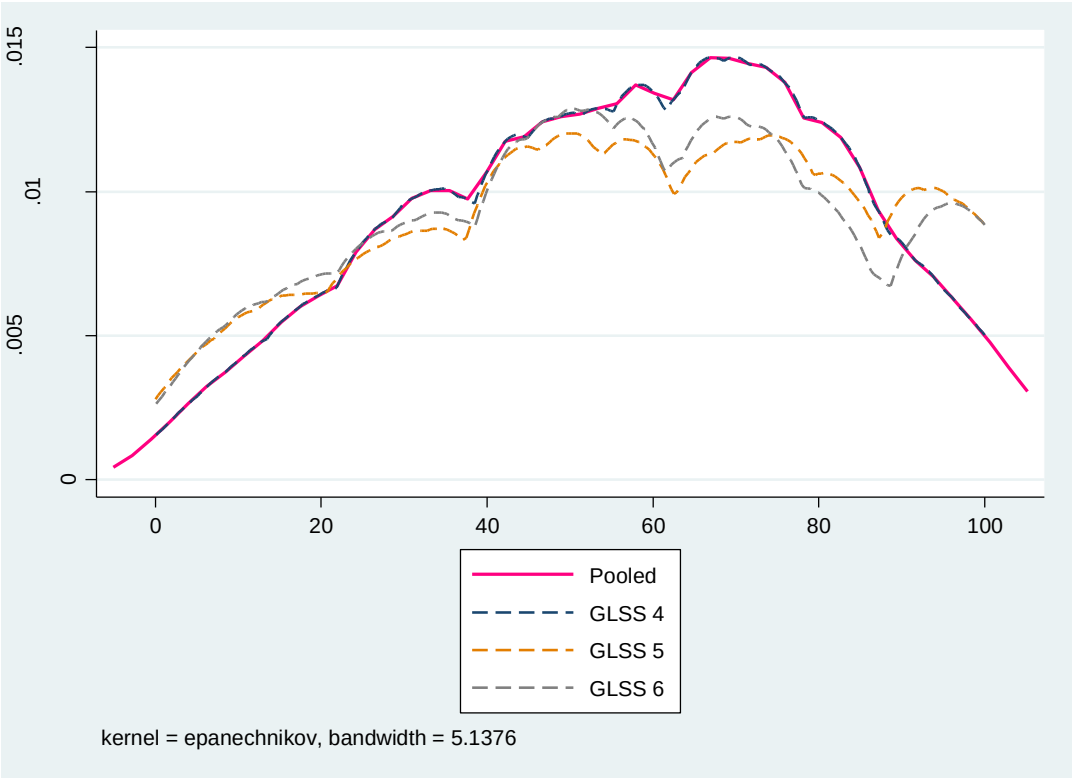


Table 6 shows selected results of the analysis of determinants of maize market participation and its extent with and without corrections for selection bias[25]. The dependent variable for the probit analysis is "maize market participation" which equals 1 if the household sells any maize and 0 otherwise. The Maize Household Commercialisation Index, the dependent variable for the OLS estimations, is estimated as the ratio of total value sales of maize to total value of maize production and it is, as

[25] The full results are reported in Appendix 1.11 for exposition purposes.

before, expressed in percentages. As in the analysis above, three identifier variables are used in the selection models: two education variables and ownership of bicycle.

Compared to the all-household models, the selection coefficient in the analysis of maize market participation is found to be slightly smaller. Moreover, although the lambda coefficients is not always significant, suggesting that the unobservable characteristics not controlled for in this analysis do not always affect the decision to participate in the maize market, the direction of the selection bias is the opposite of what observed for the entire sample. Hence, maize market participants in this sample sell 3 to 4 percentage points less than market participants with similar characteristics had they been randomly selected. The nature of the crop under scrutiny might have affected this result, as maize is mostly a staple crop and it is generally retained for house consumption. Also, the reduction of the participation rates across time might suggest that policy interventions aiming to increase market access and farmers' ability might have focused on other crops, as suggested by the Ghana Export Horticulture Cluster Strategic Profile Study (2008).

The results of the corrected OLS show that, similarly to the analysis with the all-household sample, farm size and land ownership are positively associated with both decisions of maize market participation and its extent. Moreover, producing only food crops is observed to decrease the probability to participate in the market but it increases the size of the sales. On the other hand, the effect of processing food or fish is found to reduce the extent of market participation, suggesting once again that this variable might be capturing petty trade of cooked staple or smoked fish. Substitute of cash crop income, such as non-farm income, are negatively associated with market participation decisions while access to credit is found to increase the probability to participate but not its extent. Finally, the results support the idea that, also in the maize sector, marketing decisions are mainly a men dominated arena, as gender is consistently significant and positively associated with market participation decisions.

Also similar to what observed in the household level estimations, some measures of fixed transaction costs also affect the extent of market participation. This result applies once again to ownership of radio. The ownership of a bicycle, instead, is only significant in the discrete decision of market participation and not for the decision of how much to sell, suggesting that also in this analysis this variable can be used as

identifier variable in the selection equation. This result is consistent with other studies on market participation determinants (e.g. Alene et al., 2008), suggesting that bicycles are used by maize farmers for accessing market information more than a mean of transportation of the produce. Moreover, as suggested by Figure 9 maize producers might not need to transport their produce at all as maize is commonly sold to market traders or at the farm gate.

The results also show that proportional transaction costs are relevant determinants in the analysis of maize market participation. However, the distance to the extension officer, although with the expected sign, is not significant in the analysis of the extent of maize market participation, suggesting that, although it might reduce the probability to sell maize, it does not affect the size of the produce sold. This result contradicts in a way the expectations as maize farmers were expected to rely more heavily on extension officers compared to other producers and this is not only because maize is one of the major staple crops but also because extension officers work heavily in the technical assistance for staple production. However, production and the extent of the maize marketing decision might not be related in rural areas in Ghana. Hence, it might be plausible that extension officers might play a bridging role for the access to marketing opportunities but not much more than that.

The puzzling results observed in the full sample above between remoteness and market participation is observed also in this analysis, as distance to market is still strongly and positively associated with a higher extent of market participation. This finding suggests that also for maize growers being located further away from markets does not reduce their market participation extent. As for the analysis of the entire sample, and as suggested by Figure 9, maize farmers do usually sell at farm gate or to traditional intermediaries, such as market traders. As discussed in the previous section, it is indeed possible that also for maize growers consolidated relationship with buyers might have reduced transaction costs measured by remoteness. In addition, it is also a common practice among staple producers located in remote areas to sell through other buyers which help overcoming the role of traditional intermediaries and as a consequence might allow access to a higher price than the one offered in the “formal” market.

Table 6 Determinants of maize market participation

Maize producers only		(4) Probit	(4) OLS	(4) OLS	(5) MNL	(5) MNL
VARIABLES		mfx[1]	un-corr[2]	corr[3]	Market trader	Farm gate
Male head	(0/1)	**0.099*** **	**2.829*** **	**1.844***	**0.603*** **	**0.465*** **
		(0.011)	(0.769)	(1.005)	(0.071)	(0.091)
Age head	Years	**-0.001** **	-0.015	-0.012	**-0.007*** **	-0.002
		(0.000)	(0.019)	(0.018)	(0.002)	(0.002)
Primary or lower education	(0/1)	**-0.017***	0.358	**IV**	-0.093	-0.085
		(0.010)	(0.692)		(0.070)	(0.090)
Secondary or higher education	(0/1)	**-0.038*** **	1.062	**IV**	**-0.299*** **	-0.061
		(0.013)	(0.913)		(0.090)	(0.113)
Farm labour	# member of household who work on own farm	**0.012*** **	**-0.554*** **	**-0.716*** **	**0.035***	**0.080*** **
		(0.002)	(0.158)	(0.188)	(0.018)	(0.024)
Farm size	Hectares	**0.004*** **	**0.040** **	**0.036*** **	**0.085*** **	**0.085*** **
		(0.001)	(0.019)	(0.013)	(0.009)	(0.009)
Land ownership	(0/1)	-0.006	**3.299*** **	**3.346*** **	-0.055	**-0.156** **
		(0.008)	(0.568)	(0.573)	(0.059)	(0.075)
Livestock	#	-0.000	**-0.003*** **	-0.003	-0.000	-0.001
		(0.000)	(0.000)	(0.002)	(0.000)	(0.007)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	-0.060***	0.064	0.733	**-0.367*** **	**-0.395*** **
		(0.009)	(0.619)	(0.721)	(0.061)	(0.080)
Food only production	(0/1) - 1 if household produces only food crops; 0 otherwise	**-0.168*** **	1.188	**2.933** **	**-0.809*** **	**-1.030*** **
		(0.010)	(0.744)	(1.269)	(0.068)	(0.090)
Access to credit	(0/1)	**0.034*** **	0.033	-0.216	0.188***	0.204***
		(0.008)	(0.574)	(0.607)	(0.061)	(0.077)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	**0.066*** **	**-2.844*** **	**-3.457*** **	**0.326*** **	**0.431*** **
		(0.010)	(0.704)	(0.765)	(0.068)	(0.087)
Radio	(0/1)	**0.017** **	**1.622*** **	**1.413** **	**0.118** **	0.106
		(0.008)	(0.576)	(0.595)	(0.057)	(0.075)
Bicycle	(0/1)	**0.051*** **	0.046	**IV**	**0.302*** **	-0.093
		(0.009)	(0.677)		(0.068)	(0.091)
Distance to market	(0/1) - 1 if distance is above the median; 0 otherwise	**0.035*** **	**2.487*** **	**2.063*** **	**0.168*** **	**0.487*** **
		(0.008)	(0.570)	(0.612)	(0.057)	(0.074)
Distance to extension officer	(0/1) - 1 if distance is above the median; 0 otherwise	**-0.018** **	-0.569	-0.366	-0.041	**-0.225*** **
		(0.008)	(0.564)	(0.582)	(0.057)	(0.075)
Lambda				**-7.370***		
				(4.317)		
Region dummies		Yes	Yes	Yes	Yes	Yes
Year Dummies		Yes	Yes	Yes	Yes	Yes
Observations		12,156	9,386	12156	8741	8741
Censored observations				2770		
Obs. P %		77				
Predicted obs %		81				
LR chi2		1738.93***			2131***	
R-squared		0.1333	0.096		0.12	
Wald				784***		
Rho				-0.286		
Sigma				25.75		

[1]Marginal effects are presented

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In order to investigate how market participation determinants change according to different sale outlets, I then estimate a multinomial logit model that compares the main sale outlets to the choice of not-participation. Within the market participation regimes I compare the traditional marketing system (via market traders) to less traditional systems (other farm gate sales, sales via cooperatives or farmers' organisation and sales to pre-harvest contractors). Following this, I have used a categorical variable which includes three mutually exclusive categories for the estimation of the multinomial logit model: 1) farm gate, cooperatives, pre-harvest contractors; 2) market trader; 3) non-market participation. Missing data problems reduced the available sample, as data on sale outlets are only available for 8,741 households of the total 9,386 maize producers who participate in the market.

Among this sub-set of maize growers, the data show that, on average, about half of the maize growers in this sample sell their produce to market traders. Pre-harvest, farm gate and group marketing via cooperatives occur more often in forest agro-ecological zones, where Brong-Ahafo, Ashanti and Eastern regions are located. Across survey years, marketing transactions at farm gate or via contractors and cooperatives increased more compared to sales to market traders (Figure 12).

Figure 12 Maize market participation, by outlet of sales

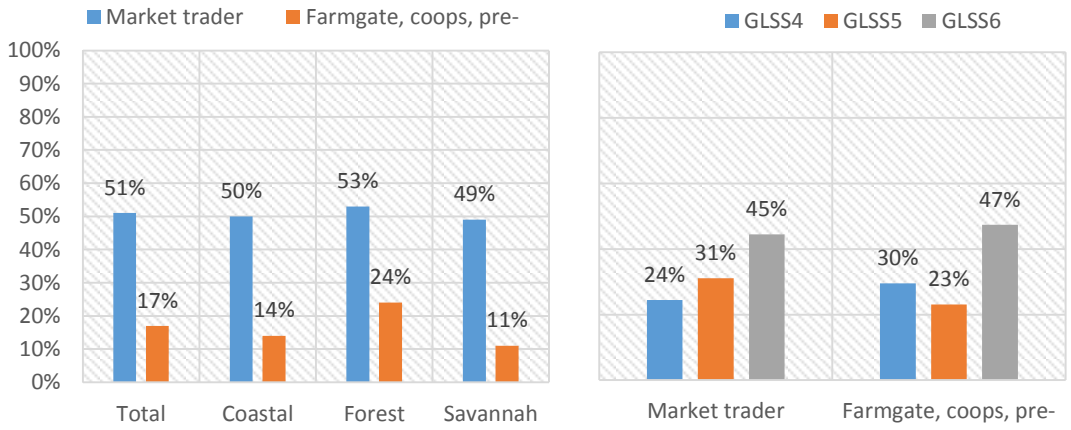


Figure 13 shows that also the proportion of sales towards market traders has reduced compared to alternative outlets.

Figure 13 Maize Commercialisation Index, by outlet of sales

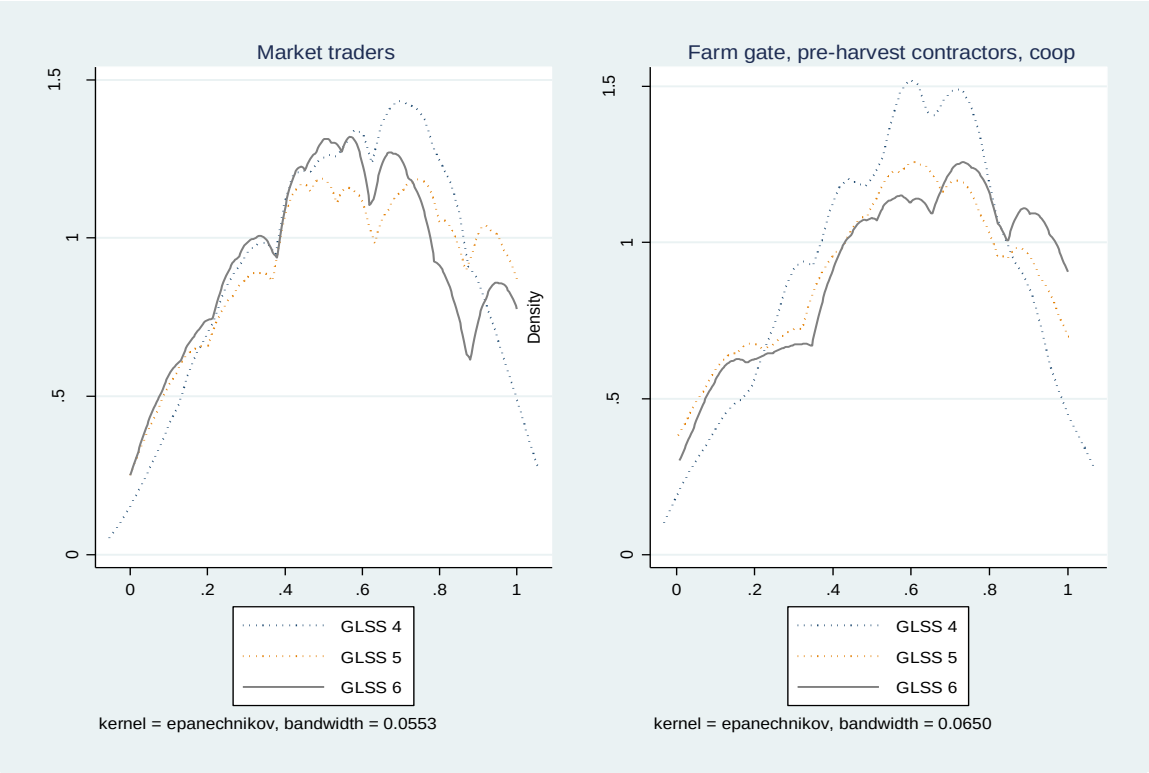
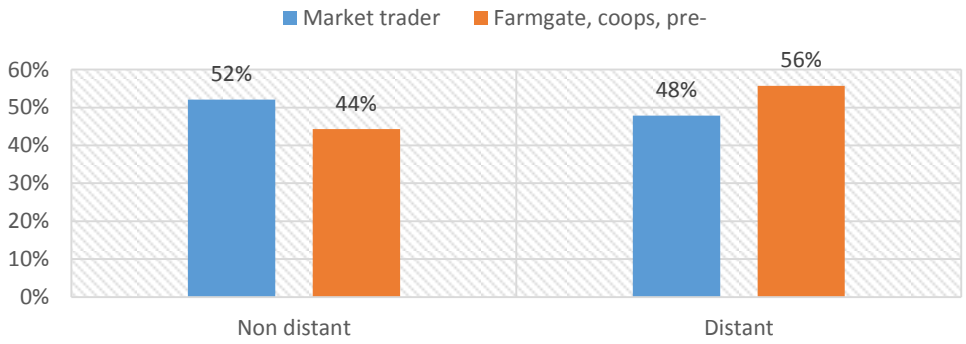


Table 6 (last two columns) shows the MNL estimations where the base category is non-market participation. Consistently with the all-household estimations, the results of the MNL show a positive relationship between market participation and remoteness.

Nonetheless, an interesting result is that the magnitude of the coefficient of distance to market is bigger in the case of the choice of farm gate, contractors and cooperatives compared to sales to a market trader. This result might support the idea that avoiding sales intermediaries, such as market traders, compared to not selling at all, has a bigger association with market participation than selling to a market trader. Quartey et al. (2012) find that market traders generally offer a lower sale price for maize compared to pre-harvest contractors and cooperatives in Ghana. Also, these non-traditional marketing outlets might be more common when markets are located more far away from the farm. Figure 14 shows that in the sample used for this analysis, market traders are, indeed, the most common outlet of sales for farmers who live closer to the markets while farm gate, cooperatives and pre-harvest contractors are more common for farmers located further away.

Figure 14 Maize outlet of sales, by distance to the market



Comparing these results to the findings of the all-household analysis shows that two arguments may have favoured a positive association between remoteness and market participations: social network and access to different sale outlets. Social network in the form of group marketing within cooperatives, established relationship with traditional buyers but also contacts with direct buyers at farm gate might make what is normally considered a marketing disadvantage, remoteness, a potential point of strength for farmers in the sample.

Section 7. Conclusion

The objective of this chapter is to investigate the determinants of market participation and its extent in Ghana with a focus on the role of fixed and proportional transaction costs. The analysis aims to investigate market participation with regards to both the decision to sell and not (the discrete decision of market participation) and the decision of how much to sell (the continuous decision of the extent of market participation, i.e. commercialisation). Thus, this paper investigates market participation as a two-step decision process whereby self-selection confounding effects are taken into account using the Heckman two-step approach. Similarly to several other studies on market participation, this analysis aims to identify associations and not causality, between commonly identified inhibitors and facilitators of market participation.

The dataset used is a pooled cross section from the three Ghanaian Living Standard Surveys (GLSS 4 – 1998/99; GLSS 5 – 2005/06; GLSS 6 – 2012/13). To my knowledge, no other previous study has used the latest round of the GLSS for the analysis of market participation. The final sample is composed of 14,736 households, 3117 households in 1998/99; 4,172 in 2005/06 and 7447 households in 2012/13, which corresponds to 47% of the total number of households and 81% of the rural households of the pooled sample of the three rounds of GLSS.

The analysis investigates first the determinants of market participation and its extent, commercialisation at aggregate level, i.e. household level, as measures of transaction costs is only available at household and village levels in the GLSS. Then, the analysis turns the focus on one of the most important staple grown in Ghana, maize. The crop level analysis has been motivated by the argument that different effects of different type of transaction costs can be observed more clearly, as they can have specific crop related relevance. Although measures of transaction costs are not available for every crop market transactions, GLSS collected data on preferred sale outlets for a selection of crops, mostly staple crops. Using these data, I investigate the decision of maize market participation using a multinomial logit model, which compares non-participation to participation in two different categories of sale outlets: 1) Non-traditional: farm gate, pre-harvest contractors and cooperatives and 2) Traditional: market trader.

The results support the relevance of transaction costs in market participation analysis. More specifically, both fixed and transaction costs are found to affect the decision to participation and its extent, although at different level. Moreover, the results also suggest that, in line with the previous literature, fixed costs are generally only associated with the discrete decision to participate and not with its extent (commercialisation). However, this result is only found for ownership of transport equipment, bicycle and not for the ownership of communication assets, such as radios. Hence, owning a radio is observed to affect both the discrete decision to sell and how much to sell. Conversely, owning a bicycle only affects the decision of whether to sell or not. This result suggests that owning a bicycle might facilitate the access to market information and as such facilitate market participation.

On the other hand, proportional transaction costs, as measured by remoteness from periodic markets, are observed to be positively associated with market participation, both in the household and crop level analyses. These results are not consistent with the traditional conceptual framework of market participation as well as with the related empirical evidence.

In order to validate the results and to try to explain the puzzling positive association between remoteness and market participation, I explore different options. First, I estimate the models of market participation using different specification of the distance measure. Then, I estimate the models separately by survey year. Overall, these additional estimations confirm that remoteness matters in the decision to participate in the market and that the direction of this association is positive. Farmers located further away are more likely to sell.

One of the reasons why this could be the case of farmers in Ghana is that, farmers that are located in community further away from markets have established strong relationship with traditional intermediaries, such as market traders, which in turns may have favoured their market participation. This is consistent with what Zanello et al. (2014) and Martey et al. (2012) finds in their analysis of maize farmers in Northern and Central Ghana. They both support the importance of social networks and personal relationship with buyers, which could allow farmers access to better prices for their sales and as a consequence a higher commercialisation level. Moreover, development agencies have been working quite intensively in the past years towards the reduction of

transaction costs for a better market access. The positive association between remoteness and market participation might, indeed, be explained because of the improved linkages between farmers and potential buyers that development projects have been supporting and fostering throughout the past decade. This argument is supported by the analysis of market participation across traditional and non-traditional sale outlets for maize. The results of this analysis suggest that selling at non-traditional outlets, such as farm gate, cooperatives and pre-harvest contractors, favours market participation more than selling at traditional intermediaries, such as market traders. These findings are in line with what Quartey et al. (2012) find in the analysis of price differentials across different marketing channels in Ghana.

In conclusion, I believe that, although within its limitations, this chapter contributes to the literature of market participation for several reasons. First, the analysis includes three rounds of Ghana Living Standard Survey, one of which, GLSS 6, has just recently been released for public use. To my knowledge, this dataset has not been used for a similar analysis as yet.

Furthermore, the results re-affirm the importance of including different measures of transaction costs, fixed and proportional, in the market participation analysis together with classical determinants, such as farm and household's characteristics. In line with previous studies, measures of fixed transaction costs, such as ownership of bicycles, are found to affect only the discrete decision to sell or not to sell and not the decision of how much to sell. Transport assets are indeed found to be used as a mean to access information and not as a vehicle for transporting produce to the market.

Furthermore, the unexpected positive association between remoteness and market participation may also contribute to the literature of market participation, especially with regards to Ghana, where marketing transactions often occur via informal marketing channels. The results of this analysis are in line with the argument that Zanello et al. (2014) and Martey et al. (2012) market transactions in Ghana heavily rely on personal relationships with buyers, especially when markets are further away from the farm. Also, in line with Quartey et al. (2012), the findings suggest in the case of maize growers that farmers located further away might have the opportunity to sell their produce to better outlets, such as contractors and cooperatives.

Overall, this analysis reinforces the importance of developing value chains linkages between farmers located in remote areas and buyers, traditional or non-traditional. Whether or not this holds for all types of crops it is not easy to say as GLSS data donot provide enough information at crop level and tends to focus on marketing information specifically for staple crops, such as maize. The lack of detailed crop level information motivated the primary data collection described in the following chapter.

CHAPTER 2

The adoption of exotic varieties of mango in Ghana

Primary data collection

Source 1 Field trip, February 2012

Introduction

In the past decades, non-traditional cash crops have been supported by the national government in Ghana as a way to foster agricultural commercialisation and reduce poverty. Among the crops supported, exotic varieties of mango have been welcomed by national and international agencies as one of the crops with the highest potential in addressing small farmers' poverty in Ghana, due to its higher weather resistance compared to other cash crops.

Currently available secondary data do not offer enough information on non-traditional cash crop production. For example, GLSS does not provide data on the varieties of mango produced, on related production and sales values as well as on the crop level market transactions. Considering the strong poverty reduction potential that has been advocated for these crops, improving our understanding of the dynamics of the adoption of these non-traditional cash crops as well as of the impact that the adoption itself has on farmers' well-being, motivated the collection of primary data used in this thesis.

This chapter describes the design and implementation of the data collection exercise, carried out in the summer 2012, whereby with the help of 8 enumerators, I collected data from 305 farmers (196 adopters and 109 non-adopters of exotic varieties of mango) in three regions: Northern, Brong-Ahafo and Eastern regions.

The rest of the chapter is organised as follows: Section 1 provides an overview of the development of the mango market and discusses the motivation for the primary data collection; Section 2 describes the design and implementation phases of the field work and Section 3 concludes.

Section 1. Background and motivation for primary data collection

Exotic varieties of mango, such as Keitt and Kent, were introduced relatively recently in Ghana. In 1997 a NGO, ADRA, with funding from USAID implemented the program called "Food for Peace", which established the first commercial orchards of mango farming in the Volta region. Free seeds and training were distributed to farmers willing to participate. This program was then followed by a more successful and more export oriented program, also financed by USAID, the Trade and Investment Programme for Competitive Export Economy (TIPCEE). Started in 2004, the program aimed to support non-traditional cash crop production within every region of the country. Mango was one of the non-traditional cash crops supported. A more systematic approach was adopted during this program, as technical training in pre and post-harvest management techniques was provided to a large number of farmers across the country. Also, with the use of GPS technology, TIPCEE started the first mapping of mango farmers in Ghana.

At the same time, major international donors, such as GIZ and the World Bank, and national agricultural initiatives (e.g. HEII) joined their efforts to make sure that what is called the "golden fruit" fully realised its potential. Through the establishment and consolidation of farmers' organisations, better extension services, training and so on, the adoption of exotic varieties of mango, among other non-traditional export crops, became, indeed, part of the Ghanaian strategy for poverty reduction via increased export market participation.

The adoption and diffusion of exotic varieties of mango for export became part of a broader food security strategy based on the idea that perennial tree crops are long lasting and more weather resistant, especially during dry seasons, than food crops. In the case of lack of rainfalls, tree crops can still generate fruits and income that can be used to buy food[26].

[26] In 2008 the Ghana Export Horticulture Cluster Strategic Profile Study defined exotic varieties of mango as one of the non-traditional cash crops with the highest potential in reducing poverty via participation of small, poorly endowed farmers in export markets and as a consequence to premium international prices. The report claim that the production of mangoes suits well small farming compared to other non-traditional export crops, as, for example, banana, because it is less labour intensive. Furthermore, mango production can be easily adapted to the changes in consumer preferences at relatively low cost if compared to the other major non-traditional export crop, pineapple, even by very small holders. The grafting process, whereby farmers only need to cut one branch of their mango trees and "graft" the new variety in the trunks of the trees, is not very expensive and does not require specific skills or technology to be implemented compared to other cash crops. ADRA, for example, claims that when farmers had to shift their production from the Smooth cayenne to the MD2 variety of pineapples, the process resulted and it still is

Following the implementation of several projects in support of mango adoption, production and export rose substantially in the past years from almost nothing in 2000 to about 1000 tonnes in 2008 and almost doubled in 2013 (p. 11). Nowadays, commercial production of exotic varieties can be found in three specific production belts: the Southern Belt, (Greater Accra, Eastern and the Volta Region); the Transitional Belt (Brong Ahafo Region and Ashanti Region) and the Northern Belt (Northern, Upper East and West Regions)[27].

Figure 1 Major mango producing areas in Ghana

Source 2 TIPCEE (USAID)

very expensive. Also, ADRA reported that each farmer had to spend at least 8000 Ghc to adapt their production to the new European demand.

[27] Differently from other mango producing countries, the southern belt of Ghana has two harvest seasons: the major season taking place from April to July and the minor one from December to February. Due to the higher humidity, the southern belt usually experiences more pest and diseases (e.g. fruit flies) than the other two areas, where the production conditions, especially in the Northern Belt, are quite similar to so called SKBo triangle (Sikasso, Korhogo and Bobo Dioulasso) in Cote d'Ivoire, major mango producing areas in West Africa.

The group of mango producers in Ghana is very diverse especially with regards to farm size, which mostly varies according to the location. While in both the Southern and Transitional Belts some of the producers are large businesses and they operate as producers and exporters (e.g. Bomarts), in the Northern Belt production is mainly composed of very small farmers who participate in either the Integrated Tamale Fruit Company (ITFC) contract farming or African Development Bank funded bloc farm system[28]. For both these schemes, only an acre of land per farmer is used for the production of mango.

Notwithstanding this diversity, one of the few analyses of the Ghanaian mango sector argue that more than a third of mango farmers are "poor complex diverse-risk-prone farmers" with small farm sizes (less than 4 acres, on average). Their assets are mainly land and low productivity family labour; they may be share-croppers and may not be able to adequately feed their families all year round. Moreover, the study also argues that the majority of mango farmers do generally heavily rely on staple crops for their nutrition and they usually are poor and risk averse (CATRD, 2006)[29].

Furthermore, Zakari (2012) argue that mango farmers do generally face a number of constraints in accessing export premium prices. Hence, export of fresh fruits to European Union or United States requires the satisfaction of stringent sanitary and phytosanitary requirements. According to these requirements, fruits must be faultless, with perfect colour, size and weight.

The vast majority of mango production in Ghana does not satisfy these requirements. The produce is often of lower quality than expected and this is mainly due to the existences of market and production related inefficiencies, which can be summarised as follows: 1) pest and diseases, such as fruit flies; 2) weather shocks, such as lack or

[28] Block farmers are large farms that are divided in blocks of one acre. Each acre is cultivated by one farmer. Inputs, trainings and output are managed and shared collectively within the framework of a purposively constituted farmers' organisation.

[29] Aside from individual farmers, mango is also produced on a large scale in bigger plantations. This is, for example, the case of the nucleus farm of ITFC and the plantation managed by Farm Management Services Limited (FMSL). ITFC was established in 1999 and mainly operates in the Northern region. It produces, processes and exports fresh and dried mango, mostly to EU. The nucleus farm is of approximately 200 hectares with about 1,200 outgrowers, organised under an ITFC-umbrella farmers' organisation called Organic Mango Outgrowers Association (OMOA), and located in three districts of the Northern region. The farm is irrigated and it is certified organic by Soil Association UK and Global GAP. Farm Management Services Limited (FMSL) was also established quite recently (early 2000s) and it is located in the Eastern region. FMSL is a mango plantation sharing scheme between six major clients for a total of 1,300 hectares of land under exotic varieties of mango, which is mainly exported to the Netherlands.

excess of rainfall which causes bush fires and flower abortion[30]; 3) lack of adequate inputs[31]; 4) poor infrastructure (inadequate form of irrigation; bad road conditions; unadapt trucks for transport of fresh produce; unadapt packaging; lack of refrigerating facilities; lack of clear quality standards); 5) high freight costs; 6) lack of marketing information systems[32]. Figure 2 shows a mango affected by fruit flies (top left); a young mango tree affected by a decaying disease (top right); an abandoned water tank in a mango farm (bottom left) and an example of the road condition in the Northern region (bottom right).

Figure 2 Mango production challenges

[30] The latest episode dates back to December 2014 when excessive rain caused flower abortion nationwide, which reduced drastically the production and its quality. As a consequence, some processors have been forced to import mango produce from Brazil (as in the case of Bomarts) to accommodate the demand of fruit juice and processed mango from EU.

[31] Inputs are often provided by farmers' organisation. However, the main input suppliers are large nurseries and agrochemical dealers, such as Agrimat and Dizengoff, which are mainly located in Greater Accra. The long distances from some major production areas increases the challenges of getting the right inputs at the right time, especially for poorly endowed and small farmers located in the Transitional and Northern Belt.

[32] Specialised traders in the mango distribution do not exist in Ghana, so that fruit traders include mango in their portfolio only during mango season. The distribution activities are mainly dominated by market women (local traders) who normally buy mangoes directly from the farms during the harvest season. Retailers then buy mangoes from traders to sell them to the final consumers. However, market women, also often involved in the harvest themselves, generally sell mangoes directly to the final consumers and less often to intermediaries or middlemen.

As a consequence of these inefficiencies, only farmers with certified production (Global Gap, organic, Fair Trade, or trader specific certifications) can effectively access the benefits of the exotic mango production[33], whereas the majority of mango growers often face considerable harvest losses. This is, for example, the case of the outgrowers under ITFC who are claimed to lose 75% of their produce, annually (Zakari, 2012). Still in the context of outgrowers in the Northern region, farmers do not even realize sometimes that they will be facing such a high rejection rate as the grading of the fruits is usually done at the time the produce reaches the buyer and farmers are not involved in the selection process. In reality, farmers normally end up selling a very small amount of their produce at export prices while the majority of the harvest ends up being sold in the local market at a much lower price, or used for processing dried fruits.

The situation tends to be slightly better in other regions, such as Brong-Ahafo and Eastern regions, where a more business oriented attitude allows farmers to manage their marketing strategies more effectively and, as a consequence, are more often able to benefit from higher prices. Nonetheless, the inefficiencies listed above do also apply in these contexts.

As discussed before, several projects have been put in place since the early 2000s, which tried to address market and production related difficulties in the mango sector, one of which supported the establishment of the Shed 9 Fruit Terminal in the Tema harbour.

However, despite the high attention that the mango sector has attracted among donors and government agencies, there is overall a general lack of knowledge about mango farmers themselves, their specific constraints, their experiences and their perception on the benefits, if any, of being involved in the mango production. Very often, national institutions and development agencies do not even know whether or not mango production is still operational in some farms. After almost a decade from the Ghana Export Horticulture Cluster Strategic Profile Study and the completion of TIPCEE, the

[33] Farmers are usually certified in groups, under the GLOBAL GAP 2 option. For example, selected farmers in the Yilo Krobo Mango Farmers' Organisation (YKMFO). Founded with the support of TIPCEE, this association mainly operates in the Eastern region and it includes some of the most productive mango farmers of the entire country, some of which also received Global Gap certification for organic export. Aside from YKMFO, high quality certified production is carried out also by farmers in the Volta Mango Growers Association, formed in 2005, whose first orchard was established by ADRA in 1997 and the Papaya and Mango Producers and Exporters Association of Ghana which is instead an association of privately owned companied that produce high quality papaya and mango.

impression is that nothing or very little is known about mango farmers' production decisions and welfare.

In trying to address this lack of knowledge on such an important sector of the Ghanaian small farming economy, I decided to collect primary data. I have designed and carried out a field study and collected detailed information on mango and non-mango producers in the three main mango producing areas in Ghana: Eastern, Brong-Ahafo and Northern regions.

From these three regions, I have surveyed 305 farmers, selected using a snowball sampling procedure, with an over-representation of mango and very small farmers (about 64% and 62% of the sample, respectively). Hence, the total sample included 196 mango and 109 of non-mango farmers, of which 189 were very small farmers (less than three acres of land) and the rest medium and large farmers (more than three acres). In total, 17 villages were surveyed in seven districts (Figure 3).

Figure 3 Geographical distribution of the sample

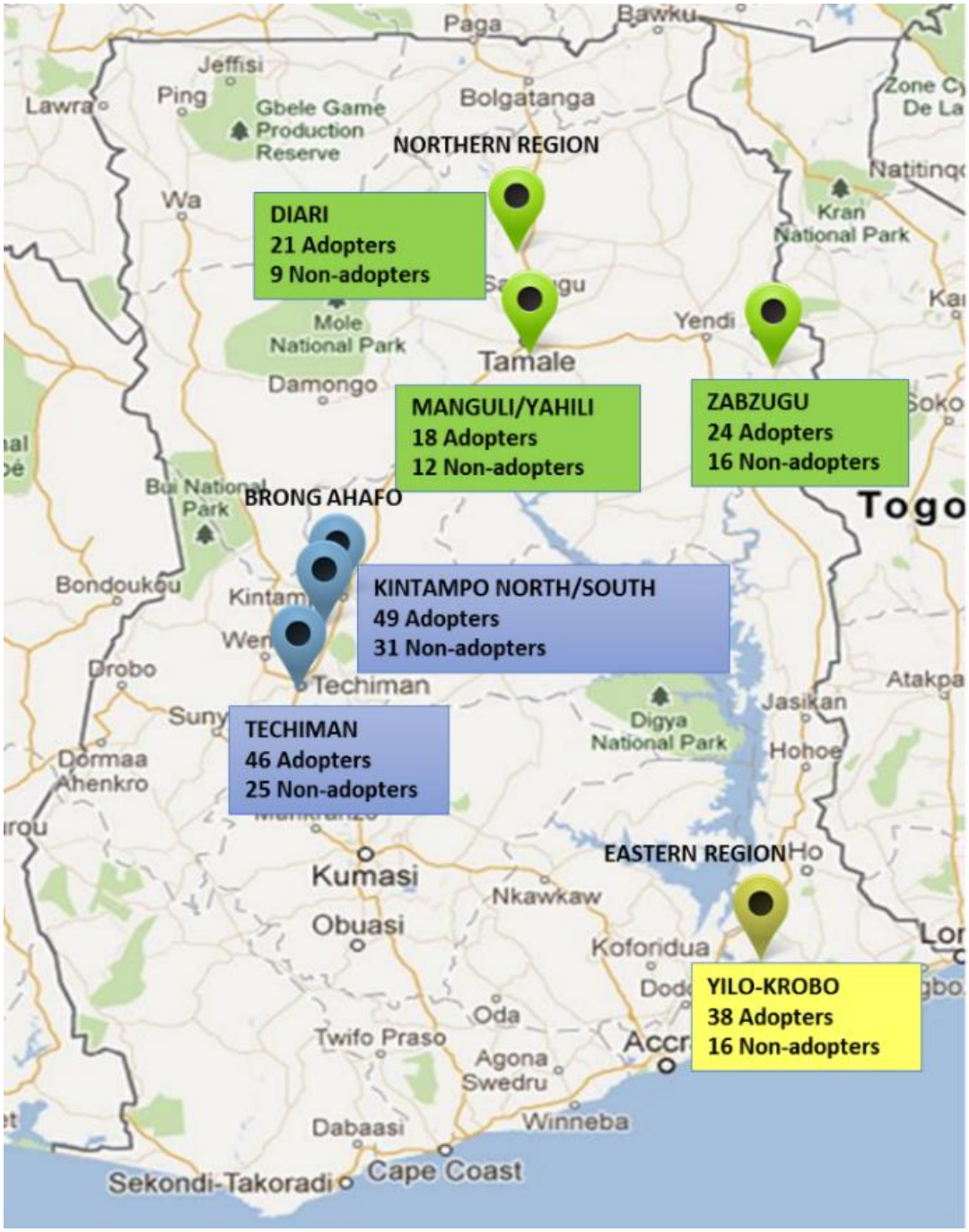


Table 1 Sample distribution by farm size

Region	Small (farm size equal or less than three acres)	Large (farm size more than three acres)	Total
Northern	77 (77%)	23	100 (100%)
Brong-Ahafo	84 (56%)	67	151 (100%)
Eastern	28 (52%)	26	54 (100%)
TOTAL	**189 (62%)**	**116**	**305** (100%)

Section 2. Primary data collection in detail

The field work was mainly composed of two phases: the “Design” phase the “Data Collection” phase. The “Design” phase lasted approximately seven months during which I designed the fieldwork and it included a 10 day-exploratory visit in late February 2012 with the main objective of identifying a local partner for the main “Data Collection” phase, which instead lasted for two and half months.

2.1 The Design Phase

During the design phase, I planned and organised the field work. Aside from desk reviews for the design of the survey tools and plan, I carried out an exploratory visit in Ghana from the 14th to the 22nd of February 2012. The main objective of the exploratory visit was to gather information on the feasibility of the data collection and analysis. More specifically, the visit intended to identify a partner for the implementation of the survey activities and to gain a deeper understanding of the mango value chain in Ghana. I carried out several key informant interviews whose content was designed before arriving in the country and adapted according to the new information obtained. The key informant interviews involved some of the major stakeholders of the mango value chain, such as the Ministry of Agriculture, SNV, GIZ, ADRA, USAID and some mango farmers’ organisations.

The exploratory visit was very successful in accomplishing both the objective of identifying a partner as well as in improving my understanding of the mango sector in Ghana, which informed the planning of the data collection.

The German Development Agency in Ghana (GIZ) showed a great interest in supporting the field work. GIZ is one of the main actors in the mango value chain with the Market-Oriented Agriculture Programme implemented in Ghana since 2004 and expected to be completed by 2016. The objective of this programme is to enhance the participation of small farmers in selected value chains, including mango, and their main interventions are the creation and strengthening of mango farmers’ organisation, the development of value chain committee (composed of farmers, processors and other relevant actors, at district and at regional level) as well as the provision of training in the most essential pre and post-harvest management techniques specifically tailored for mango production, such as, for example, tree pruning, weed control, plant protection

and fertilisers' use. They work in all major mango producing area, apart from the Eastern Region. Considering the relevance of GIZ in the mango sector and their established activities in the sector, I have identified them as partner of my research activities. A preliminary budget and field work plan was shared with them at the time of the meeting in Accra and a revised plan was then submitted after my return in UK.

The revised plan included also insights gathered from other key informant interviews and the brief field trip I have carried out in the last two days of the exploratory visit in the Yilo-Krobo and Dagme districts in the Eastern and Greater Accra regions, respectively. The final expected budget was agreed to about £10,000 for a sample of 360 households (later reduced to 305 households for logistic reasons). During the field work I managed to reduce the budget to about £9,000. The agreed duration of the field work was about three months over three regions: Eastern, Brogh-Ahafo and Northern regions.

The choice of these regions was driven by their relevance in the mango production in Ghana. According to the TIPCEE estimations, these regions produce more than 40% of the Ghanaian mangoes (Figure 1). Due to their strategic location they also represent the three belts of the mango production: Southern Belt, Transitional Belt and Northern Belt, with the Southern Belt being the first to be introduced to mango and Northern Belt the latest. Differences in locations translates in dissimilarities in problems and inefficiencies of each marketing system and production activities with the Southern Belt mainly affected by humidity-related fruit diseases and the Northern regions by dry weather and bush fires.

The relevance of the selected regions was also driven by the fact that they reflect different modalities of participation in the market for mango. The Southern Belt is mainly dominated by independent farmers closely located to the Tema Harbour and to the main processors and exporters in the country and so somehow advantaged with respect to the other belts. The Northern Belt is the only place where contract farming has been implemented and, finally, the Transitional Belt, of more recent development, stands somehow between the two.

The survey tools

The design phase also included the finalization of the following survey tools[34]: 1) Village Level Questionnaire; 2) Household Level Questionnaire. The tools were shared with and reviewed by the central and regional GIZ offices. Some adjustments were made in the length of both questionnaires, in the content of specific mango related modules, as well as on the expected schedule and logistic arrangement for the main data collection.

The Village Level Questionnaire aimed to capture the main characteristics of the villages sampled, with a focus on potential inhibitors and facilitators of adoption of mango. The following modules were included in the final questionnaire:

1. Roster (with demographic, infrastructure and shock information)
2. Agricultural production
3. Agricultural inputs and storage
4. Agricultural marketing
5. Farmers' organisation
6. Development programs
7. Access to information
8. Contract farming

The Household Level Questionnaire aimed to capture a more comprehensive set of household, farm and crop level information and it was composed of the following modules:

1. Roster (with demographic information at individual level)
2. Agriculture (plot level information)
3. Agricultural production (crop level information)
4. Agricultural input (input level information)
5. Mango production (for only mango producers)
6. Agricultural marketing (crop-buyer level information)
7. Trainings and certification (crop level information)
8. Relationship and trust (household level information)
9. Farmers' organisation (household level information)
10. Adoption of innovation (household level information)
11. Risk aversion and inter-temporal preferences (household level information)
12. Assets, credit and savings (household level information)
13. Sources of income (household level information)
14. Subjective poverty (income and consumption level adequacy, economic ladder; household level information)

[34] I also developed focus group discussions and key informant interviews guides, and a protocol for the implementation of the survey activities (Manual for enumerators). A copy of each tool can be found in the Annex to this thesis.

15. Recall section (on land acquisition, number of mango adopters and subjective poverty before mango arrived in community; household level information).

The selection of the questions for each section was based on desk reviews of available secondary data from agricultural and Ghanaian surveys, with a focus on market access, social capital and value chain studies. The choice has also been driven by the type of variables that the data collected allow to construct. For example, the agricultural modules allows to construct variables such as farm size, land ownership, crop portfolio choices, at plot and household levels, as well as measures of households' market participation. The module 8 collects information on social capital in a disaggregate fashion, which will inform the construction of social capital variables in Chapter 3. Module 11 collects information on risk aversion and inter-temporal preferences following the methodology by Binswanger (1980). However, only three of the seven levels of risk aversion used by Binswanger were retained for this survey, because of time and budget constraints. Finally, modules 12 and 13 will be used for the construction of a wealth index (module 12) and a subjective measure of poverty (module 13), the impact variables of interest of Chapter 4.

The design of the survey tools has been a quite long iterative process in order to guarantee a fair trade off between the information that I wanted to collect in the field and what it could have been reasonable to include in the formal questionnaire. Aside for the quality of the data collected, my main concern was to avoid respondent fatigue. Respondent fatigue is a very common cause of measurement errors, incomplete or refusal to participate if the survey activities are expected to be too long. After several iterations, the main household questionnaire was estimated to last for not longer than one and one half hours. All the tools were tested during the pilot described below.

2.2 The Data Collection Phase

This phase started with data collection in Diari, Savelugu-Nanton district in the Northern region, in the first week of August 2012. In total, the data collection in the three regions selected lasted for about two and half months and it concluded with a presentation of the preliminary findings and impressions from the field work to GIZ Central Office and to the main representatives of the Ministry of Agriculture. A mid-term review was also presented at the end of the data collection in the second region, Brong-Ahafo, in the end of August 2012.

The pilot

Before the main data collection, I carried out a four day long data collection pilot in one of the enumeration areas, the village of Manguli in the Tamale Municipality in the Northern Region. The objective of the pilot was to test the research tools, to let the enumerator familiarize with them and to make the necessary changes to the research tools, if needed[35].

The pilot lasted for four days starting on the 28th July 2012, immediately after the conclusion of the training of the enumerators, described below. The first day was dedicated to selection of farmers, village level questionnaire and focus group discussions. The following days were dedicated to the collection of data with the farmers' survey. Farmers received a pack of biscuits and a bottle of cola as a compensation for their time spent in the survey activities.

Overall, the outcome of the pilot was quite good. Aside some logistic delays, the data collection was carried out without major interruptions. Also, the enumerators proved to have understood the main survey dynamics and no major mistakes were made in the data collection itself, which at the end of the four days, lasted on average 1 and half hour, as expected during the design phase. Nonetheless, testing the survey tools provided considerably important insights which improved both the delivery of the survey instruments as well as the quality of the data collected during the main enumeration phase.

The main data collection

Once the pilot was completed and the tools finalised and validated, the data collection started. For each enumeration area, I organised the field activities around five main components:

1. Training of enumerators
2. Sample selection
3. Orientation phase
4. Farmers' survey
5. Key informant interviews, where appropriate

[35] The village of Manguli was selected because GIZ had contact with the leader of the local group of mango farmers who was able to provide a list of mango and non-mango farmers prior to our trip to the village and because the village is relatively close to Tamale.

Training of enumerators

After the first meeting with the enumerators at the regional GIZ office, enumerators were asked to attend a three days training. The training usually covered two sessions. The first session was dedicated to the description of the research and its objectives. A second session thoroughly described all the research phases, tools and instruments. During the training, every enumerator was encouraged to raise issues and problems with the understanding of the research instruments. A special session was dedicated to the practice of administrating both the village and household level questionnaire during and after the training hours. Enumerators were also asked to practice with friends or family in their own village and return the day after with a filled questionnaire. After the completion of the training each enumerators was provided with the necessary research tools (printed questionnaires and codebook, pens, calculators, ID card, etc.).

Figure 4 Team of enumerators

Enumerators were also divided into two groups: one group (composed of two enumerators) was responsible for the implementation component 2 (sample selection and mapping exercise) and the second was made responsible of the component 3 (orientation phase). At the end of the training each enumerator was also provided with a

Personal Work Plan with a list of activities and responsibilities for the entire duration of the data collection exercise. The Plan also included a section for the recording of the households interviewed during the farmers' survey. Names, addresses and contacts of each farmer were recorded in this section and cross-checked with the submitted questionnaire at the end of each survey day. Figure 4 shows the team of enumerators for the Northern region[36].

Sample selection and mapping exercise

The sample selection was originally designed to follow a random, stratified sampling procedure, using region and farm size as main criteria for the stratification. However, since the exploratory visit in Ghana, it became evident that getting a comprehensive listing of farmers containing this type of information would have been extremely challenging. Data on the location of mango farmers in Ghana are rare, scarce and not reliable. Where existent, most of the times they are about newly established mango farmers that are not harvesting yet and so they do not qualify for this research. In addition, they are not up-to-date. In some cases, farmers are not producing mango any more[37].

Furthermore, getting the list of all the farmers and their farm size for the districts selected proved to be almost impossible. Every year a farmer's registration is supposed to be implemented at district level with the collection of all sorts of information about every farmer in the district. These data are then sent to the regional capital's MOFA office that forwards it to Accra. However, the retrieval of these data was complicated by the following difficulties:

1. MIS (Market Information System) officers in the districts' MOFA offices were not often available. After being asked to send the list of farmers with the farm size, only a few of them replied and one of them sent a list in a format that could not be opened with the usual Windows software.
2. In general, emails are not feasible for the purpose. Physically reaching and scheduling a meeting with MIS officers proved to be difficult and time consuming.
3. In some cases, the offices did not even have electricity and so it was not possible to retrieve data from the local computers and paper copies were not available.

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[36] More details on the training can be found in the "Manual for enumerators", attached in Appendix 2.2.

[37] For example, based on GIZ information, the district of West Mamprusi in the Northern region was supposed to be a quite well established mango production area. However, after trying to reach the few contacts I managed to find, I finally realised that the group of mango farmers was not existent anymore, mainly due to bush fires that had destroyed the cultivation. Only one mango farm was still operational at the time of the survey.

As a consequence of these constraints, a purposive, linear snow-ball sampling procedure was used for both mango and non-mango farmers, using location, farm size and mango production as main selection criteria[38]. Mango farmers and very small farmers (three or less acres of land[39]) were over-sampled, 60% and 80% of the sample respectively.

Where no farmers could have been identified ex-ante, we conducted a mapping exercise with the help of local Agricultural Extension Officers and representative of farmers associations. This exercise aimed to identify farmers in the village who, based on the selection criteria, could fit the purpose of the analysis. Two days were usually dedicated to this preliminary mapping exercise. Specific directions were provided to the enumerators in their Personal Work Plan regarding the number of households to identify, the number of mango and non-mango farmers as well as the number of small and non-small farmers.

Orientation Phase

The orientation phase immediately followed or overlapped with the mapping exercise. Two of the four enumerators were responsible for the implementation of this component. The main activities of this phase were: contacting the village, preparing our arrival, implementing focus group discussions (one with mango farmers and one with non-mango farmers) with farmers identified during the mapping exercise and carrying out the village level data collection.

More specifically, before arriving in the village, one enumerator usually contacted a village representative for organising the field work activities of the day. A chief of the village or other informed representative of the village were the preferred interlocutors,

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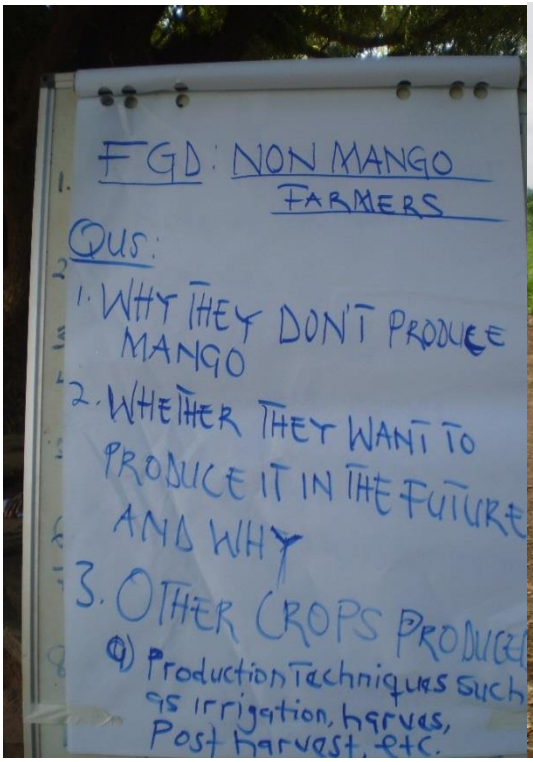
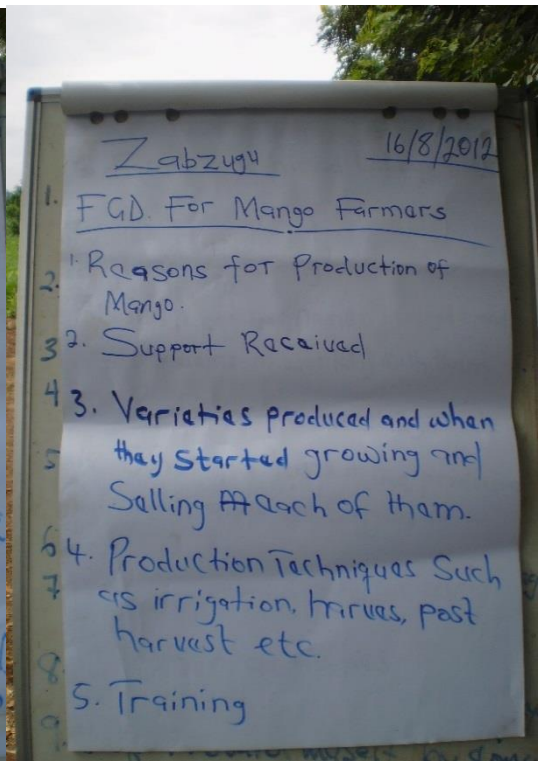
[38] Although it allows identification of hard-to-reach populations in a cost efficient and relatively simple way, the snowball sampling procedures poses substantial challenges with respect to the representativeness of the sample as very little information was available about the true distribution of the true population. Sampling bias is likely to affect the sample used for this analysis. It is indeed possible that sampled subjects present similar traits and characteristics and, as a consequence, represent only a selected group of the true population. Moreover, the use of snowballing sampling procedures has also implications for exchangeability and iid assumptions of the econometric analysis because of the lack of independence between observations. As a consequence, the regression estimates might be, indeed, biased. However, without knowledge of the underlying distribution of the population of mango and non-mango farmers it is difficult to conclude the direction or magnitude of this bias.

[39] In the definition of the farm size criteria I could have not used secondary data, such as, for example, the Ghana Living Standard Surveys, for two reasons: 1) the number of mango producers in this datasets is extremely low, suggesting that these surveys might be representatives of the mango population; 2) there is no distinction between local mango and exotic varieties of mango. Instead, I have followed the only mango study available at the time of the field work design: CATRD (2006) that argue that the majority of mango farmers had 4 or less acres of land. As my research focus aimed to include also very small farmers I have lowered this average value to 3 acres to make it consistent with official data from the Ministry of Agriculture, which identify the average land holding in Ghana agriculture of about 1.2 hectares (about 3 acres).

who were then asked to organise farmers, identified through the mapping exercise for the focus group discussions and the main survey.

Figure 5 Focus group discussions





The focus group discussions were normally run with about 10 farmers for each group (Figure 5). Enumerators were trained as both moderator and assistant for the focus group discussions. The moderator was responsible of asking questions and animating the discussion while the assistant was in charge for taking notes and making sure that the recording equipment was working fine. Transcripts of the discussions were then prepared and submitted at the end of the enumeration exercise together with correctly filled questionnaires. The two focus group discussions aimed to gather information on the decision to adopt mango, the main issues related to production and post-harvest issues as well as farmers and village level general socio-economic characteristics. Specific instructions were given to the enumerators to make sure that farmers and locals knew that we valued their time very much and that their help was extremely precious. A thorough description of the research preceded any activity in the field and before any data collection every farmer was asked to sign a consent form, in the case they accepted to participate. Confidentiality was guaranteed at every level of the field activities.

Farmers' survey

The farmers' survey was implemented after the village survey and the focus group discussions. The survey collected in-depth data on farmers, households' members, farms, crops produced and sold, buyers, relationship with other market actors, income and assets. A specific module was dedicated to the production of mango. Generally, each enumerator was able to finish four questionnaires per day. During the enumeration days, my supervision role mainly consisted of implementing a thorough quality check. The quality check strategy was based on two main activities: 1) accompanying one enumerator at the time during their data collection; 2) thoroughly validating each completed questionnaire the end of each enumeration exercise. The enumerators were asked to submit the clean and fully filled questionnaires, for entry and consistency checks. If errors or inconsistencies were found, enumerators were then asked to go back to the household and fill the specific section again. This strategy proved quite efficient as mistakes were corrected as soon as possible, reducing at the minimum the additional time that, in these cases, farmers would have needed to dedicate to the data collection.

shows an example of how the data collection occurred in the field.

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quality check. The quality check strategy was based on two main activities: 1) accompanying one enumerator at the time during their data collection; 2) thoroughly validating each completed questionnaire the end of each enumeration exercise. The enumerators were asked to submit the clean and fully filled questionnaires, for entry and consistency checks. If errors or inconsistencies were found, enumerators were then asked to go back to the household and fill the specific section again. This strategy proved quite efficient as mistakes were corrected as soon as possible, reducing at the minimum the additional time that, in these cases, farmers would have needed to dedicate to the data collection.

Figure 6 Enumeration in the field

The data collection activities started in the middle of the rainy season in Ghana. Although this was not generally a problem with travel between cities, the bad road conditions coupled with excessive rains, made it impossible sometimes to carry out our daily schedule. Rains also affected the propensity of farmers to participate in focus group discussions as happened in Diari, one of the first districts surveyed in the Northern Region, where after reaching the village, we had to face the reality that farmers had all gone back home. However, luckily, after waiting a couple of hours, my

team of enumerators managed to gather the farmers back at the village and the activities were implemented as planned.

Another challenge faced during the main data collection was the considerable distance between farmers and the difficulty in accessing them via public transportation. While in the Northern region, GIZ provided a car for the data collection, in the other two regions of the field work me and my team had to rely on public transportation, in the form of taxis, buses and mini-buses, which is not always available in remote areas. Although not always easy, the team proved once again to be able to face these difficulties and the enumerators very rarely missed a scheduled appointment. In addition, I also managed to visit few mango farms which were located further away from the enumeration areas.

Furthermore, more than 11 official local languages are spoken in Ghana. The enumerators did not speak all of the languages spoken in the sampled areas. Fortunately, this did not cause problems in the enumeration as in the Northern and Brong-Ahafo regions asenumerators were fluent in the local languages while in the Eastern regions the enumerators could also rely on an official translator who worked with us for the entire duration of the survey. In order to make sure that the activities were implemented at the right standard, during the enumeration, I often asked one of the enumerators to give me a summary of the conversations and, if needed, I asked him to intervene in the conversation. After an initial period of adjustment, notwithstanding the language barrier, I was able to understand what was asked and to cross check the answers on time.

Another challenge of the data collection concerned the relatively difficult times that mango farmers had faced during the harvest season that preceded the field work. Since the beginning of the data collection, it became clear that farmers, especially, in the Northern region had been struggling in their mango production because of the occurrence of bush fires, fruit flies and other diseases. As a consequence, the data used in this thesis are likely to reflect these challenges and the consequent poor harvest estimates.

Finally, during the main data collection I had to face some health problems. Already in the first week of the field work I had to be hospitalised for a case of malaria. Health problems, although less serious that this first time, accompanied me for entire duration

of the survey activities[40]. Luckily, the enumerators were able to work alone in those days that I could not follow them in the interviews. However, on a total of two-months a half, I have been able to be in the field during enumeration all the time apart from probably 7 to 10 days in total.

Overall, the main data collection has been a quite intense and tiring experience, with activities starting as early as 4 am in the morning and finishing not before sunset, after which I would normally work on the preparation of the next day activities. However, the strong motivation and enthusiasm that my enumerators and I had during the field activities helped us carrying on even in difficult circumstances and achieving the timely and in-budget completion of all the planned activities.

Key informant interviews

Finally, when appropriate, I carried out key informant interviews with the relevant stakeholders, such as ITFC, HPW, Blue skies, Bomarts and local farmers' organisation. Figure 7 shows two mango pack houses visited in the Eastern region.

Figure 7 Mango packhouses (Bomarts; MiDa - Akorley)

[40] In addition, one of my enumerator suffered heart problems while we were in the field in the Brong-Ahafo region, and he had to go back to his town for health checks and rest.

The top picture shows the Bomarts' pack house, one of the few exporters in the sector, while the bottom pictures show the newly built public pack house in Akorley with financial support by the Millenium Challenge Account. This pack house can be used by local farmers and it was managed, at the time of the survey, by a Dutch/Ghanaian company (Kingdom Premium Fruits).

Section 3. Conclusion

This chapter provides an overview of mango market in Ghana and describes the field study in Ghana, during which I collected the data used for the analyses in Chapter 3 and Chapter 4 of this thesis.

The fieldwork, with financial and logistic support by GIZ, was organised around two phases: a design and main data collection phase. The design phase lasted for about seven months during which I organised the activities and designed the survey instruments. The main data collection phase lasted for about two and half months, during which I collected data from 305 farmers, 196 mango farmers and 109 non-mango farmers in three regions in Ghana, with the help of eight enumerators.

The sampling strategy was based on a snowball procedure due to the lack of available listing at the time of the survey, which did not allow for the ideal random selection. Nonetheless, three criteria were used for the selection of farmers: farm size, location and mango adoption. Small farmers (less than three acres) and mango farmers were over-sampled.

Two main survey tools were used: a village and a household questionnaires. In addition, in each village visited two focus group discussions were carried out, one for mango farmers and one for non-mango farmers.

All 305 household level and 17 village level questionnaires were filled during the data collection. The completeness and the consistency of the data were quite consistent across the three regions, although a couple of times enumerators were asked to re-fill the entire questionnaire due to major inconsistencies and mistakes. In most cases, minor mistakes were corrected in the field with additional short visits to the farmers in the sample. Additional quality checks were also run at the end of the field work, when preliminary results of the field work were presented to GIZ and representatives of the Ghanaian Ministry of Agriculture.

Despite some logistic, weather and personal related difficulties, the overall results of the data collection exercise proved to be quite satisfactory not only for the quality of the data collected but also from a personal experience point of view.

CHAPTER 3

The adoption of exotic varieties of mango

A case study from Ghana

Introduction

Innovations are essential part of anybody's life. Henry Ford once said "If you always do what you've always done, you'll always get what you've always got." I believe that this short quote summarises perfectly the idea that there is an irresistible desire of trying the new and the unknown imbedded in the human nature, no matter gender, social status or location differences. And this desire is intrinsically motivated by the ambition to improve ourselves as balanced by the need to minimize risks and losses.

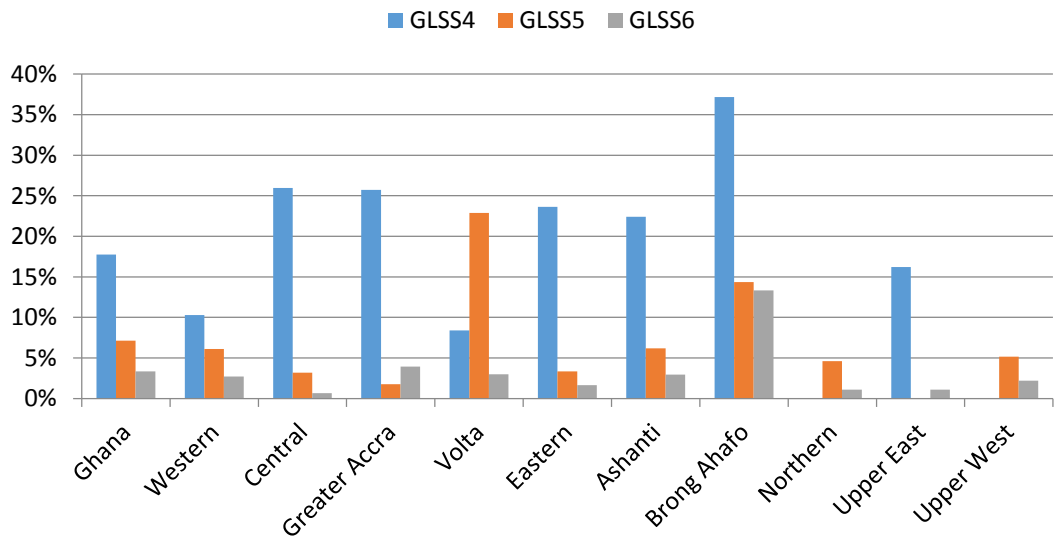
Farmers in developing countries are often exposed to innovations, such as new crops, resistant varieties of known crops or new technologies that donors, NGOs or national governments think could be beneficial for their livelihoods. Some of them decide to adopt and some others just don't and probably they never will. This puzzling evidence has motivated scholars for decades and, although a great deal of knowledge has been produced on the reasons behind numerous adoption and non-adoption processes, there always are niches of "unexplored" and "new" that need further attention.

This is the case of exotic varieties of mango in Ghana, which, as explained in Chapter 2, have been introduced in the country on a massive scale in the late 1990s and as such can be considered an innovation. Although unsustainable in the early stages, international donors and national government in Ghana have joined their efforts in supporting mango adoption and in reducing farmers' constraints in accessing its benefits, especially for small and poor farmers. As shown in the introduction of the thesis, this effort effectively managed to increase mango production and export quantity through the years. Nonetheless, the frequent pests and diseases and unexpected weather related shocks occurrence have shown that production trends are not stable but, instead, extremely vulnerable to common and idiosyncratic shocks.

Lack of experience and knowledge about the mango production itself are some of the main factors that currently constraint exotic mango producers, often forcing farmers to

engage in dis-adoption processes. Data from the Ghanaian Living Standard Surveys suggest, indeed, that, although production increased through the years, the number of mango producers reduced drastically in the past decades (Figure 1).

Figure 1 Mango producers in Ghana (GLSS)



However, available secondary data, such as GLSS, do not provide detailed information on the variety of mango produced and as such it becomes difficult to understand what had really happened in the subsector of exotic varieties of mango. Moreover, the strong political interest and the amount of national and international financial investments in the sector have not found a commensurate attention in the academic arena or in field research. In the past, quite a few studies on determinants of product innovations have focused on traditional cash crops, for example cocoa, or non-traditional cash crops, such as pineapple and horticultural crops[41], but only few, mainly qualitative analysis, have been specifically carried out on the adoption of exotic varieties of mango. To my knowledge mango adoption has been investigated by only two studies: CATRD, (2006) and van Melle and Buschmann (2013). Both studies use a value chain and case study approach, which mostly translated in a qualitative analysis of the sector.

This paper contributes to the innovation adoption literature as it investigates the adoption process of exotic varieties mango (adoption, time of adoption and intensity of adoption) using primary data collected from mango and non-mango adopters, as

[41] For example, Conley and Udry (2010) investigated the adoption of pineapple in Ghana with a focus on social networks, or Afari-Sefa (2006, 2010) who analysed the horticultural export sector or high value chains access by small farmers.

described in Chapter 2. As far as I know, aside from project related small M&E surveys, few other studies have collected detailed data from mango producers and as such this analysis could contribute to the understanding of the main mango production and marketing related challenges in Ghana.

The analysis especially focuses on the role of social capital factors. Usually overlooked in the classic adoption literature, the importance of including factors such as existing relationships and trust, often solely the domain of the sociological studies, has gained reconnaissance also in the economic literature in the past decade. The lack of official information channels, the consequent high risks involved and the long gestation period that characterise the adoption process of exotic varieties of mango make social capital an important factor in the adoption of these cash crops. The decision to adopt mango, aside from assets constraints, could, indeed, depend on the existence of relationships with the key innovation agents (development agencies, NGOs or previous adopters), and with how much these innovation agents and facilitators are considered trustworthy.

The rest of the paper is structured as follows: Section 1 describes the theoretical framework; Section 2 reviews the most common empirical findings that inform the empirical analysis (Section 3); Section 4 presents the econometric models and challenges; Section 5 discusses the results and Section 6 concludes.

Section 1. Theoretical model of adoption with social capital

The literature on adoption is quite vast and diverse. Maertens and Barrett (2012) summarise the different conceptual approaches to innovation adoption around five questions: (i) What do farmers value and over what time period? (ii)What type of information does the farmer absorb and from whom? (iii) How does the farmer learn, i.e., how does he update beliefs? (iv) How do beliefs translate into actions? And (v) Do agents interact strategically?. Depending on the answers to these five questions, theoretical and, as a consequence, empirical models may differ quite substantially. The model presented here mostly relates to the discrete decision to adopt or not. However, similar theoretical intuitions can be associated with different dimensions of adoption, its time and intensity, and similar models are deemed to have implications also for different levels of the adoption process.

The most common theoretical model for innovation adoption is the expected discounted utility model which assumes that farmers value the expected profit with and without the adoption of innovation and decide accordingly. In order to take this decision a farmer needs to address several uncertainties that are embedded in the adoption process. These uncertainties are related to difficulties to predict the returns, or future stream of expected benefits generated by the innovation, expressed as:

$$E[U(\pi_f - \pi_p) \geq 0 \quad (1)$$

where π_f is the expected present value of the future stream of net benefits under adoption; π_p is the subjective estimate of the expected present value of the enterprise's future stream of net benefits under no adoption.

Classical models of adoption predict that the expected profitability of the innovation may depend on objective constraints (differences in agro-ecological zones and climatic conditions – Deressa et al., 2009); supply-side constraints (heterogeneity in farmers' absorptive capacity – Berger, 2001); market inefficiencies (limited access to credit– Coady, 1995) and information barriers (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Wossen et al., 2015). These constraints, *z*, for household *h*, can be expressed as follows:

$$z_h = f(A_h, G_h, I_h) \quad (2a)$$

where z is function of private, A_h (land, equipment, etc – absorptive capacity), and public, G_h (institutions and markets, infrastructure – supply side constraints), assets and information barriers I_h.

The information barriers, I_h, (about inputs and/or outputs) may differ with the type of the innovation. The "target input" models, for example, assume that farmers might need to learn about the optimal use of the input for the new technology and choose to adopt conditional on this information and as such they investigate the role of "learning by doing" in the innovation adoption (Besley and Case, 1993)[42]. Other authors focus, instead, on a different, often more complex, learning dynamic which involves "learning by seeing" the output generated by the innovation itself. This process may involve awareness exposure to the innovation (Adegbola and Gardebroek, 2007; Diagne and Demont, 2007), imitation and interaction with adopters of the innovation (Foster and Rosenzweig, 1995). Conley and Udry (2001) claim that the "learning by seeing" generates an incomplete flow of information on the adoption and that farmers, cognizant of the potential for missing important information, weight this "incomplete" learning by the value of each innovation.

Once farmers have acquired the relevant information, either on input or output, for the adoption process, a Bayesian updating process is usually assumed. The Bayesian updating process informs not only the decision to adopt but also its timing and its intensity. Hence, it postulates that farmers might use the information learned for strategic delays in adoption instead of engaging in "imperfect" learning from others' experiences. This behaviour is assumed to increase with the forward-looking farmers' attitude (Foster and Rosenzweig, 1995).

More recently, attention has been given to the social components of the adoption dynamics which goes beyond the simple learning process. The renovated interest in social capital in connection with innovation has increased due to often occurring

[42] Learning has been introduced in the adoption of innovation literature since the seminal work by Warner (1974) who was among the first scholars to claim that learning processes, through trials and imitation, are fundamental in adoption. Fischer et al (1996) use a Bayesian random model for the adaptation through time using the information of yield and prices related to the innovation and the difference of them with the old technology or crop. They found that the "effective" information can be measured by the number of years of using the innovation. An extended theoretical framework by Ghamin and Pannell (1999) includes both risk aversion and information in the maximization of the utility of the net present value of the profits using two main indicators: learning by doing (skill improvements: the more skilled with the innovation, the more land or input will be used for the innovation); information on the performance of the innovation (learning by using - this information can lead to an increase or decrease of the land allocated to the new crop or to the innovation).

difficulties to interpret inconsistencies in the adoption process using the standard economic models (Landry et al., 2002). Asymmetry of information, failing or missing markets and institutions are the norm in most of developing countries. Individuals, firms or communities have to rely on other sources to smooth risks and uncertainties embedded in the innovation adoption process. And these sources are often social in nature. Information, resources and safety nets can, indeed, be gathered via formal and informal social channels, in the form of relationship and networks. Social interactions are also claimed to overcome institutional and markets vacuums, influencing people preferences and constraints, lowering transaction costs and facilitating exchange of information which in turns enables individuals to overcome social and economic dilemmas (Grootaert and Bastelaer, 2002; van Rijn et al., 2012).

Bandiera and Rasul (2006), following the framework set up by Bardhan and Udry in 1999, formally re-introduced social components in the innovation adoption theoretical literature, in the form of social networks. Their framework is then expanded by Matuske and Qaim in 2009 to address the role of similarities within social networks in innovation adoption. These authors support the idea that instead of investigating the "know-how" component of the adoption process, the "know-who" should deserve more attention. Social networks are claimed to be more conducive of essential adoption requirements than other types of capital, as they can foster adoption via a consistent flow of information within the network, which reduces search and screening costs of adoption (Dakhly and de Clerk, 2004; Kaasa, 2009). Social networks can also improve the innovation process via the occurrence of "synergy effects", where different innovative ideas produce an even higher innovative collective action, and the "realization effects" due to the access to combined resources (Boahene et al., 1999; Bandiera and Rasul, 2006; van Rijn et al., 2012).

Social networks are often defined as the "structural" component of the social capital and it mainly refers to the number and type of relationship that an individual is involved into. These relationships are further classified into two categories: bonding and bridging structural social capital. The former refers to ties between people with similar characteristics (e.g. between farmers, or between people from the same ethnic or religious background, etc.) while bridging structural social capital refers to relationships and ties between people with different livelihoods, economic status and role in the

community, for example, between farmers and community leaders, extension officers, development agencies (Grootaert, 2002).

However, social networks are only one of the two main components of the social capital. Another important component, often overlooked in the adoption studies is the so called "cognitive social capital", which mainly refers to a more subjective dimension of social capital, and it is expressed in the form of trust and norms. Three types of trust have been identified in the literature: the general trust in the future, the society and so on; the trust in other individuals and the trust in the institutions. Trust is believed to facilitate innovation as it fosters cooperation, reduces transaction costs such as bargaining and enforcement costs, reduces risks and uncertainty and allows individual to rely on others in the case of need, i.e. self-insure against risk (Narayan and Prichett, 1999; van Rijn et al., 2012). Sociologists define trust and norms as the essential enabling mean for social cooperation and collection action (Woolcock and Narayanm, 2000; Bowles and Gintis, 2002) and economists claim that innovation exchange cannot occur without trust and vice versa (e.g. Tsai and Ghashal, 1999; Kaasa, 2009).

Although trust and norms are claimed to be strongly correlated, the role of norms in the adoption framework is, however, not straightforward. For example, the reciprocity norm predicts that people act for the benefits of others and expect the same in the case of need (Fountain, 1998), which assumes that people are trustworthy and as such should foster innovation (Isham, 2002; van Rijn, et al., 2012). However, there are other norms that could act as barriers for the adoption of innovation. This is the case of, for example, conformity and sharing. Conformity to community norms and to authority as well as the norm of "social sharing" can indeed hinder the capability of an individual to adopt innovations if the community norms or what supported by the authority in the community does not allow for it or if it is commonly accepted that benefits from innovation have to be shared within a wide network of relatives (Moser and Barrett, 2006; Kassie et al., 2013; Wossen et al., 2015). This coupled with the difficulties to measure norms explain why the role of norms in the adoption process still remain an unanswered and challenging question.

These recent developments in the adoption literature suggest that the adoption process should also be conditioned to social capital components. Hence, equation (2) can be re-written as follows:

$$z_h = f(A_h, G_h, I_h, SK_h) \tag{2b}$$

Where SK_h represent the social capital in the form of relationships and trust of the farmer *h*. Finally, following the expected discounted utility model, the optimization problem can be written as (3):

$$Max\ E[U_h(\pi_{fi} - \pi_{pi}) = \gamma z_h + \varepsilon^i \tag{3}$$

where ε is the error in the expectation on the return from innovations i. From (3), the decision to adopt the innovation *i* by farmer *h* occurs if the expected utility of the net present value of profits is positive, conditional to the constraints in (4):

$$Y_h^{*i} \begin{cases} 1,\ if\ E[U(\pi_f - \pi_p) > 0,\ \gamma z_h\ \geq\ -\varepsilon^i \\ 0,\ if\ E[U(\pi_f - \pi_p) \leq 0,\ \gamma z_h <\ -\varepsilon^i \end{cases} \tag{4}$$

Following Wossen et al. (2015), Y_h^{*i} represents the latent decision to adopt that is empirically estimated using an observable binary discrete choice Y_h^i of whether the farmer adopts or not adopt the innovation under analysis, expressed as:

$$Y_h^i \begin{cases} 1,\ if\ \ Y_h^{*i} > 0 \\ 0,\ otherwise \end{cases} \tag{5}$$

Using (2b), then the empirical equation of the adoption decision conditional on the different constraints can be re-written as a reduced form of the equations (2b) to (5):

$$Y_h^i = \alpha + \beta_1 A_h + \beta_2 G_h + \beta_3 I_h + \beta_4 SK_h + \varepsilon \tag{6}$$

where A_h is a vector of private assets (land, equipment, etc – absorptive capacity), G_h is a vector of public assets (institutions and markets, infrastructure – supply side constraints), I_h I a vector of variables that controls for information barriers, and SK_h is a vector of social capital variables.

Section 2. Empirical evidence on determinants of innovation adoption

Classical economic models of adoption focus on the supply-side and market inefficiency constraints. These models find that adoption is mainly driven by factors of production (farm size, farm labour, land ownership and so on), farmers' characteristics, such as risk aversion, household's demographic characteristics as well as public assets that capture market inefficiencies (such as access to credit) (Coady, 1995; Berger, 2001; Foster and Rosenzweig, 1995; Wossen et al., 2015).

As discussed in the previous section, the effect of social capital in the innovation adoption has been gaining wider recognisance in the empirical literature in the past decade. Laundry et al. (2002) found a strong evidence that different forms of social capital positively influence the innovation adoption across 440 manufacturing firms in Montreal. Bandiera and Rasul (2006) with their seminal paper on the role of structural bonding social capital, find a strong evidence of a positive effect of the adopters' social networks in the adoption of a new crop, sunflower, in Northern Mozambique. They also find that there exist a threshold size of the network after which the adoption rates reduce due to overcrowding effects.

A positive effect of bonding social capital is also found in a study of adoption of sustainable agricultural practices in rural Tanzania (Kassie et al., 2013) where membership in farmers' organisation is used as a proxy of closeness to peer social networks. In Ghana, Barr (2000) analyses the effect of social capital and technical information flow in the manufacturing sector. She also found that bonding social capital, measured as the number of contacts a firm has with similar firms, increases firm productivity, performance and innovation adoption.

Matuscke and Qaim in 2009 extend Bandiera and Rasul (2006) model in a study of the adoption of hybrid wheat and hybrid pearl millet in India. Their main finding suggests that information flow occurs along homophilous rather than heterophilous lines and as such only the "closest" possible social networks should be investigated in the adoption decision. Hence, they found that what they call "exogenous social network" analysis, which controls for the specific characteristics of the closest possible social network and

not only for its size as in Bandiera and Rasul (2006), has a bigger effect on the adoption decision.

However, other authors such as van Rijn et al. (2012) do not find consistent effects of bonding social capital on innovation adoptions across seven Sub-Saharan African countries. Also, other authors, such as Moser and Barrett (2006), point out that these studies all ignore the possibility that the information conveyed by previous adopters may also be negative and as a consequence the effect of the bonding social capital could be negative and, as such could discourage, instead of encouraging, adoption. This could explain inconsistencies of results about bonding social capital.

More consistent findings are found for the bridging social capital which, for example, is found to be strongly and positively associated with innovation adoption and this result is consistent across all the countries under scrutiny in the analysis by van Rijn (2012). This finding challenges the idea that homophilous lines are that most important information sources as suggested by Matuscke and Qaim (2009). Conversely, the result by van Rijn et al. (2012) supports the argument, introduced by Granovetter (1973), that weaker lines, often not between peers, are more conducive of innovations than potentially stronger ties between similar households (peers). Weaker and vertical ties may, indeed, foster synergy and realization effects described above and may help overcome community level norms of conformity.

The empirical evidence on cognitive social capital is mixed. Trust is often found not significant in explaining the adoption process. For example, in their study of firms in Montreal, Laundry et al. (2002) finds that trust in clients, suppliers, government and other agencies do not affect the propensity to adopt innovations and its intensity. The sign of the effect, although not significant, is negative and as such also contradicts the expectation that a trustworthy environment should facilitate innovation. In the same direction is the study by Kassie et al. (2013) who find a significant but negative effect of trust in government in the adoption of crop and risk diversifying practices, such as legume intercrop. Similarly, trust has a negative effect on innovation in the cross-country analysis by van Rijn et al. (2012) in Sub-Saharan Africa. These findings support the argument that a high level of cognitive social capital might result in an in-ward looking behaviours in communities which in turns reduces the propensity to innovate. Nonetheless, other authors found a positive relationship between trust and innovation.

This is the case, for example, of Kaasa (2009) who studies the effect of social capital on innovative activities using regional level data. He found that both general trust and institutional trust increase the probability to adopt innovation. Similarly, Wossen et al. (2015) show that general trust is positively associated with the adoption of farm land management practices in Ethiopia. However, as for Laundry et al. (2002), their measure of trust is never significant at the conventional level.

The empirical evidence on the effect of norms on innovation adoption is more scarce compared to the other social capital components. One of the main reasons for this is that norms generally pertain to a group of individual, community or to a society in general and this wide dimension usually does not match the unit of analysis, which is commonly at individual, household or firm level.

Nonetheless, the existing evidence is quite informative of the potential role of this type of cognitive social capital in the adoption process. For example, Kaasa (2009), one of the few studies to investigate adoption innovation at the regional level, shows that different norms have different, if any, effect on innovation activities. Four types of norms are investigated: the norm of civic participation, i.e. the norm and practice of voting; the norm of helping and decency; the norm of active social participation and the norm of orderliness. His results show that the most important facilitator of innovation activities is the norm of civic participation which is found consistently significant and positively related to innovation. This finding supports the argument that a stable and reliable legal system provides the necessary expectation of protection in the future whereby firms are more prone to engage in innovative activities (Dakhli and de Clercq, 2004; Tabellini, 2006).

On the other hand, while the norm of helping and decency and social participation are not significant, the norm of orderliness is significant and negatively associated with the innovation adoption. This negative relationship supports the idea that norms of "good citizenship" usually do not match with deviation from the status quo via innovative activities (Dakhli and de Clercq, 2004). This result confirms that conformity could play an inhibitor role in the adoption process[43].

[43] Other studies investigate the link between "procedural formalism" and social networks. For example, Bonleu (2014) studies how the size of social networks affects procedural formalism in the OECD housing market.

In conclusion, social capital factors in the form of relationship, trust and common norms have been found relevant in the farmers' and firms' decision to innovate. The next section describes how I plan to investigate the adoption decision with regards to the product innovation under scrutiny: exotic varieties of mango in Ghana.

Section 3. Analysis of the adoption of exotic varieties of mango in Ghana

Following the conceptual framework and empirical evidence discussed above, I investigate the role of four main determinants (supply side constraints, market inefficiencies, learning and social capital) with regards to the decision to adopt exotic varieties of mango, its time and its intensity[44], using primary data collected during the fieldwork in 2012. From (6), the adoption decisions will be estimated using the following equation:

$$Y_h^i = \alpha + \beta_1 A_h + \beta_2 G_h + \beta_3 I_h + \beta_4 SK_h + \varepsilon \qquad (6)$$

Y_h^i takes value of 1 if the farmer adopted mango and 0 otherwise in the case of the discrete adoption decision; it takes value of 1 if the adopter is an earlier adopter and 0 otherwise in the analysis of the determinants of the time of adoption. For the analysis of the intensity of adoption, a count variable, the number of mango trees cultivated or planted by each mango farmer, expressed in natural logarithm, will be used. In addition, A_h is a vector of private assets (land, equipment, etc. – absorptive capacity), G_h is a vector of public assets (institutions and markets, infrastructure – supply side constraints), I_h controls for information barriers and SK_h is a vector of social capital variables.

The following paragraphs describes how I define the dependent and explanatory variables and provides an overview of the characteristics of the farmers according to their adoption status (adopters vs non-adopters; early (earlier) vs late (later) adopters; less vs more intense adopters.

[44] The decision to model additional levels of the adoption analysis (time and intensity) has been motivated by the evidence that some farmers can free ride and delay adoption in order to accumulate more knowledge before innovating or before deciding to invest more intensively in the innovation.

3.1 The dependent variables

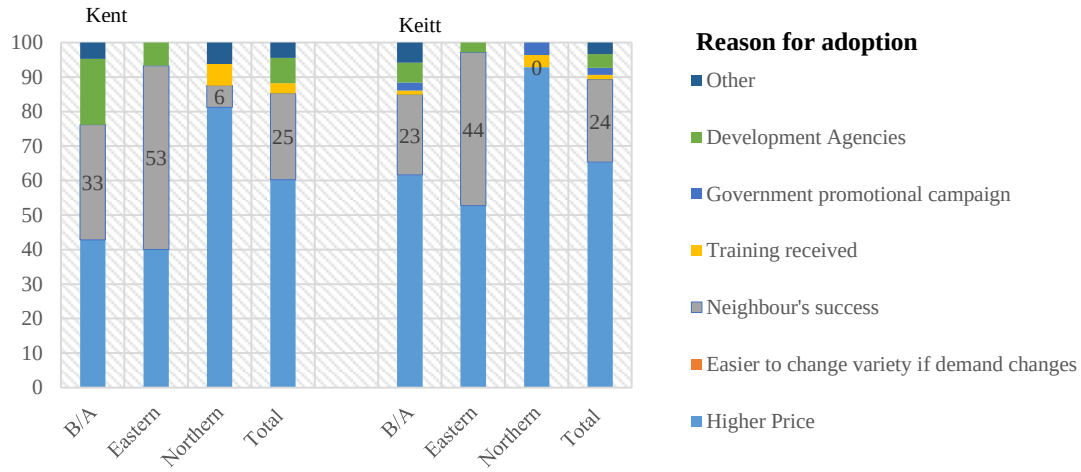
The decision to adoption exotic varieties of mango

Exotic varieties of mango are defined as those varieties that are not indigenous to the Ghanaian context, which include a number of different varieties, such as Keitt, Kent, Palmer, Julie.

In this analysis, mango adoption is defined as the discrete decision to adopt exotic varieties of mango and it is measured by a dummy variable which takes the value of 1 if the farmer produces mango and 0 otherwise. 196 households in the sample produce mango, 95 adopters are located in Brong-Ahafo region, 63 in the Northern region and 38 in the Eastern region. The most common exotic varieties adopted in the sample are Keitt and Kent, which are produced by 77% and 35% of the adopters in the sample, respectively.

In order to better understand the factors that influenced adoption of these varieties in my sample, I have explicitly asked mango farmers what was the original reason for the adoption. As Figure 2 shows, the majority of the adopters declared that the main reason of adoption was the expected higher price that they would have had access to. Nonetheless, on average 30% of the adopters claimed that the most important propellant for their decision to adopt has been the success of neighbouring farmers, suggesting that a social component of learning and knowledge accumulation was experienced. The role of this knowledge accumulation process seems to vary across regions and it looks substantially stronger in the Eastern and Brong-Ahafo region, while it seems negligible

Figure 2 Reason for adoption



in the Northern region (Figure 2). These regional differences are somehow expected, and they can be explained by the relative shorter experience in mango production of the farmers in the Northern region, as described below.

The decision of the time of adoption

Over the total sample of adopters, the majority of the farmers adopted exotic varieties of mango in the early 2000s (Figure 3). Exotic varieties of mango were adopted earlier in the Eastern region (Southern Belt) while the latest adoptions occurred in the Northern region. Using the distribution of the time of adoption, the definition of earlier and later adopters is based on the imposition of two arbitrary cut-offs, an absolute and a relative cut-off.

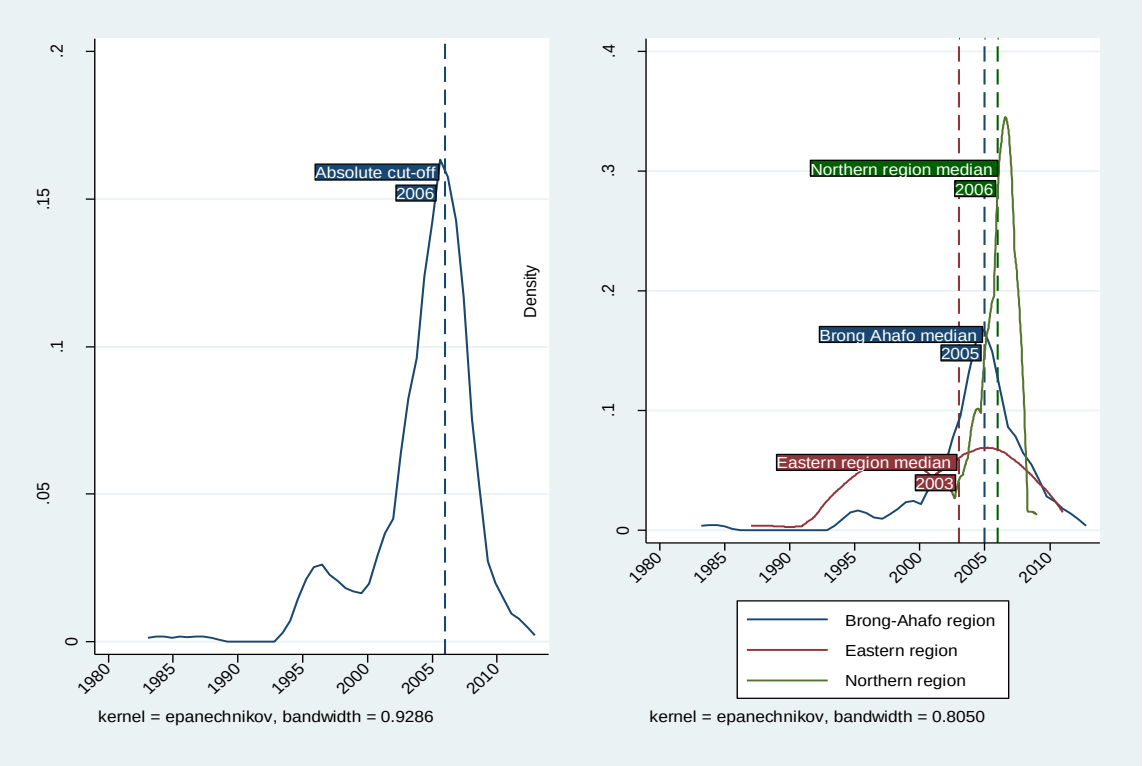
According to the *absolute cut – off*, a farmer is defined as a late adopter of mango if he/she started the production of mango after 2006. The year 2006 is an important date for the diffusion of mango throughout the country: it is a few years after the beginning of two important programs for the diffusion of mango in Ghana: TIPCEE and MOAP by USAID and GIZ, respectively; it is also the year when other schemes, such as bloc farms[45], became common in the Northern region. Also, this cut-off allows including in both early and late adopters, farmers who have harvested at least once before the data collection. Hence, the gestation period of mango trees usually lasts for four years. Because the data collection occurred in 2012, farmers who adopted in 2006 or later may have harvested mango for two years (late adopters – 37 farmers) or less (very late adopters – 56 farmers), for a total of *93 late adopters*. Early adopters are, instead, farmers who may have harvested for three years or more and this group may include both the very early adopters – innovators (24 farmers who adopted before 1999 – when ITFC started its operations in the Northern region) and the intermediate adopters between 1999 and 2006 (79 farmers), for a total of *103 early adopters*.

According to this threshold, on average 64% of the farmers in the Eastern and Brong-Ahafo regions were early adopters of exotic varieties of mango, while 73% of farmers in the Northern region adopted after 2006 and as such can be defined as late adopters. This finding is in line with the expectations that farmers in the Northern region were the

[45] Bloc farms are large farms that are divided in blocs of one acre. Each acre is cultivated by one farmer. Inputs, trainings and output are managed and shared collectively within the framework of a purposively constituted farmers' organisation.

latest to adopt the exotic varieties of mango compared to the Southern and Transitional Belts (Eastern and Brong-Ahafo regions).

Figure 3 Time of adoption



Although the absolute cut-off provides interesting insights on the inter-regional differences in the time of adoption, I also use an alternative measure of the time of adoption, which aims to unveil intra-regional differences. Instead of using 2006 as cut-off, the median value of the year of adoption at regional level is used to define what I call a *"relative" measure of the time of adoption*[46]. The median year of adoption is 2005 for Brong-Ahafo region; 2003 for Eastern region and 2006 for the Northern region. According to this measure, *78 farmers* can be defined as *earlier adopters* (about 40% of the total sample of adopters) and *118* are defined as *later adopters*. One advantage of having a more localised threshold is to unveil the relative time of adoption

[46] In the recall section of the questionnaire I collected data on the year when mango was first introduced in the district. This information can be useful for the identification of a regional cut off for the time of adoption because it represents the starting point for the farmers' awareness exposure to this innovation[46]. One option for identifying a "regional" cut off would be to use the values of the year of first introduction as the threshold for the definition of earlier adopters. However, only few farmers adopted before or at that specific year and this is also true for more established mango producing areas in Brong-Ahafo and Eastern regions. In my sample the majority of the farmers interviewed in these regions adopted 12 to 20 years after the year of the first introduction of mango in the district, while farmers in the Northern region adopted quite soon after the introduction of mango in the district. This may mean either that earlier adopters stopped the production, or they were not sampled because very busy and big or, finally, that diffusion really started only in the mid-late 1990s.

within the same region. Thus, when using this regional defined cut-off, 56% of the farmers in the Brong-Ahafo region adopted later relatively to the other farmers in the same region. Moreover, while earlier and later adopters are of equal size for the Eastern region, the distribution between later and earlier adopters in the Northern region remains the same as when an absolute cut off of time of adoption is used, as the two cut-offs coincides. Even accounting for intra-regional differences the Northern region stands out for the highest proportion of later adopters.

The decision of the intensity of adoption

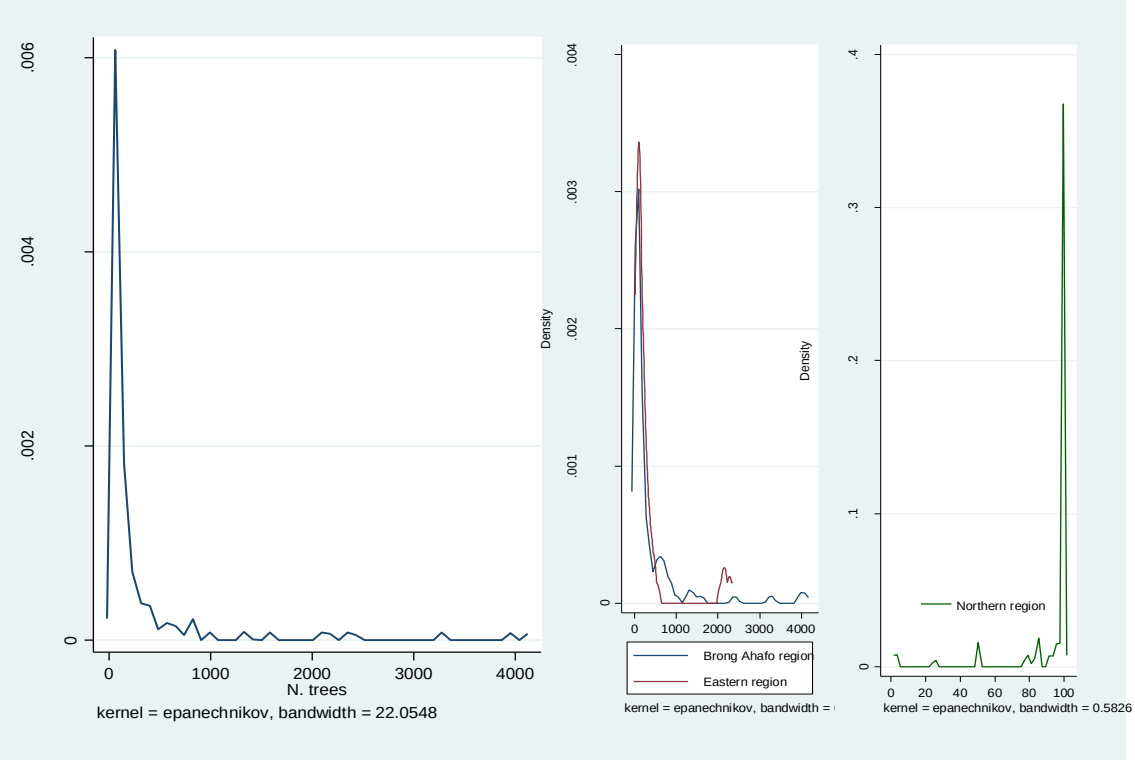
Different measures of intensity of adoption are available in the literature and they tend to differ depending on the type of the innovation. For example, while Ben-Houassa (2011) and Matuschke and Qaim (2009) use a measure of the area under the innovation (quantity of fertilizer per hectares and share of area under hybrid wheat and pearl millet, respectively), other authors, such as Beltran et al. (2013) in their study of the adoption of herbicide in the production of rice in the Philippines, use expenditures on innovation. On the other hand, Pomp and Burger (1995) measure the intensity of adoption of cocoa simply with a count variable of the number of cocoa trees planted, for a sample of farmers in Indonesia.

Notwithstanding the validity of the measures which take into account the farm size or the expenditures for the innovation, the preferred measure of intensity to adopt mango in this analysis follows the paper by Pomp and Burger (1995). I believe that this measure fits better the purpose of this analysis as mango trees, similarly to cocoa trees, are perennial trees whose cultivation requires specific spacing between trees and less scope for intercropping than other crops. It is indeed a common practice to plant 100 trees per acre of land where not often other crops are cultivated at the same time. As a consequence, it is reasonable to assume that farmers who adopt more intensively would do it via acquisition of more land instead of planting more trees in the available land. Thus, a measure that takes into account the area under innovation could not be necessarily a better measure than the simple measure of the number of trees planted.

Following Pomp and Burger (1995), I here defined the intensity of adoption as a count variable of the number of mango trees planted. Figure 4 shows that the majority of the adopters have less than 1000 trees which correspond to approximately 10 acres of land cultivated under mango. Nonetheless, the two graphs in the right hand side of Figure 4,

also show that intensity of adoption is, once again, extremely different between regions. Hence, farmers in Brong-Ahafo and Eastern regions produce mango more intensively than farmers in the Northern region. More specifically, looking at the overall average number of trees across the three regions confirms that the average number of trees per farmer is the smallest in the Northern region (92 trees on average) and it is the highest in the Brong-Ahafo region (more than 369 trees).

Figure 4 Intensity of adoption



Similarly, using terciles of distribution of the number of mango trees, Northern region stands out again as the majority of farmers are either less or intermediate intense adopters and none of them can be defined as "most" intense adopter (Table 1). Overall, the sample of mango farmers includes *67 least intense adopters* (1st tercile*), 70 intermediate intense adopters* (2nd tercile) and *59 most intense adopters* (3rd tercile)[47].

[47] The distribution in terciles also show that in the Brong Ahafo region, the majority of the farmers are distributed at the two ends of the intensity levels, cultivating either on average 50 trees (half acre) or more intensively, with on average 802 trees (8 acres). A similar story can be observed in the Eastern region, where, however, more than half of the farmers can be classified as most intense adopters.

Because of the substantially rigid space requirements inherent in the mango tree cultivation, these differences in intensity of adoption are reflected in the size of the area under mango production. Mango farms are extremely small (1 acre on average) in the Northern region, while they are substantially bigger in the other two regions (on average 6 acres in the Brong-Ahafo region and about 7 acres in the Eastern region). Relatively to the total farm size, the share of the mango farm is the highest in the Eastern region (65%), suggesting a higher degree of specialization for farmers in this region while it is the lowest, once again, in the Northern region (35%).

Table 1 Intensity of adoption

	Total Mean (sd)	Brong-Ahafo region Mean (sd)	Eastern region Mean (sd)	Northern region Mean (sd)
N. trees	270	368	320	92
	(578)	(729)	(576)	(21)
1st tercile - n.trees	53	51	55	54
	(22)	(20)	21)	(34)
2nd tercile- n.trees	103	112	116	100
	(8)	(11)	(9)	(2)
3rd tercile- n.trees	716	802	546	0
	(913)	(992)	(729)	0
Mango farm size (acres)	4.57	5.82	7.33	1.02
	(9.53)	(10.45)	(12.95)	(0.14)
Share mango farm size (%)	47.46	48.61	64.98	35.18
	(23.99)	(25.54)	(25.25)	(9.84)
N	196	95	38	63

3.2 The explanatory variables

The choice of the explanatory variables has been informed by the empirical and theoretical literature described in section 1 and 2. The list of explanatory variables as well as their expected sign is reported in Table 2. In addition, the following paragraph discusses the measures of social capital that have been used in the past literature as explanatory variables and describes how social capital is defined in this analysis.

Table 2 List of explanatory variables

Variable	Description	Expected sign
Age head*	Years*	+/-
Male head	=1 if head is a man; 0 otherwise	+
Higher education	=1 if head awarded secondary or higher education; 0 otherwise	+/-
Farm labour	Number of household's members working on own farm	+
Farm size*	Acres*	+
Land ownership	=1 if any land is owned; 0 otherwise	+
Production of other cash crops	=1 if other cash crops are produced; 0 otherwise	+
Livestock ownership	Number of livestock owned	-
Access to non-farm income	=1 if any household's member earn non-farm income; 0 otherwise	-
Access to credit	=1 if any household's member had access to credit in the past 12 months; 0 otherwise	+/-
Ownership of tractor	=1 if a tractor is owned; 0 otherwise	+
Ownership of mobile	=1 if a mobile phone is owned; 0 otherwise	+
Ownership of radio	=1 if a radio is owned; 0 otherwise	+
Ownership of bicycle	=1 if a bicycle is owned; 0 otherwise	+
Ownership of motorcycle	=1 if a motorcycle is owned; 0 otherwise	+
Ownership of car	=1 if a car is owned; 0 otherwise	+
Roads conditions	Number of months of impassable roads	-
Moderate risk aversion	=1 if head is moderately risk averse; 0 otherwise [Base= extreme risk aversion]	+
No risk aversion	=1 if head is no risk averse; 0 otherwise [Base= extreme risk aversion]	+
Impatience	= 1 if head is impatient; 0 otherwise	-
Experience in farming*	Number of years of experience in farming	+
Training	= 1 if any household's member received any training; 0 otherwise	+
Social capital	See variables in Table 3	+/-

*At the time of adoption for mango farmers; current values for non-mango farmers

Measures of social capital

The measurement of social capital is empirically quite challenging. An important decision that needs to be taken in the study of adoption decision is the identification of the appropriate reference group (Maertens and Barrett, 2012). Membership in farmers' organisations, insurance groups or even funeral insurance groups and labour sharing arrangements are often used as proxy of social capital (Wossen et al., 2015; Moser and Barrett, 2006; Kassie et al., 2013). Other authors, such as Bandiera and Rasul (2006) or Martens and Barrett (2012), who also focus on the structural bonding component of

social capital, use an explicit measure of social network which is based on farmers' contacts and links with previous adopters of the innovation[48]. Overall, these authors only look at the role of farmers or peers as change agents in the innovation adoption process.

However, as Hartwich and Scheidegger (2010) claim, the adoption of innovation requires a systemic set-up whereby the knowledge accumulation process does not occur only through a single change agent, but a set of innovation agents may be relevant for the decision to engage in adoption dynamics. These players may include buyers, input providers, farmers' organisation, development agencies as well as local extension officers, and so on. They suggest that a measure of social capital should capture not only the number of interactions with each change agent but also the strength of each interaction.

In Ghana, Barr (2000) uses two measures of social capital: total number of contacts with nine types of change agents, which include bridging and bonding social capital types of agents[49] and a "social capital diversity index", which goes from 1 to 9, and it is estimated as the sum of the existing relationship between the firm and each of the nine types of change agents.

Similarly, van Rijn et al. (2012) use a measure of frequency of contacts of farmers with other farmers in the village (structural bonding social capital) and with extension officer, NGOs, and R&D project staff (structural bridging social capital). They also try to control for the strength of these contacts and interactions, maintaining a neat distinction between the different levels of social capital, which also includes several indicators of the cognitive component (trust and village norms). Finally, Kaasa (2009) strongly supports the argument that social capital variables should be investigated separately and the construction of indexes should be discouraged, as different change agents or norms might affect differently the process of innovation adoption.

Following the argument that the innovation process requires a set of change agents, in the section 7 of the questionnaire used for this analysis, I collected detailed data on the

[48] Different methods can be used to empirically identify these links but the main idea is that farmers are asked about their closest sources of information on farming. Usually, the three most important links are asked for in social network surveys.

[49] Firms in the same line of business; firms in different line of business, firms in other regions; firms from different ethnic origins; firms from other countries; bank officials; politicians and government officials.

frequency and strength of the relationship and trust that each farmer had with and in several change agents. The change agents included in the data collection were the following: 1) input suppliers;2) credit providers; 3) land owners; 4) extension officers; 5) other government officers; 6) farmers' organisations; 7) development agencies; 8) NGOs; 9) other producers. For each change agent, three questions were asked:

1) Do you have any relationship with [change agent] (Yes/No)?
2) How would you rate the strength of your relationship with [change agent]? (1 very weak - 5 very strong).
3) How trustworthy they are? (1 not trustworthy - 3 very trustworthy)[50].

Using these data, I construct different variables for each component of the social capital and for different levels of aggregation. Following van Rijn et al. (2012) and Kaasa (2009), I retain a high level of disaggregation across seven of the change agents listed above[51] and three clusters of variables: contacts and relationship; strength of relationships and level of trust. I also use more aggregate measures of social capital following the work by Barr (2000) and Kaasa (2009)[52]. The aggregate measures are the following:

1) Two measures of *diversity* of social capital defined as the sum of the relationships with all or selected change agents;
2) Two measures of *intensity of diversity* of social capital, defined as the sum of the strength of the relationships with all or selected change agents;
3) A measure of *general trust*, defined as the sum of the level of trust across all or selected change agents;
4) Three indexes of social capital estimated with principal component analysis[53]:
    a. Structural Bonding capital Index
    b. Structural Bridging capital Index

[50] The definition of the levels of trust and relationship have been informed by value chains studies, as, for example, Purcell et al (2008). During the field work, the enumerators were provided with a description of each level and they were asked to read them during the enumeration directly to the farmer. The levels of strength of relationship were defined as follows: 1) Very weak: Meet once a year, no formal agreement, no intention of continuing the relationship; 2) Weak: Meet more than once, no formal agreement, not sure whether to continue the relationship; 3) Moderate: Meet regularly in the year, verbal agreement, intention to continue the relationship; 4) Strong: Meet often during the year, written agreement, commitment to continue the relationship for a determined period; 5) Very strong: Meet very often during the year, written agreement, intention to renew relationship after the agreement. The levels of trusts were defined as: 1) Not at all trustworthy: Very bad past experience personal or of known people, no expected fulfilments in the future; 2) Good past experience but some uncertainty about future fulfilments; 3) Very trustworthy: Very good previous experience and complete trust in future fulfilments.

[51] Land owner and other government officers did not provide enough variation in the sample and as a consequence they were dropped from the analysis.

[52] One of the major drawbacks in using such level of disaggregation is the existence of high multicollinearity. In the past studies this issue is explicitly addressed with statistical tests, such as Variance Inflation Factor analysis and the Condition Index analysis. Following Kaasa (2009), I have run different specifications of the multicollinearity tests using the stata command "collin". This command reports both the VIF values and the condition index. I have run the analysis using both household level variables as in Kaasa (2009) and village averages as in van Rijn (2012). The results of this analysis are quite mixed and a selection of results can be found in details in the Appendix 3.1.

[53] A detailed description of the construction of these indexes can be found in Appendix 3.2

c. Cognitive capital Index

Table 3 lists the social capital variables that I use for the empirical analysis[54].

Table 3 Measures of social capital

Type of social capital	Name of variable	Description	Expected sign
Disaggregates			
Structural bonding capital 1	Relationship with other members of FO	=1 if farmer has contacts with other farmers in FO; 0 otherwise	+/-
Structural bonding capital 2	Membership in FO	=1 if farmer is member of a FO; 0, otherwise	+/-
Structural bonding capital 3	Social network	=1 if any previous adopter was known; 0 otherwise*	+/-
Structural bonding capital 4	Strength Relationship with other farmers	(1/5)	+/-
Structural bridging capital 1	Relationship with input suppliers	=1 if farmer has contacts with input suppliers; 0 otherwise	+
Structural bridging capital 2	Relationship with credit providers	=1 if farmer has contacts with credit providers; 0 otherwise	+
Structural bridging capital 3	Relationship with extension officers	=1 if farmer has contacts with extension officers; 0 otherwise	+
Structural bridging capital 4	Relationship with development agencies	=1 if farmer has contacts with development agencies; 0 otherwise	+
Structural bridging capital 5	Relationship with NGOs	=1 if farmer has contacts with NGOs; 0 otherwise	+
Structural bridging capital 6	Strength Relationship with input supplier	(1/5)	+
Structural bridging capital 7	Strength Relationship with credit provider	(1/5)	+
Structural bridging capital 8	Strength Relationship with extension officer	(1/5)	+
Structural bridging capital 9	Strength Relationship with development agencies	(1/5)	+
Structural bridging capital 10	Strength Relationship with NGOs	(1/5)	+
Cognitive social capital 1	Trust in other farmers	(1/3)	+/-
Cognitive social capital 2	Trust in other members of FO	(1/3)	+/-
Cognitive social capital 3	Trust in input supplier	(1/3)	+/-
Cognitive social capital 4	Trust in credit provider	(1/3)	+/-
Cognitive social capital 5	Trust in extension agent	(1/3)	+/-
Cognitive social capital 6	Trust in development agencies	(1/3)	+/-
Cognitive social capital 7	Trust in NGOs	(1/3)	+/-

[54] In the empirical analysis I have also tried to estimate the determinants of adoption and its dimension using dummy variables of the social capital categorical variables (strength of the relationship and trust). The use of categorical variables in econometric analysis is often discouraged as their inclusion would mean assuming that there is no difference in the effect that each level has on the dependent variable. For example, in the case of the strength of the relationship it would mean assuming that the differential effect of having a weak instead of a very weak relationship would be the same as the difference between a strong and a very strong relationship. Following this argument I have estimated the econometric models described below using dummies instead of categorical variables. The base categories are the very and low levels of each variable. The results are not attached to these documents for exposition purposes. Overall, the results indicate that, although with some actor specific differences, having a higher or the highest level of trust or relationship increases the effect on the dependent variable compared to the lowest categories. The coefficients are often the highest in the case of the highest categories and generally only the two highest levels are significant. Also, from the exploratory analysis of these variables it looks like there is not much variation between all the levels of the categorical variables, with the majority of the observations concentrated at the two ends of the categories. As a consequence, I believe that using the categorical variables in the main analysis as in the case of this data, although categorical variables, the distribution of the observations across the categories is pretty much concentrated at the two ends and as such resembles enough the characteristics of dummy variables.

Type of social capital	Name of variable	Description	Expected sign
Aggregated			
Structural social capital	Diversity social capital	Total number of relationships	+
Structural social capital	Intensity of diversity of social capital	Total strength relationships	+
Cognitive social capital	General trust	Total trust score	+/-
Structural social capital	Diversity of selected change agents	Total number of relationships	+
Structural social capital	Intensity of diversity of selected change agents	Total strength of relationships	+
Cognitive social capital	Trust in selected change agents	Total trust score	+/-
Structural Bonding capital	Index	PCA	+/-
Structural Bridging capital	Index	PCA	+
Cognitive capital	Index	PCA	+/-

3.3 Overview of selected characteristics of adopters

Using the definitions of adoption and its sub-components described above, this section describes the main differences in selected farmers' characteristics between adopters and non-adopters, and within the group of adopters, between different time and intensity of adoption. For comparison purposes, the intensity of adoption is reported in terciles, and as such the descriptive analysis is based on the comparison between the least intense adopters (1st tercile) and the most intense adopters (3rd tercile).

The results in Table 4 show that mango farmers (including early, earlier and more intense adopters) are most commonly men, older and living in bigger households than their comparison group. However, at the time of adoption mango farmers were, instead, younger and their household, in the case of early adopters, was significantly smaller than later adopters. Although current family size is bigger for adopters, the degree of involvement of family members in own farm activities is, instead, smaller compared to non-adopters. A similar result is found in the case of early and earlier adopters, while no significant difference is observed according to the intensity of adoption[55].

[55] The lower family involvement in the farm activities could be justified on two grounds: 1. Adopters' households are generally wealthier and can afford to hire labourers for their farm activities and as such family members can work in other sectors, which generates resources that could potentially feed into the expenditures on innovation; and 2. More family members are working in other sectors to generate financial resources needed for the adoption of innovation and as part of a risk-reducing strategy for coping with less than expected returns from the innovation itself. In other words, the size of farm labour and access to non-farm income can be linked and access to non-farm income by households' members could act as complement of the adoption of innovation.

Table 4 Selected summary statistics by adoption statuses

		Adoption			Time – absolute cut off			Time – relative cut off			Intensity		
Variable		Non adopters	Adopters		Early	Late		Earlier	Later		1st tercile	3rd tercile	
		Mean	Mean	p-value	Mean	Mean	p-value	Mean	Mean	p-value	Mean	Mean	p-value
Age Head	Years	46.77	50.28	0.019**	51.83	48.57	0.054*	53	49	0.015**	50.97	53.25	0.283
Age at the adoption	Years	46.77	42.59	0.005***	41.62	43.66	0.230	42	43	0.371	43.84	43.85	0.996
Male Head	0/1	0.85	0.93	0.022**	0.94	0.92	0.635	0.95	0.92	0.494	0.85	0.95	0.071*
Higher education	0/1	0.14	0.24	0.034**	0.31	0.16	0.014**	0.29	0.20	0.144	0.21	0.47	0.001***
HH size	#	5.55	6.12	0.038**	5.91	6.34	0.169	6	6	0.254	6.03	6.54	0.215
HH size at the adoption	#	5.55	5.14	0.134	4.63	5.71	0.000***	4	6	0.000***	5.19	5.37	0.661
Total family labour	#	3.39	3.04	0.065*	2.64	3.47	0.000***	2.62	3.31	0.001***	3.09	3.08	0.986
Farm size	Acres	3.98	9.98	0.001***	13.61	5.96	0.003***	14.62	6.91	0.004***	3.68	24.43	0.000***
Farm size at the adoption	Acres	3.98	8.82	0.004***	12.86	4.35	0.001***	13.63	5.65	0.002***	3.53	21.60	0.000***
Land ownership	0/1	0.51	0.66	0.010**	0.79	0.53	0.000***	0.74	0.61	0.053*	0.84	0.85	0.860
Production other cash crops	0/1	0.22	0.28	0.290	0.35	0.19	0.015**	0.31	0.25	0.415	0.43	0.39	0.628
Livestock	#	18.94	24.51	0.159	27.89	20.75	0.171	29.24	21.37	0.139	13.49	38.56	0.001***
Experience	Years	15.74	16.62	0.513	17.25	15.92	0.403	18.03	15.69	0.149	15.31	16.53	0.543
Experience at the adoption	Years	15.74	8.93	0.000***	7.05	11.01	0.012**	6.88	10.28	0.035**	8.18	7.12	0.575
Training	0/1	0.26	0.79	0.000***	0.77	0.81	0.504	0.81	0.77	0.544	0.60	0.86	0.001***
Extreme risk aversion	0/1	0.33	0.29	0.418	0.31	0.26	0.418	0.29	0.28	0.819	0.37	0.32	0.552
Moderate risk aversion	0/1	0.54	0.60	0.304	0.56	0.65	0.243	0.60	0.61	0.900	0.57	0.51	0.513
No risk aversion	0/1	0.13	0.11	0.676	0.13	0.10	0.517	0.13	0.10	0.567	0.06	0.17	0.051*
Impatient	0/1	0.29	0.31	0.749	0.31	0.31	0.986	0.31	0.31	0.931	0.30	0.22	0.323
Access to credit	0/1	0.14	0.27	0.010**	0.22	0.31	0.163	0.22	0.30	0.224	0.21	0.31	0.219
Access to non-farm income	0/1	0.57	0.72	0.094*	0.67	0.78	0.324	0.69	0.75	0.654	0.58	0.98	0.007***
Ownership of tractor	0/1	0.02	0.02	0.902	0.04	0.00	0.055*	0.05	0.00	0.013**	0.00	0.07	0.030**
Ownership of mobile	0/1	0.76	0.88	0.009***	0.89	0.86	0.484	0.87	0.88	0.843	0.88	0.97	0.078*
Ownership of radio	0/1	0.90	0.91	0.796	0.91	0.90	0.821	0.91	0.91	0.935	0.85	1.00	0.002***
Ownership of bicycle	0/1	0.62	0.70	0.182	0.69	0.71	0.758	0.72	0.69	0.640	0.58	0.63	0.610
Ownership of motorcycle	0/1	0.20	0.30	0.061*	0.34	0.26	0.215	0.37	0.25	0.080*	0.19	0.42	0.005***
Ownership of car	0/1	0.06	0.15	0.015**	0.18	0.11	0.131	0.19	0.12	0.157	0.07	0.36	0.000***
Road conditions	# months	3.56	2.93	0.005***	2.95	2.90	0.824	2.78	3.03	0.310	2.82	3.48	0.020**
N		109	196		103	93		78	118		67	59	

The data on asset endowments show that ownership of mobile phone, motorcycle, car is more common for adopters compared to non-adopters, and, within the group of adopters, early (earlier) and more intense adopters also own more often a tractor[56]. Also, adopters have a higher access to non-farm income (and credit) than non-adopters, which could suggest complementarities between substitute to crop cash income and innovation adoption. However, while an analogous trend can be seen for more intense adopters, no differences are often found according to the time of adoption.

The main livelihood activity of adopters is farming. Farm size is consistently bigger for adopters, early, earlier adopters and more intense adopters, both using current values and values at the time of adoption. Land is also owned more commonly by adopters, early and earlier adopters, while it does not differ according to the intensity of adoption. The production of other cash crops and the number of livestock owned, instead, do not often differ according to the adoption statuses.

The length of experience in farming is, also, much longer for adopters, early, earlier and most intense, although the difference with their comparison groups is not statistically significant at conventional levels. It is, on the other hand, significant the difference in the experience in farming at the time of the adoption. Using past values of years of experience until the time of adoption, shows, indeed, a reverse scenario, where adopters were less experienced in farming than non-adopters, and this is also true for all the adoption sub-components (time and intensity). Indeed, it seems that farmers who adopted mango had practiced agricultural activities for fewer years than non-adopters at the time when they took the decision to innovate.

Nonetheless, although less experienced, overall adopters (and more intense adopters) received much more training than non-adopters (or less intense adopters), while no statistically significant difference is observed in training experiences according to the time of adoption.

[56] However, although the ownership of this type of assets is generally associated with a higher economic status, the lack of data on the value of these assets is per se a limitation in the definition of this association. However, although bearing this in mind and considering that the sample is mostly composed by very small farmers, it is reasonable to assume that assets such as tractors or car could, overall, be a signal, although imprecise, of a better economic status.

Risks and time preferences do not seem to differ much across adoption statuses, although more intense mango farmers are observed to be more risk neutral then less intense adopters[57].

Finally, the number of months during which the village roads are considered impassable are significantly lower for adopters and less intense adopters which suggests that these farmers might face lower transaction costs in accessing good transport links and infrastructures. However, road condition seems not to differ according to the time of adoption.

Table 5 reports summary statistics of the social capital variables across different adoption statuses. The results show that social capital differs substantially across adopters and non-adopters and within its dimensions and it is significantly higher for mango adopters. While almost all the variables show significant differences between adopters and non-adopters, less differences are observed across the subsample of later and earlier adopters as well as less and more intense adopters. More specifically, the data show that, potentially, different change agents can be related to the decision of the time and the intensity of adoption. For the time of adoption, contacts and the strength of the relationship with input suppliers and NGOs are significantly higher for early and earlier adopters than late and later adopters. On the other hand, contacts with development agencies and FO are found to significantly differ between less and more intense adopters.

Finally, aggregate measures of social capital are shown to be substantially different between adopters and non-adopters and between less and more intense adopters, but they are not observed to be often significantly different according to the time of adoption.

In conclusion, adopters seems better endowed with both physical, human and social capital than non-adopters and that the degree at which these different endowments are observed might differ according to the time and the intensity of adoption.

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[57] The lack of significance of differences in risk aversion might be related to the imprecision of the variables used. The module on risk aversion in the questionnaire followed the methodology by Binswanger (1980) but only three of the seven level of risk aversion used in his paper were retained for this survey. This choice was mainly driven by the time and budget constraints of the field work. In addition, the majority of studies who use this methodology estimate risk aversion levels using Constant Partial Risk Aversion coefficients. This procedure was not followed for this analysis. Hence, the variables used are simply dummies created straight from the answers in the questionnaire, and so they are likely to be affected by imprecisions.

Table 5 Social Capital summary statistics by adoption statuses

		Adoption			Time of adoption - abs			Time of adoption -rel			Intensity of adoption		
		Non adopters	Adopters		Early	Late		Earlier	Later		1st terc	3rd terc	
		Mean	Mean	p-value	Mean	Mean	p-value	Mean	Mean	p-value	Mean	Mean	p-value
Structural bonding capital													
Relationship with Farmers Organisation (FO)	0/1	0.14	**0.63**	0.000***	0.58	0.68	0.172	0.67	0.60	0.360	0.34	**0.71**	0.000***
Membership in Farmers Organisation (FO)	0/1	0.15	**0.63**	0.000***	0.57	**0.69**	0.096*	0.67	0.60	0.360	0.33	**0.73**	0.000***
Social network	#	0.53	0.53	0.943	0.55	0.51	0.37	0.52	0.55	0.471	0.58	**0.63**	0.184
Strength of relationship with other farmers	1/5	3.47	**3.66**	0.070**	3.6	3.73	0.25	3.62	3.69	0.488	3.63	**3.75**	0.336
Structural bridging capital													
Relationship with input suppliers	0/1	0.83	**0.95**	0.000***	**0.99**	0.9	0.006***	**1.00**	0.92	0.008***	1	0.98	0.288
Relationship with credit providers	0/1	0.11	**0.26**	0.002***	0.23	0.28	0.458	0.24	0.26	0.765	0.16	0.29	0.096
Relationship with extension officers	0/1	0.36	**0.78**	0.000***	0.78	0.78	0.89	0.77	0.79	0.756	0.7	0.81	0.147
Relationship with Dev Agencies	0/1	0.04	**0.53**	0.000***	0.49	0.57	0.239	0.54	0.52	0.769	0.24	**0.69**	0.000***
Relationship with NGOs	0/1	0.1	**0.35**	0.000***	**0.45**	0.25	0.003**	**0.44**	0.30	0.046**	0.37	0.37	0.998
Strength of relationship with input suppliers	1/5	1.99	**2.87**	0.000***	**3.02**	2.7	0.036**	**3.09**	2.72	0.018***	2.88	3.05	0.275
Strength of relationship with credit providers	1/5	0.34	**0.8**	0.003***	0.75	0.86	0.584	0.77	0.82	0.802	0.54	0.92	0.120
Strength of relationship with extension officers	1/5	1.11	**2.72**	0.000***	2.75	2.7	0.833	2.73	2.72	0.965	2.4	2.86	0.113
Strength of relationship with Dev Agencies	1/5	0.09	**1.88**	0.000***	1.81	1.96	0.571	2.00	1.80	0.455	0.84	**2.76**	0.000***
Strength of relationship with NGOs	1/5	0.28	**1.18**	0.000***	**1.52**	0.8	0.002***	**1.46**	0.99	0.049**	1.22	1.37	0.629
Cognitive social capital													
Trust in input suppliers	1/3	1.69	**2.17**	0.000***	**2.25**	2.08	0.083*	**2.33**	2.06	0.008***	2.12	2.19	0.461
Trust in credit providers	1/3	0.21	**0.62**	0.000***	0.53	0.71	0.259	0.55	0.66	0.490	0.37	0.63	0.133
Trust in extension officers	1/3	0.78	**1.9**	0.000***	1.8	2.01	0.18	1.83	1.94	0.512	1.54	**1.9**	0.059*
Trust in Farmers Organisation (FO)	1/3	0.28	**1.7**	0.000***	1.53	**1.89**	0.066*	1.76	1.67	0.664	0.87	**1.81**	0.000***
Trust in Development Agencies	1/3	0.07	**1.38**	0.000***	1.21	**1.56**	0.075*	1.36	1.39	0.877	0.57	**1.69**	0.000***
Trust in NGOs	1/3	0.22	**0.79**	0.000***	**0.97**	0.59	0.017**	0.94	0.69	0.139	0.78	0.81	0.844
Trust in other farmers	1/3	2.4	**2.54**	0.057*	2.42	**2.67**	0.000***	**2.46**	2.58	0.091*	2.46	2.42	0.664
Aggregates													
Diversity social capital	#	3.05	**4.94**	0.000***	4.84	5.04	0.4	5.05	4.86	0.438	4.04	**5.1**	0.000***
Intensity of diversity of social capital	#	9.37	**17.11**	0.000***	16.85	17.4	0.559	17.67	16.75	0.332	13.55	**18.25**	0.000***
General trust	#	6.97	**12.31**	0.000***	11.54	**13.15**	0.030**	12.24	12.35	0.891	9.3	**11.98**	0.000***
Diversity of selected change agents	#	3.05	**4.94**	0.000***	4.84	5.04	0.400	5.05	4.86	0.438	4.04	**5.1**	0.000***
Intensity of diversity of selected change agents	#	5.4	**11.91**	0.000***	12.02	11.78	0.732	12.51	11.51	0.150	9.31	**13.58**	0.000***
Trust in selected change agents	#	3.75	**8.31**	0.000***	7.93	8.72	0.125	8.35	8.28	0.899	6.21	**8.64**	0.000***
Structural Bridging Index	#	1.29	**2.94**	0.000***	3.08	2.8	0.109	**3.14**	2.82	0.070*	2.53	**3.37**	0.000***
Structural Bonding Index	#	2.02	**2.77**	0.000***	2.66	2.89	0.177	2.86	2.71	0.390	2.23	**2.75**	0.005***
Cognitive Index	#	1.61	**3.4**	0.000***	3.19	**3.64**	0.029**	3.41	3.40	0.960	2.53	**3.53**	0.000***

Section 4.Econometric model and main challenges of the econometric analysis

The innovation adoption decision is often estimated using binary models, such as probit (Pomp and Burger, 1995; Matuschke and Qaim, 2009; Isham, 2002), linear probability models (Bandiera and Rasul, 2006) or OLS (Barr, 2011). When different dimensions of adoption are investigated, a double-hurdle model is often used (Noltze et al., 2012; Beltran et al., 2013) where Tobit is the preferred estimation procedure for the intensity of adoption (Pomp and Burger, 1995; Matuschke and Qaim, 2009). Heckman and instrumental variables models are also used for the control of self-selection in innovation adoption (Adegbola and Gardebroek, 2007; Jagwe et al., 2010; Ben-Houassa, 2011). Finally, duration models are used for the analysis of the time of adoption (Abdulai and Huffman, 2005; Schipmann and Qaim, 2010).

Following the literature on the analysis of innovation adoption using cross sections and taking into account the limitations of the data described below, I will model the analysis of adoption decision and its dimensions using a simple methodology, mainly based on probit and OLS models. I will also control for selection biases using Heckman two step and maximum likelihood models, when appropriate. The preference for these models follows the same considerations discussed in Chapter 1.

Main challenges

The main challenges of this econometric analysis are the lack of time-varying information on the variables of interests (in this cross section dataset), as well as endogeneity, heterogeneity in the unit of comparisons and multicollinearity of the social capital variables.

The adoption of innovation is a dynamic process which involves knowledge accumulation and adaptation of expectations through time. The use of a cross section in the estimation of mango adoption could affect the results of the analysis. Hence, panel data offer the best set up for an unbiased estimation of the adoption models. However, the difficulties and the high costs involved in the collection of this type of data have motivated scholars towards alternative solutions to these issues. An alternative to panel data in the adoption analysis has been suggested by Besley and Case (1993) who claim

that it would be possible to re-create the dynamic nature of the adoption process via recall data on each farmer's adoption history and on as many time-varying variables as possible. Another option could be the use of available secondary data on the average year of adoption. Using these data, matching techniques can be explored to match adopters and non-adopters with households surveyed in past years.

Another major issue of the adoption analysis is endogeneity, due to reverse causality and selection biases. The majority of the determinants of adoption may have been affected by the adoption decision. For example, farm size, land ownership as well as the ownership of some assets, might have changed through time explicitly because of the adoption of the innovation. In the analysis of mango adoption, for example, farmers may have had to acquire more land for the cultivation of mango or have been able to acquire (or sell) new (old) assets depending on the returns of the innovation. Another source of endogeneity comes directly from the social capital variables as relationship and trust might have been affected by the adoption process. Also, mango adopters might be systematically different from other farmers due to their higher ability and entrepreneurship skills. Selection bias is, indeed, likely to affect the analysis of the time of adoption and its intensity if self-selection into innovation adoption is not controlled for.

Dealing with this type of endogeneity problems has received wide attention in the literature where recall data on specific variables, in line with the procedure suggested by Besley and Case (1993), could reduce the reverse causality issues, and where specific econometric models, such as Heckman models, which are normally preferred to Tobit and maximum likelihood models (as described in Chapter 1) have been used to attenuate selection biases. Less often endogeneity of social capital variables has been addressed. Among the few that attempted to control for this issue there are Wossen et al. (2015) and Barr (2000). They both use instrumental variables within the two stage least square framework.

Finally, farmers' heterogeneity is also deemed to affect this analysis. The heterogeneity originates from the fact that the sample of non-adopters may be incorrectly composed of dis-adopters, i.e. farmers who adopted mango in the past and then dis-adopted; future adopters and "never" adopters, which could affect the precision of the estimations.

Farmers heterogeneity needs to be control for at the time of the adoption and ideally adopters should be compared to "never" adopters at the time of adoption.

The following paragraphs describe the strategies that I have put in place to try addressing some of these concerns.

Firstly, in line with Besley and Case (1993), the data collected for this analysis did, indeed, include some recall data. However, due to time and budget constraints, the collection of a comprehensive list of recall information proved to be unfeasible. Hence, only selected recall data were collected at household level with the recall year being the year of adoption. Due to the limited amount of information at the time of adoption for only adopters, the data do not allow for any panel-like analysis. The use of secondary data is also excluded for the purpose of this analysis because, although Ghana Living Standard Survey data are available for the year 2006, which corresponds to the average year of adoption in the sample, this survey does not have any module on social capital.

Nonetheless, the contribution of the recall data in the analysis of mango adoption needs to be seen in the attempt to reduce biases caused by reverse causality and farmers' heterogeneity, with respect to some observable characteristics that the available qualitative studies suggested as the most likely to have been affected by the adoption process itself. These variables are land acquisition and farm size. Farm size is included in the econometric model with current value for non-adopters and values at the time of adoption for adopters. Similarly, also age and experience in farming are modified to take in to account the different characteristics of adopters at the time of adoption. Hence, these two variables are defined as years of the head of the household at the time of adoption for adopters and current years for the non-adopters. In the analysis of time and intensity of adoption, the values of farm size, age and experience date back to the year of adoption for both groups of adopters in the sample.

In addition to the use of recall data, I also estimate Heckman models for addressing selection bias for the estimation of the model of the time of adoption and its intensity, i.e. systematic differences between adopters and non-adopters that can be driven by unobservable characteristics. The choice of this model instead of Tobit models follows the same practical considerations explained in the Chapter 1. However, differently from the analysis of market participation in Chapter 1, there is no clarity on a consistent theoretical framework for the selection of the identifier variables necessary for the

estimation of the Heckman models in the innovation adoption context. Some authors use more generic farmers and location characteristics (such as location and age in Ben-Houassa, 2011), while others use proxies of other transaction costs as captured by ownership of assets and road conditions, as in the case of Schipmann and Qaim (2010). Following previous examples and using similar theoretical considerations used for the analysis of commercialisation in Chapter 1, I explore the possibility of using proxies of transaction costs to control for self-selection in the innovation adoption. However, compared to the analysis of market participation, the analysis of the time and intensity of adoption could also require an element of risk aversion in the selection process. Following the theoretical framework above, farmers may, indeed, delay the choice to adopt and to adopt more intensively innovations because they are not willing to take the risk inherent in the adoption process per se or because they would like to acquire more information on the innovation through time. As a consequence, for Heckman models of the analysis of the time and intensity of adoption I also explore the possibility to use risk aversions dummies as identifier variables in the first stage. In addition, as land ownership is often claimed to be a necessary asset for trials and learning by doing I also use land ownership as an identifier variable in the selection equation.

Finally, I address the issue of the endogeneity of social capital variables. It is worth mentioning that recall data on social capital were not collected based on the assumptions that, first, relationships and social network tend to be quite stable across time and second that mango adoption would have occurred relatively recently and as such changes in the social capital were not foreseen at the time of the data collection. However, the data collected show that, indeed, some farmers have adopted mango much before than the expected period and as such social capital variables might be endogeneous. However, an instrumental variable model could be impracticable with the data that I am using as any of the instruments used in the previous literature either were not collected during the survey or do not apply to the innovation of exotic varieties of mango. For example, Wossen et al. (2015) instrument their social capital variables using the following variables: 1) idiosyncratic shocks (experience of death of a household member); 2) head born in the village 3) migration of adult members of the household 4) social status of head of the household in the village. Although data on shocks were collected during my field work, I am not convinced that it would be a good instrument for social capital in the context of mango adoption and especially because, differently

from Wossen et al. (2015), who measure social capital with memberships in funeral insurance groups or other similar groups, my measures of social capital are not directly related to shocks and as such I do not believe they can be considered a valid instrument[58]. Aside from endogeneity of social capital variables, I try to contain the issues of multicollinearity of these variables, estimating different types of social capital separately in the adoption models. Although maybe imprecise, this approach aims to limit the imprecision caused by multicollinearity related problems in the estimations.

In conclusion, the analysis of adoption processes poses several empirical challenges that have been recognised and, often, addressed in the past literature not without caveats and limitations. In this chapter, I try to follow previous approaches within the limits of the collected primary data. The following section discusses the results of the estimations.

[58] On the other hand, Barr (2000) instruments her variable on frequency of contacts with change agents using the following instruments: 1) ethnic origins; 2) his measure of diversity of social capital 3) sectoral and time dummies. Although I have been able to construct a measure of diversity of social capital with my data, the lack of additional variables, such as ethnic origins and the different unit of analysis (firms in Barr (2000) and small farmers in this analysis), make also this strategy not applicable to this study.

Section 5. Results

Given the data available, this section does not aim to identify any causal relationship but rather to highlight existing correlations and associations between common farmers' and village level characteristics and the adoption of the innovation under scrutiny, exotic varieties of mango.

Table 6 and Table 7 show the estimation results for the adoption of mango, the time of adoption (using either the absolute cut-off, 2006, or the relative cut-off, regional median) and its intensity (natural logarithm of number of trees planted) of the basic model. The basic model in Table 6 includes demographic, household and farm level characteristics, where robust standard errors clustered at the regional level are used. Social capital variables are not included in this model. The model reported in this table is the most comprehensive of seven different specifications (in Appendix 3.3) run for the four dependent variables, where the group of characteristics have been added in a step wise fashion. The results are generally consistent between the seven specifications and as a consequence, only the most comprehensive model is discussed here for exposition purposes.

Table 7, instead, reports the results of the adoption models which include in the specifications the explanatory variables already included in the basic model in Table 6 as well as social capital variables as listed in Table 3. The social capital variables are included in the models in a separate and clustered fashion[59]. In the Appendix 3 a more comprehensive list of results can be found[60]. For exposition purpose Table 7 is a summary of the results and only lists the coefficients related to the different social capital variables.

Marginal effects are reported for the models of adoption and the time of adoption using the absolute cut-off, while selection bias corrected probit marginal effects and OLS coefficients are reported for the analysis of the relative time of adoption and intensity of

[59] I have also estimated the models with village level social capital variables in trying to address endogeneity issue of the social capital variables. However, the coefficients estimated became extremely large suggesting that the model was not correctly specified and that an upward bias was instead generated. As a consequence I decided to use simpler variables as in Table 3.

[60] As shown in the tables in the Appendix 3.3, in the model A8, I included dummies of relationships with all the change agents; in the model A9, I included the variables on the strength of relationship; in the models A10-A13 bonding social capital are included in the estimation; in the model 14 I included the level of trust, and, finally, in the models A15 to A23, I included aggregate variables of social capital, one at the time.

adoption, when appropriate. Selection bias was only found to be relevant in the analysis of the intensity of adoption and the time of adoption when a relative cut-off is used. Three identifier variables are used for the analysis of the intensity of adoption (land ownership and two variables of risk aversion) and four for the time of adoption (ownership of radio, land ownership and two variables of risk aversion). Measures of fixed transaction costs, such as ownership of radio, did not qualify as identifier variables in the analysis of the intensity of adoption and, as a consequence, were also included in the second stage.

Table 6 shows that the lambda coefficients in the analysis of intra-regional time of adoption (relative cut-off) is positive suggesting a positive correlation between unobservables in the adoption decision and the decision of when to adopt. On the other hand, the negative lambda coefficient for the analysis of the intensity of adoption suggests the opposite, i.e. negative correlation between unobservables. The positive correlation between unobservables can be explained with the argument that more able farmers would be more likely to adopt and to delay the adoption and this is in line with the idea that farmers may sometimes free ride and delay adoption to acquire more information on the adoption itself and this could be positively related to the higher ability and entrepreneurship of the farmers themselves. A similar argument could explain the negative correlation observed in the analysis of intensity of adoption, as more able farmers or farmers with higher entrepreneurial skills could invest less extensively in the mango cultivation, which finds also justification in the fact that several interventions supporting mango production may not target large farmers.

The results in details

The estimations of the basic models in Table 6, which do not include social capital variables, show that common determinants of innovation adoption are relevant in the analysis of adoption of exotic varieties of mango. Farm size is observed to be consistently significant and positive in the adoption process and its dimensions (time and intensity). Hence, the findings suggest that a bigger farm size facilitates the discrete decision to engage in mango production, it reduces the time of adoption and it increases the number of trees cultivated. These results support the empirical literature that farm size positively affects the adoption process (Feder, 1982; Just, Zilberman, and Rausser, 1980).

Table 6 Determinants of adoption - basic model

Basic model		(1)	(2)	(3a)	(3b)	(4a)	(4b)
		Adoption	Time Absolute cut-off[61]	Time Relative cut-off[62]	Time Relative cut-off	Intensity	Intensity
		Probit	Probit	Uncorr-Probit	Corr-Probit Heck	Uncorr – OLS	Corr-OLS Heck
VARIABLES		mfx	mfx	mfx	mfx	coeff	coeff
Age head[63]	Years	-0.001	-0.001	-0.004	-0.003	0.004	0.004
		(0.003)	(0.005)	(0.003)	(0.005)	(0.005)	(0.006)
Male head	(0/1)	**0.181*** **	-0.074	-0.092	IV	**0.421***	0.208
		(0.062)	(0.252)	(0.108)		(0.254)	(0.255)
Higher education	(0/1)	-0.003	**-0.080****	-0.006	-0.013	**0.372***	**0.389*** **
		(0.013)	(0.039)	(0.049)	(0.070)	(0.195)	(0.145)
Farm labour	#	-0.017	**0.147*** **	**0.131*** **	**0.134*** **	-0.063	-0.035
		(0.022)	(0.012)	(0.012)	(0.015)	(0.055)	(0.047)
Farm size[64]	Acres	**0.013****	**-0.014*** **	**-0.009*** **	**-0.021*** **	**0.029*** **	**0.027*** **
		(0.005)	(0.002)	(0.002)	(0.007)	(0.004)	(0.005)
Land ownership	(0/1)	**0.230*** **	-0.206	-0.080	IV	-0.133	IV
		(0.063)	(0.139)	(0.150)		(0.216)	
Production other cash crops	(0/1)	**-0.091*** **	**-0.101*** **	0.035	**0.087***	-0.311	**-0.303****
		(0.035)	(0.007)	(0.047)	(0.046)	(0.199)	(0.142)
Livestock ownership	#	0.001	-0.001	-0.001	**-0.001***	0.002	0.002
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Access to non-farm income	(0/1)	**0.064***	0.011	0.009	0.008	0.089	0.061
		(0.038)	(0.023)	(0.034)	(0.027)	(0.101)	(0.078)
Access to credit	(0/1)	0.112	0.154	0.122	0.112	0.143	0.090
		(0.085)	(0.137)	(0.114)	(0.134)	(0.160)	(0.143)
Ownership of tractor	(0/1)	**-0.346*** **	*dropped*	*dropped*	*dropped*	0.042	0.228
		(0.066)				(0.535)	(0.489)
Ownership of mobile	(0/1)	0.087	0.085	0.128	0.132	-0.154	-0.230
		(0.118)	(0.169)	(0.165)	(0.149)	(0.126)	(0.192)
Ownership of radio	(0/1)	**-0.093*** **	**0.137*** **	0.073	IV	**0.324****	**0.381***
		(0.027)	(0.032)	(0.136)		(0.146)	(0.211)
Ownership of bicycle	(0/1)	**0.057****	-0.040	-0.053	-0.050	0.139	0.025
		(0.026)	(0.114)	(0.122)	(0.116)	(0.156)	(0.134)
Ownership of motorcycle	(0/1)	0.006	-0.068	-0.101	-0.107	**0.415*** **	**0.341*** **
		(0.053)	(0.142)	(0.128)	(0.150)	(0.130)	(0.129)
Ownership of car	(0/1)	**-0.032*** **	0.028	0.023	0.052	**0.386****	**0.467****
		(0.009)	(0.093)	(0.074)	(0.060)	(0.194)	(0.182)
Road conditions	#	**-0.035****	0.020	0.046	**0.053***	0.056	**0.096*** **
		(0.018)	(0.032)	(0.029)	(0.030)	(0.037)	(0.037)
Moderate risk averse	(0/1)	**0.123*** **	0.042	0.035	IV	-0.080	IV
		(0.036)	(0.065)	(0.063)		(0.138)	
No risk averse	(0/1)	0.034	-0.033	-0.053	IV	0.123	IV
		(0.078)	(0.078)	(0.125)		(0.224)	
Impatient	(0/1)	-0.022	-0.060	-0.017	0.005	**-0.270****	**-0.238***
		(0.064)	(0.095)	(0.081)	(0.077)	(0.136)	(0.126)
Experience in farming[64]	Years	**-0.012*** **	0.006	**0.008*** **	**0.010*** **	-0.009	0.001
		(0.002)	(0.005)	(0.003)	(0.004)	(0.005)	(0.008)
Training	(0/1)	**0.503*** **	-0.043	**-0.125****	**-0.200***	**0.619*** **	0.224
		(0.112)	(0.221)	(0.063)	(0.112)	(0.186)	(0.256)
Constant						3.398***	3.682***
						(0.444)	(0.551)
Lambda					**1.217***		**-0.629***
					(0.678)		(0.350)
Observations		305	196	196	305	196	305

[61] =1 if late adopter; = 0 if early adopter. Cut-off year=2006

[62] =1 if later adopter; =0 if earlier adopter. Cut-off year= regional median of year of adoption

[63] At the time of adoption for mango farmers; current for non-mango farmers.

On the other hand, the results also show that land ownership, although relevant in the discrete adoption decision, does not affect the time of adoption. This result contrasts previous findings in the literature, where land ownership is valued as important asset in the definition of the expected returns of innovative activities, and as such one would expect that owning land would accelerate the time of adoption. Nonetheless, a possible reason for this inconsistency with past studies can be related to the customary land market set up that is specific for the Ghanaian context. Communal land is, indeed, the traditional feature of the land market in most of the villages in Northern Ghana. 82% of the farmers in my sample in the Northern regions do not own any land while 91% and 79% of the farmers do in the Eastern and Brong-Ahafo regions, respectively[64].

Aside from land ownership and farm size, the results also show that other asset endowments might be relevant in the process of adoption. Ownership of a bicycle is positively associated with mango adoption but it is not relevant for the decision of when and how much to adopt. On the other hand, ownership of a car is negatively associated with the decision to adopt but positively associated with the intensity. Similarly ownership of tractors is negatively associated with the discrete decision to adopt but it is not significant in the analysis of intensity of adoption[65]. The negative association of these assets with adoption may be capturing the economic status of the households that are producing mango[66]. Thus, ownership of assets, such as car and tractors, are normally associated with a higher economic status[67]. However, the target population of the majority of the programs supporting the adoption of mango is composed of small and poor farmers, who are likely to be relatively less endowed than other farmers. These could explain why an unexpected negative relationship between generally considered predictors of wealth is, instead, observed in the case of mango adoption.

Among household's characteristics, family labour and access to non-farm income are also important determinants of adoption. However, family labour is observed to affect only the time of adoption: the higher the number of household's members working on

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[64] Using regional clustered standard errors, especially when using a "relative" regionally defined cut-off, might have affected the results.
[65] It is also automatically dropped from the estimation of the time of adoption suggesting that mango farmers rarely own a tractor (only 4 farmers in the mango farmers' sample).
[66] One other reason why these variables are negatively associated with adoption (or not significant) may be related to the sampling choices. Hence, as described in Chapter 2, very small farmers were over-samples during the field work and as such it is highly likely that these small farmers do not own these assets as it might not be economically efficient, as in the case of tractors, or they might be relatively poorer than other bigger farmers.
[67] Indicators of value and quality of the assets might be a better predictor of these relationship. However, this data was not collected during the fieldwork.

the family farm, the longer is the time the household would wait to adopt. The lack of significance for the discrete adoption decision might be explained by the fact that family labour is not necessarily a requirement for mango production, which is claimed to be less labour intensive than other cash crops. On the other hand, as anticipated in the descriptive analysis, access to non-farm income is observed to be a complement of the adoption process but it does not affect the time and the intensity of adoption.

Also in line with the expectations, the results show that experience in farming (at the time of adoption for mango farmers) is an important predictor of the adoption decision. More specifically, the findings suggest that a longer experience in farming is negatively associated with the adoption decision and it is observed to delay the decision to adopt. Farmers with a long history of agricultural activities may decide to not engage in innovative activities or to engage later. This result, although may be capturing the effect of age in the adoption decision, could also be related to the substitution effect of other production decisions. Hence, the production of other cash crops is found to be strongly significant and negatively associated with the mango adoption, the relative time of adoption and the adoption intensity. Nonetheless, producing other cash crops might also capture the access to the information that could be useful for the mango production too. This might explain why producing other cash crops reduces the time of adoption, when an absolute cut-off is used (column 2).

Among demographic characteristics, gender of the head of the household is only found to affect the initial decision to adopt or not adopt. Being a man increases the likelihood of adoption of exotic varieties of mango. This result supports the argument that export crops are indeed a male dominated sector in agriculture. Education instead is found to be positively related with the time of adoption and its intensity, supporting the empirical evidence that education is a sign of a higher absorptive capacity and as such is a facilitator and an accelerator of innovative activities.

Finally, risk aversion plays a significant role in the adoption of exotic varieties of mango. Compared to extreme risk adverse farmers, being moderately risk adverse is found to be positively associated with the decision to adopt or not adopt. Nonetheless, this variable does not affect either the time or the intensity of adoption where, instead, impatience is found to be relevant. This result suggests that impatient farmers would plant less tress than more patient farmers. The long gestation period of mango trees and

the risks associated with the high and intense pre-gestation activities coupled with the current unexpected shocks may be the reason of this negative association. Farmers may accept to adopt mango but not to invest extensive resources in it because they might prefer more immediate returns from other cultivations, possibly cash crops, whose association with the intensity of mango adoption is indeed negative and strongly significant.

After the analysis of the basic model reported in Table 6, I have, then, introduced social capital in the analyses, using different specifications and combinations of the variables listed in Table 3. The main results are summarised in Table 7. This table reports the marginal effects and the coefficients from separate estimations. Hence, each result reported in the table has been extracted from the results of the estimations of the basic model with the addition of one component of social capital variables at the time: structural bonding, structural bridging and cognitive, in their disaggregated or aggregated form[68]. As for the results in Table 6, robust standard errors where used and, where appropriate, selection corrected OLS and probit coefficients are reported.

The results in Table 7 suggest that, in line with the recent empirical evidence, social capital determinants of adoption should not be overlooked, especially in the analysis of the simple discrete decision to adopt or not adopt. Hence, social capital components are observed to be strongly and positively associated with the adoption decisions.

More specifically, among the structural bridging social capital, the adoption of mango is associated with having contacts and a strong relationship with several change agents, such as input suppliers, extension officers and development agencies. The strongest size of the association with adoption is observed for development agencies, which supports the evidence that development agencies have played an important role as change agents in the adoption of exotic varieties of mango in Ghana.

Compared to previous literature, the size of the results tends to be quite consistent. For example, a relationship with extension officers would increase the probability to adopt by 14 percentage points ceteris paribus in my analysis, while Schipmann and Qaim find an effect equal to 11 percentage points.

[68] The choice to include them one at the time is due to the nature of the social capital variables themselves that are highly correlated with each other. A detailed multicollinearity test can be found in Appendix.

Furthermore, the estimates in Table 7 suggest that having a relationship with development agencies would increase the probability to adopt, ceteris paribus, by 45 percentage points. The association between adoption and relationship with development agencies has rarely been investigated empirically. Amongst the few studies that do investigate the effect of different components of social capital, van Rijn et al., (2012) find a strong and positive association between adoption of agricultural innovation in Sub-Saharan countries and a set of structural bridging social capital actors. The results of their poisson models suggest that a for a one unit change in bridging social capital, the difference in the logs of the innovation count variable (1-20) is expected to change by 4.31, which corresponds to an increase on the average number of innovations by about 20%. Bandiera and Rasul (2006) do not explicitly investigate the role of development agencies in adoption. However, they use as control variable participation in development programs, which is found to increase the probability to adopt by, on average, 30 percentage points. Although imprecise due to different modelling approaches, the comparison with these previous studies shows that the association estimated between relationship with development agencies and adoption in this analysis is higher than what observed in the past empirical evidence. A possible reason could be that the role of development agencies in the context of exotic varieties of mango in Ghana has been more intense that in the other two cases presented. Hence, while van Rijn et al. (2012) investigate the role of social capital on a variety of different innovations, for which the role of different bridging agents may be averaged, Bandiera and Rasul, 2006 studies the adoption of one crop, sunflower, which was provided by only one NGO[69].

Moving from the discrete decision to adopt to its dimensions (time and intensity), some differences in the role of different bridging actors can be observed. For example, in the analysis of time of adoption which highlights inter-regional differences (absolute cut-off) NGOs, credit providers as well as input suppliers but not development agencies are observed as the main change agents.

[69] In addition, the size of the coefficients might be due to problems of endogeneity of the social capital variables in my analysis, which might have caused an upward bias and as such a higher magnitude of the association.

Table 7 Social capital

Note: this table includes only the social capital variables. The full models can be found in Appendix 3

Basic model and social capital		(5) Adoption	(6) Time adoption Absolute cut-off[70]	(7) Time adoption Relative cut-off[71]	(8) Intensity
VARIABLES		Probit mfx	Probit mfx	Heck[72]/Probit mfx	Heck[17]/OLS coeff
Structural bonding social capital					
Relationship with Farmers' Organisation (FO)	(0/1)	**0.317*** **	0.120	-0.096[1]	**0.849*** **
		(0.084)	(0.085)	(0.092)	(0.197)
Membership in Farmers' Organisation (FO)	(0/1)	**0.275*** **	**0.194***	-0.090[1]	**0.430** [1]**
		(0.095)	(0.103)	(0.084)	(0.194)
Social network	#	**-0.161***	0.017	**0.234*** [1]**	0.031
		(0.088)	(0.233)	(0.077)	(0.229)
Strength of relationship with other farmers	(1/5)	0.056	0.086	0.019	0.097
		(0.055)	(0.074)	(0.037)	(0.066)
Structural bridging social capital					
Relationship with input suppliers	(0/1)	**0.383*** **	**-0.428*** **	dropped	0.544
		(0.148)	(0.068)		(0.565)
Relationship with credit providers	(0/1)	**-0.433** **	**-0.087***	-0.004[1]	0.675
		(0.217)	(0.047)	(0.124)	(0.557)
Relationship with extension officers	(0/1)	**0.144*** **	0.070	**0.139** [1]**	-0.402
		(0.035)	(0.102)	(0.064)	(0.339)
Relationship with Dev Agencies	(0/1)	**0.454*** **	0.093	-0.081[1]	**0.579***
		(0.052)	(0.260)	(0.222)	(0.306)
Relationship with NGOs	(0/1)	0.084	**-0.217*** **	-0.146[1]	0.192
		(0.057)	(0.083)	(0.111)	(0.441)
Strength of relationship with input suppliers	(1/5)	**0.046*** **	**-0.062** **	**-0.099*** [1]**	-0.009
		(0.017)	(0.031)	(0.020)	(0.040)
Strength of relationship with credit providers	(1/5)	-0.059	**-0.048*** **	-0.032[1]	-0.003
		(0.056)	(0.014)	(0.023)	(0.048)
Strength of relationship with extension officers	(1/5)	0.025	0.030	**0.050*** [1]**	-0.028
		(0.018)	(0.037)	(0.027)	(0.041)
Strength of relationship with Dev Agencies	(1/5)	**0.177*** **	0.024	-0.041[1]	**0.164*** **
		(0.021)	(0.066)	(0.046)	(0.042)
Strength of relationship with NGOs	(1/5)	0.026	**-0.063***	-0.031[1]	-0.035
		(0.018)	(0.037)	(0.034)	(0.037)
Cognitive social capital					
Trust in input suppliers	(1/3)	**0.091***	**-0.145** **	**-0.224*** [1]**	0.082
		(0.051)	(0.060)	(0.040)	(0.057)
Trust in credit providers	(1/3)	-0.064	**-0.103*** **	-0.052[1]	-0.020
		(0.076)	(0.033)	(0.034)	(0.059)
Trust in extension officers	(1/3)	0.038	**0.083*** **	**0.086*** [1]**	-0.011
		(0.033)	(0.030)	(0.009)	(0.057)
Trust in Farmers' Organisation (FO)	(1/3)	**0.072** **	-0.014	-0.045[1]	**0.270*** **
		(0.029)	(0.040)	(0.043)	(0.082)
Trust in Development Agencies	(1/3)	**0.192*** **	0.040	-0.008[1]	**0.152** **
		(0.028)	(0.115)	(0.094)	(0.071)
Trust in NGOs	(1/3)	0.016	-0.070	-0.021[1]	**-0.087***
		(0.046)	(0.047)	(0.049)	(0.048)
Trust in other farmers	(1/3)	-0.006	**0.312*** **	**0.152*** [1]**	-0.059
		(0.041)	(0.109)	(0.035)	(0.145)
Aggregates					
Structural Bridging Index	#	**0.167*** **	-0.075	**-0.080** [1]**	0.029
		(0.027)	(0.057)	(0.113)	(0.054)
Structural Bonding Index	#	**0.126*** **	0.032	**-0.054*** [1]**	**0.195** **

[70] =1 if late adopter; = 0 if early adopter. Cut-off year=2006

[71] =1 if later adopter; =0 if earlier adopter. Cut-off year= regional median of year of adoption

[72] Heckman corrected

Basic model and social capital		(5) Adoption	(6) Time adoption Absolute cut-off[70]	(7) Time adoption Relative cut-off[71]	(8) Intensity
VARIABLES		Probit mfx	Probit mfx	Heck[72]/Probit mfx	Heck[17]/OLS coeff
		(0.043)	(0.067)	(0.013)	(0.075)
Cognitive Index	#	**0.214*** **	0.078	0.027	**0.279*** **
		(0.049)	(0.050)	(0.044)	(0.060)
Diversity social capital	#	**0.159*** **	-0.006	-0.055[1]	**0.094***
		(0.012)	(0.051)	(0.043)	(0.055)
Intensity of diversity of social capital	#	**0.046*** **	-0.002	**-0.014*[1]**	**0.029** **
		(0.006)	(0.009)	(0.008)	(0.013)
General trust	#	**0.063*** **	0.013	0.005	**0.045*** **
		(0.012)	(0.015)	(0.014)	(0.017)
Diversity of selected change agents	#	**0.228*** **	-0.013	-0.059[1]	**0.178*** **
		(0.021)	(0.091)	(0.071)	(0.062)
Intensity of diversity of selected change agents	#	**0.066*** **	-0.003	-0.004	**0.055*** **
		(0.010)	(0.016)	(0.013)	(0.017)
Trust in selected change agents	#	**0.084*** **	0.020	0.013	**0.076*** **
		(0.016)	(0.026)	(0.022)	(0.023)

The role of NGOs, credit providers and input suppliers as facilitator of early adoption is in line with the fact that the some activities, especially the ones related to NGOs and credit providers, have been carried out at different times in different regions. Late adopters (absolute cut-off) are, indeed, more located in the Northern region where activities in support of mango adoption came much later than, for example, in the Southern belt.

On the other hand, when intra-regional differences are taken into account in the analysis of the time of adoption (regional cut-off), the role of NGOs is not significant anymore. Instead, a positive association between *earlier* adoption is observed with input suppliers only. Furthermore, the results also show that extension officers might delay the time of adoption within regions. This result could be justified by the fact that extension officers working for the Ministry of Agriculture have very little experience with innovation activities, especially with regards to exotic varieties of mango. From field observation and focus group discussions carried out during the field work, farmers claimed that the amount of information provided by extension officers is generally quite low and not accurate. As a consequence, it might be plausible to think that extension officers might be expression of the "conformity" norm of the cognitive social capital, which is often found negatively associated with innovation and early adoption.

This finding contrasts with previous empirical evidence as, for example, in the analysis of time of adoption in Schipmann and Qaim (2010). Using a duration model, they found that the speed of adoption increases quite substantially if the farmer has a contact with

extension officers. Nonetheless, the product innovation investigated in that case was sweet pepper which was introduced as product innovation in early 2000s, similarly to exotic varieties of mango, but its diffusion was much more rapid across producers and domestic consumers. Also, it is not clear from their study how extension officers are defined. In this analysis, extension officers are explicitly identified with officers of the Ministry of Agriculture, and as such other types of extension activities are excluded from this category, which might not be the case in analysis such as Schipmann and Qaim (2010).

Moreover, aside from the different definition of extension officers, the inconsistency of my results with this type of literature might support the importance of understanding the nature of the social capital relevant for the specific innovation under scrutiny. In this analysis of exotic varieties of mango in Ghana, I believe that extension officers cannot be considered the main innovators or change agents for earlier adoption as exotic varieties of mango were introduced via other actors, which could explain the observed negative association in the analysis of time of adoption.

This type of association could also be driven by the negative flow of information generated by current adopters, due to shocks and harvest losses and probably shared with local extension officers. Bush fires and floods in the Northern regions as well as pest and diseases in the South have sometimes completely destroyed entire mango farms. More recently in December 2014, the abundance of rain has caused the nationwide abortion of flowering of mango trees which has reduced to the minimum the production expectation for the next harvest season. These developments might have generated negative expectations on the return of the innovation and as such induced a delay in the adoption. This is in line with what Moser and Barrett (2006) claim about the role of negative expectations on adoption of innovations and could explain why relationship with local extension officer is found to delay adoption, as they might have contacts with previous adopters and share their experiences with other farmers in the community.

Bonding social capital and the effect of social network are often found to be positively associated with innovation adoption (e.g. Bandiera and Rasul, 2006). The results in Table 7 show that being a member of a farmers' organisation and having contact with a farmers' organisation play a positive effect on the decision to adopt and its intensity,

supporting the argument that homophilus ties are important in the adoption decision (Matuscke and Qaim, 2009).

The size of the effects of bonding social capital on adoption tend to be quite consistent with previous findings as bonding social capital, measured as membership or contacts with farmers' organisation, is found to increase the probability to adopt from 28 to 32 percentage points, ceteris paribus. For example, Bandiera and Rasul (2006) find an average effect of 39 percentage points, with a minimum of 27 to a maximum of 58 percentage points, depending on the size of the social network, while Isham (2002) finds that bonding social capital increases the probability to adopt fertilizer in Tanzania by 30 percentage points.

On the other hand, the finding on the role of the size of the social network on adoption contradicts the expectation because it is found to be negatively associated with the discrete adoption decision and earlier adoption, when a relative cut off is used. Similarly, being a member of farmers' organisation seems to delay the adoption in the analysis of inter-regional differences (absolute cut-off).

These results could support the argument that, although bonding social capital is important for the decision to adopt per se, having contacts with other farmers may induce future adopters to wait for "better" times in order to acquire more information on the innovation itself. Two possible reasons have been used in the literature to explain the nature of this relationship: "over-crowding" effect and negative returns of the innovation. The over-crowding effect refers to the sigmoid distribution of the adoption rates drawn from the sociological literature (Bandiera and Rasul, 2006). This literature assumes that the speed of diffusion of adoption will be positive until a maximum amount of adopters is reached, after which the speed of adoption will decrease until no one else will adopt the innovation under scrutiny.

This argument could play a role in this analysis and it may be highly linked to the nature of the sampling strategy. Hence, villages and districts with a high concentration of adopters have been purposively selected during the sampling process. It is indeed possible that the adoption rates might be quite high in the location chosen and that an overcrowding effect could be playing a role. Another possible explanation is the effect of the experience of negative returns from innovation from a number of adopters in the

village, as described above. This idea, common among the learning by "seeing" scholars, fits the context of the mango adoption in Ghana.

The effect of cognitive social capital is usually quite difficult to estimate, as it requires detailed information on trust and community norms and rules. The variables on trust that I use are, indeed, quite limited in their ability to capture such complex dynamics. Nonetheless, I believe that they show some interesting and consistent results. Hence, trust in input suppliers, farmers' organisation and development agencies is found to be strongly significantly and positively associated with the discrete adoption decision. Once again, the role of the development agencies as change agent is the strongest for mango adoption. The decision to adopt earlier than others is instead affected negatively by the trust in other farmers and in extension officers. As explained above, it is likely that a negative flow of information on the negative returns of mango production might have been channelled through these two change agents. A higher trust in these agents could then indeed delay the adoption process.

The negative effect of cognitive social capital is consistent with the results of previous studies, such as van Rijn et al., (2012), Dakhli and de Clercq, (2004) and Kaasa (2009), who claim that cognitive social capital, in the form of conformity and good citizenship rules, may hinder adoption and early adoption.

However, although as mentioned above, this explanation may hold for trust in extension officers, I believe that the negative association between trust in other farmers observed in this analysis does not relate to the role of these community rules but, instead, provides support to the argument that bonding social capital is indeed quite important in the adoption decision. Farmers do trust each other and do communicate about both failures and successes. As a consequence of the numerous difficulties that adopters are facing in the production of exotic varieties of mango, it is plausible to believe that, indeed, adoption and its dimensions are affected negatively if farmers trust other farmers.

Finally, the results of the aggregate measures of social capital confirm that social capital matters in the innovation process. A strongly significant and positive relationship is observed for all the aggregate variables for the discrete adoption decision and its intensity. On the other hand, the time of adoption at inter-regional level (absolute cut-off) seem not be affected by any of these variables, suggesting that more disaggregated

measures of social capital could be more appropriate in this analysis across different regions. Nonetheless, the results of the intra-regional analysis of the time of adoption (relative cut-off) show that, in line with previous social network studies, bonding social capital is positively associated with earlier adoption. However, the findings also suggest that other social capital components, such as bridging social capital, should not be overlooked, as it is also found to be positively associated with earlier adoption in this analysis[73].

The role of social capital in reducing barriers to adoption

One of the main arguments in support of the importance of social capital in the context of innovation adoption in developing countries is their ability to provide farmers with access to information that otherwise, due to institutional and market inefficiencies, they might not be able to obtain.

In order to understand whether social capital can help farmers overcoming physical and human capital deficiencies in the context of the adoption of exotic varieties of mango, I estimate the basic model as in Table 6 with the addition of interaction of aggregate measures of social capital with selected common determinants of adoption. The equation (6) is then re-formulated as follows:

$$Y_h^i = \alpha + \beta_1 A_h + \beta_2 G_h + \beta_3 I_h + \beta_4 \mathrm{SK}_h + \beta_5 \mathrm{SK}_h * i_h + \varepsilon \qquad (7)$$

where i_h is a vector of farm size, land ownership, credit, ownership of communication assets, such as radio, and risk aversion. The results of the models with the interactions between aggregate measures of social capital and selected adoption determinants are summarised in the Appendix 3.5 and not presented here for exposition purpose.

The results show that, while the usual determinants remain statistically significant, social capital may mitigate the relevance of some of the classical determinants of adoption and its time but not for its intensity. For example, bridging social capital facilitates and accelerates adoption if the farmers are not extreme risk averse. Moreover, this type of social capital facilitates adoption and early adoption if farmers have larger

[73] In order to validate the robustness of the results I have also run additional estimations on a subset of farmers. One of the main differences between adopters and non-adopters highlighted in Section 3 was the size of the cultivated farm. In order to reduce the systematic difference in farm endowments between adopters and non-adopters I have run the analysis of the adoption and its dimensions on the subset of farmers with similar farm size. The results show that the estimations discussed above do not change much when the biggest farmers are dropped from the analysis. The size, the significance as well as the direction of the coefficients estimated in the full model remain very similar also in these estimations. The full discussion and results can be found in Appendix 3.4.

farm size. When intra-regional differences are taken into account, the higher the bridging social capital the lower is the effect of farm size on earlier adoption. Finally, the effect of land ownership on adoption is reduced in the presence of higher bridging social capital.

On the other hand, the effect of bonding social capital is mainly significant for credit and ownership of radio in the case of the discrete adoption decision and for farm size and ownership of radio for the decision on when to adopt. More specifically, having a higher bonding social capital reduces the importance of having access to credit, which is overall found to decrease adoption[74].

Finally, cognitive social capital affects the effects of credit and risk aversion for the adoption decision, and the effects of road conditions, credit, risk aversion, farm size and ownership of radio for the decision on when to adopt. Having a higher cognitive social capital facilitate and accelerate adoption for those farmers with access to credit and who are less risk averse. Furthermore, a stronger cognitive social capital seems to help farmers in overcoming bad road conditions, i.e. farmers located in villages where roads are impassable for a higher number of months tend to adopt earlier than others. Nonetheless, cognitive social capital per se is found to increase adoption but also to increase the time of the adoption itself[75].

These analyses use aggregate measures of social capital. As a consequence, although providing interesting results, do not allow the identification of specific change agents that might be relevant in the adoption context. As a consequence, in order to understand the effect on the adoption decisions of single change agents, I also estimate the basic model for sub-samples of farmers who are observed to have a relationship with some of the actors used in the social capital analysis. I use these samples one at the time and run the basic model analysis of the determinants of adoption and its dimensions in separate estimations, as expressed as follows:

$$Y_h^i \,|(\mathrm{SK}_h^i = 1) = \alpha + \beta_1 A_h + \beta_2 G_h + \beta_3 I_h + \varepsilon \qquad (8)$$

[74] However, ownership of radio hinders adoption even more in presence of higher bonding social capital, suggesting a complementarity between bonding social capital and ownership of communication assets for access to information. Similar results are observed in the analysis of the time of adoption.

[75] The role of social capital in reducing transaction costs related to the road conditions is also observed in the estimations when other measures of social capital are included, as, for example, the diversity indicators, the intensity of diversity of social capital and general trust.

Where the adoption status Y_h^i is conditional to household *h* to have relationship with specific change agent, ($SK_h^i = 1$).More specifically, following the results in Table 6, I have selected the relevant social capital actors for each dimension of the adoption process[76]. Table 8 shows only the most insightful results, which are observed in the case of farmers with relationship with farmers' organisation or extension officers[77].

Table 8 Determinants of adoption, subsets of farmers

	Adoption	Intensity	Time adoption - abs	Adoption	Time adoption-rel
VARIABLES	FO	FO	FO	Extension officers	Extension officers
Age head[1]	-0.002***	-0.001	-0.007	-0.001	-0.009***
	(0.000)	(0.007)	(0.008)	(0.003)	(0.002)
Male head	0.035	0.641*	-0.160	0.093	0.020
	(0.021)	(0.346)	(0.293)	(0.093)	(0.227)
Higher education	-0.007	0.626***	-0.147***	-0.102***	-0.009
	(0.024)	(0.236)	(0.051)	(0.029)	(0.059)
Farm labour[1]	0.001	-0.022	0.125***	-0.007	0.150***
	(0.002)	(0.047)	(0.013)	(0.027)	(0.031)
Farm size[1]	0.001	0.028***	-0.015***	0.011***	-0.008***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)
Land ownership	0.027	-0.087	-0.143	0.054**	-0.152**
	(0.022)	(0.194)	(0.199)	(0.022)	(0.064)
Production other cash crops	-0.010	-0.735**	-0.137	-0.063***	0.142***
	(0.013)	(0.288)	(0.215)	(0.002)	(0.036)
Livestock ownership	0.000**	0.002	-0.002*	0.001	-0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Access to non-farm income	0.009	-0.022	0.031	0.023	-0.043
	(0.006)	(0.088)	(0.071)	(0.029)	(0.043)
Access to credit	0.004	0.144	0.173	0.076	0.207***
	(0.005)	(0.150)	(0.153)	(0.059)	(0.056)
Ownership of tractor	*dropped*	-0.230	*dropped*	*dropped*	*dropped*
		(0.576)			
Ownership of mobile	-0.013**	-0.043	0.172	0.094	0.369**
	(0.006)	(0.121)	(0.217)	(0.171)	(0.157)
Ownership of radio	-0.010	0.157	0.239***	-0.059	-0.017
	(0.012)	(0.144)	(0.031)	(0.045)	(0.218)
Ownership of bicycle	0.000	-0.062	-0.037	0.008	0.016
	(0.005)	(0.182)	(0.228)	(0.045)	(0.171)
Ownership of motorcycle	-0.001	0.467***	-0.140	-0.019	-0.104
	(0.004)	(0.121)	(0.182)	(0.039)	(0.128)
Ownership of car	*dropped*	0.430*	-0.028	0.080**	-0.039
		(0.228)	(0.085)	(0.038)	(0.043)
Road conditions	0.005	0.068	0.041	-0.024**	0.063***
	(0.005)	(0.046)	(0.029)	(0.010)	(0.019)
Moderate risk averse	0.039***	-0.205	0.067	0.171***	0.046
	(0.011)	(0.176)	(0.158)	(0.049)	(0.171)
No risk averse	0.008	-0.196	-0.010	0.078	-0.028
	(0.009)	(0.237)	(0.148)	(0.064)	(0.234)
Impatient	-0.049	-0.175	-0.167	-0.077**	-0.014
	(0.040)	(0.124)	(0.120)	(0.032)	(0.095)
Experience in farming[1]	-0.001**	-0.001	0.005	-0.008***	0.008*
	(0.000)	(0.005)	(0.010)	(0.002)	(0.005)
Training	0.908***	-0.063	0.132	0.244***	-0.146***
	(0.060)	(0.356)	(0.270)	(0.063)	(0.035)

[76] For the discrete adoption decision I re-run the basic model for those farmers who have a relationship with: 1) input suppliers; 2) extension officers; 3) development agencies and 4) farmers' organisation. These actors were found quite consistently significant in the determinant of the adoption. Similarly, for the inter-regional analysis of the time of adoption I use the sub-sample of adopters with a relationship with: 1) input suppliers; 2) credit providers; 3) NGOs and 4) farmers' organisation. For the intra-regional analysis of the time of adoption, only the relationships with input providers and extension officers are considered. Finally, for the analysis of the intensity of adoption I select a sub-sample of adopters with a relationship with development agencies and farmers' organisation.

[77] The full results can be found in Appendix 3.5.

VARIABLES	Adoption FO	Intensity FO	Time adoption - abs FO	Adoption Extension officers	Time adoption-rel Extension officers
Observations	117	123	123	188	153

1At the time of adoption for mango farmers; current for non-mango farmers; FO=farmers' organisation

These results tend to suggest that when focusing on the role of single change agents the contribution of social capital in mitigating innovation barriers might differ compared to the analyses that use aggregate measures. For example, in contrast with what discussed above, these results show that bonding social capital, in the form of membership in farmers' organisation, does reduces some transaction costs, as measured by road conditions and ownership of radios, on both the discrete adoption decision and its intensity, while it does not change much the estimation of the determinants of time of adoption. This finding could suggest that farmers' organisations could act as substitute for a common source of information, such as radio, and could facilitate access to relevant information for mango adoption and its intensity, that common transaction costs might hinder[78].

Also, in the decision to adopt, for members of farmers' organisations, most of physical capital, such as farm size and land ownership, which are often strategic in the learning by doing process, become not significant[79]. This result could suggest that being part of a farmers' organisation might reduce the need of the farmers for trials and experimentation on own land as similar information on failures and successes related to the innovation adoption may be obtained from simply participating in activities within farmers' organisation and by interacting with other farmers and, possibly, previous adopters.

Aside from the role of farmers' organisation (bonding social capital), the results also suggest that having a relationship with local extension officers (bridging social capital) might affect the determinants of the decision to adopt and the time of adoption, both between and within regions. In the decision of whether to adopt or not, the findings of these estimations suggest that the adoption decision is not associated anymore with transport and farm assets, such as tractor, but it is associated with lower age and

[78] The results also show that ownership of mobile phones is found to reduce the probability to adopt if the farmer is member of a farmers' organisation. This counterintuitive result might suggest that farmers with mobiles are able to gather information also from other sources, not necessarily linked with local farmers' organisation, which might hinder the decision to adopt.

[79] According to these results, the consistent role of, for example, farm size and land ownership, found in previous empirical evidence and in this chapter, in the adoption decision described above seems to be reduced by social capital.

education, lower endowment with communication assets, such as mobile phones, and lack of access to credit. Instead, for the group of farmers who are observed to have a relationship with extension officers the probability to adopt is positively associated with low education, with ownership of a car and with less impatience than other farmers. On the other hand, for the decision on when to adopt, farmers with a relationship with extension officers are more likely to adopt earlier if they are younger, they don't have access to credit and they don't own communication assets such as mobiles. In addition, the major determinants observed in the estimation of the full sample, such as farm size and land ownership, are still significant and with the same sign. In addition, gender does not affect the adoption anymore, while farm size and land ownership are still significant in this analysis. The analysis of the time of adoption also suggests a relationship with extension officers, especially if combined with access to credit, would delay adoption of mango.

A similar story is observed for the subsample of farmers with a relationship with NGOs in the analysis of inter-regional differences of the time of adoption. More specifically, these results tend to show that early adopters are farmers with lower education, with bigger farm size, with land ownership and less experienced in farming. Also, the access to non-farm income for these farmers tends to delay the adoption. However, differently from the analysis of extension officers, having contacts with NGOs is found to reduce some communication transaction costs, as the ownership of radio becomes not significant while the ownership of a mobile becomes relevant for early adoption. These results might find support in the fact that farmers with contacts with NGOs gather information via these change agents and owning a mobile phone might facilitate this information exchange. However, the sample of farmers for this estimation is quite small (69) and as such further interpretation of these results might be misleading[80].

The findings of these additional analyses tend to support, overall, the idea that adoption decisions are affected by social capital. More specifically, the analyses of the interactions of aggregate measures of social capital and selected adoption determinants show that, although social capital goes in parallel with some of the main constraints of

[80] Among other forms of structural bridging social capital, development agencies for the intensity analysis and input suppliers for the discrete adoption decision and its time do not seem to affect the relevance of the main determinants of adoption.

the adoption process, such as farm size, it might facilitate early adoption for landless farmers, farmers with no access to credit and located in more remote areas.

The results also suggest that a certain degree of disaggregation in the measures of social capital might provide additional insights on the role of single change agents. More specifically, while membership in farmers' organisation is observed to play a role in reducing farmers' constraints in the adoption process, especially related to access to information, conventional forms of bridging social capital, such as extension officers, could also favour adoption of lower educated and poorly endowed farmers, although they do not affect farm size and land ownership constraints.

Section 6. Conclusion

Exotic varieties of mango, such as Kent and Keitt, can be considered an innovation in the Ghanaian context as they have been introduced on massive scale in the late 90s by a NGO (ADRA). Since then, several donors and national agencies in Ghana have tried to attenuate farmers' difficulties in the accessing the expected benefits of so called "golden fruit". Their main interventions focus on the establishment and consolidation of farmers' organisations, better extension services and training within an overall poverty reduction strategy.

Notwithstanding the strong political interest and the amount of national and international financial investments in the sector, the latest estimates from the Living Standards Surveys show that the number of producers has been falling in the past 20 years. The numerous production and weather related challenges, that mango adopters face, provides support for the argument that adoption decision regarding exotic varieties of mango might not be straightforward, especially among small farmers.

Past literature has investigated the adoption of product innovation mostly focusing on traditional cash crops, such as cocoa, or horticultural crops, fruits and vegetables. However, apart from few studies, such as Conley and Udry (2010), few authors have empirically investigated the decision to adopt non-traditional cash crops in Ghana.

This paper contributes to the product innovation adoption literature as it investigates the determinants of the adoption of exotic varieties of mango, a non-traditional cash crop for Ghana, with primary data collected in 2012 from both adopters and non-adopters. In order to provide a comprehensive overview of the adoption process, I also investigate the factors that affect the decisions of when and how much to adopt.

The analysis dedicates a special attention to the role of social capital and its components (structural bonding, structural bridging and cognitive) in the adoption process. The relevance of social capital in the adoption of innovation has only recently re-gained recognisance in the literature. Nonetheless, seminal papers such as Bandiera and Rasul (2006) as well as Conley and Udry (2010) mostly focus on the role of one of the many components of social capital, the bonding component within social network analysis. Only few authors in the adoption of innovation literature, especially in the context of

agricultural innovation, have investigated the role of social capital in all of its components (structural bridging, bonding and cognitive).

My paper follows the latter strand of the literature as it tries to empirically unveil the role of the social capital in all of its components, in both the most disaggregated way (at change agent level) as well as in its aggregate specification, using composite indexes.

Overall, the main results of the analysis suggest that social capital determinants of adoption should be not overlooked in the adoption of exotic varieties of mango in Ghana, supporting the recent evidence in the literature of innovation adoption that there exists a positive relationships between the "know-who" and the adoption dynamics.

Also, in line with Kaasa (2009) and van Rijn et al. (2012), the findings support the importance of retaining a high level of disaggregation of the social capital variables in the adoption models as it contributes in unveiling links and direction of effects that may be change-agent specific.

For example, among structural bridging social capital, the role of development agencies tend to be relevant in the decision of how much to adopt but not in the time of adoption, in which case NGOs, credit and input suppliers might be more important. On the other hand, extension officers are found to delay the adoption decision. This is in line with the fact that extension officers are generally not considered innovators within local communities and with the argument of expectations of negative returns from innovation by Moser and Barrett (2006).

Trust and cognitive social capital, although within the limitation of the data, are also found to be relevant in the adoption decisions. Overall, similar change agents observed for the bridging social capital are also relevant in the case of cognitive social capital. For example, the results suggest once again a negative effect of extension officers on the adoption decisions. This finding is in line with previous empirical evidence that cognitive social capital might hinder adoption because of conservative local rules and norms of good citizenship and status quo.

Finally, the most consistent result regarding social capital determinants concerns the effect of structural bonding capital. Contrary to what found in van Rijn et al., (2012) but in line with Bandiera and Rasul (2006), bonding social capital, measured as membership in farmers' organisation, is found strongly and positively associated with

the adoption and adoption's intensity decisions, supporting the strong effort of development agencies and national government in enforcing these local institutions. Hence, in the context of mango adoption, farmers' organisations do play a considerable role. They do not only provide technical advice on how to face production and climate related challenges, they also provide a network of contacts among other farmers and local and international buyers. They, indeed, offer a social capital platform where farmers can acquire information for making an "informed" adoption decision. An informed decision that, in line with Moser and Barrett (2006), might also be a "non-adoption" or a "delayed-adoption" decision. This argument could explain why the size of social network has a negative effect on the decision to adopt and why trust in other farmers is associated with later adoption.

In conclusion, this analysis, notwithstanding its limitations in addressing causality, is in line with the recent empirical evidence, in supporting the argument that social capital endowments are important determinants in the innovation decisions. Although bonding social capital seems to be more relevant in the context of mango adoption, also other social capital components, bridging and cognitive, play a role in the farmers' decision to adopt and, as such, should take part in the innovation adoption theoretical framework.

This analysis is one of the few that explicitly investigate the role of social capital for mango in Ghana and I believe it provides interesting insights for future policy interventions, one of which regarding the strengthening of the role of farmers' organisations and a better integration of national extension services in the diffusion of innovation at local level.

CHAPTER 4

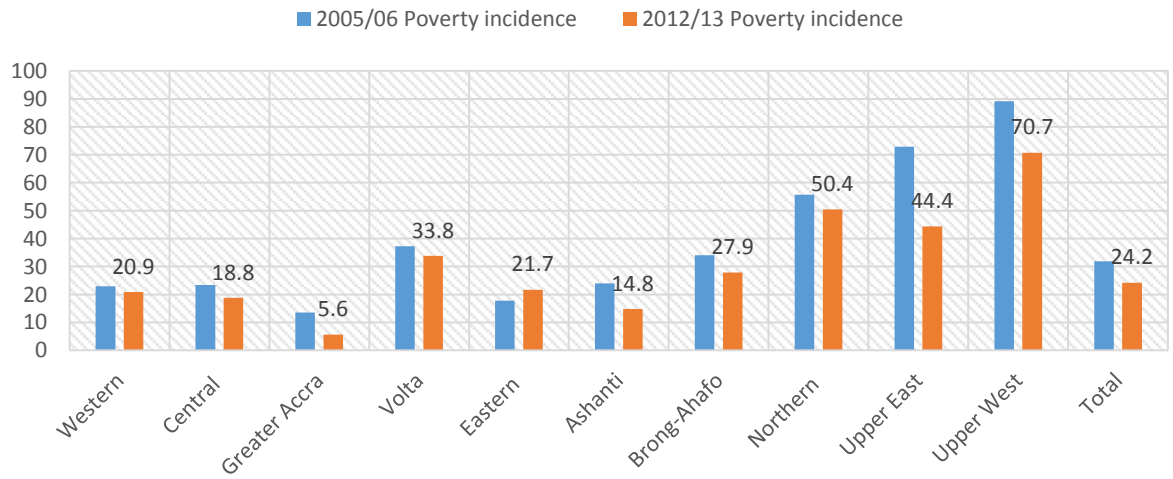
The analysis of the impact of mango adoption on poverty

A case study from Ghana

Introduction

Among western African countries Ghana has been one of the fastest growing economies in the recent decades. The share of population under the poverty line has decreased considerably in less than two decades, from above 50% in 1991/1992 to about 32% in 2005/06 and 24% in 2012 (World Bank Data, 2015). The Human Development Index ranked Ghana 135th out of 187 countries in 2013, showing a constant improvement in other measures of well-being, such as life expectancy, literacy and education (UNDP, Human Development Report, 2013). Although an overall reduction of poverty, estimated as the equivalent for a minimum food basket providing 2,900 calories per adult equivalent per day, has been observed, regional differences are found across the country, with northern regions being poorer than southern and central regions (Figure 1).

Figure 1 Poverty Incidence (%)



Source 3 GLSS 6, Poverty report (2015)[81]

[81] The report estimated the poverty profile using data from GLSS 5 and GLSS 6 on household food and non-food expenditures, adjusted for regional differences in cost of living. GLSS official poverty line (GhC 1,314) is estimated as the equivalent of a minimum food basket providing 2,900 calories per adult equivalent per day. As there are many

The lack of infrastructure, missing or poorly-functioning markets, inadequate skills development, financial services and technical assistance are only some of the major constraints in these regions. As a consequence, farmers tend to experience substantial difficulties in accessing assets and credit that would facilitate a shift from subsistence to a more commercialised agriculture, and higher living standards (Coulombe and Wodon, 2007).

The adoption of cash crops, both traditional and non-traditional, has been always welcomed by the international community as a gateway for providing premium prices and, hence, better livelihood opportunities to farmers in developing countries. The exotic varieties of mango are an innovation in the Ghanaian context as described in Chapter 3. The adoption of these varieties has been widely advocated in the past decade by development agencies and national government as one of the biggest and potentially very effective agricultural development in addressing small farmers' poverty. Its potential in reducing poverty derives from the possibility for farmers to access premium prices that international markets can offer.

Nonetheless, its real impact on farmers' poverty remains unclear. Access to premium prices for exotic varieties of mango requires the production of high quality fruits which is sometimes challenging for poorly endowed farmers. Some of the main challenges in delivering high quality mangoes are occurrence of pests and diseases, lack of appropriate knowledge on pre- and post-harvest management techniques, uncertainty on quality requirements as well as lack of structured marketing information systems. As a consequence, poorer, less skilled, and less commercialised farmers might be excluded from the expected gains.

In the light of the difficulties that mango production poses for farmers, my analysis aims to evaluate the impact that adoption of exotic varieties of mango had on poverty in rural Ghana. I will answer this question with primary data collected in Ghana between July 2012 and September 2012, as described in Chapter 2.

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ways of specifying the poverty lines the full report provides the full distribution of consumption around this poverty line.

The rest of the paper is organised as follows: Section 1 describes the conceptual framework and empirical evidence of the impact of innovation adoption on poverty; Section 2 describes the measures of poverty used in this paper and presents selected farmers' characteristics according to their poverty status; Section 3 discusses the evaluation problem and the preferred empirical strategy; Section 4 presents and discusses the results of the impact of adoption of mango on both objective and subjective measures of poverty. This section also describes the results of the impact analysis on different subsets of mango farmers (late or early adopters vis-à-vis non-adopters) and it provides insights on differences between mango and non-mango farmers that help to understand the results. Finally, Section 5 concludes.

Section 1. Conceptual framework and empirical evidence

Adoption of innovation is often motivated by the desire to generate a positive improvement in the adopter's economic status and it is generally supported by national and international agencies in the context of poverty reduction. The effect of the adoption of product innovations[82], and specifically high-value crops, on poverty has received wide attention in the literature (e.g. von Braun and Immink, 1994; McCulloch and Ota, 2002; Mendola, 2007). The relationship between adoption and poverty is generally expressed as:

$$Y_i = f(X_i, D_i, \varepsilon_i) \quad (1)$$

$$D_i = f(x_i, \eta_i); \;\; D = 1,0 \quad (2)$$

Where Y_i refers to the measure of poverty of the household *i* and D_i represents the discrete innovation adoption decision that takes the value of 1 if the household *i* decides to adopt and 0 otherwise. The poverty status of the household *i* in (1) is function of a set of observable characteristics (X_i) and a set of unobservable characteristics (ε_i). The adoption of the innovation is driven by a sub-set of observable household's characteristics (x_i) and unobservables expressed in η_i.

Since the seminal work by von Braun et al. (1989), several studies have investigated the impact of adoption D_i on poverty and well-being outcomes Y_i and have found that adoption of innovations, both product and process, does, indeed, have a positive effect on the adopter's income and poverty compared to non-adopters (e.g. von Braun and Immink, 1994; McCulloch and Ota, 2002; Berdegué et al., 2006; Mendola, 2007; Schipmann and Qaim, 2010).

The main direction of causality between adoption and poverty outcomes often materializes through what Minot and Roy (2007) call the direct "farm linkage" between adoption and poverty. The farm linkage describes the effect that the production of high-

[82] Innovations can be of two types: process innovation and product innovation. In the context of agricultural systems, process innovation refers to the adoption of improved varieties, tools or production systems that are deemed to improve the efficiency and the productivity of the current cultivations. On the other hand, product innovation describes the adoption of crops, tools and machineries as well as systems that are completely new to the adopter and are seen as potential substitutes of the old equivalents. The decision to adopt a new product, for example, a new crop, is explained by classical model of adoption as driven by the expectation of higher profits from the cultivation of one crop instead of the other (see Chapter 3). Generally, the literature defines these crops as "high-value crops", whose higher value is generated by the access to premium prices offered by the international market. This is, for example, the case for tropical fruit and vegetables and, in the case of this analysis, exotic varieties of mango in Ghana.

value crops may generate on farmers' income, directly. According to the general conceptual framework set up by Minot and Roy (2007), the overall observed increase in demand for the product innovation would increase producers' income via access to higher prices, in the short run, and, as such, decrease poverty in the long run. However, Minot and Roy (2007) also recognize that the poverty effects will only materialize if poor farmers are involved in the production, in the short run, and if the production itself is labour intensive, in the long run. Thus, under the assumption that adopters are relatively poorer, smaller and more labour abundant than other farmers, Minot and Roy (2007) framework predicts that the adoption of high-value crops should foster poverty reduction effects[83].

The empirical evidence supports this argument. For example, von Braun and Immink (1994) in their study of the effect of the adoption of snow peas in Guatemala, argue that, indeed, the effect of the adoption on farm's income is quite noticeable. They observe a 38% higher increase in adopters' income during the time of their survey (1983-85) compared to non-adopters. Similarly, in their study of the adoption of export horticulture crops by small farmers in Kenya, McCulloch and Ota (2002) find that adopters had four times as much income per adult equivalent than non-adopters. Although the evidence supports the adoption-income positive linkage, whether higher income translates into poverty reduction is often not explicitly investigated. In addition, these studies usually aim to capture associations between adoption and farmers' income, without addressing the issue of causality between the two. One of the more recent studies that aims to capture a causal effect of adoption on poverty is the one by Mendola (2007)[84]. She directly models the poverty impact of adoption of high yielding varieties of rice in rural Bangladesh using a propensity score matching methodology. Through this impact evaluation approach, she finds a strong and positive causal relationship between adoption and household's well-being as well as a negative consistent relationship between adoption and the probability to be poor for small and medium farmers.

[83] Poorer farmers are deemed to be generally small farmers and labour abundant and as such considered to be more effective in the management of labour intensive cultivations (Lipton, 2006; Murphy, 2012) than larger farmers, due to the relaxation of the common agency problems.

[84] Similarly, causality is addressed by Carletto et al (2011) who use instead a Diff-in-Diff methodology on a long panel dataset started by von Braun and Immink in early 90s.

In addition to the *direct* poverty effect of adoption, Minot and Roy (2007) also describe three other linkages that are claimed to capture indirect poverty effects: backward, employment and consumer price linkages. The backward linkage refers to the effect that the adoption has on the activities that support agricultural production.[85] Labour inputs might also be affected by the adoption of non-traditional cash crops, as this type of crops might require higher labour intensity than staple crops. The higher labour intensity could translate in more intense use of family labour and new opportunities for hired labour, which, in turn, could increase wages[86]. Higher wage and employment opportunities generated by both backward and employment linkages could, then, generate additional income flows and, as such, produce a poverty reduction effect[87]. Finally, the substitution of staple crops production with high-value crops cultivation could increase the price of the former via increase demand and reduced supply in the local market (Little, 1994). Higher food prices, then, would negatively affect net food buyers and, overall, generate an increase of poverty. However, the empirical evidence does not unequivocally suggest that this effect occurs in the context of developing countries (Minot and Baulch, 2003)[88].

In conclusion, adoption of non-traditional cash crops, especially if they can be considered product innovations, might have a poverty reducing effect, via increased farm income and increases employment and wage opportunities.

The next section describes the approach I aim to use for the investigation of the impact that the adoption of exotic varieties of mango had on a sample of 305 adopters and non-adopters in Ghana.

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[85] This is the case, for example, of input provision. The adoption of non-traditional cash crops increases the demand for non-traditional inputs, such as fertilizers and pesticides, which could generate new business opportunities and higher income flow for existing suppliers. The additional cash flow generated could improve the general economic status of input suppliers, which can increase local employment opportunities. The empirical evidence supports the existence of backward linkages between adoption and poverty (e.g. Kimenye, 2002; Ali and Abedullah, 2002).

[86] Moreover, if the main destination of sales of non-traditional cash crops is the international market there is scope for locals to establish business partnership with export companies for both processing and shipping activities, which could spur self and wage employment in both farm and non-farm sectors.

[87] However, as in the case of the farm linkage described above, the poverty impacts could vary considerably, depending on the type of crop adopted as well as on the degree of involvement of poor farmers in different sectors, (production, processing, input provision or wage employment) (Minot et al., 2007).

[88] For example, Minot and Baulch (2003), in their study on adoption of coffee, fruits and vegetable in Vietnam, find that the substitution effect for the cultivation of staple crops, such as rice, did not produce negative outcomes as far as food accessibility is concerned. Instead, the product innovation was accompanied by the increase in food cropping intensity and productivity, which counteracted the reduction of land availability for staple crops.

Section 2. Analysis of the impact of innovation adoption on poverty

The data used in this analysis come from the fieldwork carried out in 2012. As discussed in Chapter 2, the field survey did not contain a detailed consumption or income module and, instead, focused on assets and a set of subjective well-being questions to identify poor households[89]. The poverty measures used in this paper are in line with the consideration of providing the best measures of welfare and well-being possible under tight budget and time constraints of small surveys. The following paragraphs describe the construction and the characteristics of both objective and subjective measures of poverty.

2.1 The objective measure of poverty: the wealth index

The wealth index was estimated using principal component analysis (PCA). Following the methodology set out by Filmer and Pritchett (2001) and McKenzie (2003) the choice of wealth components included the following assets: farm size, drinking water, private toilet, ownership of a tractor, ownership of a motorcycle, ownership of a car and ownership of a generator[90]. The main results of the construction of the wealth index using PCA are summarised in Table 1 below.

Table 1 Results of the PCA

Principal components analysis				
Variable (standardised)	Comp1	Standard deviation	Impact factor (Score comp1/SD)	Unexplained
Farm size (acres)	0.3801	14.99	0.0254	0.5823
Drinking water (0/1)	0.4385	0.401	1.0945	0.4443
Private toilet (0/1)	0.3970	0.474	0.8381	0.5445
Tractor (0/1)	0.1584	0.139	**1.1388**	0.9275
Motorcycle (0/1)	0.2534	0.442	0.5728	0.8144
Car (0/1)	0.3913	0.319	**1.2257**	0.5573
Fridge (0/1)	0.4254	0.437	0.9735	0.4769
Generator (0/1)	0.2868	0.170	**1.6920**	0.7622
Cumulative variance explained by 1st component= **0.3613**				
Kmo measure of sampling adequacy =0.7683				

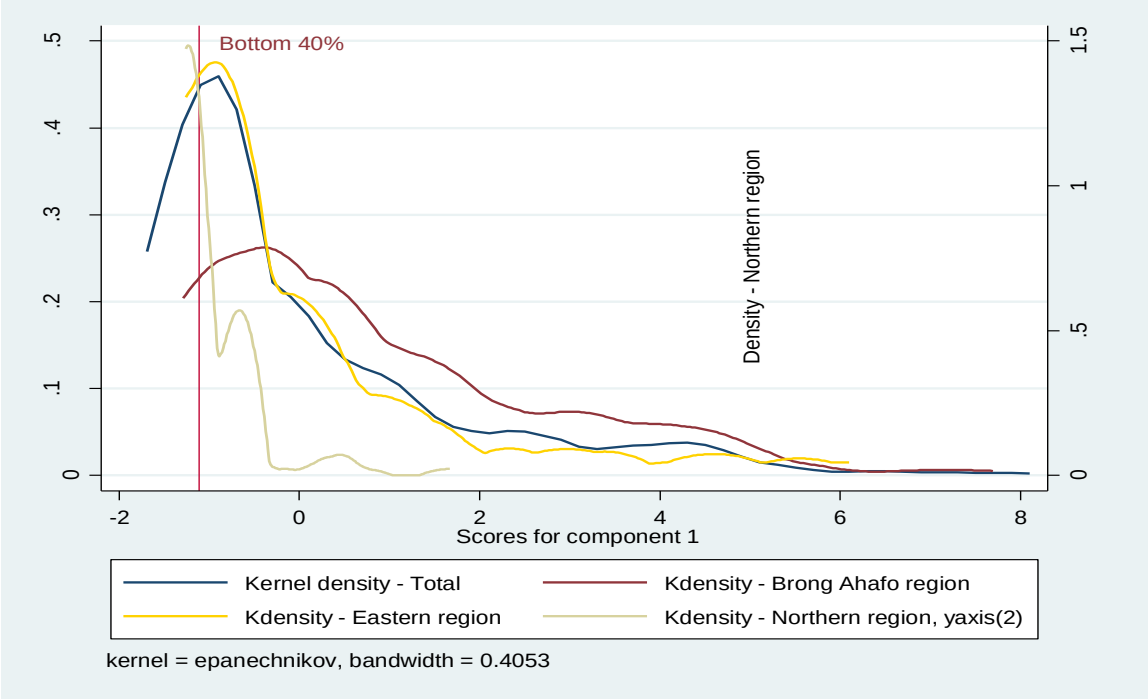
[89] A brief review of the different poverty measures can be found in Appendix 4.1.

[90] In Appendix 4.2 describe in detail the main results and the methodology followed in the estimation of the wealth index. The assets listed above were selected because they provided the highest cumulative variance explained by the first component (36%) and the highest KMO measure of sampling adequacy (0.76).

The results of the PCA show that all the assets included in the estimation have a positive score or weight in the identification of the social-economic status of the households in the sample. The highest impact factors (column 4, Table 1), calculated as the ratio the standard deviation to the score of the first component, are attributed to the ownership of a generator, a car or a tractor, while the lowest is calculated for farm size. The interpretation of the score is quite straightforward. For example, a household that owns a generator has an asset index which is higher by 1.69 points than a household that does not own it. Similarly, owning a car increases the asset index by 1.123 points. These weights are generally in line with expectations and previous findings in Ghana (e.g. Booysen et al., 2008).

Figure 2 reports the distribution of the wealth index across the sample. The majority of the farmers are located in the left hand side of the distribution (blue line), which suggests that a high proportion of farmers in the sample has a low level of wealth, under the assumption that the selected components included in the index are good predictors of wealth itself. At regional level, farmers located in the Brong-Ahafo region are observed to be better off that the rest of the sample (red line) while farmers in the Northern regions are the worse off.

Figure 2 Distribution of the wealth index, total and by regions



Using the index of wealth, I then construct the measure of poverty based on the imposition of an arbitrary threshold. The definition of poverty threshold based on the wealth index has not been unequivocal in the literature, where different procedures have been suggested (Vyas and Kumaranayake, 2006). Nonetheless, for this analysis I follow Filmer and Prichett (2001) approach, which defines poor households as those households at the bottom 40% of the distribution of the wealth index and rich households as those located at the top 20% of the distribution[91].

According to this definition, 42% (127) of the households in the sample can be defined as "poorly endowed" or poor, while 21% (64 households) are "well-endowed", or non-poor, and the remaining 114 households have intermediate socio-economic status and they are included in the empirical analysis in the group of "non-poor households", for a total of 178 non-poor households.

2.2 The subjective measures of poverty

Following the literature on subjective well-being (Stevenson and Wolfers, 2008; Ravallion and Loshkin, 2010; Ravallion, 2012), I collected data on the four subjective poverty measures: "Economic Ladder", the "Minimum Income", the "Income Evaluation" and "Consumption Adequacy". These measures of subjective poverty will be used for two main purposes: testing the validity of the poverty measure using the asset index and to calibrate the objective poverty analysis. The main measurement of poverty is based on the Economic Ladder question, while the other subjective measures of well-being (minimum income, income evaluation and consumption adequacy) for explaining empirical results and for testing internal coherence of the subjective poverty line (in Appendix 4.4).

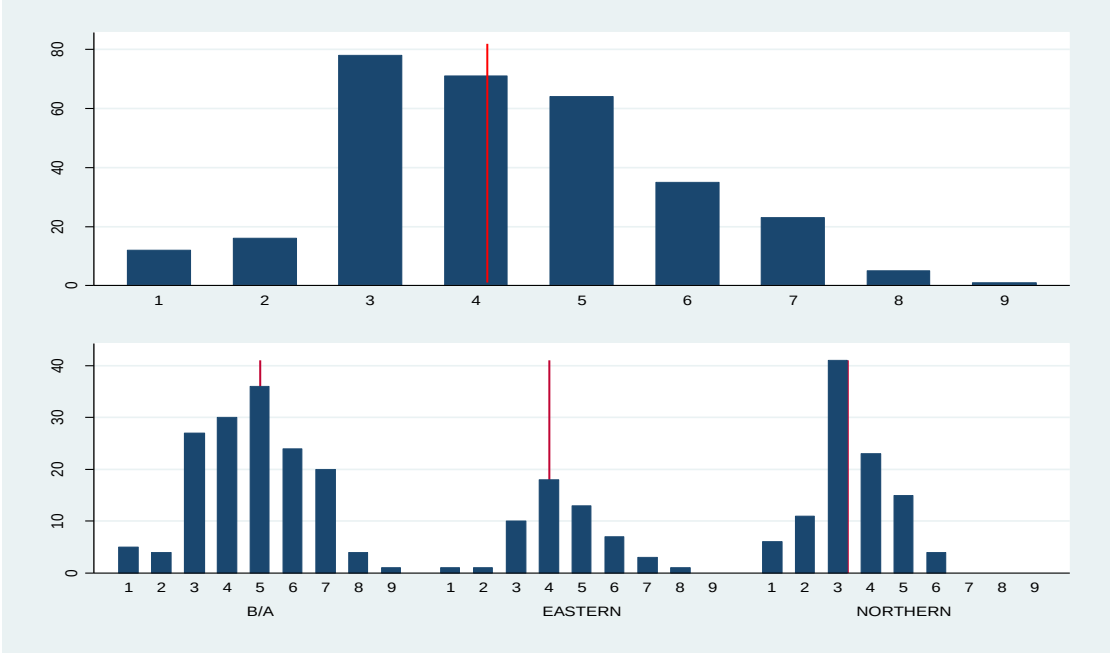
[91] An alternative to this definition would be to identify a poverty line following the rule suggest by Rawls in 1971, whereby the poverty line is set at the ½ the median of the index. However, the 40% threshold is appropriate in the context of this analysis because, as shown in Appendix 4.5, the distribution of wealth is pretty similar before this threshold while it jumps right after the threshold to reach the highest wealth level for about 20% of the sample. Nonetheless, to check the sensitivity of the poverty rates to the choice of the wealth index threshold I re-estimated the number of poor and non-poor households by region and districts using two additional thresholds: bottom 30% and 50%.Appendix 4.3 shows the number of households that are poor and non-poor under the three different thresholds, 30%, 40% and 50%. Generally, the choice of a higher or lower threshold tend not affect the poverty ranking across regions and districts, with the Northern regions being the poorest and the Brong-Ahafo the wealthier. It is the severity of the poverty within each region that seems to be slightly more sensitive to the choice of the threshold. For example, in the Northern region, the choice of a lower cut off would reduce the group of poor households by 25% (17 households out of 68 households) while the choice of a higher thresholds will increase it by 34% (23 households out of 68 households).

The "Economic Ladder" question was formulated as follows: *"Please imagine a 9-step ladder where on the bottom, the first step, stand the poorest people, and on the highest step, the ninth, stand the rich. On which step are you TODAY and 12 MONTHS AGO?"*.

Figure 3 shows that the majority of the households report that they are amongst the poorest fraction of the population in their villages (step 3 and 4). The regional analysis shows that households are relatively poorer in the Northern region which is consistent with the regional distribution of objective poverty, observed in Figure 2.

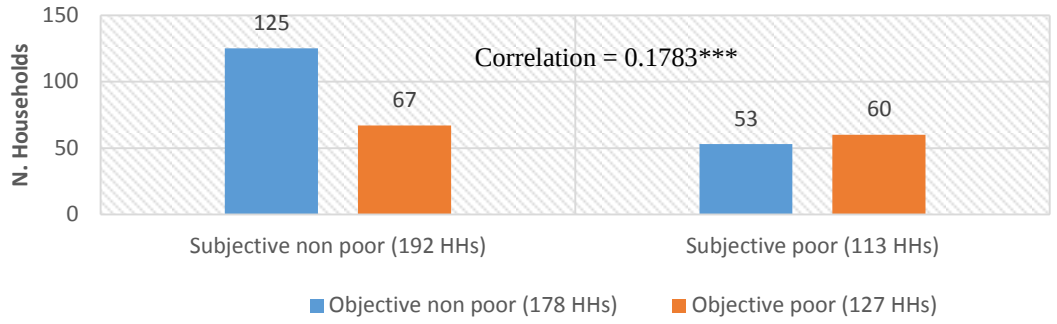
However, the nature of the economic ladder question is merely local and context specific as it specifically asks the farmer to relate him or herself to other people. Assuming that such a comparison is more likely to happen with people located close by, I define "poor" those households who placed themselves on a lower step than the *median value* of the economic ladder measured at district level. This definition also follows the "relative deprivation" argument according to which poverty is mostly a relative/contextual concept (Ravallion and Loshkin, 2010). Using this definition of subjective poverty, 113 households can be defined as subjective poor in the total sample and 192 can be defined as subjectively non-poor.

Figure 3 Economic Ladder, total and by region



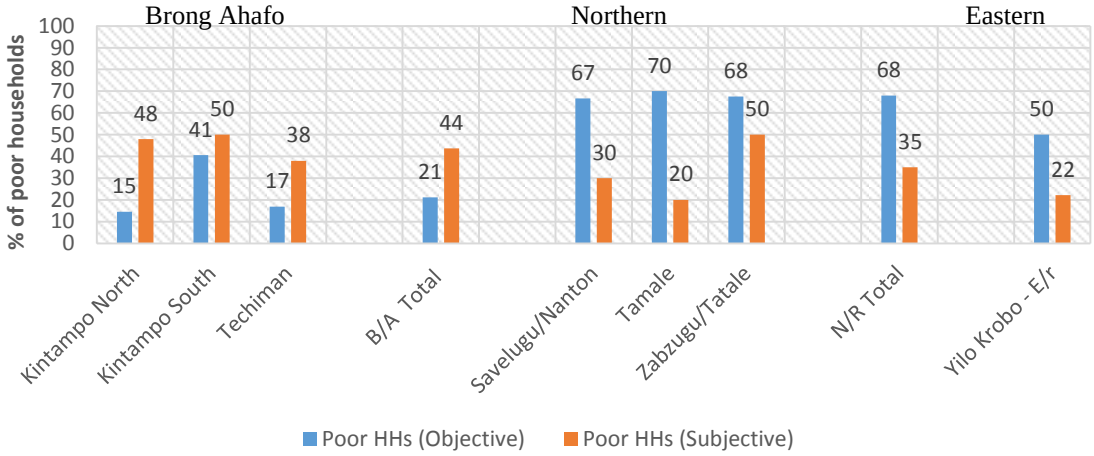
The comparison between subjective and objective measures of poverty shows that there is a positive correlation between these two measures (Figure 4)[92]. Overall, 60 farmers are "consistently poor", defined as poor for both the objective and subjective measure of poverty, while 125 farmers are "consistently non-poor", as they fall in the non-poor category regardless of the type of poverty measure used. Nonetheless, for 120 farmers the poverty status changes when a different measure is used: 67 farmers, defined subjective non-poor are instead poor according to the objective poverty definition, while 53 farmers, subjectively poor, fall in the category of objectively non-poor .

Figure 4 Objective and Subjective poverty, compared



When looking at poverty rates at regional and district levels, the use of different poverty measures provides insights on how poverty is perceived (subjectively) and experienced (objectively) at regional level (Figure 5).

Figure 5 Objective and Subjective poverty, by region



[92] A positive correlation between objective and subjective measures of well-being persists and it holds for any measure of subjective poverty used (Appendix 4.5).

Although farmers located in the Northern region are generally the poorest using the wealth index criterion, subjective poverty rates are the lowest in one of the Northern region's districts (Tamale) when compared to all the other regions and districts in the sample, followed by farmers in the Eastern region. Hence, Brong Ahafo farmers, the richest according to the objective measure of poverty, are, instead, the poorest when a subjective measure of poverty is used. In fact, households in the Northern region *feel* much richer than what they actually are, according to the wealth index, and relative to the other regions in the sample[93].

2.3 Are mango farmers better off than non-mango farmers?

Mango farmers in the sample tend to be better off than non-mango farmers, regardless of the measure of poverty used (Figure 6).

Figure 6 Poverty status, by mango adoption

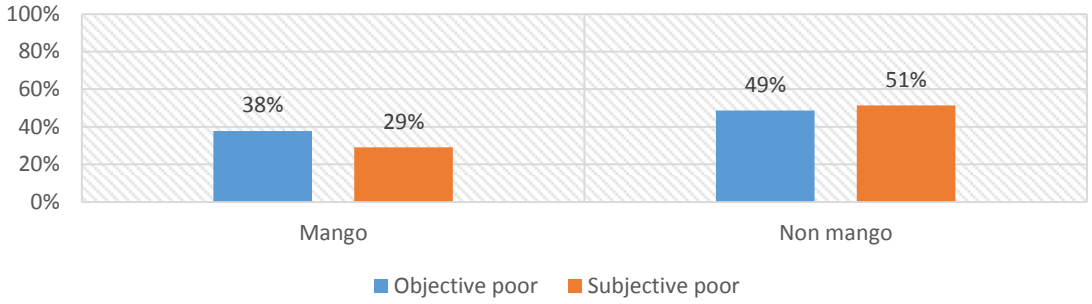


Table 2 reports summary statistics by adoption and poverty status. Considering the similarities of the results when using objective or subjective measures of poverty, I only report in this section the results of the analysis of the objective poverty[94].

Overall, the lower poverty status of mango farmers does not seem related to specific characteristics. Hence, mango and non-mango farmers tend to be quite similar in terms

[93] The differences between objective and subjective poverty rates have been explained in the past literature simply as a consequence of the "relative deprivation" concept of poverty, whereby the personal socio-economic status is mainly determined in relation to the well-being of neighbours or friends. It is worth specifying that the relative concept of poverty is however not a prerogative of the subjective measures. It could be used only with more objective measures of wealth. In the context of this study, however, only subjective measures are used in a relative perspective. Furthermore, Ravallion (2013) argues that inconsistency between subjective and objective poverty rates may be caused by the so called "latent heterogeneity of scales". According to this idea, farmers may not be aware of the different living standards existing in other regions and they interpret the scale using different definitions of poverty and welfare. The latent heterogeneity in scales could induce the "frame of reference bias" but it poses non negligible methodological problems if an econometrical model is estimated using the subjective measure of poverty. However, this is not the case of this paper, as I am going to use this subjective measure of poverty for providing support and calibrating the poverty analysis based on the wealth index.

[94] Appendix 4.6 shows some summary statistics by poverty status across the entire sample. The additional summary statistics for subjective measures of poverty according to the adoption status can be found in Appendix 4.7.

of household, farm and livelihood characteristics. However, while characteristics of poor farmers do not differ much according to their adoption status, a higher degree of discrepancies between mango and non-mango farmers can be observed within the group of *non-poor* households.

More specifically, *non-poor* mango farmers are generally older, better educated, less impatient and better endowed with household, farm and transport assets than *non-poor* non-mango farmers, including farm size and land ownership. They also hire more labour than non-mango farmers, they received more training and more visits by local extension officers and they are more often members of farmers' organisations.

Poor mango farmers are generally similar to poor non-mango farmers in terms of asset endowment. Nonetheless compared to non-mango farmers, they tend to live in bigger households, where more people are married, have awarded higher education and are engaged in non-farm employment. Moreover, the number of livestock they own is on average higher than non-mango farmers and they own more often transport assets, such as bicycles. As for non-poor households, mango farmers received more training, participate more often in farmers' organisation and received more visits by local extension officers compared to non-mango farmers.

In conclusion, this exploratory data screening suggest that the adoption of product innovation does not necessarily lead to a higher economic status contrary to what predicted by previous studies as a number of mango farmers are also poor. At the same time, this simple explanatory analysis might also indicated that mango adoption occurs mostly amongst better off and better equipped farmers, which could explain the systematic differences among non-poor farmers[95]. In order to control for these differences between mango and non-mango farmers across the entire sample, the following paragraphs describe the approach I use for the analysis of the impact of adoption on well-being via matching techniques.

[95] This could be explained by the high initial investment and the high quality requirement necessary for the establishment of the mango trees that could put off the poorest farmers. On the other hand, these results could also suggest that poor mango farmers have yet to benefit from their adoption and as a consequence the differences in terms of their characteristics cannot be observed yet.

Table 2 Selected summary statistics, by mango adoption

		Objective non poor			Objective poor		
		Non mango Mean	Mango Mean	p-value	Non mango Mean	Mango Mean	p-value
Male head	(0/1)	0.88	0.94	0.121	0.83	0.92	0.129
Age head	Years	46.38	51.56	0.009***	47.19	48.18	0.669
Primary education head	(0/1)	0.13	0.07	0.270	0.06	0.04	0.677
Higher education head	(0/1)	0.34	0.60	0.062*	0.27	0.49	0.060*
No risk aversion	(0/1)	0.20	0.15	0.415	0.06	0.05	0.951
Impatience	(0/1)	0.54	0.40	0.096*	0.55	0.46	0.334
HH size	#	5.84	6.24	0.290	5.25	5.92	0.091*
Dependency ratio	(%)	80.40	71.91	0.517	76.17	70.62	0.615
N. Married	#	2.00	2.20	0.176	1.68	2.28	0.002***
N. Male adults	#	1.86	2.11	0.227	1.77	2.00	0.273
N. HH members with higher education	(%)	6.86	11.90	0.054*	3.21	6.84	0.053*
N. HH members with non-farm employment	(%)	12.74	14.61	0.452	9.94	16.01	0.037**
Fridge	(0/1)	0.27	0.52	0.002***	0.00	0.00	.
Radio	(0/1)	0.91	0.94	0.433	0.89	0.85	0.567
TV	(0/1)	0.52	0.73	0.005***	0.15	0.27	0.111
Mobile	(0/1)	0.80	0.93	0.016**	0.72	0.80	0.297
Sewing machine	(0/1)	0.14	0.30	0.029**	0.08	0.04	0.399
Drinking water	(0/1)	0.13	0.44	0.000***	0.00	0.00	.
Bicycle	(0/1)	0.59	0.64	0.525	0.66	0.80	0.084*
Car	(0/1)	10.71	23.77	0.042**	0.00	0.00	.
Farm size	(acres)	4.51	13.95	0.002***	3.42	3.43	0.971
Farm size[1]	(acres)	4.51	12.40	0.007***	3.42	2.93	0.114
Land ownership	(0/1)	0.50	0.76	0.000***	0.53	0.50	0.755
N. Livestock	#	24.23	26.83	0.683	13.36	20.68	0.049**
Hired	#	6.36	13.43	0.002***	4.62	6.15	0.293
Tractor	(0/1)	0.04	0.03	0.921	0.00	0.00	.
Cash crops production	(0/1)	0.30	0.37	0.399	0.13	0.12	0.862
Training	(0/1)	0.32	0.80	0.000***	0.19	0.76	0.000***
FO	(0/1)	0.18	0.61	0.000***	0.11	0.65	0.000***
N. visits extension off.	#	1.34	3.71	0.013**	1.02	4.49	0.025**
Innovation	#	0.36	0.24	0.271	0.38	0.20	0.151
N							

[1]At the time of adoption for mango farmers; current for non-mango farmers

Section 3. The evaluation problem and the empirical strategy

The literature described above suggests that adopting a product innovation does, indeed, generate positive outcomes in terms of increase income, employment opportunities and also poverty. However, the descriptive statistics related to the sample of mango and non-mango farmers used in this analysis suggests that adoption might not necessarily lead to higher well-being. The following paragraphs describe the challenges and solution adopted for the evaluation of the impact that adoption of mango had on objective and subjective poverty in my sample.

The main challenge in the empirical analysis of the adoption poverty impact is reverse causality between adoption and poverty, whereby poverty can affect adoption and adoption can affect poverty. The latter is the aim of the evaluation question and can be expressed as in (1). The reverse effect that poverty has on the adoption occurs because the vector of observable characteristics x_i also includes the poverty status Y of the household *i*:

$$x_i \in Y_i$$

In the presence of reverse causality, the evaluation framework requires the identification of a counterfactual for comparison of poverty outcomes. The ideal counterfactual for a rigorous impact evaluation would require observing the same household both in adoption and non-adoption status (Rosembaum and Rubin, 1983). In other words, the impact of the adoption would be estimated as the difference between the case when the household decides to adopt and the case had it not adopted, the so called average treatment effect on the treated (ATET) expressed as:

$$ATET = E(Y_i^1 - Y_i^0 | D_i = 1) = E(Y_i^1 \mid D_i = 1) - E(Y_i^0 \mid D_i = 1) \qquad (3)$$

where Y_i^1 is the poverty status of the household *i* in the case of adoption, D_i=1, and Y_i^0 is the poverty status of the household *i* had it not adopted, $D_i = 0$. In reality, this scenario does not materialize as we observe household *i* in either one or the other adoption status (treatment or control group, in the impact evaluation jargon). As a consequence, the problem of finding a comparison household that could approximate the ideal counterfactual arises.

In comparing different households, two main issues need to be taken into account: 1) systematic differences between adopters and non-adopters, which lead to selection biases; and, 2) heterogeneity in the group of non-adopters.

In the context of experimental analysis, using data collected via randomised control trials, these issues can be rightly considered negligible. The innovation adoption and non-adoption is, indeed, followed from the start and spill-overs between adopters and non-adopters are kept under control until the end of the intervention under scrutiny. However, impact evaluations of this type are generally quite costly both money and time wise[96].

Non-experimental impact evaluations rely on specific assumptions and parametric methods to identify unbiased counterfactual within the heterogeneous group of non-adopters based on selected unobservables, as in the case of instrumental variables and selection models a-la Heckman, or simply controlling for as many as possible observable characteristics, as, for example, in the case of propensity score matching techniques (PSM).

The main idea of the matching estimators is to identify observations who are very similar based on specific characteristics and evaluate, on them, the average impact as the difference between the effect on the treated and what would had been the effect on the treated had they not adopted. Similarly to other econometrical methods mentioned above, the first stage of the matching procedure is the estimation of the selection model. The results of this estimation are then used for the calculation of the propensity scores, according to which observations are matched.

In this paper, I chose to use propensity score models for the impact evaluation analysis. Matching methods have, indeed, some advantages with respect to standard regression methods that try to control for selection bias, such as instrumental variables and Heckman models. The main advantage lies on the higher flexibility in the functional form. Hence, matching models do not require assumption on the functional form of the equation to estimate, whereas usual regression methods impose often a linear form of the relationship which may or may not be accurate (Angrist and Pischke, 2009).

[96] Also, quite often, even experimental evaluations are forced to use non- experimental techniques to address unexpected implementation issues that jeopardised the random nature of the innovation adoption as well as the containment of spillovers between groups.

Secondly, with matching, the assumption of constant additive treatment effects across individuals, which is required in simple regression, Heckman and bivariate normal selection estimation procedures, can be relaxed (Mendola, 2007). Hence, heterogeneous treatment effects are permitted, and can be retrieved via sub-group analysis. This involves selecting the sub-group of interest and re-matching within that group and it makes PSM a flexible tool for studying programme effects on groups of particular interest (Bryson et al., 2002; Mendola, 2007). Finally, matching avoid the anguish of looking for valid instruments, which often proves a quite questionable solution.

Notwithstanding the advantages in using matching techniques, these methods are not free of limitations themselves. Matching only on specific characteristics does not allow controlling for unobservables that might drive technology adoption and poverty, which are, instead, controlled for by IV and Heckman models. Moreover, as only observable characteristics are controlled for in the matching models, the actual selection of these characteristics, i.e. matching criteria, requires specific accuracy.

Although the seminal and extensive work by Barbara Sianesi (e.g. Sianesi, 2004) and the paper by Caliendo and Kopeinig (2008) provide useful guidance for the definition of the selection model, only few practical established rules exist (Kassie et al., 2011; Caliendo and Kopeinig, 2008; Rosembaum, 2002). Table 3 summarises some of the desirable and essential criteria used in the past literature for the choice of the matching observables.

Table 3 Rules for Selection of matching variables

Desirable	Essential
1. The economic theory should guide the choice of the covariates 2. Only variables that affect simultaneously the participation and outcome should be included 3. Only variables that are statistically significant at conventional level should be retained in the model	4. As many variables as possible should be included to reduce the unobservable heterogeneity bias (CIA condition) 5. The matching variables should guarantee enough overlap of the observations in the sample (Balance and Common support conditions) 6. Exogeneity: Time-invariant variables should be included 7. Exogeneity: only variables calculated prior to the participation/adoption should be included

According to these rules, the first desirable source of matching criteria should be drawn from the economic theory on the determinants of the treatment investigated, which is in

this case the adoption of innovation. Nonetheless, in order for these observable characteristics identified by the economic theory to be valid in the choice of a valid counterfactual, three essential conditions need to be satisfied: 1) Conditional Independence Assumption, 2) balance and 3) common support.

According to the Conditional Independence Assumption (CIA, Lechner, 2000) or the ignorable treatment assignment assumption (Rosenbaum and Rubin, 1983), for a given set of covariates, participation in a program (or adoption in my case) must be independent of potential outcomes, such that there may be systematic differences between treated and non-treated even after controlling for observables that can be attributed to the treatment effect on the outcome (Smith and Todd, 2005). Following Sianesi (2004) and the literature cited therein, the CIA can be defined as:

$$Y_i^0 \perp D_i | \, X_i = x_i \tag{4}$$

where X_i are the covariates used in the selection model for the calculation of the propensity scores. If the CIA condition holds, the required counterfactual can be identified as follows:

$$E(Y_i^0 | D_i = 1) = E_{X_i|D_i=1}[E(Y_i^0 | X_i, D_i = 1)] \tag{5}$$

$$= E_{X_i|D_i=1}[E(Y_i^0 | X_i, D_i = 0)]$$

$$E_{X_i|D_i=1}[E(Y_i | X_i, D_i = 0)]$$

where the observed outcomes of the counterfactual $D_i = 0$ are averaged with respect to the distribution of the covariates X_i in the treatment group $D_i = 1$. This condition requires that conditional on the choice of X_i, there would be no unobserved heterogeneity left that affects both the outcome and the selection in the adoption process. In other words, it requires the chosen set of covariates to be as broad as possible (criterion 4, in Table 3). In order for this assumption to hold an extensive knowledge of the factors that affects the adoption process as well as outcome of the analysis is required.

Equation (5) links the CIA to the other two conditions necessary for the matching procedure: balance and common support. The balance condition requires that $P(D_i) = 1|X_i < 1$ over the set of X_i covariates. This condition assures that every observation in

the treatment group have a counterpart in the control group based on the chosen covariates. This should, in turn, guarantee the estimation of a propensity score that statistically balance the covariates between treated and control subpopulations and provides enough overlap for the matching procedure to be applicable (the common support and balance conditions) (Rubin and Thomas, 1992b).

After choosing the favourite specifications of the selection model that satisfies the essential conditions of the matching procedure, it is crucial to verify that the matching actually works correctly. The verification of the quality of the matching between treated and control group is usually done using the following criteria (Rosembaum and Rubin, 1983; Diprete and Gangl, 2004; Kassie et al., 2011; Caliendo and Kopeinig, 2008):

1. The difference in means of most of the covariates should be not significant after matching so that
2. The reduction of the standardised bias after matching should be substantial and in the region of 3-5%. The standardised bias is defined as follows:

$$SB(X) = 100\frac{\bar{X}_t - \bar{X}_{NT}}{\sqrt{\frac{V_T(X)+V_{NT}(X)}{2}}} \quad (6)$$

Where $\bar{X}_t - \bar{X}_{NT}$is the difference in sample means of the treatment and control groups and $V_T(X) + V_{NT}(X)$is the sum of the corresponding variances. The bias reduction is then calculated as:

$$BR = 100\ (1 - \frac{B(X)_{after}}{B(X)_{before}}) \quad (7)$$

3. The Pseudo-Rsquared should be lower after matching.
4. Similarly, the Likelihood Ratio Test should be lower and not significant after matching.

Once the internal validity of the matching is tested, then, different algorithms can be used for the estimation of the ATET, which include nearest neighbours, kernel and mahalanobis and their variants. The following section describes the implementation of matching techniques to my sample.

The empirical strategy in detail

Following the literature, I estimate the Average Treatment Effect on the Treated as in (3) of the adoption of mango. The objective of this analysis is to understand whether the

adoption of mango may or may not have had an effect on the farmers' poverty, using the data collected during the field work. More specifically, the analysis aims to estimate the average effect of the adoption of mango on mango farmers' poverty as specified in (3), where Y_i^1 is the observed poverty status for the mango farmers and Y_i^0 is the poverty status of the mango farmers had they not adopted mango. The analysis falls in the category of the non-experimental impact evaluation analysis.

The identification of the counterfactual

The identification of the counterfactual has been carried out using matching techniques. The match is estimated using observable characteristics of mango and non-mango farmers. Following the criteria set out above, I have first considered those observable characteristics that economic theory of innovation adoption described in Chapter 3 predicts as determinants of adoption: demographic, farm and household's characteristics as well as different types of social capital. A selection model based on the full set of adoption determinants satisfy most of the desirable criteria for the selection of the matching criteria (1 and 2) as well as some of the essential conditions because it includes a considerable number of dimensions affecting the adoption process which attempts to reduce the extent of the unobservable bias on the impact of adoption on poverty. However, this model fails to satisfy the balance and the common support conditions (Rubin and Thomas, 1992b). [97].

As a consequence, I chose to use a more parsimonious model specification for the matching estimations than what predicted by the economic theory. Sianesi (2004) argues that an in-depth knowledge of the institutional context under analysis could provide useful insights for the matching methodology. One of the advantages of being an active participant in the collection of the data is that I gained important insights of the differences between mango and non-mango farmers that could inform the selection of matching criteria. Using this information, the models in Table 4 proved to be the best for the identification of a valid counterfactual, as far as common support is concerned (Figure 7).

[97] Using the set of covariates of the model drawn from the economic theory does not provide enough overlap between observations in my sample (in Appendix 4.8). The ability to generate a good balance and common support is crucial for the validity of the evaluation analysis. In order to overcome the lack of common support, I tried, following the procedure suggested by Heckman et al (1998), to includes in the matching criteria only variables that are statistically significantly different between treatment and control group at conventional level. Notwithstanding several iterations and attempts to find the right matching model, this method also failed to provide a good common support.

Table 4 Selection models

M1	M2	M3	M4	M5
Primary education (0/1)	Primary education (0/1)	Primary education (0/1)	Primary education (0/1)	Primary education (0/1)
HH members in non- farm employment (%)	HH members in non-farm employment (%)	HH members in non-farm employment (%)	HH members in non-farm employment (%)	HH members in non-farm employment (%)
N. male adult (#)	N. male adult (#)	N. male adult (#)	N. male adult (#)	N. male adult (#)
N. Married (#)	N. Married (#)	N. Married (#)	N. Married (#)	N. Married (#)
Hired labour (0/1)	Hired labour (0/1)	Hired labour (0/1)	Hired labour (0/1)	Hired labour (0/1)
Age head (years)	Age head (years)	Age head (years)	Age head (years)	Age head (years)
Age head squared	Age head squared	Age head squared	Age head squared	Age head squared
Male head (0/1)	Male head (0/1)	Male head (0/1)	Male head (0/1)	Male head (0/1)
Impatience (0/1)	Impatience (0/1)	Impatience (0/1)	Impatience (0/1)	Impatience (0/1)
Cash crop production (0/1)	Cash crop production (0/1)	Cash crop production (0/1)	Cash crop production (0/1)	Cash crop production (0/1)
HH size	HH size	HH size	HH size	HH size
Training*	Training*	Training*	Training*	Training*
FO*	FO*	FO*	FO*	FO*
Extension office	Extension office	Extension office	Extension office	Extension office
	Innovations*	Innovations*	Innovations*	Innovations*
		No risk aversion (0/1)	No risk aversion (0/1)	No risk aversion (0/1)
			Farm size**	Farm size**
				Land ownership (0/1)
Common support: from 187 (M1) to 297 (M5)				

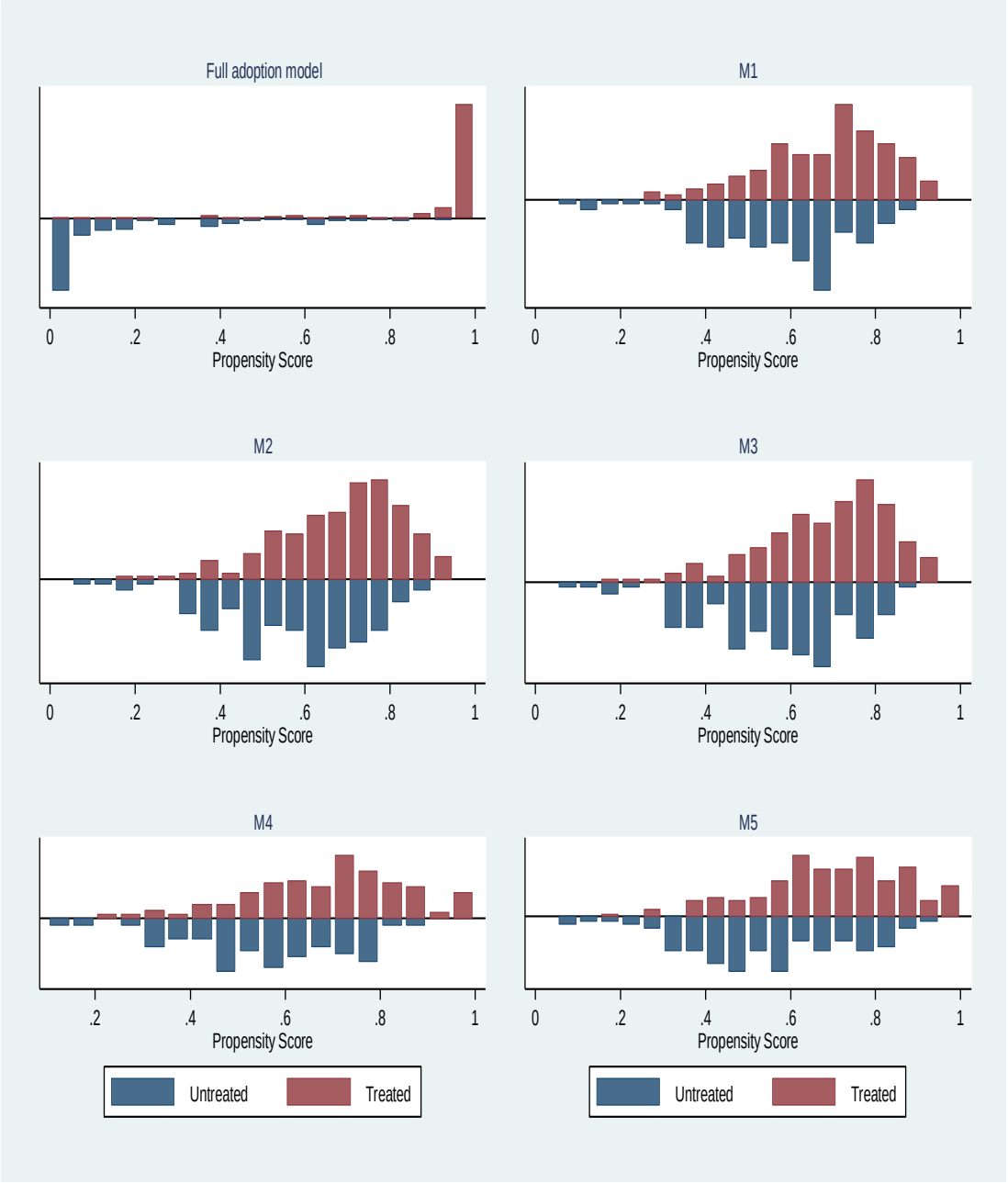
* Village level; ** At the time of adoption for adopters; current values for non-adopters

Aside from common support, these models also satisfy the other matching quality requirements and conditions described above. First of all, the standardised bias, which is caused by the lack of balance, i.e. differences in means of the matching criteria before and after the matching, reduces substantially after matching. Also, its size is often lower than the suggested threshold of 5%. Additionally, after matching Pseudo R-squared values are lower and Likelihood Ratio Test is most of the times insignificant, which support the validity of the selection models M1-M5.

These results together with the existence of a good common support suggest that the quality of the matching estimation could be considered satisfactory[98].

[98] The full list of results can be found in the Appendix 4.9.

Figure 7 Common support



Section 4. The average treatment effect on the treated

Following the methodology described in Section 3, I estimate the Average Treatment Effect on the Treated (ATET) of the mango adoption on poverty. This section presents and discusses the results of the ATET estimation. I carry out two separate analyses. The first uses the objective measure of poverty estimated using principal component analysis on a set of household's and farm's assets. The second uses the subjective measures of poverty, based on the Economic Ladder question, as described in Section 2. I use different algorithms for the estimation of the ATET and the overall results are discussed below[99]. Table 5 summarises the results of the estimations.

The findings show that adopting mango would reduce the chance of being poor by between 5% (objective) and 20% points (subjective), on average across the different matching algorithms. The size of this effect is in line with findings in previous studies. For example, Mendola (2007) estimates that adopting innovation decreases poverty from 9% to 18% points in her study of technology adoption in rural Bangladesh. Using a treatment effect model instead of PSM techniques, Carletto et al. (2011) also find similar results. More specifically, they estimate a reduction in monetary and non-monetary poverty (consumption and asset based index, respectively) from a minimum of 7% to a maximum of about 30% for continuous adopters of snow pea in Guatemala.

However, the results in the Table 5 also show that the significance of the impact estimated changes according to the measure of poverty used. Hence, while the effect of the adoption of mango on objective poverty, measured by the wealth index, is never statistically significant, when the subjective measure is used, the effect of adopting mango is almost always negative and statistically significant at conventional levels[100].

[99] More specifically, the ATET estimations have been carried out using the following matching algorithms: Nearest, nearest 10 and 20 Neighbours, with and without specific level of caliper, with and without replacement; Kernel, Kernel normal, with and without specific level of band width and mahalanobis.

[100] The underestimation of the ATET using objective measures of poverty is in line with previous studies, as, for example, the recent analysis by Posel and Rogan (2014) who compare the use of objective and subjective measures of poverty in South Africa.

Table 5 Average treatment effect on the treated, mango adoption

Mango adoption		NN	Caliper 01	NN_Norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	0.016	0.018	-0.009	-0.072	-0.051	-0.074	-0.038	-0.038	-0.039	0.016	-0.027	0.016	**-0.129***
M1	ATET subjective	**-0.172***	-0.152	**-0.174*****	**-0.169***	**-0.211*****	**-0.224*****	**-0.146***	-0.146	**-0.190*****	**-0.172***	**-0.127***	-0.172	**-0.172****
	N. On support	295	280	218	192	295	295	280	280	295	295	280	295	295
	ATET objective	-0.027	-0.028	-0.037	-0.083	-0.081	-0.068	-0.063	-0.063	-0.052	-0.027	-0.05	-0.027	-0.118
M2	ATET subjective	**-0.187****	**-0.190***	**-0.174*****	**-0.250*****	**-0.256*****	**-0.247*****	**-0.215****	**-0.215*****	**-0.225*****	**-0.187****	**-0.209****	**-0.187***	**-0.214*****
	N. On support	296	288	218	193	296	296	288	288	296	296	288	296	296
	ATET objective	-0.09	-0.097	-0.046	-0.011	-0.093	-0.089	-0.089	-0.089	-0.061	-0.09	-0.105	-0.09	**-0.149***
M3	ATET subjective	**-0.191****	**-0.205****	**-0.183****	**-0.149**	**-0.260*****	**-0.265*****	**-0.228*****	**-0.228*****	**-0.228*****	**-0.191****	**-0.218****	**-0.191****	**-0.229*****
	N. On support	297	285	218	196	297	297	285	285	297	297	285	297	297
	ATET objective	-0.08	-0.102	0	-0.064	-0.086	-0.059	-0.079	-0.079	-0.041	-0.08	-0.087	-0.08	-0.115
M4	ATET subjective	-0.115	-0.121	**-0.156****	-0.115	**-0.237*****	**-0.243*****	-0.117	-0.117	**-0.208*****	-0.115	-0.119	-0.115	**-0.201****
	N. On support	283	266	218	187	283	283	266	266	283	283	266	283	283
	ATET objective	-0.038	-0.042	-0.028	0.026	-0.053	-0.049	-0.055	-0.055	-0.066	-0.038	-0.05	-0.038	**-0.148****
M5	ATET subjective	**-0.242****	**-0.242****	**-0.174****	**-0.192****	**-0.213*****	**-0.217*****	**-0.229****	**-0.229****	**-0.231*****	**-0.242****	**-0.239*****	**-0.242****	**-0.192****
	N. On support	291	274	218	187	291	291	274	274	291	291	274	291	291

*Note: NN=nearest neighbour; Caliper 01= nearest neighbour with caliper width of 0.01; NN_Norep= nearest neighbour, no replacement; NN_Norepcal= nearest neighbour, no replacement with caliper width of 0.01; NN 10= nearest 10 neighbours; NN 20= nearest 20 neighbours; NN 10 cal= nearest 10 neighbours with caliper width of 0.01; NN 20 cal= nearest 20 neighbours with caliper width of 0.01; Kepan= kernel; Knorm=kernel normal; Kbw01=kernel with bandwidth of 0.01; Knormbw01=kernel normal with bandwidth of 0.01

4.1 Discussion of ATET results on subjective poverty

The impact on subjective poverty reduction is also supported by the data on the alternative measures of subjective well-being collected during the field work. Table 6 shows that poor mango farmers, although with similar income requirement per adult equivalent, do value their income and food consumption more than non-mango farmers.

Table 6 Subjective measures of poverty

	Subjective non-poor			Subjective poor		
	Non mango	Mango		Non mango	Mango	
	Mean	Mean	P-value	Mean	Mean	P-value
Minimum income-pae (Ghc/month)	770.22	826.65	0.703	556.12	638.12	0.428
Income evaluation (current; 1-5)	3.23	3.39	0.212	2.54	3.09	0.001***
Income evaluation (12 months ago; 1-5)	2.94	3.01	0.551	2.63	2.93	0.039**
Food consumption adequacy (current; 1-5)	3.58	3.50	0.464	2.79	3.39	0.000***
Food consumption adequacy (12 months ago; 1-5)	3.26	3.31	0.674	2.80	3.23	0.000***
N	53	139		56	57	

The impact on these difference measures of subjective poverty might be due to two dynamics: 1) perceptions of own well-being relative to other farmers located close by and 2) expectations that adoption will increase well-being in the future. Perceptions may be changing faster than asset endowments and may not reflect temporary reduction in actual wealth if this reduction is caused by covariant shocks, shared with other people in the village, or when there is expectation of idiosyncratic recover from the shock itself.

Both of these possible explanations might be relevant to this analysis, as shocks related to mango production might be shared across the village (as, for example, fruit flies or excessive rains). Also, the impression from field observations and focus group discussions supports the argument that farmers in my sample do generally believe that mango production will provide them with consistent positive returns in the future.

These results are in line with the empirical evidence on the determinants of subjective well-being as, for example, Ravallion and Lokshin in 2002 who point out the role of perceptions of past and future income on current self-rate economic welfare in Russia. Similarly, Knight et al. (2009) show that past and future income shapes the extent of current happiness and poverty in rural China.

4.2 Discussion of ATET results on objective poverty

The lack of significance of the impact on objective poverty suggests that mango adoption does not necessarily lead to a higher wealth. This result contrasts with previous empirical evidence from the literature on adoption of product innovation, especially cash crops, which usually find a positive impact on farmers' objective wealth (e.g. von Braun and Immink, 1994; Mendola, 2007; Schipmann and Qaim, 2010)[101].

The inconsistency of these findings, however, might be explained by the specific nature of the innovation analysed. In the paragraph 4.2.1) I discuss why mango farmers might not be benefitting from adoption, focusing on the differences in agricultural returns, shocks, farming ability and marketing opportunities (Table 7).

Aside from differences between adopters and non-adopters, the lack of a significant impact on objective wealth might be related to the heterogeneity within the group of mango farmers itself. Following the argument by Carletto et al. (2011), it might be that some adopters have yet to experience gains from adoption because of the relatively short experience with the innovation. In order to investigate whether the time of adoption has contributed to these results, I estimate the ATET separately for late and early adopters (Table 8 and Table 9, in paragraph 4.2.2).

Finally, I conclude with a discussion on the reasons why some mango farmers are poor, highlighting the heterogeneity of the group of mango farmers in terms of intensity and quality of production as well as with regards to access to different marketing opportunities (4.2.3). I then estimate the ATET for the sample without poor mango farmers (Table 11) and also without poor non-mango farmers (Table 12), to investigate whether the difficulties faced by poor mango farmers, in particular, do affect the final results.

[101] In order to verify whether this contrasting evidence is specifically related to the nature of the innovation investigated here, I also estimate the ATET for a more generic group of cash crops producers, which also includes mango adopters. The findings, in Appendix 4.10, suggest that, differently from the case of mango adoption, producing cash crops such as cocoa, cashew, coffee, etc. (including mango), reduces both objective and subjective poverty. In addition, the ATETs on these two measures of wealth are very close to each other but they are also both negative and often statistically significant. Thus, when a more general definition of cash crop is used, the results of the analysis tend to be often consistent with the previous literature.

4.2.1. Direct and indirect channels of impact of adoption on poverty

Recalling the discussion of Section 1, the main direct channel through which the adoption of mango could affect poverty is via higher farm income from higher value of sales, conditional on the access to the premium international price for the sale of good quality fresh fruits. In addition, increased employment in non-farm and off-farm sectors is also claimed to contribute to the poverty reduction effect of non-traditional cash crops adoption.

Comparing mango and non-mango farmers in the sample[102], Table 7 shows that mango farmers do not have either statistically significant different agricultural returns than other farmers or higher access to non- and off-farm employment opportunities than non-mango farmers.

More specifically, although higher in the case of non-poor households, neither farm income, defined as the percentage of total income earned from agriculture, nor the total value of sales differ significantly between mango and non-mango farmers[103]. Moreover, although mango farmers are found to produce on average more crops, no difference in both commercialisation index (estimated as in Chapter 3) and in the proportion of sales is observed between mango and non-mango farmers, who however tend to consume slightly more of their harvest compared to mango farmers.

These findings seem to suggest that in relation to farm income, contrary to what predicted by Minot and Roy (2007), adopters of exotic varieties of mango have not benefited from the product innovation at least in the 12 months before the data collection. And this could explain why the ATET results do not show a significant impact of adoption on objective poverty.

In order to investigate why mango farmers have not been able to access higher agricultural returns, I now analyse production and marketing constraints that might have affected mango farmers' earnings.

Experts of the mango sector claim that in the past years mango production has been affected enormously by the occurrence of different shocks, as, for example pests and

[102] I use here the sample of farmers who fall in the common support of the most comprehensive model (M5), as presented in Table 4.
[103] I have also explored the differences between mango farmers and other cash crops and food only producers and the results are generally similar to the ones presented in this section and, thus, not presented for exposition purposes.

diseases[104]. As a consequence of these shocks, the lack of quality in mango produce might have undermined the access to the premium price and, as a consequence, affected the sales returns at the time of the data collection.

This argument finds support in the data (Table 7), which shows that mango farmers have experienced more often pests and disease shocks, in the 12 months before data collection, compared to other farmers in the sample. In addition, mango farmers are found to live in villages where theft and frauds are claimed to be more serious compared to villages where non-mango farmers are located. These results find support from the field discussions when some farmers, especially in the Northern region, claimed that they were reluctant in investing on their mango production because, for example, of the risk that other farmers could steal from their plot, especially when land is communal. Land insecurity and the consequent reluctance in production enhancing investments might have impacted on the quality of their produce.

Aside from production shocks, another potential constraint in accessing higher returns, could be the lack of the necessary skills in harvest and post-harvest management techniques that would allow farmers to produce high quality crops and sell them for higher prices. This argument does not seem to hold in my sample as some mango farmers also awarded organic production certifications, which should suggest that some of them are, indeed, able to produce high quality mangoes. However, the proportion of mango farmers with a certification is, instead very small, although statistically different from non-mango farmers.

In addition to production ability and occurrence of shocks, the lack of higher agricultural returns for mango farmers might be related to the different marketing channels that they might have access to. Looking at the type of buyers and preferred selling points by adoption and poverty status shows that mango farmers do generally trade with market women, especially if poor, and their most common selling point is at the farm gate. Conversely, non-mango farmers are found to have access to a wider spectrum of marketing opportunities, including pack-houses and local traders (Figure 8). These discrepancies in marketing channels occurs despite similar distances to periodic market between mango and non-mango farmers and better road conditions for

[104] From discussion with main mango value chain operators. in December 2014, for example, as mentioned in Chapter 2 and 3, the excess of rain caused flower abortions in almost all the mango farms nationwide which will affect not only the quality but also the size of the production in the next major harvest season (starting in May 2015).

the former (Table 7) and suggest that mango farmers might not have necessarily different access to better marking channels, as argued by supporters of mango adoption.

Overall, this exploratory analysis suggests that adoption of exotic varieties of mango did not affect the direct or the indirect poverty impact channels as identified by Minot and Roy (2007). This could be explained by the poor quality of the mango harvest in the 12 months preceding the data collection, which could have been caused by the higher occurrence of harvest and post-harvest shocks or by the heterogeneous ability to cope with these shocks. The low quality of mango might have hindered the access to premium sales opportunities and as a consequence to higher production returns.

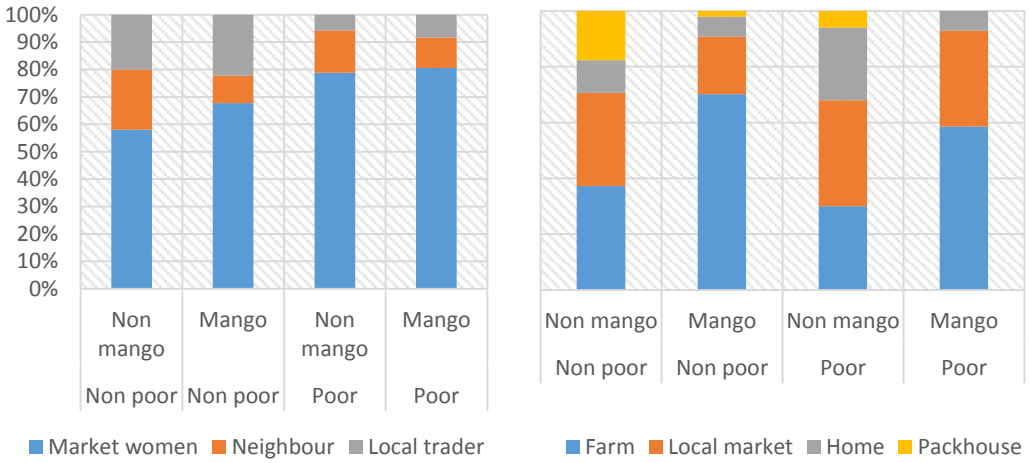
In order to investigate whether mango production related factors can also explain poverty within mango farmers the next paragraphs discuss the main differences regarding mango cultivation between poor and non-poor mango farmers.

Table 7 Selected direct and indirect indicators of objective poverty impacts

		Total			Objective Non-poor			Objective Poor		
		Non mango	Mango		Non mango	Mango		Non mango	Mango	
		Mean	Mean	p-value	Mean	Mean	p-value	Mean	Mean	p-value
Farm income	%, total	70.57	67.43	0.219	66.64	65.78	0.814	74.72	69.84	0.155
Trade income	%, total	17.53	17.50	0.988	21.09	18.25	0.395	13.78	16.41	0.385
Total value of sales	GhC	7465	15559	0.517	12644	24223	0.453	1992	1276	0.453
Total value of sales*	GhC	1972	3030	0.171	1952	4121	0.453	1992	1276	0.453
N. crops	# produced	2.34	2.64	0.011**	2.27	2.63	0.050**	2.42	2.65	0.080*
Harvest consumed	%, total	27.28	22.22	0.059*	23.29	15.85	0.030**	31.50	31.51	0.998
Harvest sold	%, total	66.97	66.27	0.824	71.48	73.39	0.623	62.21	55.88	0.199
CI[1]	(%)	33.03	30.62	0.363	37.48	34.98	0.528	28.32	24.25	0.192
Distance to market	Periodic market, Km	4.64	4.46	0.709	4.87	4.90	0.963	4.41	3.82	0.406
Roads	# months impassable	3.56	2.90	0.005***	3.51	3.09	0.156	3.61	2.64	0.009***
Non-farm	# in non-farm employment	0.66	0.81	0.154	0.73	0.81	0.569	0.58	0.80	0.150
Non-farm se	# in non-farm self-employment	0.57	0.68	0.224	0.61	0.64	0.794	0.53	0.74	0.136
Non- farm we	# in non-farm wage employment	0.09	0.13	0.480	0.13	0.18	0.533	0.06	0.05	0.951
Off-farm	# in off-farm employment	0.00	0.01	0.440	0.00	0.00	.	0.00	0.01	0.400
Pests	(0/1)	0.37	0.77	0.000***	0.45	0.80	0.000***	0.28	0.74	0.000***
Theft	Seriousness (1/5)	2.81	3.05	0.046**	2.55	2.90	0.043**	3.08	3.27	0.238
Fraud	Seriousness (1/5)	3.93	3.55	0.027**	3.50	3.23	0.296	4.38	4.01	0.051*
Land disputes	Seriousness (1/5)	3.50	3.42	0.658	3.34	3.33	0.982	3.68	3.54	0.634
Ethnic conflict	Seriousness (1/5)	4.53	4.38	0.324	4.64	4.48	0.328	4.42	4.24	0.519
Certification	(0/1)	0.01	0.13	0.000***	0.02	0.15	0.009***	0.00	0.11	0.013**
N		109	182		56	108		53	74	

1 Household Commercialisation Index: ratio value sales to value of production.

Figure 8 Marketing channels, by adoption and poverty status



4.2.2. Heterogeneity of mango farmers

The lack of a significant impact on objective poverty might be also cause by the heterogeneity in the group of the mango farmers in the sample that might have hindered their ability to reach higher returns from the adoption itself. The first source of heterogeneity that I explore here is the time of adoption. Then I investigate what are the main discrepancies between poor and non-poor mango farmers and I adapt the ATET analysis in order to understand whether this type of heterogeneity affects the significance of the poverty impacts.

Heterogeneous time of adoption and impact on poverty

As described in Chapter 3, there is a considerable difference within the group of mango farmers. Differences in the time of adoption might affect the ability of adopters in accessing the benefits of the innovation. More specifically, following the argument by Carletto et al. (2011), it might be that later adopters have yet to benefit from mango adoption compared to earlier adopters.

In order to investigate whether the *time of adoption* affected the ATET results, I estimate the ATET for the samples of early and late mango adopters. Table 8 summarises the results of the ATET estimation which compares late adopters to non-adopters of mango. Table 9 shows the ATET results comparing early and non-adopters.

The results from these two additional estimations show that, overall, while a negative effect is still observed especially for the subjective poverty, suggesting that even late adopters do feel less poor than non-adopters, the size of the impact is reduced substantially compared to Table 5. The findings also suggest that the poverty impacts are rarely significant in the case of late adopters, while they are significant, for subjective poverty, in the case of early adopters (Table 9). These results are in line with previous findings, as, for example, in Carletto et al. (2011) who found that, although the impact of adoption of the product innovation on poverty was negative and significant for earlier adopters, the impact becomes much smaller and non-significant for later adopters.

Table 8 Average treatment effect on the treated, late adopters vs non adopters[105]

Later adopter		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	-0.105	-0.083	0.047	-0.017	0.048	0.064	0.018	0.018	0.046	-0.105	-0.006	-0.105	-0.058
	ATET subjective	-0.105	-0.095	-0.174	-0.172	-0.144	**-0.134***	-0.054	-0.054	**-0.135***	-0.105	-0.067	-0.105	**-0.174***
M1	N. On support	195	193	195	167	195	195	193	193	195	195	193	195	195
	ATET objective	0.081	0.104	0.058	0.161	0.041	0.050	0.016	0.016	0.041	0.081	0.037	0.081	-0.035
	ATET subjective	-0.093	-0.104	**-0.151***	-0.143	-0.137	-0.149	-0.108	-0.108	**-0.141***	-0.093	-0.102	-0.093	**-0.140***
M2	N. On support	195	186	195	165	195	195	186	186	195	195	186	195	195
	ATET objective	0.057	0.083	0.046	-0.021	0.045	0.035	0.041	0.041	0.011	0.057	0.051	0.057	-0.034
	ATET subjective	**-0.253***	-0.181	**-0.149***	**-0.188***	-0.148	**-0.137***	-0.158	-0.158	-0.159	**-0.253****	-0.162	**-0.253***	**-0.161***
M3	N. On support	196	181	196	157	196	196	181	181	196	196	181	196	196
	ATET objective	-0.011	-0.014	0.046	-0.039	0.041	0.035	0.064	0.064	0.012	-0.011	0.047	-0.011	-0.023
	ATET subjective	-0.161	-0.137	**-0.172****	**-0.216***	-0.139	-0.136	-0.144	-0.144	-0.158*	-0.161	-0.155	-0.161	-0.149
M4	N. On support	196	182	196	160	196	196	182	182	196	196	182	196	196
	ATET objective	0.116	0.158	0.023	0.078	0.019	0.019	0.077	0.077	0.009	0.116	0.116	0.116	-0.058
	ATET subjective	-0.128	-0.145	-0.140*	-0.098	-0.136*	-0.106	-0.140	-0.140	-0.131	-0.128	-0.144	-0.128	-0.140
M5	N. On support	195	185	195	160	195	195	185	185	195	195	185	195	195

Table 9 Average treatment effect on the treated, early vs non-adopters

Early adopters (212)		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	0.000	0.011	**-0.194*****	-0.058	-0.104	-0.122	-0.057	-0.057	-0.114	0.000	-0.046	0.000	**-0.245*****
M1	ATET subjective	-0.143	-0.146	**-0.276*****	**-0.346*****	**-0.230*****	**-0.286*****	**-0.236****	**-0.236****	**-0.248****	-0.143	**-0.219****	-0.143	**-0.214*****
	N. On support	207	198	207	161	207	207	198	198	207	207	198	207	207
	ATET objective	**-0.194***	-0.198	**-0.194*****	-0.120	-0.087	-0.111	-0.177	**-0.177***	**-0.102***	**-0.194***	-0.176	-0.194	**-0.224****
M2	ATET subjective	**-0.255****	**-0.267****	**-0.296*****	**-0.360*****	**-0.266*****	**-0.336*****	**-0.229***	**-0.229****	**-0.256*****	**-0.255****	**-0.224***	**-0.255****	**-0.276*****
	N. On support	207	195	207	159	207	207	195	195	207	207	195	207	207
	ATET objective	-0.143	-0.129	**-0.184*****	-0.167	-0.115	-0.112	-0.112	-0.112	-0.112	-0.143	-0.127	-0.143	**-0.265*****
M3	ATET subjective	**-0.224***	**-0.226****	**-0.296*****	**-0.313****	**-0.268*****	**-0.326*****	**-0.205***	**-0.205***	**-0.257*****	**-0.224****	**-0.208***	**-0.224***	**-0.245****
	N. On support	207	202	207	157	207	207	202	202	207	207	202	207	207
	ATET objective	-0.181	-0.130	-0.108	-0.061	-0.027	-0.047	-0.038	-0.038	-0.043	-0.181	-0.071	-0.181	**-0.169***
M4	ATET subjective	**-0.289****	**-0.333****	**-0.289*****	**-0.327*****	**-0.267*****	**-0.249****	**-0.314****	**-0.314*****	**-0.272*****	**-0.289****	**-0.319****	**-0.289*****	**-0.181****
	N. On support	192	178	192	158	192	192	178	178	192	192	178	192	192
	ATET objective	-0.119	-0.114	**-0.143***	-0.040	-0.077	-0.076	-0.078	-0.078	-0.084	-0.119	-0.081	-0.119	**-0.179***
M5	ATET subjective	**-0.286****	**-0.266****	**-0.274*****	**-0.280****	**-0.248****	**-0.249*****	**-0.243***	**-0.243***	**-0.271*****	**-0.286****	**-0.263****	**-0.286****	**-0.202***
	N. On support	193	188	193	159	193	193	188	188	193	193	188	193	193

[105] I have also estimated the ATET between early and late adopters using both the absolute and relative cut off as defined in Chapter 3. Although the signs of the effects are in line with the expectations (being a late (later) adopters increases poverty), the results are not consistent throughout. The full results can be found in Appendix 4.10. I have then estimated ATET also for the subsample of large (more than 3 acres) and small farmers (less than 3 acres) separately. The results show that small farmers have not benefited either in objective and subjective terms from mango adoption.

Other sources of heterogeneity between mango farmers

The previous analysis still suggests that the impact of the adoption on objective poverty does not occur and that mango farmers are not benefitting from adoption, regardless of the heterogeneity driven by their time of adoption. This might suggest that heterogeneity within the group of mango farmers might be driven by other characteristics. The following paragraphs discuss differences in terms of intensity and quality of mango production, social capital and marketing opportunities between poor and non-poor mango farmers.

Although the majority of mango farmers are classified as objectively non-poor, 38% of the sample of mango farmers (74 households) is, instead, defined poor[106]. Aside from differences in livelihood and production choices (in Appendix 4.6), poor mango farmers are found to differ in relation to their involvement in the mango production. Table 10 shows that poor mango farmers are low-scale mango producers with an average of 90 trees per farmers which corresponds to one acre of land under mango cultivation. Moreover, poor mango farmers have earned substantially less from the production of mango than non-poor mango farmers. The total value of sales is about 2700 GhC for non-poor farmers compared to 237 GhC of poor farmers.

Table 10 Selected summary statistics, mango farmers

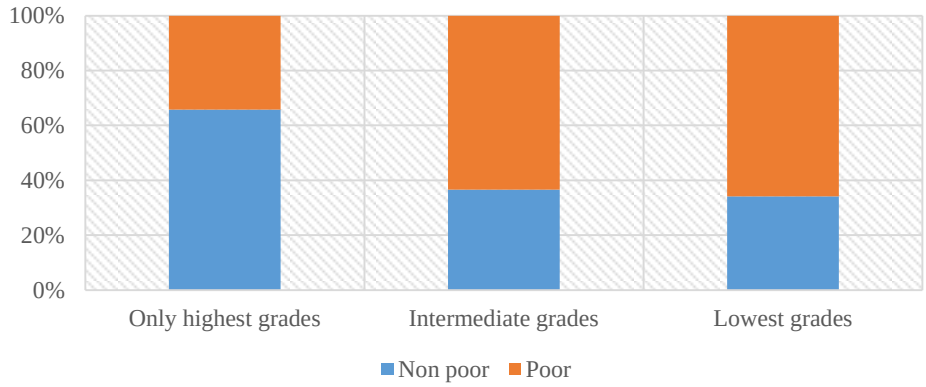
		Objective non poor Mean	Objective poor Mean	P-value
Total value of sales of mango	GhC	2687	237	0.009***
Price mango per kg	Ghc	0.62	0.31	0.158
N. Trees	#	380	90	0.001***
Variety produced		Keitt, Kent	Keitt, Kent	
Harvest consumed	%	15.38	31.51	0.000***
Harvest sold	%	74.07	55.88	0.000***
Training	(0/1)	0.80	0.76	0.444
Certification	(0/1)	0.20	0.11	0.084*
Year adoption mango		2004	2005	0.125
N		122	74	

Although not significant at conventional levels, the selling price of mango received by non-poor mango farmers is twice as big compared to poor mango farmers, which could be related to the different quality of mango produced by poor and non-poor farmers.

[106] Using the subjective measure of poverty, the proportion of poor mango farmers is 30% of the sample (57 households). This proportion, however, varies considerably by region and district, as seen in Figure 5.

An indicator of this poor quality could be the *grade* at which the produce is sold. Grades are normally defined by national agencies or buyers and they establish a selection of criteria on colour, size and weight, which need to be satisfied for the product to be accepted. While for other more consolidated crops, for example cocoa, grading systems are well established and known, obtaining accurate data on quality criteria related to the mango production is quite difficult in Ghana as the grading system is not well established at institutional level[107]. Figure 9 shows that there is certain degree of difference in terms of farmers' perception of the quality of their produce and that poor mango farmers might not have been able to access premium prices compared to non-poor farmers due to the lower quality of their produce.

Figure 9 Mango grading, by poverty status



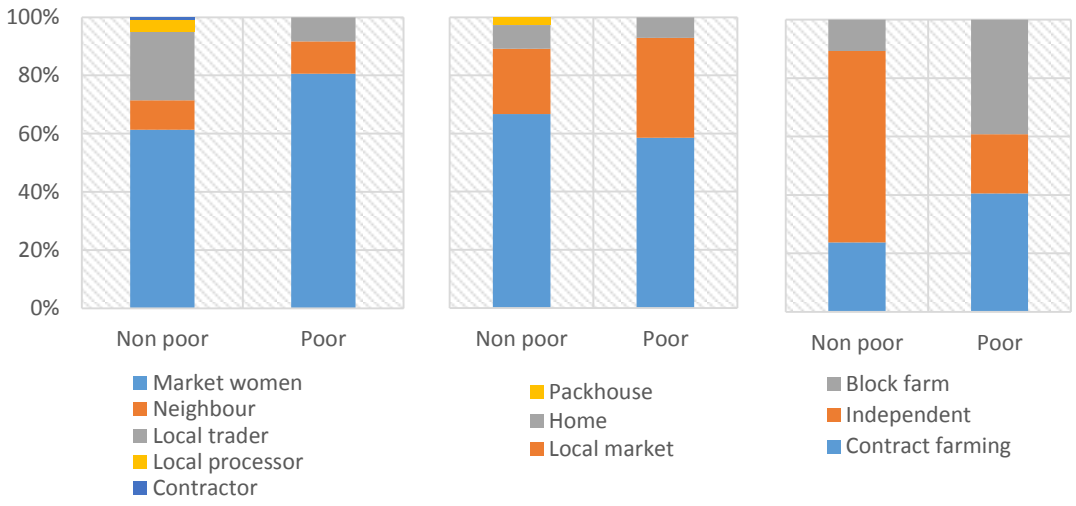
The access to information about harvest and post-harvest management techniques might provide insights on the differences in the ability of mango farmers in dealing with production difficulties. The access to relevant information might occur via different channels, such as longer experience in mango production, access to training and social capital. The experience in mango farming mango does not seem to differ between poor and non-poor mango farmers, although poor mango farmers adopted mango generally slightly later than non-poor mango farmers. Similarly no major differences can be

[107] Nonetheless, farmers do have a common knowledge on what the grades are and what could be the premium prices associated with a higher grade. During focus group discussions, farmers generally claim that grade "A" is generally the highest and mangoes that reach this grade are generally sold fresh for export, at the highest price per unit. The grading scale goes down to the grade D, which includes mangoes of lower quality (for shape, colour and imperfections) that are normally sold in the local market or to processing companies, at lower price. This information was gathered from discussion with stakeholders of the mango value chain. During the field activities, I perceived that every farmer would have associated his/her own production of mango to the highest grade possible. A question in the survey asked farmers to rate their production according to the grading system they normally use. The answers to this question show that poor farmers produced more low quality mangoes, graded C or lower; whereas the majority of non-poor mango farmers produced A graded mangoes or a combination of them with lower quality ones.

observed in the access to training opportunities in the 12 months preceding the data collection[108].

Finally, one last exploratory analysis regards the marketing opportunities. Hence, it may be plausible to think that the incapability of poor farmers to have access to premium prices may be related to a lower market orientation compared to non-poor mango farmers (Figure 10).

Figure 10 Mango farmers marketing channels, by poverty status



These findings show that poor mango farmers, although producing similar number of crops and the same variety of mango (mainly Keitt and Kent) than non-poor mango farmers, tend to be less market oriented, i.e. they consume more and sell less of their produce than non-poor mango farmers; they produce mango less intensively, and of lower quality; they tend to sell exclusively to market women while non-poor farmers also trade with processors and other local traders; they sell mostly at the farm or in the local market and not in dedicated pack-houses, compared to non-poor farmers. Finally,

[108] I also investigate if there is any difference in in social capital between poor and non-poor mango farmers. The measures used are the ones used in Chapter 3. The only different measure is the "social network" variable, which is, in this case, directly drawn from the questions in the survey. The question directly asked mango farmers the number of previous adopters known at the time of adoption (1=none; 2=less than 10 and 3= more than 10). The results, in Appendix, show that, although non-poor mango farmers have stronger relationship with input suppliers, and poor farmers have a stronger relationship with land owners overall social capital tend not to systematically differ between poor and non-poor mango farmers, suggesting that mango farmers can have access to similar sources of information. The latter result is explained by the fact that, as described above, poor farmers do not generally own land.

poor mango farmers also tend to be involved in contract farming and block farm systems while non-poor farmers are generally independent sellers[109].

These results tend to suggest that overall mango adopters differ quite considerably according to their poverty status and that mango adoption did not necessarily benefit less endowed, less market oriented and low skilled farmers. In order to reduce the heterogeneities within the group of mango farmers, I now estimate the ATET on two sub-samples: 1) non-mango farmers and non-poor mango farmers (231 households, Table 11); 2) non-poor farmers (both mango and non-mango farmers; 178 households, Table 12) [110].

The results show that when poor mango farmers are dropped from the sample, the impact of adoption on poverty changes considerably. More specifically, the findings show that a strong and significant poverty reducing effect for both objective and subjective measures of poverty, which is consistent with previous empirical evidence. Similar results are also found for the subsample of "only" non-poor farmers (both non-mango and mango farmers), although the ATET estimations are less consistent throughout the different matching algorithms.

Overall, these additional estimations tend to suggest that the heterogeneity within the group of mango farmers might affect the impact that the adoption has on farmers' well-being. This heterogeneity might be related to the relative different experience in dealing with difficulties related to the production and marketing of mango itself. Poor mango farmers tend to produce low quality crops that are sold at a much lower price than crops produced by non-poor mango farmers. The difficulties that poor farmers are facing in benefitting from mango adoption are considerable and they affect the analysis of the ATET in my sample.

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[109] This last finding contrasts the empirical evidence of the past literature on the benefits of contract farming especially for small farmers (Minten et al., 2009; Miyata et al., 2009). In my sample, contract farmers are normally located in the Northern region, where ITFC operates. The first impressions from the field suggested that these farmers did not have enough understanding about mango production and its potentiality. Their waiting attitude contrasted enormously with the one, mostly business oriented, of the farmers located in Brong-Ahafo and Eastern regions where independent production is more common. The results of this analysis seem to confirm the observation gathered from the field that, indeed, mango farmers located in the Northern region are lagging behind mango farmers located in other parts of the country.

[110] I re-estimated the asset index and the subjective measure of poverty for each of these subsamples. The ATETs between only poor farmers cannot be estimated because there is no variance in asset endowments for this group of farmers which hinders the possibility to re-estimate the asset index for this subsample of farmers.

Table 11 Average treatment effect on the treated, non-poor mango farmers

Non poor mango farmers (231)		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	-0.190*	-0.221**	-0.422***	-0.367***	-0.287***	-0.324***	-0.267***	-0.267***	-0.265***	-0.190	-0.253**	-0.190*	-0.431***
M1	ATET subjective	-0.241**	-0.317***	-0.284***	-0.267***	-0.234***	-0.279***	-0.290***	-0.290***	-0.225**	-0.241**	-0.297**	-0.241**	-0.259***
	N. On support	225	213	218	169	225	225	213	213	225	225	213	225	225
	ATET objective	-0.259***	-0.294***	-0.422***	-0.373***	-0.279***	-0.324***	-0.275***	-0.275***	-0.262***	-0.259***	-0.274**	-0.259**	-0.397***
M2	ATET subjective	-0.233**	-0.255**	-0.284***	-0.220**	-0.236***	-0.276***	-0.235**	-0.235**	-0.232**	-0.233**	-0.234**	-0.233*	-0.293***
	N. On support	225	211	218	168	225	225	211	211	225	225	211	225	225
	ATET objective	-0.259**	-0.279**	-0.422***	-0.328***	-0.283***	-0.322***	-0.258**	-0.258**	-0.262***	-0.259**	-0.269***	-0.259**	-0.431***
M3	ATET subjective	-0.190	-0.231*	-0.284***	-0.230*	-0.235***	-0.278***	-0.246**	-0.246**	-0.230***	-0.190*	-0.259**	-0.190*	-0.276***
	N. On support	225	213	218	170	225	225	213	213	225	225	213	225	225
	ATET objective	-0.267**	-0.293**	-0.386***	-0.283***	-0.275***	-0.325***	-0.281**	-0.281**	-0.243**	-0.267***	-0.280**	-0.267**	-0.406***
M4	ATET subjective	-0.059	-0.107	-0.267***	-0.113	-0.204**	-0.238***	-0.134	-0.134	-0.159*	-0.059	-0.118	-0.059	-0.257***
	N. On support	210	184	210	162	210	210	184	184	210	210	184	210	210
	ATET objective	-0.374***	-0.388	-0.394***	-0.356***	-0.323***	-0.356***	-0.357***	-0.357***	-0.338***	-0.374***	-0.370***	-0.374***	-0.354***
M5	ATET subjective	-0.212*	-0.247*	-0.263***	-0.237**	-0.194**	-0.215**	-0.262**	-0.262**	-0.212**	-0.212*	-0.271**	-0.212*	-0.172**
	N. On support	208	194	208	194	208	208	194	194	208	208	194	208	208

Table 12 Average treatment effect on the treated, non-poor farmers

Non poor mango and non-farmers (178)		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	-0.339***	-0.365***	-0.321***	-0.350***	-0.305**	-0.293***	-0.381***	-0.381***	-0.291***	-0.339***	-0.382***	-0.339**	-0.275**
M1	ATET subjective	-0.202	-0.219	-0.089	-0.200	-0.187*	-0.177*	-0.208	-0.208	-0.186*	-0.202	-0.231*	-0.202	-0.138
	N. On support	165	152	112	96	165	165	152	152	165	165	152	165	165
	ATET objective	-0.342***	-0.363**	-0.321***	-0.310**	-0.289***	-0.276***	-0.320**	-0.320**	-0.280**	-0.342***	-0.333***	-0.342***	-0.198*
M2	ATET subjective	-0.234	-0.275**	-0.089	-0.119	-0.186*	-0.174*	-0.198	-0.198	-0.180**	-0.234*	-0.227*	-0.234**	-0.207*
	N. On support	167	158	112	98	167	167	158	158	167	167	158	167	167
	ATET objective	-0.211	-0.228	-0.304***	-0.349**	-0.261**	-0.296***	-0.185	-0.185	-0.226*	-0.211*	-0.188	-0.211	-0.229*
M3	ATET subjective	-0.174	-0.207*	-0.089	-0.140	-0.139	-0.159	-0.134	-0.134	-0.153	-0.174	-0.150	-0.174	-0.202**
	N. On support	165	148	112	99	165	165	148	148	165	165	148	165	165
	ATET objective	-0.189	-0.222	-0.268***	-0.190	-0.207*	-0.232**	-0.164	-0.164	-0.186	-0.189	-0.189	-0.189	-0.222**
M4	ATET subjective	-0.111	-0.111	-0.089	-0.048	-0.076	-0.071	-0.080	-0.080	-0.089	-0.111	-0.093	-0.111	-0.144
	N. On support	146	137	112	98	146	146	137	137	146	146	137	146	146
	ATET objective	-0.235	-0.342**	-0.232**	-0.342**	-0.245**	-0.240**	-0.333**	-0.333**	-0.250**	-0.235	-0.334**	-0.235	-0.216*
M5	ATET subjective	-0.059	-0.101	-0.089	-0.079	-0.122	-0.087	-0.089	-0.089	-0.097	-0.059	-0.098	-0.059	-0.039
	N. On support	158	135	112	94	158	158	135	135	158	158	135	158	158

Section 5. Conclusion

This chapter investigates the impact of the adoption product innovation on poverty. The product innovation analysed is the exotic varieties of mango (mostly Keitt and Kent) in the context of rural Ghana. The data were collected during the field work carried out in 2012 and it included 196 adopters and 109 non adopters of mango.

The empirical methodology uses propensity score matching techniques for the identification of the counterfactual among the heterogeneous group of non-adopters. I explore different matching criteria and methods for the selection of the valid counterfactual and, then, I estimate the Average Treatment Effect on the Treated.

I use two types of poverty measures: objective and subjective. The objective measure is based on the estimation of an asset index using principal component analysis, while the subjective measure is derived from the "Economic Ladder" survey question. The identification of the poverty thresholds follows the previous literature. More specifically, a household is defined "objective" poor if its asset index is below the 40^{th} percentile of the entire distribution, while a household is defined "subjective" poor if its answer to the Economic Ladder question was below the median answer at district level.

Following these definitions, 127 "objectively" poor households and 113 "subjectively" poor households can be identified in the sample. Although a certain degree of overlapping can be observed between objective and subjective poverty rates, there exist some difference in poverty rates within and between regions depending on the poverty measure used. More specifically, farmers located in the Northern region are generally subjectively less poor than they "objectively" are, while the reverse is observed for farmers in Brong-Ahafo region.

The main advantage of using a subjective measure of poverty is that it provides a more comprehensive picture of the household's poverty profile, which is in line with the argument of multi-dimensional nature of poverty. Moreover, the use of subjective measures also helps addressing the underestimation of wealth that can occur when only objective measures are used (Posel and Ragan, 2014).

The main findings of this analysis suggest that mango adoption has a significant poverty reducing impact. However, this impact regards almost exclusively the subjective

poverty. Mango adoption is, indeed, found to not impact objective poverty. Although in contrast with previous findings, the lack of impact might have been caused by the occurrence of shocks in the period preceding the data collection, which in turn might have affected farmers' asset endowments, suggesting that the results might be dependent on peculiarities of the crops investigated, exotic varieties of mango. Poor mango farmers in the sample do, indeed, struggle to produce a high quality fruit that could be exported or sold at a higher price than the one offered in the local market. The results also show that when the group of poor mango farmers is excluded from the analysis, the effect of adoption on objective poverty becomes significant, suggesting that the difficulties that poor mango farmers are facing in reaching objective returns from the innovation should not be overlooked.

Nonetheless the poverty reducing impact observed in the case of subjective poverty suggests that farmers do feel less poor as a consequence of their adoption status. This might be driven by the experience of past high production returns or from positive expectations from the future. This result is in line with previous literature as, for example, Ravallion and Lokshin (2002) and Knight et al. (2009), who show that past and future income shapes the extent of current happiness and poverty.

Overall, notwithstanding its limitations (cross sectional nature of the data, limited number of matching criteria, etc.), this analysis provides some interesting insights on the effect and the perception of the effect that a product innovation, such as exotic varieties of mango, had in rural Ghana. To my knowledge this is the first study that explicitly attempted to evaluate the issue empirically and as such it could be a valuable source of information for future, more rigorous impact evaluations.

CONCLUSION

The recent developments in the national agricultural policies in Ghana identify market participation and innovation adoption as two of the most important priorities for agricultural transformation and poverty reduction. Notwithstanding the financial and political commitment received, market participation and innovation adoption rates remain considerably low in rural Ghana.

The main objective of this thesis is to investigate farmers' decision to participate in the market and to adopt product innovation as well as the impact of the latter on poverty in rural Ghana. I use both secondary data, from the Ghana Living Standard Surveys, as well as primary data collected during the summer 2012.

Chapter 1 analyses the determinants of market participation and commercialisation using a sample of rural households from three rounds of the GLSS (GLSS4, GLSS5, GLSS6). The analysis is run at both household and crop level, with the latter focused on one of the most common staple crops in Ghana, maize. A Heckman two step approach is used to control for self-selection into market participation. Specific attention is given to the role of transaction costs in market participation decisions. Both measures of proportional and fixed costs are included in the models and estimated together with classic explanatory variables (household, farm and village characteristics). The results of this chapter show that, aside from classic determinants, such as farm size or land ownership, transaction costs play a relevant role in the decision to participate in the market in Ghana. Within the measures of proportional transaction costs, the results show an unexpected, positive, relationship between remoteness and market participation, i.e. being further away from the market increases the likelihood of participating in the market. Although inconsistent with past empirical evidence, this result finds support from studies of commercialisation specific to the Ghanaian context. Zanello et al. (2014) and Martey et al. (2012) both suggest that remoteness might not be as important in Ghana as it might be in other developing countries, as it is personal ties and relationships with buyers which favour market participation and play a significant role in reducing transaction costs. Furthermore, in the past decades several projects have been put in place by development agencies and national government aiming to create strong linkages between primary producers, especially if located in remote areas, other farmers, and buyers (both processors and exporters), who mostly operate closely to

markets. The existence of stronger linkages between primary producers and other relevant actors of wider social networks, across and within different value chains (food and/or cash crops), might explain this unexpected positive association between remoteness and market participation.

GLSS data do not offer a wide range of information that would allow the investigation of the role of social networks and social capital, defined as linkages with other operators along the lines of relevant value chains. This motivated the collection of primary data that I have carried out in the summer 2012. The field work focused on the adoption of one non-traditional cash crop targeted for its poverty reduction potential by the Ghana Export Horticulture Cluster Strategic Profile Study (2008), i.e. exotic varieties of mango. I collected data on household, farm and social capital characteristics from 305 farmers (196 mango adopters and 109 non-adopters). I use this data to investigate the role of social capital on product innovation adoption (Chapter 3) and its effect on poverty (Chapter 4).

Chapter 3 analyses the factors that affect the decision to adopt exotic varieties of mango, the decision of when to adopt and how much. The empirical investigation is based on probit, OLS and Heckman models and it includes measures of social capital in both aggregated and disaggregated fashion. More specifically, three components of social capital are considered: structural bridging, structural bonding and cognitive. The disaggregated measures are computed for seven innovation change agents (input suppliers, credit providers, extension officers, farmers' organisation, development agencies, NGOs and other farmers). The results show that social capital plays a considerable role in the decision to adopt or not the product innovation under scrutiny, and that different change agents might influence the decision of when to adopt and how much to invest in the innovation. While development agencies are found to accelerate the decision to adopt, NGOs are instead found to affect the decision of how much to adopt. Moreover, farmers' organisation and extension officers are found to facilitate the decision to adopt product innovation and, often, to reduce common small farmers' constraints, such as farm size, land ownership and access to credit. On the other hand, having contracts with and trust in these change agents is also found to delay the decision to adopt, supporting the idea that the production difficulties that adopters are currently facing in the mango sector might have created negative expectations on the benefits

from adoption that might have been channelled to other farmers through these change agents and discouraged earlier adoption.

Finally, Chapter 4 questions the impact that adoption of product innovation, such as exotic varieties of mango, has had on poverty in the sampled areas. Development agencies have been advocating the poverty reducing potential of this product innovation since early 2000s but few studies have attempted to investigate it empirically. Using propensity score matching techniques, I estimate the Average Treatment Effect on the Treated comparing mango and non-mango farmers. I use two measures of poverty. An "objective" measure, which is computed based on asset data using the principal component analysis, and a "subjective" measure of poverty, constructed using the "Economic Ladder" question, as presented in Ravallion (2012). The estimations of the ATETs show that the adoption of innovation has had, indeed, a positive effect on farmers' poverty reduction. However, a statistically significant effect is only observed in the case of subjective poverty, suggesting that mango farmers "feel" less poor that they actually are. The lack of effect on objective poverty contrasts with previous empirical evidence (e.g. von Braun and Immink, 1994; Mendola, 2007). In order to explain why adopters' poverty has not changed in objective terms, I investigate whether different sources of heterogeneity within the group of mango farmers affected the results. I first re-estimate the ATETs comparing non-adopters and sub-samples of either late or early adopters of mango and then I investigate whether other sources of heterogeneity, such as intensity and quality of mango production, might have contributed to the unexpected lack of impact on objective poverty. Interestingly, when the ATET is estimated excluding mango farmers who are struggling in achieving high quality of their produce, the impact on objective poverty becomes highly significant, suggesting that mango production difficulties are effectively constraining mango farmers, especially if poor, in achieving benefits from its adoption.

The main limitation of the analyses in this thesis is the presence of endogeneity, due to reverse causality and selection bias. Although the use of Heckman models attempts to minimise the effect that endogeneity has on the final results, the extent to which the effect is limited can be questionable. This is because self-selection bias is controlled for using purposively selected observable characteristics. These observable characteristics are much clearer in the market participation conceptual framework, which identifies in measures of fixed transaction costs the controls for self-selection, than they are in the

adoption models. The identification of the variables that can capture selection bias can, indeed, be quite difficult without a specific conceptual framework that justifies their use[111].

Apart from selection biases, reverse causality of other control variables such as access to credit, food only production and access to non-farm income, might have affected the results. The main challenge in identifying instrumental variables for addressing this issue is linked to the fact that similar factors that are believed to affect the potentially endogenous variables (such as farm size, land ownership and so on) are also believed to affect market participation and adoption, and their role in addressing endogeneity specifically for these analyses can be considered questionable.

Furthermore, specifically for the analysis of the determinants of innovation adoption (Chapter 3) and its impact on poverty (Chapter 4) two additional problems might be affecting the precision of the results. The first is heterogeneity in the units of comparison and the second is related to the measures of social capital variables. The heterogeneity originates from the fact that the sample of non-adopters may be incorrectly composed of dis-adopters, i.e. farmers who adopted mango in the past and then dis-adopted; future adopters and "never" adopters. Also within the group of adopters, farmers might be systematically different with respect to the intensity, time and quality of their adoption as shown in the end of Chapter 4. Ideally, farmer's heterogeneity needs to be control for at the time of the adoption and adopters should be compared to "never" adopters at the time of adoption. The use of recall data, disaggregating the samples according to selected sources of heterogeneity and the use of propensity score marching techniques in the poverty analysis aimed to reduce the potential systematic differences within the group of adopters and across the entire sample.

The information on social capital used in Chapter 3 and Chapter 4 was obtained using a simple approach during the data collection, mainly drawn from value chain analysis. The social capital measures can be improved on two fronts. Firstly the use of recall data

[111] Nonetheless, due to the similarities between innovation adoption and market participation analysis in the case of this thesis, I assume that self-selection might be driven by similar observable characteristics in both the decision to participate in the market and in the adoption of a crop, mango, whose main adoption driver is its marketability. Thus, I control for self-selection in the adoption process also using measures of fixed transaction costs. In addition, in the analysis of the time and intensity of innovation adoption I control for self-selection also using risk aversion variables.

for social capital at the time of the adoption[112]. In addition, social capital measures can be improved using social network analysis approaches. For example, within the structural component, a measure of social network, as in Maertens and Barrett (2012) or Bandiera and Rasul (2006), would provide more precise insights on the role that social networks, and their size, play in the innovation decisions. Similarly, more comprehensive information on communal norms and rules could also enrich the definition of cognitive social capital and improve the estimation of its effect on adoption decisions. These measures require more time that I had during the data collection and, as such, were not used[113].

Moreover, due to time and budget constraints, it was only possible to collect cross section data during the field work. Panel data based on revisits to the household in the sample would offer additional insights and help to address some of the endogeneity problems. Revisiting the households in the sample would also be beneficial in light of the difficulties that mango farmers faced in the harvest season preceding the data collection.

The collection of additional data could also focus more on the use of inputs in the context of mango production. Considering the importance of the correct use of inputs such as pesticides, in pre- and post-harvest mango management techniques, further analysis is needed to understand what determines the choice of inputs and the intensity of their use, and what role social capital plays also in this context, in line with the framework set up by Conley and Udry (2010) within the pineapple sector.

An input-level analysis could also be beneficial in the analysis of market participation in Chapter 1, with a focus on the determinants of demand for inputs, following, for example, Alene et al. (2008). In addition to an input level analysis, considering the importance that gender of the head of the household has on market participation decisions, a disaggregated gender analysis could provide additional insights on the role of gender of the household in the decision to commercialise or not in both the input and

[112] Recall data on social capital was not collected during the field work based on two assumptions: 1) social capital tend not to change drastically within a short amount of time; 2) the time of adoption was expected to be much more uniform and recent than what observed in the field.

[113] However, notwithstanding these challenges, the fact that several different social capital variables produce consistent results across several different specifications and models is somehow reassuring. Also, in order to minimise the effect of multicollinearity, I include different social capital variables separately (one at the time) in the adoption models, which although does not allow to capture joint effects of different types of social capital on the innovation adoption, provides, I believe, satisfactory and consistent results throughout.

output sides. Finally, the analysis of market participation with GLSS data would benefit from additional data at market transaction level for a wider set of crops. Following Zanello et al. (2014), detailed data on how market transactions occur, including communication assets used and costs involved, would provide a better approximation of the transaction costs involved in the decision to participate in the market.

Notwithstanding these limitations, this thesis contributes to the literature on several fronts. First, I use the latest Ghana Living Standard Survey, collected in 2012/2013 and only recently released for public use. To my knowledge no other previous studies on market participation has used this dataset. Moreover, the collection of primary data from mango producers constitutes a useful contribution to the adoption of innovation in the Ghanaian context. Only a couple of other studies[114] have empirically investigated the adoption processes and their effect on poverty for those non-traditional cash crops that have been targeted by international and national actors for their poverty reducing potential. As far as I know, no other studies had carried out a similar analysis for exotic varieties of mango at the time of my field work. I believe that the data collected in 2012 offers valid insights for future researchers in the field of exotic mango adoption, especially in relation with the role of different types of social capital.

The use of disaggregated measures of social capital within the context of innovation adoption also constitutes an additional contribution to the study of non-traditional cash crops in Ghana. Conley and Udry (2010) have carried out a similar analysis for the pineapple sector, but they only focused on one component of the social capital realm, i.e. structural bonding, measured as the size of social networks. In this thesis, I widen the spectrum of social capital components, investigating the role of a wider range of innovation agents and types of social capital. Although challenging at times, as, for example, in the case of cognitive social capital, the approach used in Chapter 3 aims to be one of the initial steps towards a more comprehensive investigation of the role that social capital plays in innovation adoption in the Ghanaian context, where, as discussed above, social capital might be more relevant in the market participation and innovation decisions than in other developing countries.

Some puzzling results of this thesis tend to reflect the particular features of the Ghanaian agricultural context and, in a way, contribute to re-affirm the importance of

[114] CATRD (2006) and van Melle and Buschmann (2013).

taking in to account location specific peculiarities for empirical analyses. This is the case, for example, of the positive relationship between remoteness and market participation. As discussed above, this unexpected result can be explained looking specifically at the Ghanaian marketing systems and their development through times. Similarly, the different role observed for development agencies, NGOs, farmers' organisation and extension officers in the decision to innovate and its dimensions, found in Chapter 3, is typical of the recent history of agricultural transformation occurred in Ghana.

The adherence of the results to location specific characteristics creates the scope for some policy recommendations that could help to foster market participation, innovation adoption and its impact on poverty, specifically within the Ghanaian context. These policy recommendations cover more general aspects of market participation and innovation adoptions, as, for example, education systems, marketing information and provision of interventions that are specific for the mango sector.

The first policy recommendation regards the role of education in market participation. The results suggest that education does not favour market participation. Instead, more educated farmers refrain from participating in the agricultural market. This might suggest that either the agricultural sector does not allow for adequate returns of education or that the education system does not link appropriately with the farming sector. Specific interventions are required in fostering the linkages between education and agriculture especially in the context of accessing better opportunities via market participation and adoption of innovation, where the ability to access and interpret different information is essential.

Given that households with higher education are likely to have access to higher return activities off-farm or in non-farm activities, the improvement of the primary or lower years of the secondary education system with a higher focus on commercialisation, business skills and use of innovative technologies for market access might yield benefits for households where agriculture is an important activity. This should be accompanied by a systematic reform of the marketing information system. Platforms such as that created by Esoko, which provide marketing information (prices, potential buyers and so on) on mobiles phones, should become the common tools for farmers, especially in light of the recent development in mobile network coverage in Ghana. In addition, and

specifically for the non-traditional cash crops sector, more clarity on the quality standards required for the access to the export market should be achieved at national level.

A better information flow should involve more closely farmers' organisations that are observed to play a relevant role in fostering innovation in the case of exotic varieties of mango. While strengthening of farmers' organisation is widely supported by national and international actors in Ghana, and in light of the results of this thesis should be supported even more, much wider attention should be given to the role of Ministry of Agriculture extension officers, who are found to influence both the decision to adopt and the decision of when to adopt. However, from focus group discussions and key informant interviews, farmers and other actors in the mango sectors claim that extension officers often lack of the necessary knowledge and skills to support local adopters. The Ministry of Agriculture should support a bigger involvement of these figures in the innovation processes, especially with regards to the production of exotic varieties of mango, that require timely interventions during all production stages. Technical training and participation of extension officers in the definition and implementation of innovation related interventions might help fostering the diffusion and sustainability of the innovation adoption process in the rural Ghana.

Finally, still in the context of innovation adoption, not enough support has been provided in the past years on pre- and post-harvest management techniques for exotic varieties of mango. During TIPCEE an intense assistance to mango farmers was started and GIZ is currently working with a selection of farmers' organisation for the provision of these activities[115]. However, field observations and the results of this thesis tend to suggest that farmers do still suffer from the occurrence of pest and diseases, as well as, unexpected weather shocks that seem to have affected their economic returns in the year before the data collection. A better and timely provision of technical assistance on the use of inputs, such as specific pesticides for fruit flies (including traps) and irrigation, should be guaranteed. As suggested above, a better involvement of extension officers from the Ministry of Agriculture, who are closely located to farmers, might also contribute to this purpose. Finally, a wider coverage of training for awarding

[115] Water tanks, for example, were provided for example in the Northern region but left in disuse after few years of the completion of the specific interventions. Moreover, pesticides were also distributed by GIZ but some farmers failed to use them correctly and some mango trees were severely damaged as a consequence of this misuse.

certifications for high-quality produce should go hand-in-hand with these activities, in order for farmers to access export markets benefits and for the poverty reducing potential of the innovation adoption to fully materialise also for the poorest group of adopters.

And this is specifically because the majority of mango farmers do truly believe in the benefits of the adoption and that mango is, indeed, a “golden fruit” or a “pension fund”, as some of them claimed during the focus group discussions. A timely and more focused attention to the needs especially of small and poorly endowed mango producers could indeed make a big difference in their ability to finally achieve the expected, and hoped, economic returns. Further research is, of course, needed to understand how these needs change with time and this thesis represents a step towards that goal.

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APPENDICES

CHAPTER 1: APPENDICES

Appendix 1.1. Market participation analysis for farming households with more than 20% of total income from agriculture

Table 1 Determinants of market participation, agriculture income > 20% of total income

Dependent variable Probit: Market participation (0/1) Dependent variable OLS: Commercialisation Index (0-100) VARIABLES		(8) Probit mfx[1]	(8) OLS un-corr[2]	(8) OLS corr[3]	(9) Probit mfx[1]	(9) OLS un-corr[2]	(9) OLS corr[3]	(10) Probit mfx[1]	(10) OLS un-corr[2]	(10) OLS corr[3]
Male head	(0/1)	0.08***	1.98***	1.53	0.06***	1.30*	1.23	0.06***	1.23	0.94
		(0.01)	(0.77)	(0.94)	(0.01)	(0.79)	(0.88)	(0.01)	(0.79)	(0.87)
Age head	Years	-0.00***	-0.01	-0.01	-0.00***	-0.00	-0.01	-0.00***	-0.00	-0.00
		(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)
Basic education	(0/1)	-0.02**	0.85		-0.02**	0.78		-0.02**	0.85	
		(0.01)	(0.72)		(0.01)	(0.72)		(0.01)	(0.72)	
Higher education	(0/1)	-0.02	2.78***	2.50***	-0.02	2.67***	2.37***	-0.01	2.85***	2.55***
		(0.01)	(0.94)	(0.87)	(0.01)	(0.95)	(0.87)	(0.01)	(0.95)	(0.87)
Farm labour	# member of household who work on own farm	0.01***	-0.67***	-0.76***	0.01***	-0.70***	-0.73***	0.01***	-0.71***	-0.78***
		(0.00)	(0.16)	(0.18)	(0.00)	(0.16)	(0.18)	(0.00)	(0.16)	(0.18)
Farm size	Hectares	0.00***	0.04*	0.03***	0.00***	0.03*	0.03***	0.00***	0.03*	0.03**
		(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)
Land ownership	(0/1)	-0.01**	3.52***	3.67***	-0.01**	3.46***	3.57***	-0.01**	3.50***	3.66***
		(0.01)	(0.58)	(0.59)	(0.01)	(0.58)	(0.59)	(0.01)	(0.58)	(0.59)
Livestock	#	0.01*	-0.00***	-0.00*	0.01	-0.00***	-0.00*	0.01	-0.00***	-0.00*
		(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	-0.02***	2.12***	2.33***	-0.02***	2.01***	2.15***	-0.02***	2.07***	2.29***
		(0.01)	(0.66)	(0.68)	(0.01)	(0.66)	(0.68)	(0.01)	(0.66)	(0.68)
Food only production	(0/1) - 1 if household produces only food crops; 0 otherwise	-0.11***	0.87	1.78	-0.12***	0.88	1.42	-0.12***	0.97	1.93*
		(0.01)	(0.79)	(1.19)	(0.01)	(0.79)	(1.08)	(0.01)	(0.79)	(1.07)
Access to credit	(0/1)	0.04***	-0.47	-0.70	0.03***	-0.56	-0.65	0.03***	-0.65	-0.85
		(0.01)	(0.59)	(0.64)	(0.01)	(0.59)	(0.62)	(0.01)	(0.59)	(0.62)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	0.06***	-4.65***	-5.06***	0.06***	-4.59***	-4.82***	0.06***	-4.64***	-5.04***
		(0.01)	(0.69)	(0.78)	(0.01)	(0.69)	(0.75)	(0.01)	(0.69)	(0.74)
Radio	(0/1)				0.02***	2.40***	2.39***	0.02***	2.41***	2.32***
					(0.01)	(0.59)	(0.60)	(0.01)	(0.58)	(0.60)
Bicycle	(0/1)				0.04***	0.59		0.04***	0.64	

Dependent variable Probit: Market participation (0/1) Dependent variable OLS: Commercialisation Index (0-100) VARIABLES		(8) Probit mfx[1]	(8) OLS un-corr[2]	(8) OLS corr[3]	(9) Probit mfx[1]	(9) OLS un-corr[2]	(9) OLS corr[3]	(10) Probit mfx[1]	(10) OLS un-corr[2]	(10) OLS corr[3]
					(0.01)	(0.68)		(0.01)	(0.68)	
Distance to market	(0/1) - 1 if distance is above the median; 0 otherwise							0.03***	2.57***	2.35***
								(0.01)	(0.58)	(0.60)
Distance to extension officer	(0/1) - 1 if distance is above the median; 0 otherwise							-0.02***	-1.60***	-1.41**
								(0.01)	(0.57)	(0.59)
Lambda				-4.71			-2.61			-4.72
				(4.54)			(3.92)			(3.87)
Region dummies		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		11347	9368	11347	11347	0.12	11347	11347	9368	11347
Censored observations				1979			1979			1979
Obs. P %		83			83			83		
Predicted obs %		89			89			89		
LR chi2		1884***			1933***			1958***		
R-squared		0.18	0.13		0.18	0.13		0.18	0.13	
Wald				1218***			1244***			1250***
Rho				-0.18			-0.10			-0.18
Sigma				25.82			25.71			25.77

[1]Marginal effects are presented
[2]OLS Un-corr= OLS on market participants only; not corrected for self-selection into market participation
[3]OLS corr=2nd stage of Heckman two step; corrected for self-selection into market participation
[4] Extreme values have been replaced with average values of each round of GLSS.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1.2. Market participation analysis with a lower cut-off of Household Commercialisation Index

Table 2 Determinants of market participation and its extent, lower cut-off (25% HCI)

Dependent variable Probit: Market participation (0/1) Dependent variable OLS: Commercialisation Index (18-100) VARIABLES		(11) Probit mfx[1]	(11) OLS un-corr[2]	(11) OLS corr[3]	(12) Probit mfx[1]	(12) OLS un-corr[2]	(12) OLS corr[3]	(13) Probit mfx[1]	(13) OLS un-corr[2]	(13) OLS corr[3]
Male head	(0/1)	0.12***	1.36**	0.85	0.11***	0.79	-0.31	0.11***	0.74	-0.69
		(0.01)	(0.69)	(1.76)	(0.01)	(0.71)	(1.37)	(0.01)	(0.70)	(1.37)
Age head	Years	-0.00***	0.01	0.01	-0.00***	0.01	0.02	-0.00**	0.01	0.02
		(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)
Basic education	(0/1)	-0.02*	0.15	IV	-0.02*	0.13	IV	-0.02*	0.19	IV
		(0.01)	(0.64)		(0.01)	(0.64)		(0.01)	(0.64)	
Higher education	(0/1)	-0.05***	2.30***	2.41***	-0.05***	2.25***	2.65***	-0.05***	2.38***	2.86***
		(0.01)	(0.81)	(0.92)	(0.01)	(0.81)	(0.88)	(0.01)	(0.81)	(0.88)
Farm labour	# member of household who work on own farm	0.01**	-0.34**	-0.37**	0.01**	-0.36**	-0.42**	0.01**	-0.37**	-0.45**
		(0.00)	(0.16)	(0.19)	(0.00)	(0.16)	(0.18)	(0.00)	(0.16)	(0.18)
Farm size	Hectares	0.00	0.03	0.03**	0.00	0.03	0.03**	0.00	0.03	0.03**
		(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)
Land ownership	(0/1)	0.03***	3.30***	3.17***	0.03***	3.27***	2.93***	0.03***	3.30***	2.85***
		(0.01)	(0.53)	(0.69)	(0.01)	(0.53)	(0.63)	(0.01)	(0.53)	(0.64)
Livestock	#	-0.00	1.03	1.03	-0.00	0.88	0.92	-0.00	0.87	0.90
		(0.00)	(0.79)	(0.63)	(0.00)	(0.71)	(0.64)	(0.00)	(0.71)	(0.64)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	-0.05***	0.55	0.79	-0.06***	0.44	1.09	-0.05***	0.51	1.32
		(0.01)	(0.58)	(0.94)	(0.01)	(0.58)	(0.83)	(0.01)	(0.58)	(0.83)
Food only production	(0/1) - 1 if household produces only food crops; 0 otherwise	-0.17***	2.43***	3.18	-0.17***	2.38***	4.42**	-0.17***	2.40***	4.97**
		(0.01)	(0.70)	(2.45)	(0.01)	(0.70)	(1.93)	(0.01)	(0.70)	(1.94)
Access to credit	(0/1)	0.02**	-0.77	-0.86	0.02**	-0.86	-1.05*	0.02**	-0.93*	-1.17**
		(0.01)	(0.54)	(0.61)	(0.01)	(0.53)	(0.58)	(0.01)	(0.53)	(0.59)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	0.04***	-4.71***	-4.89***	0.04***	-4.67***	-5.13***	0.04***	-4.75***	-5.33***
		(0.01)	(0.62)	(0.82)	(0.01)	(0.62)	(0.75)	(0.01)	(0.62)	(0.75)
Radio	(0/1)				0.03***	1.70***	1.45**	0.03***	1.71***	1.38**
					(0.01)	(0.54)	(0.63)	(0.01)	(0.54)	(0.64)
Bicycle	(0/1)				0.04***	0.90	IV	0.04***	0.93	IV
					(0.01)	(0.62)		(0.01)	(0.62)	
Distance to market	(0/1) - 1 if distance is above the median; 0 otherwise							0.04***	2.12***	1.52**
								(0.01)	(0.53)	(0.69)
Distance to extension officer	(0/1) - 1 if distance is above the median; 0 otherwise							-0.01	-1.23**	-1.04*
								(0.01)	(0.53)	(0.56)
Lambda				-3.01			-7.77			-9.95
				(9.26)			(7.19)			(7.23)

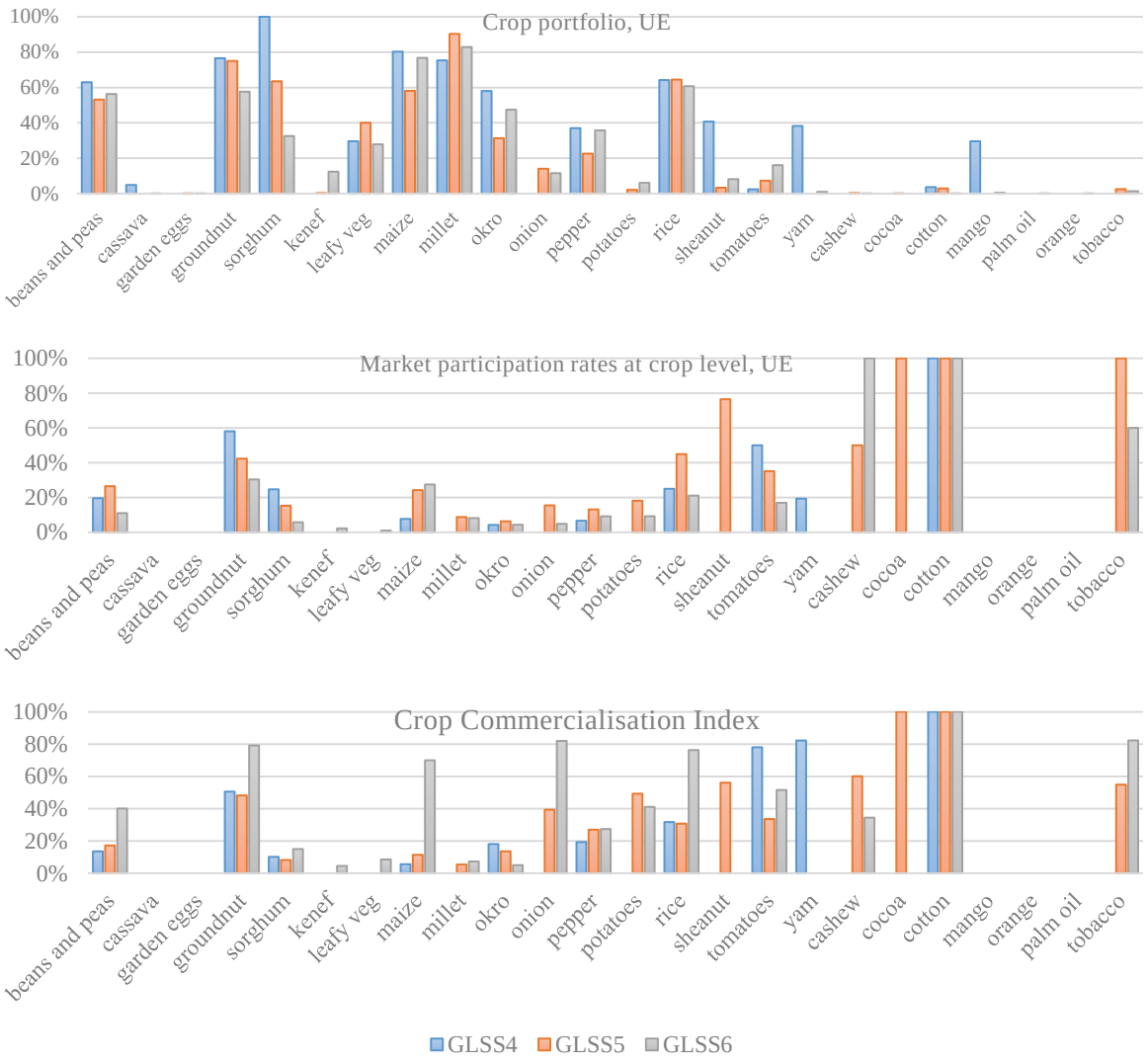
Dependent variable Probit: Market participation (0/1) Dependent variable OLS: Commercialisation Index (18-100) VARIABLES	(11) Probit mfx[1]	(11) OLS un-corr[2]	(11) OLS corr[3]	(12) Probit mfx[1]	(12) OLS un-corr[2]	(12) OLS corr[3]	(13) Probit mfx[1]	(13) OLS un-corr[2]	(13) OLS corr[3]
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,736	8,250	14,736	14,736	8,250	14,736	14,736	8,250	14,736
Censored observations			6486			6486			6486
Obs. P %	56			56			56		
Predicted obs %	57			57			57		
LR chi2	1790***			1814***			1834***		
R-squared	0.09	0.11		0.09	0.11		0.09	0.11	
Wald			671***			653***			642***
Rho			-0.14			-0.34			-0.43
Sigma			22.22			22.84			23.28

[1]Marginal effects are presented
[2]OLS Un-corr= OLS on market participants only; not corrected for self-selection into market participation
[3]OLS corr=2nd stage of Heckman two step; corrected for self-selection into market participation
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1.3. Market participation in the Upper East Region

Figure shows that Upper East experienced the lowest rates with a minimum of 36% during 2012/2013. The rates have been declining since 1998/99 when the average market participation rate was about 68%. A possible explanation for this negative trend could be the change in production and marketing preferences of the farmers located in the area, towards perennial or longer gestation crops for which the market participation would maybe occur in the future. However, a closer look at the Upper East crop portfolio, suggests that farmers are not more involved in the production of perennial crops, such as mango or palm oil (Figure 1).

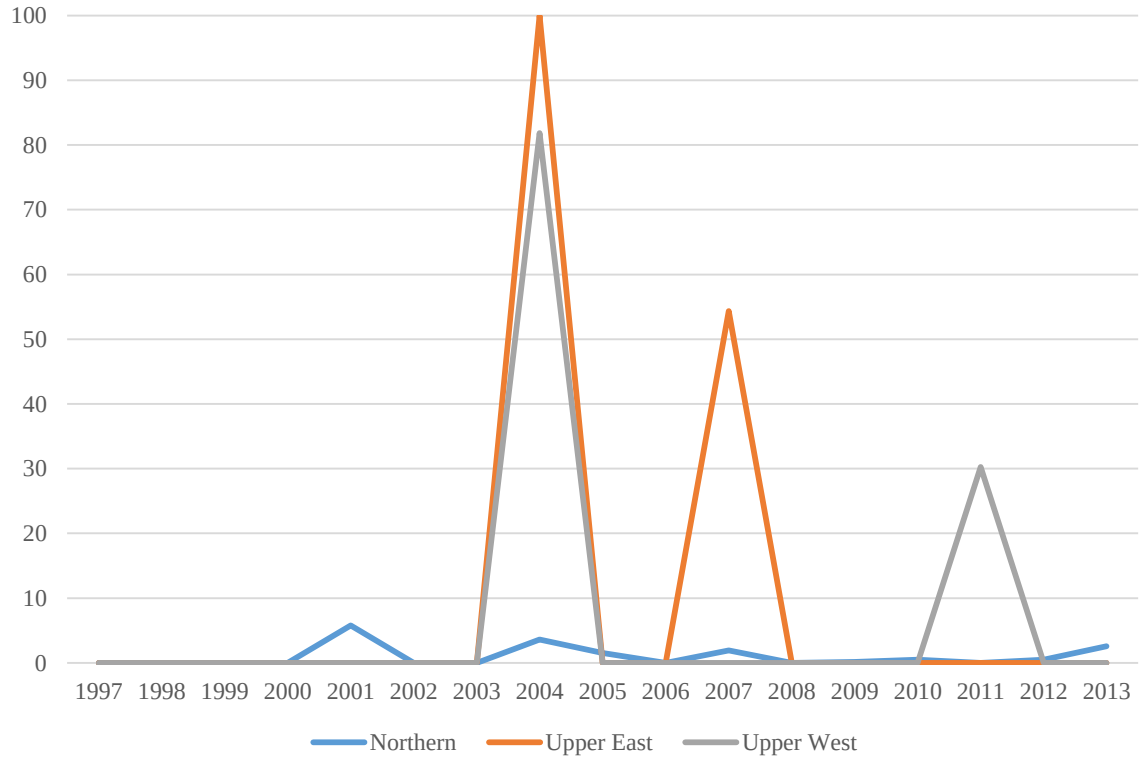
Figure 1 Upper East production and marketing choices across GLSS rounds



If production choice is not the main problem, then looking the drop in market participation rates could be increase in productivity of the occurrence of shocks and stressors in the region. According to the Agricultural Stress Index by FAO, the Upper East experienced the highest level of agricultural stress in 2004 (100%) and a milder, although still very high (above 50%), agricultural stress in 2007/08 Figure 2). Neighbouring regions, such as Upper West and Northern regions, seem to have experienced similar stressors in 2004, although at lower intensity, as in the case of

Upper West, or at a minimum intensity, as in the Northern region. The higher risk in agricultural production in this region might have pushed less productive farmers out of the market. If so, we would expect market participants to be better endowed after 2004 for this region. Figure 2 shows the average values of selected farm characteristics of market and non-market participants in Upper East across the three GLSS rounds. The results seem to support the idea that, indeed, market participants after 2004 (GLSS5) are better endowed than farmers in GLSS4. The difference, however, seems to lower in 2012 (GLSS6). For example, farm size, value of farm equipment and for access to credit are substantially higher in 2005/06 for market participants which could suggest that a higher threshold for market access.

Figure 2 Agricultural Stress Index, Northern Ghana



Source 4 FAO, 2014

Table 3 Farm endowment, Upper East Region

		Market participants			Non-Market participants		
		GLSS4 Mean	GLSS4 Mean	GLSS4 Mean	GLSS4 Mean	GLSS4 Mean	GLSS4 Mean
Farm labour	#	2.79	3.41	2.42	2.59	2.81	2.02
Farm size	Ha	2.79	12.30	3.13	2.01	1.71	2.65
Tractor	(0/1)	0.02	0.35	0.57	0.00	0.16	0.29
Value of farm equipment	GhC	0.00	60.62	116.63	0.00	36.15	72.73
Access to credit	(0/1)	0.17	0.16	0.28	0.14	0.09	0.25

Appendix 1.4. The estimation of the asset index

The Asset Index is constructed using the Multiple Correspondence Analysis (MCA). Previous studies (e.g. Traisac and Martin – Prevel, 2012[116]; Booysen et al., 2008[117]) have shown that MCA is more appropriate for the analysis of binary and categorical variables, than, for example, principal component analysis. The MCA, an extension of the simple correspondence analysis, allows to visualize and analyse the correlation between variables. The results are then used to predict an index using the first dimension of the correspondence matrix, under the condition that the first condition explains the highest possible cumulative variance of the outcome predictors used in the estimations of the index. If appropriately estimated, the results of MCA will produce a polarization between positive and negative predictors of the chosen outcome variable.

The asset index has been estimated separately for the three GLSS rounds and the results are shown below. The variables that have been used for the estimations are described in Table 4:

Table 4 MCA components

Variable	Values
Source of drinking water	1 river/stream/lake 2 unprotected well 3 protected well 4 borehole 5 public standpipe 6 Water truck or vendor 7 Indoor pipe or pumping
Source of light	1 solar/candle 2 kerosene/gas 3 electricity"
Type of toilet	1 bush 2 public toilet 3 bucket/kvip 4 pit/flush
Ownership of fridge	0 No 1 Yes
Ownership of a sewing machine	0 No 1 Yes
Ownership of stove.	0 No 1 Yes

The categorical variables have been re-coded in a way that higher values correspond to higher "valued" assets. For example, type of toilet is defined as follows: 1"bush" 2"public toilet" 3"bucket/kvip" 4"pit/flush"; light is defined as: 1"solar/candle" 2"kerosene/gas" 3"electricity" and so on. The dummy variables take the value of 1 if the asset (fridge, sewing machine or stove) is owned and 0 otherwise.

On average, the first dimension of the asset indices estimated explained almost 80% of the cumulative variance, which suggests that the indices are capturing well the

[116] Traissac, P. and Y. Martin-Prevel (2012). "Alternatives to principal components analysis to derive asset-based indices to measure socio-economic position in low- and middle-income countries: the case for multiple correspondence analysis". Int. J. Epidemiol. (2012) 41 (4):1207-1208.
[117] Booysen F. et al. (2008). "Using an asset index to assess trends in poverty in seven Sub-Saharan African countries", World Development, 36.

association between the selected variables. Because in all the three cases a higher value of the index corresponds with smaller endowments, the inverse of the index has been used for the analysis, to help with the interpretation, i.e. the higher the asset index, the more endowed is the household.

GLSS4

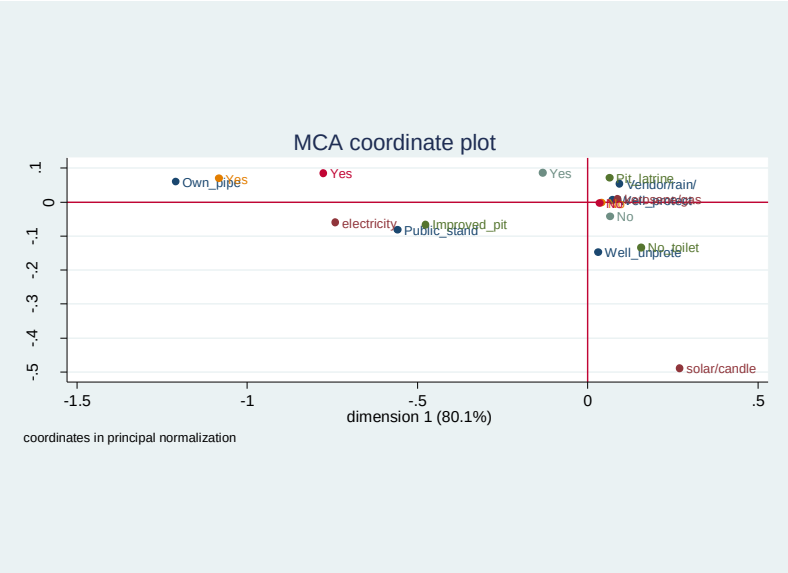
Multiple/Joint correspondence analysis
Number of obs = 3117
Total inertia = .0522961
Method: Burt/adjusted inertias
Number of axes = 2

Dimension	principal inertia	percent	cumul percent
Dim1	0.041871	80.07	80.07
Dim2	0.00303	5.79	85.86
Dim3	0.000405	0.78	86.63
Dim5	6.43E-05	0.12	86.76
Total	0.052296	100	

Statistics for column categories in principal normalization

	Overall			Dim 1			Dim 2		
	mass	quality	%inert	coord	sqcorr	contrib	coord	sqcorr	contrib
Water									
Vendor/rai~e	0.073	0.739	0.022	0.093	0.555	0.015	0.054	0.184	0.07
Well unpro~d	0.023	0.624	0.016	0.030	0.025	0.001	-0.147	0.599	0.167
Well prote~d	0.054	0.623	0.009	0.073	0.619	0.007	0.006	0.004	0.001
Public sta~e	0.013	0.798	0.097	-0.559	0.781	0.095	-0.082	0.017	0.028
Own pipe	0.004	0.905	0.113	-1.209	0.903	0.127	0.060	0.002	0.004
Light									
solar/candle	0	0.531	0.005	0.270	0.125	0.001	-0.488	0.406	0.038
kerosene/gas	0.148	0.846	0.026	0.088	0.837	0.027	0.009	0.008	0.004
electricity	0.018	0.848	0.222	-0.741	0.842	0.233	-0.060	0.006	0.021
Toilet									
No toilet	0.04	0.773	0.042	0.157	0.448	0.023	-0.133	0.325	0.233
Pit latrine	0.1	0.736	0.024	0.064	0.332	0.01	0.070	0.403	0.164
Improved p~t	0.027	0.888	0.132	-0.475	0.871	0.143	-0.066	0.017	0.038
Fridge									
No	0.161	0.908	0.006	0.041	0.904	0.006	-0.003	0.004	0
Yes	0.006	0.908	0.15	-1.083	0.904	0.169	0.069	0.004	0.01
Sewing m.									
No	0.112	0.914	0.014	0.065	0.639	0.011	-0.043	0.274	0.067
Yes	0.055	0.914	0.029	-0.133	0.639	0.023	0.087	0.274	0.137
Stove									
No	0.16	0.924	0.004	0.035	0.914	0.005	-0.004	0.011	0.001
Yes	0.007	0.924	0.09	-0.776	0.914	0.103	0.085	0.011	0.017

Figure 3 MCA Asset Index, GLSS 4



GLSS 5

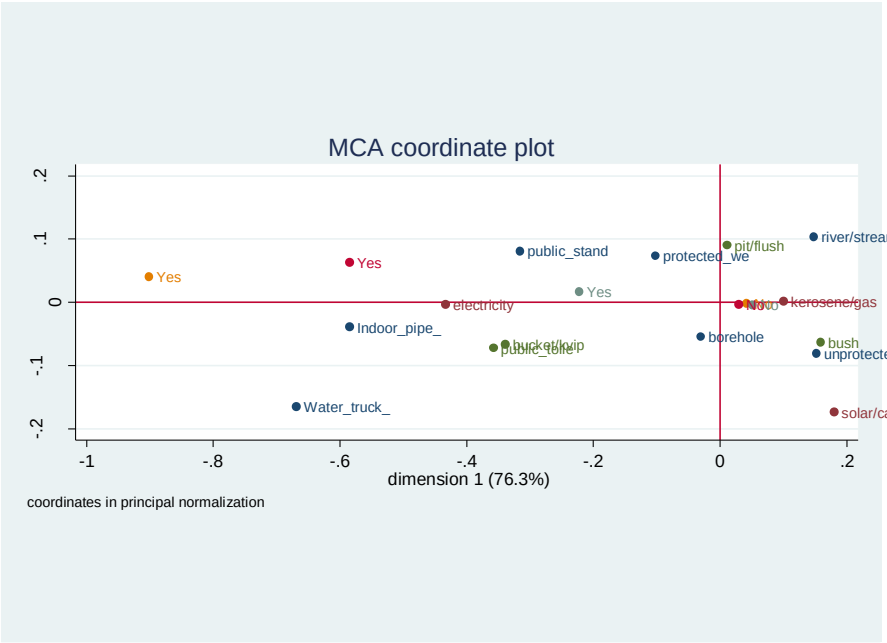
Multiple/Joint correspondence analysis — Number of obs = 4136
Total inertia = .0354055
Method: Burt/adjusted inertias — Number of axes = 2

Dimension	principal inertia	percent	cumul percent
Dim 1	0.027003	76.27	76.27
Dim 2	0.001992	5.63	81.89
Dim 3	0.000683	1.93	83.82
Dim 4	5.05E-05	0.14	83.96
Dim 5	2.22E-05	0.06	84.03
Dim 6	5.00E-06	0.01	84.04
Dim 7	2.57E-08	0	84.04
Total	0.035406	100	

Statistics for column categories in principal normalization

	Overall			Dim 1			Dim 2		
Categories	mass	quality	%inert	coord	sqcorr	contrib	coord	sqcorr	contrib
Water									
river/stre~e	0.044	0.766	0.053	0.148	0.513	0.036	0.104	0.253	0.24
unprotecte~l	0.01	0.58	0.014	0.152	0.452	0.008	-0.081	0.128	0.032
protected ~l	0.008	0.737	0.005	-0.102	0.484	0.003	0.073	0.253	0.023
borehole	0.093	0.623	0.016	-0.031	0.151	0.003	-0.054	0.473	0.138
public sta~e	0.009	0.783	0.035	-0.316	0.734	0.033	0.081	0.049	0.03
Water truc~r	0	0.388	0.007	-0.669	0.366	0.003	-0.165	0.022	0.003
Indoor pip~g	0.002	0.953	0.023	-0.585	0.948	0.029	-0.039	0.004	0.002
Light									
solar/candle	0.001	0.341	0.003	0.18	0.177	0.001	-0.174	0.164	0.009
kerosene/gas	0.135	0.829	0.046	0.1	0.828	0.05	0.002	0	0
electricity	0.031	0.826	0.201	-0.434	0.826	0.218	-0.003	0	0
Toilet									
bush	0.065	0.864	0.062	0.159	0.746	0.061	-0.063	0.117	0.129
public toi~t	0.019	0.785	0.089	-0.358	0.754	0.088	-0.072	0.031	0.049
bucket/kvip	0.013	0.837	0.053	-0.339	0.806	0.056	-0.066	0.031	0.029
pit/flush	0.07	0.599	0.027	0.011	0.009	0	0.090	0.59	0.287
Fridge									
No	0.159	0.837	0.009	0.042	0.836	0.01	-0.002	0.002	0
Yes	0.007	0.837	0.203	-0.901	0.836	0.223	0.041	0.002	0.006
Sewmach									
No	0.136	0.987	0.010	0.051	0.981	0.013	-0.004	0.006	0.001
Yes	0.031	0.987	0.044	-0.222	0.981	0.057	0.017	0.006	0.004
Stove									
No	0.159	0.848	0.005	0.029	0.838	0.005	-0.003	0.01	0.001
Yes	0.008	0.848	0.092	-0.585	0.838	0.101	0.063	0.01	0.016

Figure 4 MCA Asset Index, GLSS5



GLSS 6

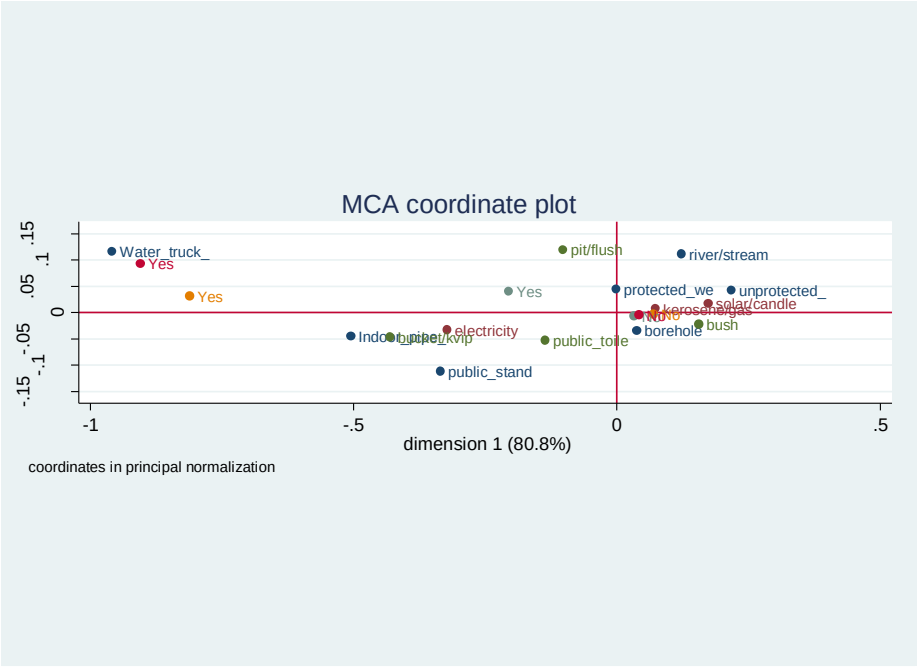
Multiple/Joint correspondence analysis — Number of obs = 7412
Total inertia = .0463324
Method: Burt/adjusted inertias — Number of axes = 2

Dimension	principal inertia	percent	cumul percent
Dim 1	0.037448	80.82	80.82
Dim 2	0.001683	3.63	84.46
Dim 3	0.000663	1.43	85.89
Dim 4	4.24E-05	0.09	85.98
Dim 5	9.91E-06	0.02	86
Dim 6	7.25E-06	0.02	86.02
Dim 7	4.14E-07	0	86.02
Total	0.046332	100	

Statistics for column categories in principal normalization

	Overall			Dim 1			Dim 2		
Categories	mass	quality	%inert	coord	sqcorr	contrib	coord	sqcorr	contrib
Water									
river/stre~e	0.035	0.598	0.035	0.122	0.327	0.014	0.112	0.272	0.261
unprotecte~l	0.009	0.77	0.013	0.218	0.743	0.012	0.042	0.028	0.01
protected ~l	0.004	0.119	0.001	-0.002	0	0.000	0.045	0.119	0.004
borehole	0.098	0.59	0.009	0.038	0.323	0.004	-0.034	0.266	0.068
public sta~e	0.012	0.727	0.045	-0.335	0.654	0.036	-0.112	0.073	0.09
Water truc~r	0.004	0.892	0.084	-0.959	0.879	0.091	0.116	0.013	0.03
Indoor pip~g	0.005	0.832	0.032	-0.506	0.825	0.032	-0.045	0.006	0.006
Light									
solar/candle	0.102	0.821	0.081	0.173	0.813	0.081	0.018	0.008	0.019
kerosene/gas	0.008	0.165	0.006	0.073	0.163	0.001	0.007	0.002	0
electricity	0.057	0.834	0.153	-0.322	0.825	0.157	-0.033	0.009	0.036
Toilet									
bush	0.082	0.894	0.049	0.155	0.876	0.053	-0.022	0.018	0.024
public toi~t	0.039	0.865	0.021	-0.136	0.753	0.019	-0.052	0.112	0.064
bucket/kvip	0.009	0.983	0.036	-0.431	0.971	0.044	-0.046	0.011	0.011
pit/flush	0.036	0.677	0.028	-0.102	0.286	0.010	0.119	0.391	0.304
Fridge									
No	0.154	0.87	0.018	0.069	0.869	0.019	-0.003	0.001	0.001
Yes	0.013	0.87	0.212	-0.811	0.869	0.228	0.031	0.001	0.008
Sewmach									
No	0.144	0.954	0.004	0.033	0.919	0.004	-0.006	0.036	0.004
Yes	0.023	0.954	0.023	-0.206	0.919	0.026	0.041	0.036	0.022
Stove									
No	0.159	0.913	0.007	0.042	0.903	0.007	-0.004	0.01	0.002
Yes	0.007	0.913	0.144	-0.905	0.903	0.161	0.093	0.01	0.038

Figure 5 MCA Asset Index, GLSS 6



Appendix 1.5. Additional estimations – Tobit and Craggit

Table 5 Tobit and Craggit

Dependent variable: HCI (0-100)		(14) Tobit	(15) Tobit	(16) Tobit	(17) Craggit	(17)	(18) Craggit	(18)	(19) Craggit	(19)
VARIABLES		HCI	HCI	HCI	Tier1	Tier2	Tier1	Tier2	Tier1	Tier2
Male head	(0/1)	10.62***	9.05***	8.94***	**0.43*** **	**3.81*** **	**0.37*** **	**2.91** **	**0.36*** **	**2.82** **
		(0.79)	(0.82)	(0.82)	(0.03)	(1.20)	(0.03)	(1.24)	(0.03)	(1.23)
Age head	Years	-0.06***	-0.05**	-0.04**	**-0.00*** **	-0.01	**-0.00*** **	-0.01	**-0.00*** **	-0.00
		(0.02)	(0.02)	(0.02)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)
Basic education	(0/1)	-1.91**	-1.89**	-1.73**	**-0.10*** **	0.28	**-0.10*** **	0.20	**-0.09*** **	0.33
		(0.78)	(0.78)	(0.78)	(0.03)	(1.11)	(0.03)	(1.11)	(0.03)	(1.11)
Higher education	(0/1)	-1.89*	-2.00**	-1.72*	**-0.15*** **	1.41	**-0.15*** **	1.24	**-0.15*** **	1.49
		(0.98)	(0.98)	(0.98)	(0.04)	(1.36)	(0.04)	(1.36)	(0.04)	(1.36)
Farm labour	# member of household who work on own farm	0.75***	0.62***	0.59***	**0.07*** **	**-1.11*** **	**0.06*** **	**-1.14*** **	**0.06*** **	**-1.17*** **
		(0.19)	(0.19)	(0.19)	(0.01)	(0.29)	(0.01)	(0.29)	(0.01)	(0.29)
Farm size	Hectares	0.02*	0.02*	0.02	0.00	**0.06*** **	0.00	**0.06*** **	0.00	**0.06*** **
		(0.01)	(0.01)	(0.01)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)
Land ownership	(0/1)	3.07***	2.92***	2.99***	0.01	**6.98*** **	0.01	**6.90*** **	0.01	**6.94*** **
		(0.65)	(0.65)	(0.65)	(0.03)	(0.95)	(0.03)	(0.95)	(0.03)	(0.95)
Livestock owned	#	-0.00	-0.00*	-0.00*	-0.00	-0.01	-0.00	-0.01	-0.00	-0.01
		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	-3.95***	-4.14***	-3.97***	**-0.19*** **	-0.40	**-0.20*** **	-0.54	**-0.19*** **	-0.40
		(0.69)	(0.69)	(0.69)	(0.03)	(1.02)	(0.03)	(1.02)	(0.03)	(1.02)
Food only producer	(0/1) - 1 if household produces only food crops; 0 otherwise	-13.13***	-13.35***	-13.24***	**-0.70*** **	**2.00* **	**-0.71*** **	**2.01* **	**-0.71*** **	**2.07* **
		(0.79)	(0.80)	(0.79)	(0.03)	(1.20)	(0.03)	(1.20)	(0.03)	(1.20)
Access to credit	(0/1)	1.43**	1.10*	1.03	**0.12*** **	-0.66	**0.10*** **	-0.79	**0.10*** **	-0.89
		(0.66)	(0.66)	(0.66)	(0.03)	(0.94)	(0.03)	(0.94)	(0.03)	(0.94)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	1.06	1.06	0.97	**0.25*** **	**-6.75*** **	**0.25*** **	**-6.68*** **	**0.25*** **	**-6.73*** **
		(0.73)	(0.73)	(0.73)	(0.03)	(1.04)	(0.03)	(1.04)	(0.03)	(1.04)
Radio	(0/1)		2.91***	2.90***			**0.08*** **	**3.07*** **	**0.08*** **	**3.05*** **
			(0.65)	(0.65)			(0.03)	(0.95)	(0.03)	(0.95)
Bicycle	(0/1)		4.18***	4.17***			**0.19*** **	0.89	**0.19*** **	0.91
			(0.75)	(0.75)			(0.03)	(1.09)	(0.03)	(1.09)
Distance to periodic market	(0/1) - 1 if distance is above the median; 0 otherwise			4.11***					**0.13*** **	**3.67*** **
				(0.63)					(0.03)	(0.92)
Distance to extension officer	(0/1) - 1 if distance is above the median; 0 otherwise			-1.75***					**-0.05** **	-1.37
				(0.63)					(0.03)	(0.92)
Sigma		34.71***	34.65***	34.60***		34.22***		34.19***		34.15***
		(0.25)	(0.25)	(0.25)		(0.43)		(0.42)		(0.42)
Region dummies	(0/1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	(0/1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Dependent variable: HCI (0-100)	(14)	(15)	(16)	(17)	(17)	(18)	(18)	(19)	(19)
	Tobit	Tobit	Tobit	Craggit		Craggit		Craggit	
VARIABLES	HCI	HCI	HCI	Tier1	Tier2	Tier1	Tier2	Tier1	Tier2
Observations	14,736	14,736	14,736	14,736	14,736	14,736	14,736	14,736	14,736
Left censorerd obs.	3736	3736	3736						
LR chi2	2542***	2601***	2643***	1919***		1964***		1983***	

Appendix 1.6. Market participation analysis: endogeneity checks

Table 6 Market participation determinants, endogenous variables

Dependent variable: Market participation (0/1)		(20) Probit	(21) Probit	(22) Probit	(23) Probit	(20) OLS	(21) OLS	(22) OLS	(23) OLS[2]
VARIABLES		mfx[1]	mfx[1]	mfx[1]	mfx[1]	coeff	coeff	coeff	coeff
Male head	(0/1)	0.13***	0.13***	0.12***	0.12***	1.62**	1.61**	1.62**	3.21***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.72)	(0.72)	(0.72)	(1.01)
Age head	Years	-0.00	-0.00*	-0.00	-0.00***	0.00	0.00	-0.00	-0.01
		(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)
Basic education	(0/1)	-0.02*	-0.01	-0.02*	-0.03***	0.05	0.06	0.09	IV
		(0.01)	(0.01)	(0.01)	(0.01)	(0.66)	(0.66)	(0.66)	
Higher education	(0/1)	-0.03**	-0.02**	-0.03***	-0.05***	1.06	1.09	1.22	IV
		(0.01)	(0.01)	(0.01)	(0.01)	(0.84)	(0.85)	(0.85)	
Farm labour	# member of household who work on own farm	0.02***	0.02***	0.02***	0.02***	-0.57***	-0.58***	-0.57***	-0.35*
		(0.00)	(0.00)	(0.00)	(0.00)	(0.15)	(0.15)	(0.15)	(0.20)
Farm size	Hectares	0.00	0.00	0.00	0.00	0.04**	0.04**	0.04**	0.04***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)
Land ownership	(0/1)	0.02***	0.02***	0.02***	0.00	3.60***	3.60***	3.60***	3.75***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.53)	(0.54)	(0.54)	(0.54)
Livestock	#	-0.00	-0.00	-0.00	-0.00	-0.00***	-0.00***	-0.00***	-0.00*
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Processing	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	0.08***	0.09***	0.09***	0.07***	-4.43***	-4.42***	-4.39***	-3.63***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.64)	(0.65)	(0.65)	(0.75)
Radio	(0/1) - 1 if household produces only food crops; 0 otherwise	0.03***	0.03***	0.03***	0.02***	1.69***	1.70***	1.72***	2.17***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.55)	(0.55)	(0.55)	(0.58)
Bicycle	(0/1)	0.04***	0.05***	0.04***	0.06***	0.54	0.55	0.58	IV
		(0.01)	(0.01)	(0.01)	(0.01)	(0.63)	(0.63)	(0.63)	
Distance to market	(0/1) - 1 if household processes any crop or fish; 0 otherwise	0.04***	0.04***	0.04***	0.04***	1.96***	1.95***	1.96***	2.36***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.54)	(0.54)	(0.54)	(0.59)
Distance to extension officer	(0/1)	-0.02**	-0.02**	-0.02**	-0.02**	-0.80	-0.80	-0.82	-1.01*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.53)	(0.53)	(0.53)	(0.55)
Access to non-farm income	(0/1)		-0.05***	-0.05***	-0.06***		-0.24	-0.16	-0.74
			(0.01)	(0.01)	(0.01)		(0.58)	(0.59)	(0.69)
Credit	(0/1) - 1 if distance is above the median; 0 otherwise			0.04***	0.03***			-0.64	-0.17
				(0.01)	(0.01)			(0.54)	(0.57)

Dependent variable: Market participation (0/1)		(20) Probit	(21) Probit	(22) Probit	(23) Probit	(20) OLS	(21) OLS	(22) OLS	(23) OLS[2]
VARIABLES		mfx[1]	mfx[1]	mfx[1]	mfx[1]	coeff	coeff	coeff	coeff
Food only production	(0/1) - 1 if distance is above the median; 0 otherwise				-0.21***				-1.22
					(0.01)				(1.46)
Region dummies	(0/1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	(0/1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		14736	14736	14736	14736	11000	11000	11000	14736
Censored obs									3736
Obs. P %		75	75	75	75				
Predicted obs %		77	77	77	77				
LR chi2		1622***	1656***	1682***	2205***				
R-squared		0.10	0.10	0.10	0.13	0.12	0.12	0.13	
Wald									1316**
Rho									7.98
Sigma									26.45

[1]Marginal effects are reported [2] Heckman corrected. Lambda== 7.98*

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.

Appendix 1.7. Market participation analysis, by survey year

Table 7 Market participation determinants estimated separately by survey year

Dependent variable Probit: Market participation (0/1) Dependent variable OLS: Commercialisation Index (0-100) VARIABLES		(24) GLSS4 Probit mfx[1]	 OLS un-corr[2]	 OLS corr[3]	(25) GLSS5 Probit mfx[1]	 OLS un-corr[2]	 OLS corr[3]	(26) GLSS6 Probit mfx[1]	 OLS un-corr[2]	 OLS corr[3]
Male head	(0/1)	0.09***	2.44*	1.15	0.09***	1.97	3.15*	0.12***	1.04	-0.05
		(0.02)	(1.35)	(1.84)	(0.02)	(1.34)	(1.68)	(0.02)	(1.09)	(1.39)
Age head	Years	-0.00	0.03	0.03	-0.00***	0.01	-0.00	-0.00**	-0.02	-0.01
		(0.00)	(0.04)	(0.04)	(0.00)	(0.03)	(0.03)	(0.00)	(0.03)	(0.03)
Basic education	(0/1)	-0.01	-0.96	-0.90	0.01	1.66	IV	-0.05***	-0.73	IV
		(0.02)	(1.12)	(1.17)	(0.02)	(1.21)		(0.02)	(1.06)	
Higher education	(0/1)	-0.03	0.04	0.35	-0.05	5.30**	4.24*	-0.06***	0.53	IV
		(0.03)	(2.01)	(2.13)	(0.03)	(2.38)	(2.26)	(0.02)	(1.06)	
Farm labour	# member of household who work on own farm	0.02***	-0.32	-0.67	0.03***	-0.48*	-0.32	0.01**	-0.56**	-0.64***
		(0.01)	(0.45)	(0.55)	(0.00)	(0.27)	(0.39)	(0.00)	(0.22)	(0.24)
Farm size	Hectares	0.01***	0.19*	0.15*	-0.00	0.02	0.02*	0.00***	0.18	0.17***
		(0.00)	(0.10)	(0.08)	(0.00)	(0.02)	(0.01)	(0.00)	(0.13)	(0.05)
Land ownership	(0/1)	0.08***	6.92***	5.73***	0.00	4.14***	4.23***	-0.03***	1.46*	1.74**
		(0.02)	(1.03)	(1.46)	(0.01)	(1.01)	(1.02)	(0.01)	(0.84)	(0.86)
Livestock	#	-0.00	-0.00***	-0.00*	0.16***	2.06	2.73	0.02**	-0.29	-0.38
		(0.00)	(0.00)	(0.00)	(0.05)	(2.12)	(2.55)	(0.01)	(0.70)	(0.71)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	0.02	0.82	0.63	-0.05***	-0.55	-0.84	-0.13***	-0.49	0.71
		(0.02)	(1.03)	(1.06)	(0.01)	(0.96)	(1.09)	(0.01)	(1.07)	(1.38)
Food only production	(0/1) - 1 if household produces only food crops; 0 otherwise	-0.21***	3.51**	7.02**	-0.23***	2.85**	1.07	-0.19***	-0.73	1.03
		(0.02)	(1.65)	(3.10)	(0.02)	(1.25)	(2.75)	(0.01)	(1.04)	(1.73)
Access to credit	(0/1)	0.05***	1.23	0.57	0.04***	-1.21	-0.87	0.02*	-0.39	-0.41
		(0.02)	(1.05)	(1.21)	(0.01)	(0.98)	(1.07)	(0.01)	(0.85)	(0.84)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	0.06**	-1.21	-2.03	0.04***	-3.68***	-3.34***	0.13***	-6.05***	-7.06***
		(0.02)	(1.54)	(1.60)	(0.02)	(1.19)	(1.28)	(0.01)	(0.95)	(1.21)
Radio	(0/1)	0.00	1.40	1.42	0.03**	1.64	2.10*	0.02**	1.44*	1.21
		(0.02)	(1.01)	(1.04)	(0.02)	(1.13)	(1.21)	(0.01)	(0.78)	(0.81)
Bicycle	(0/1)	0.04*	1.28		0.04**	0.15	IV	0.06***	0.05	IV
		(0.02)	(1.29)		(0.02)	(1.22)		(0.01)	(0.90)	
Distance to market	(0/1) - 1 if distance is above the median; 0 otherwise	0.01	-0.73	-0.93	-0.01	0.01	-0.16	0.08***	3.26***	2.55***
		(0.02)	(1.12)	(1.15)	(0.01)	(1.09)	(1.08)	(0.01)	(0.77)	(0.95)
Distance to extension officer	(0/1) - 1 if distance is above the median; 0 otherwise	0.05***	-2.57**	-3.25***	-0.01	0.13	0.05	-0.02*	1.04	1.24
		(0.02)	(1.05)	(1.20)	(0.01)	(1.06)	(1.06)	(0.01)	(0.78)	(0.80)
Lambda	(0/1)			-11.04			5.43			-6.80

Dependent variable Probit: Market participation (0/1) Dependent variable OLS: Commercialisation Index (0-100) VARIABLES		(24) GLSS4 Probit mfx[1]	 OLS un-corr[2]	 OLS corr[3]	(25) GLSS5 Probit mfx[1]	 OLS un-corr[2]	 OLS corr[3]	(26) GLSS6 Probit mfx[1]	 OLS un-corr[2]	 OLS corr[3]
				(9.26)			(7.71)			(5.34)
Region dummies	(0/1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yead dummies	(0/1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		3117	2374	3117	4172	3186	4172	7447	5440	7447
Censored observations				743			986			2007
Obs. P %		76			76			73		
Predicted obs %		79			80			77		
LR chi2		458***			645***			1426***		
R-squared		0.13	0.13		0.14	0.11		0.16	0.10	
Wald				270***			378***			455***
Rho				-0.46			0.21			-0.24
Sigma				23.84			25.18			27.76

[1]Marginal effects are presented
[2]OLS Un-corr= OLS on market participants only; not corrected for self-selection into market participation
[3]OLS corr=2nd stage of Heckman two step; corrected for self-selection into market participation
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1.8. Market participation analysis, with distance variables in Km

Table 8 Market participation determinants, distances in Km

Dependent variable Probit: Market participation (0/1)		(27)	(27)	(27)	(28)	(28)	(28)	(29)	(29)	(29)
Dependent variable OLS: Commercialisation Index (0-100)		Probit	OLS	OLS	Probit	OLS	OLS	Probit	OLS	OLS
VARIABLES		mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]
Male head	(0/1)	0.14***	2.19***	5.68***	0.12***	1.68**	3.61***	0.12***	1.68**	3.51***
		(0.01)	(0.70)	(1.23)	(0.01)	(0.72)	(1.02)	(0.01)	(0.72)	(1.02)
Age head	Years	-0.00***	-0.00	-0.02	-0.00***	-0.00	-0.01	-0.00***	-0.00	-0.01
		(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)
Basic education	(0/1)	-0.03***	0.14	IV	-0.03***	0.08	IV	-0.03***	0.09	IV
		(0.01)	(0.66)		(0.01)	(0.66)		(0.01)	(0.66)	
Higher education	(0/1)	-0.05***	1.26	IV	-0.05***	1.15	IV	-0.05***	1.14	IV
		(0.01)	(0.85)		(0.01)	(0.85)		(0.01)	(0.85)	
Farm labour	# member of household who work on own farm	0.02***	-0.53***	-0.03	0.02***	-0.54***	-0.27	0.02***	-0.54***	-0.28
		(0.00)	(0.15)	(0.23)	(0.00)	(0.15)	(0.20)	(0.00)	(0.15)	(0.20)
Farm size	Hectares	0.00	0.04**	0.04***	0.00	0.04**	0.04***	0.00	0.04**	0.04***
		(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)
Land ownership	(0/1)	0.00	3.72***	3.80***	0.00	3.67***	3.72***	0.00	3.68***	3.73***
		(0.01)	(0.54)	(0.57)	(0.01)	(0.54)	(0.55)	(0.01)	(0.54)	(0.55)
Livestock	#	-0.00	-0.00***	-0.00*	-0.00	-0.00***	-0.00*	-0.00	-0.00***	-0.00*
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	-0.06***	-0.13	-1.63**	-0.06***	-0.20	-1.03	-0.06***	-0.20	-0.97
		(0.01)	(0.58)	(0.78)	(0.01)	(0.58)	(0.70)	(0.01)	(0.58)	(0.70)
Food only production	(0/1) - 1 if household produces only food crops; 0 otherwise	-0.21***	1.09	-4.55**	-0.21***	1.09	-1.92	-0.21***	1.12	-1.71
		(0.01)	(0.71)	(1.84)	(0.01)	(0.71)	(1.48)	(0.01)	(0.71)	(1.47)
Access to credit	(0/1)	0.03***	-0.45	0.37	0.03***	-0.53	-0.04	0.03***	-0.56	-0.09
		(0.01)	(0.55)	(0.61)	(0.01)	(0.55)	(0.57)	(0.01)	(0.55)	(0.57)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	0.08***	-4.35***	-2.60***	0.08***	-4.32***	-3.38***	0.08***	-4.35***	-3.46***
		(0.01)	(0.65)	(0.85)	(0.01)	(0.65)	(0.76)	(0.01)	(0.65)	(0.76)
Radio	(0/1)				0.03***	1.75***	2.26***	0.03***	1.76***	2.24***
					(0.01)	(0.55)	(0.58)	(0.01)	(0.55)	(0.58)
Bicycle	(0/1)				0.06***	0.47	IV	0.06***	0.48	IV
					(0.01)	(0.63)		(0.01)	(0.63)	
Distance to market	Km							0.00	0.01	0.01
								(0.00)	(0.01)	(0.01)
Distance to extension officer	Km							-0.00	-0.01	-0.02
								(0.00)	(0.01)	(0.01)
Lambda				18.68***			10.21**			9.61**

Dependent variable Probit: Market participation (0/1)	(27)	(27)	(27)	(28)	(28)	(28)	(29)	(29)	(29)
Dependent variable OLS: Commercialisation Index (0-100)	Probit	OLS	OLS	Probit	OLS	OLS	Probit	OLS	OLS
VARIABLES	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]
			(5.63)			(4.42)			(4.40)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,736	11000	14,736	14,736	11000	14,736	14,736	11000	14,736
Censored observations			3736			3736			3736
Obs. P %	75			75			75		
Predicted obs %	77			77			77		
LR chi2	2121***			2180***			2182***		
R-squared	0.13	0.12		0.13	0.12		0.13	0.12	
Wald			1188***			1297***			1303***
Rho			0.65			0.38			0.36
Sigma			28.57			26.77			26.68

[1]Marginal effects are presented
[2]OLS Un-corr= OLS on market participants only; not corrected for self-selection into market participation
[3]OLS corr=2nd stage of Heckman two step; corrected for self-selection into market participation
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1.9. Market participation analysis, with “mean” distance thresholds

Table 9 Market participation determinants, "mean" distances thresholds

Dependent variable Probit: Market participation (0/1)		(30)	(30)	(30)	(31)	(31)	(31)	(32)	(32)	(32)
Dependent variable OLS: Commercialisation Index (0-100)		Probit	OLS	OLS	Probit	OLS	OLS	Probit	OLS	OLS
VARIABLES		mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]
Male head	(0/1)	0.14***	2.19***	5.68***	0.12***	1.68**	3.61***	0.12***	1.67**	3.27***
		(0.01)	(0.70)	(1.23)	(0.01)	(0.72)	(1.02)	(0.01)	(0.72)	(1.02)
Age head	Years	-0.00***	-0.00	-0.02	-0.00***	-0.00	-0.01	-0.00***	-0.00	-0.01
		(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)
Basic education	(0/1)	-0.03***	0.14	IV	-0.03***	0.08	IV	-0.03***	0.10	IV
		(0.01)	(0.66)		(0.01)	(0.66)		(0.01)	(0.66)	
Higher education	(0/1)	-0.05***	1.26	IV	-0.05***	1.15	IV	-0.05***	1.17	IV
		(0.01)	(0.85)		(0.01)	(0.85)		(0.01)	(0.85)	
Farm labour	# member of household who work on own farm	0.02***	-0.53***	-0.03	0.02***	-0.54***	-0.27	0.02***	-0.54***	-0.32
		(0.00)	(0.15)	(0.23)	(0.00)	(0.15)	(0.20)	(0.00)	(0.15)	(0.20)
Farm size	Hectares	0.00	0.04**	0.04***	0.00	0.04**	0.04***	0.00	0.04**	0.04***
		(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)
Land ownership	(0/1)	0.00	3.72***	3.80***	0.00	3.67***	3.72***	0.00	3.65***	3.69***
		(0.01)	(0.54)	(0.57)	(0.01)	(0.54)	(0.55)	(0.01)	(0.54)	(0.54)
Livestock	#	-0.00	-0.00***	-0.00*	-0.00	-0.00***	-0.00*	-0.00	-0.00***	-0.00*
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	-0.06***	-0.13	-1.63**	-0.06***	-0.20	-1.03	-0.06***	-0.19	-0.83
		(0.01)	(0.58)	(0.78)	(0.01)	(0.58)	(0.70)	(0.01)	(0.59)	(0.70)
Food only production	(0/1) - 1 if household produces only food crops; 0 otherwise	-0.21***	1.09	-4.55**	-0.21***	1.09	-1.92	-0.21***	1.11	-1.32
		(0.01)	(0.71)	(1.84)	(0.01)	(0.71)	(1.48)	(0.01)	(0.71)	(1.48)
Access to credit	(0/1)	0.03***	-0.45	0.37	0.03***	-0.53	-0.04	0.03***	-0.55	-0.12
		(0.01)	(0.55)	(0.61)	(0.01)	(0.55)	(0.57)	(0.01)	(0.55)	(0.57)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	0.08***	-4.35***	-2.60***	0.08***	-4.32***	-3.38***	0.08***	-4.30***	-3.54***
		(0.01)	(0.65)	(0.85)	(0.01)	(0.65)	(0.76)	(0.01)	(0.65)	(0.76)
Radio	(0/1)				0.03***	1.75***	2.26***	0.02***	1.75***	2.18***
					(0.01)	(0.55)	(0.58)	(0.01)	(0.55)	(0.58)
Bicycle	(0/1)				0.06***	0.47	IV	0.06***	0.48	IV
					(0.01)	(0.63)		(0.01)	(0.63)	
Distance to market	(0/1) - 1 if distance is above the *mean*; 0 otherwise							0.03***	0.88	1.20*
								(0.01)	(0.61)	(0.63)

Dependent variable Probit: Market participation (0/1)		(30)	(30)	(30)	(31)	(31)	(31)	(32)	(32)	(32)
Dependent variable OLS: Commercialisation Index (0-100)		Probit	OLS	OLS	Probit	OLS	OLS	Probit	OLS	OLS
VARIABLES		mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]
Distance to extension officer	(0/1) - 1 if distance is above the *mean*; 0 otherwise							-0.00	-0.32	-0.33
								(0.01)	(0.56)	(0.57)
Lambda				18.68***			10.21**			8.27*
				(5.63)			(4.42)			(4.44)
Region dummies		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		14736	11000	14736	14736	11000	14736	14736	11000	14736
Censored observations				3736			3736			3736
Obs. P %		75			75			75		
Predicted obs %		77			77			77		
LR chi2		2121***			2180***			2192***		
R-squared		0.13	0.13		0.13	0.12		0.13	0.12	
Wald				1187***			1297***			1308***
Rho				0.65			0.38			0.31
Sigma				28.56			26.77			26.50

[1]Marginal effects are presented
[2]OLS Un-corr= OLS on market participants only; not corrected for self-selection into market participation
[3]OLS corr=2nd stage of Heckman two step; corrected for self-selection into market participation
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1.10. Market participation analysis, with distance variables in Km and no extreme values of distance to market

Table 10 Market participation determinants, no extreme values of distance to market

Dependent variable Probit: Market participation (0/1)		(33)	(33)	(33)	(34)	(34)	(34)	(35)	(35)	(35)
Dependent variable OLS: Commercialisation Index (0-100)		Probit	OLS	OLS	Probit	OLS	OLS	Probit	OLS	OLS
VARIABLES		mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]
Male head	(0/1)	0.14***	2.19***	5.68***	0.12***	1.68**	3.61***	0.12***	1.69**	3.47***
		(0.01)	(0.70)	(1.23)	(0.01)	(0.72)	(1.02)	(0.01)	(0.72)	(1.02)
Age head	Years	-0.00***	-0.00	-0.02	-0.00***	-0.00	-0.01	-0.00***	-0.00	-0.01
		(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)
Basic education	(0/1)	-0.03***	0.14	IV	-0.03***	0.08	IV	-0.03***	0.08	IV
		(0.01)	(0.66)		(0.01)	(0.66)		(0.01)	(0.66)	
Farm labour	# member of household who work on own farm	-0.05***	1.26	IV	-0.05***	1.15	IV	-0.05***	1.16	IV
		(0.01)	(0.85)		(0.01)	(0.85)		(0.01)	(0.85)	
Farm size	Hectares	0.02***	-0.53***	-0.03	0.02***	-0.54***	-0.27	0.02***	-0.53***	-0.28
		(0.00)	(0.15)	(0.23)	(0.00)	(0.15)	(0.20)	(0.00)	(0.15)	(0.20)
Land ownership	(0/1)	0.00	0.04**	0.04***	0.00	0.04**	0.04***	0.00	0.04**	0.04***
		(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)
Livestock	#	0.00	3.72***	3.80***	0.00	3.67***	3.72***	0.00	3.64***	3.69***
		(0.01)	(0.54)	(0.57)	(0.01)	(0.54)	(0.55)	(0.01)	(0.54)	(0.55)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	-0.00	-0.00***	-0.00*	-0.00	-0.00***	-0.00*	-0.00	-0.00***	-0.00*
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Food only production	(0/1) - 1 if household produces only food crops; 0 otherwise	-0.06***	-0.13	-1.63**	-0.06***	-0.20	-1.03	-0.06***	-0.18	-0.91
		(0.01)	(0.58)	(0.78)	(0.01)	(0.58)	(0.70)	(0.01)	(0.58)	(0.70)
Access to credit	(0/1)	-0.21***	1.09	-4.55**	-0.21***	1.09	-1.92	-0.21***	1.14	-1.59
		(0.01)	(0.71)	(1.84)	(0.01)	(0.71)	(1.48)	(0.01)	(0.71)	(1.47)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	0.03***	-0.45	0.37	0.03***	-0.53	-0.04	0.03***	-0.55	-0.09
		(0.01)	(0.55)	(0.61)	(0.01)	(0.55)	(0.57)	(0.01)	(0.55)	(0.57)
Radio	(0/1)				0.03***	1.75***	2.26***	0.03***	1.77***	2.24***
					(0.01)	(0.55)	(0.58)	(0.01)	(0.55)	(0.58)
Bicycle	(0/1)				0.06***	0.47	IV	0.06***	0.50	IV
					(0.01)	(0.63)		(0.01)	(0.63)	
Distance to market	Km, *no extreme values*[4]							0.00*	0.03**	0.03**
								(0.00)	(0.01)	(0.01)
Distance to extension officer	Km							-0.00**	-0.02**	-0.03**
								(0.00)	(0.01)	(0.01)
Lambda				18.68***			10.21**			9.30**

Dependent variable Probit: Market participation (0/1)	(33)	(33)	(33)	(34)	(34)	(34)	(35)	(35)	(35)
Dependent variable OLS: Commercialisation Index (0-100)	Probit	OLS	OLS	Probit	OLS	OLS	Probit	OLS	OLS
VARIABLES	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]
			(5.63)			(4.42)			(4.40)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,736	11000	14,736	14,736	11000	14,736	14,736	11000	14,736
Censored observations			3736			3736			3736
Obs. P %	75			75			75		
Predicted obs %	77			77			77		
LR chi2	2121***			2179***			2185***		
R-squared	0.13	0.12		0.13	0.12		0.13	0.12	
Wald			1187***			1297***			1307***
Rho			0.65			0.38			0.35
Sigma			28.58			26.77			26.63

[1]Marginal effects are presented
[2]OLS Un-corr= OLS on market participants only; not corrected for self-selection into market participation
[3]OLS corr=2nd stage of Heckman two step; corrected for self-selection into market participation
[4] Extreme values have been replaced with average values of each round of GLSS.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1.11. Maize Market participation analysis

Table 11 Determinants of market participation, maize only producers

Maize producers only		(36) Probit	(36) OLS	(36) OLS	(37) Probit	(37) OLS	(37) OLS	(38) Probit	(38) OLS	(38) OLS
VARIABLES		mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]
Male head	(0/1)	**0.118*** **	**3.262*** **	1.666	**0.100*** **	**2.883*** **	**2.106** **	**0.099*** **	**2.829*** **	**1.844***
		(0.011)	(0.750)	(1.114)	(0.011)	(0.770)	(1.006)	(0.011)	(0.769)	(1.005)
Age head	Years	**-0.001*** **	-0.020	-0.014	**-0.001** **	-0.018	-0.016	-0.001**	-0.015	-0.012
		(0.000)	(0.019)	(0.019)	(0.000)	(0.019)	(0.018)	(0.000)	(0.019)	(0.018)
Basic education	(0/1)	**-0.021** **	0.362		**-0.019***	0.275		**-0.017***	0.358	
		(0.010)	(0.690)		(0.010)	(0.692)		(0.010)	(0.692)	
Higher education	(0/1)	**-0.042*** **	0.974		**-0.041*** **	0.852		**-0.038*** **	1.062	
		(0.013)	(0.909)		(0.013)	(0.912)		(0.013)	(0.913)	
Farm labour	# member of household who work on own farm	**0.013*** **	**-0.532*** **	**-0.770*** **	**0.012*** **	**-0.536*** **	**-0.666*** **	**0.012*** **	**-0.554*** **	**-0.716*** **
		(0.002)	(0.158)	(0.199)	(0.002)	(0.159)	(0.188)	(0.002)	(0.158)	(0.188)
Farm size	Hectares	**0.005*** **	**0.040** **	**0.034*** **	**0.004*** **	**0.040** **	**0.036*** **	**0.004*** **	**0.040** **	**0.036*** **
		(0.001)	(0.020)	(0.013)	(0.001)	(0.019)	(0.012)	(0.001)	(0.019)	(0.013)
Land ownership	(0/1)	-0.006	**3.322*** **	**3.379*** **	-0.007	**3.295*** **	**3.338*** **	-0.006	**3.299*** **	**3.346*** **
		(0.008)	(0.569)	(0.580)	(0.008)	(0.569)	(0.571)	(0.008)	(0.568)	(0.573)
Livestock	#	-0.000	**-0.003*** **	-0.003	-0.000	**-0.003*** **	-0.003	-0.000	**-0.003*** **	-0.003
		(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	**-0.059*** **	0.044	0.999	**-0.061*** **	-0.024	0.517	-0.060***	0.064	0.733
		(0.009)	(0.618)	(0.762)	(0.009)	(0.618)	(0.724)	(0.009)	(0.619)	(0.721)
Food only production	(0/1) - 1 if household produces only food crops; 0 otherwise	**-0.166*** **	1.110	**3.712** **	**-0.169*** **	1.161	**2.537** **	**-0.168*** **	1.188	**2.933** **
		(0.010)	(0.742)	(1.451)	(0.010)	(0.744)	(1.274)	(0.010)	(0.744)	(1.269)
Access to credit	(0/1)	**0.038*** **	0.132	-0.299	**0.035*** **	0.091	-0.108	**0.034*** **	0.033	-0.216
		(0.008)	(0.574)	(0.630)	(0.008)	(0.574)	(0.606)	(0.008)	(0.574)	(0.607)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	**0.068*** **	**-2.836*** **	**-3.739*** **	**0.067*** **	**-2.826*** **	**-3.316*** **	**0.066*** **	**-2.844*** **	**-3.457*** **
		(0.010)	(0.702)	(0.807)	(0.010)	(0.703)	(0.766)	(0.010)	(0.704)	(0.765)
Radio	(0/1)				**0.017** **	**1.638*** **	**1.473** **	**0.017** **	**1.622*** **	**1.413** **
					(0.008)	(0.576)	(0.593)	(0.008)	(0.576)	(0.595)
Bicycle	(0/1)				**0.051*** **	0.029		**0.051*** **	0.046	
					(0.009)	(0.678)		(0.009)	(0.677)	

Maize producers only		(36) Probit	(36) OLS	(36) OLS	(37) Probit	(37) OLS	(37) OLS	(38) Probit	(38) OLS	(38) OLS
VARIABLES		mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]	mfx[1]	un-corr[2]	corr[3]
Distance to market	(0/1) - 1 if distance is above the median; 0 otherwise							**0.035*** **	**2.487*** **	**2.063*** **
								(0.008)	(0.570)	(0.612)
Distance to extension officer	(0/1) - 1 if distance is above the median; 0 otherwise							**-0.018** **	-0.569	-0.366
								(0.008)	(0.564)	(0.582)
Lambda				**-10.707** **			-5.795			**-7.370***
				(5.071)			(4.331)			(4.317)
Region dummies		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		12,156	9,386	12156	12,156	9,386	12156	12,156	9,386	12156
Censored observations				2770			2770			2770
Obs. P %		77			77			77		
Predicted obs %		81			81			81		
LR chi2		1678.66***			1717.45***			1738.93***		
R-squared		0.1287	0.093		0.1316	0.094		0.1333	0.096	
Wald				749.97***			783.58***			784***
Rho				-0.408			-0.226			-0.286
Sigma				26.23			25.63			25.75

[1]Marginal effects are presented
[2]OLS Un-corr= OLS on market participants only; not corrected for self-selection into market participation
[3]OLS corr=2nd stage of Heckman two step; corrected for self-selection into market participation
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12 MNL - market participation for maize producers

Base: Non seller Households	(39)	(39)	(40)	(40)	(41)	(41)
VARIABLES	Market trader	Farm gate	Market trader	Farm gate	Market trader	Farm gate
Male head	0.695***	0.477***	0.610***	0.471***	0.603***	0.465***
	(0.069)	(0.088)	(0.071)	(0.090)	(0.071)	(0.091)
Age head	-0.008***	-0.003	-0.007***	-0.003	-0.007***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Basic education	-0.108	-0.088	-0.101	-0.100	-0.093	-0.085
	(0.070)	(0.089)	(0.070)	(0.089)	(0.070)	(0.090)
Higher education	-0.313***	-0.079	-0.313***	-0.094	-0.299***	-0.061
	(0.089)	(0.112)	(0.089)	(0.112)	(0.090)	(0.113)
Farm labour	0.040**	0.080***	0.034*	0.081***	0.035*	0.080***
	(0.018)	(0.024)	(0.018)	(0.024)	(0.018)	(0.024)
Farm size	0.090***	0.090***	0.086***	0.087***	0.085***	0.085***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Land ownership	-0.050	-0.156**	-0.062	-0.160**	-0.055	-0.156**
	(0.058)	(0.074)	(0.059)	(0.075)	(0.059)	(0.075)
Livestock	-0.000	-0.007	-0.000	-0.001	-0.000	-0.001
	(0.000)	(0.093)	(0.000)	(0.006)	(0.000)	(0.007)
Access to non-farm income	-0.364***	-0.400***	-0.372***	-0.402***	-0.367***	-0.395***
	(0.061)	(0.079)	(0.061)	(0.080)	(0.061)	(0.080)
Food only production	-0.796***	-1.036***	-0.811***	-1.029***	-0.809***	-1.030***
	(0.068)	(0.089)	(0.068)	(0.089)	(0.068)	(0.090)
Access to credit	0.199***	0.209***	0.184***	0.210***	0.188***	0.204***
	(0.060)	(0.077)	(0.061)	(0.077)	(0.061)	(0.077)
Processing	0.330***	0.439***	0.330***	0.439***	0.326***	0.431***
	(0.067)	(0.087)	(0.067)	(0.087)	(0.068)	(0.087)
Crop portfolio size	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Radio			0.118**	0.104	0.118**	0.106
			(0.057)	(0.075)	(0.057)	(0.075)
Bicycle			0.299***	-0.092	0.302***	-0.093
			(0.068)	(0.090)	(0.068)	(0.091)
Distance to market					0.168***	0.487***
					(0.057)	(0.074)
Distance to extension officer					-0.041	-0.225***
					(0.057)	(0.075)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.106***	-2.571***	-1.292***	-2.546***	-1.329***	-2.627***
	(0.176)	(0.235)	(0.180)	(0.239)	(0.183)	(0.243)
Observations	8,741	8,741	8,741	8,741	8,741	8,741

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1.12. An analysis of market participation by farm size –

Farm size has been found quite important in the analysis of market participation in this analysis and in previous studies. In order to understand whether there is any difference in the determinants of the decisions to participate in the market I also estimate the models of market participation separately for small and big farmers. I defined small farmers as those households with a farm size smaller than the median and bigger farmers those households with a land holding bigger than the median farm size.

The results in Table 13 show that the majority of the determinants identified in the main estimations in Table 3 and Table 4 are relevant regardless of the farm size. However, some discrepancies compared to the analysis of the whole sample can be pointed out. For example, the decision to sell produce in the market for small farmers is not affected by the size of farm labour, or ownership of radio and distance to extension officers as observed in the whole sample. Instead, a bigger relevance in this decision is exerted by the size of the farm. Among small farmers, the difference in the size of land holding affects considerably the probability to participate in the market. Conversely, land ownership is negatively associated with market participation for both small and bigger farmers. Compared to small farmers, the decision to participate for households with a bigger land holding is also affected by the size of livestock herd and by access to credit, suggesting that these alternative sources for cash income might complement market participation. On the other hand, the decision of how much to sell for small farmers is positively associated with food only production suggesting that food crops might foster commercialisation as well as other traditional cash crops, while for big farmers this decision is mainly associated with low family labour, land ownership, low size of the herd and no processing.

Finally, the association between remoteness and market participation is once again positive and significant, although it is found not relevant in the decision of the extent of market participation for small farmers.

Table 13 Determinants of market participation, by farm size

Dependent variable:		6)	(6)	(7)	(7)
Market participation (0/1)		Small	Small	Large	Large
HCI (0-100)		Probit	OLS	Probit	OLS
VARIABLES		mfx	coeff	*coeff** [118]	coeff
Male head	(0/1)	**0.06*** **	-0.74	***0.376*** **	0.635
		(0.01)	(0.97)	*(0.060)*	(1.143)
Age head	Years	**-0.00*** **	-0.02	*-0.001*	-0.015
		(0.00)	(0.03)	*(0.001)*	(0.023)
Basic education	(0/1)	**-0.03***	0.35	*-0.062*	0.217
		(0.02)	(0.97)	*(0.054)*	(0.890)
Higher education	(0/1)	**-0.05*** **	0.87	*-0.045*	1.781
		(0.02)	(1.26)	*(0.069)*	(1.145)
Farm labour	# member of household who work on own farm	0.01	**-1.53*** **	***0.032*** **	**-0.463*** **
		(0.00)	(0.32)	*(0.012)*	(0.173)
Farm size	Hectares	**0.15*** **	**2.92*** **	*-0.001*	0.023
		(0.01)	(0.68)	*(0.000)*	(0.015)
Land ownership	(0/1)	-0.02*	**2.55*** **	***-0.140*** **	**3.039*** **
		(0.01)	(0.79)	*(0.046)*	(0.737)
Livestock owned	#	-0.00	0.70	***0.782*** **	**-0.003*** **
		(0.02)	(2.24)	*(0.118)*	(0.000)
Access to non-farm income	(0/1) - 1 if household has access to self-employment non-farm income; 0 otherwise	**-0.06*** **	0.11	***-0.230*** **	-0.242
		(0.01)	(0.84)	*(0.046)*	(0.802)
Food only producer	(0/1) - 1 if household produces only food crops; 0 otherwise	**-0.21*** **	**3.83*** **	***-0.700*** **	0.063
		(0.02)	(0.97)	*(0.058)*	(1.050)
Access to credit	(0/1)	0.02	-0.86	*0.120***	-1.046
		(0.01)	(0.81)	*(0.046)*	(0.727)
Processing	(0/1) - 1 if household processes any crop or fish; 0 otherwise	**0.07*** **	**-4.63*** **	***0.287*** **	**-4.597*** **
		(0.01)	(0.96)	*(0.050)*	(0.867)
Radio	(0/1)	0.01	1.57*	*0.050*	0.867
		(0.01)	(0.81)	*(0.043)*	(0.730)
Bicycle	(0/1)	**0.04*** **	0.63	***0.091****	-0.547
		(0.02)	(0.99)	*(0.049)*	(0.828)
Distance to periodic market	(0/1) - 1 if distance is above the median; 0 otherwise	**0.03*** **	0.84	***0.163*** **	**2.568*** **
		(0.01)	(0.79)	*(0.043)*	(0.733)
Distance to extension officer	(0/1) - 1 if distance is above the median; 0 otherwise	0.01	-0.86	***-0.176*** **	-1.088
		(0.01)	(0.78)	*(0.042)*	(0.722)
Region dummies	(0/1)	Yes	Yes	Yes	Yes
Year dummies	(0/1)	Yes	Yes	Yes	Yes
Observations		7,650	4,929	7,086	6,071
Pseudo/R-squared		0.12	0.13	0.14	0.13
LR chi2		1218.87***		812.37***	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[118] For this estimation I report coefficients as the estimation of marginal effect produced very low values.

CHAPTER 3: APPENDICES

Appendix 3.1. Selected multicollinearity tests

Household level variables

Test n.1

Collinearity Diagnostics

	VIF	VIF	Tolerance	R-Squared
Rel. with input suppliers	5.71	2.39	0.1751	0.8249
Rel. with credit providers	47.1	6.86	0.0212	0.9788
Rel. with extension officers	25.02	5	0.04	0.96
Rel. with development agencies	37.56	6.13	0.0266	0.9734
Rel. with NGOs	55.93	7.48	0.0179	0.9821
Rel. other farmers	2.32	1.52	0.4305	0.5695
Trust input suppliers	6.07	2.46	0.1646	0.8354
Trust credit providers	48.33	6.95	0.0207	0.9793
Trust extension officers	26.31	5.13	0.038	0.962
Trust development agencies	39.46	6.28	0.0253	0.9747
Trust NGOs	55.97	7.48	0.0179	0.9821
Trust other farmers	2.56	1.6	0.3906	0.6094

Mean VIF 29.36

	Eigenval	Cond Index
1	8.6243	1
2	1.5554	2.3548
3	1.2509	2.6258
4	0.8909	3.1113
5	0.4866	4.21
6	0.1283	8.1995
7	0.0189	21.3673
8	0.012	26.8499
9	0.0097	29.8149
10	0.0069	35.3725
11	0.0065	36.5001
12	0.0063	37.084
13	0.0035	49.8487
Condition Number	49.8487	

Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0000

Test n.2

Collinearity Diagnostics

	VIF	VIF	Tolerance	R- Squared
Rel. with input suppliers	5.72	2.39	0.1747	0.8253
Rel. with credit providers	48.8	6.99	0.0205	0.9795
Rel. with extension officers	23.69	4.87	0.0422	0.9578
Rel. with development agencies	62.26	7.89	0.0161	0.9839
Rel. with NGOs	53.89	7.34	0.0186	0.9814
Rel. with FO	51.89	7.2	0.0193	0.9807
Trust input suppliers	6.07	2.46	0.1646	0.8354
Trust credit providers	49.76	7.05	0.0201	0.9799
Trust extension officers	25.65	5.06	0.039	0.961
Trust FO	53.69	7.33	0.0186	0.9814
Trust development agencies	64.24	8.02	0.0156	0.9844
Trust NGOs	54.29	7.37	0.0184	0.9816

Mean VIF 41.66

	Eigenval	Cond Index
1	8.3626	1
2	1.5432	2.3279
3	1.119	2.7337
4	1.0688	2.7971
5	0.4526	4.2986
6	0.3296	5.0369
7	0.0668	11.1854
8	0.0226	19.2313
9	0.011	27.6202
10	0.0072	33.9814
11	0.0069	34.72
12	0.0063	36.3486
13	0.0032	51.0461

Condition Number 51.0461
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0000

Appendix 3.2. PCA Social Capital Indexes

Structural bridging social capital index

Principal components/correlation — Number of obs = 305; Number of comp. = 2; Trace = 5

Rotation: (unrotated = principal) Rho = 0.6001

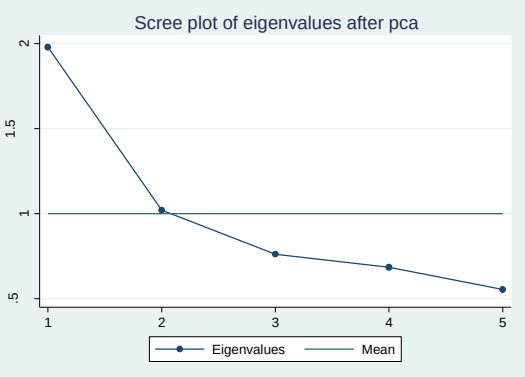
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.97972	0.958951	0.3959	0.3959
Comp2	1.02076	0.259929	0.2042	0.6001
Comp3	0.760835	0.0762946	0.1522	0.7523
Comp4	0.684541	0.130397	0.1369	0.8892
Comp5	0.554144	.	0.1108	1

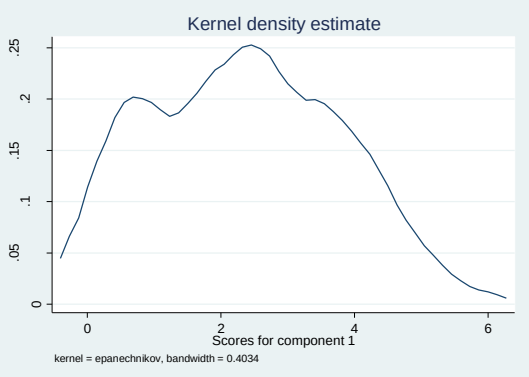
Principal components (eigenvectors)

Variable	Comp1	Comp2	Unexplained
Rel. with input suppliers	0.4842	-0.3906	0.3802
Rel. with credit providers	0.3069	0.7647	0.2167
Rel. with extension officers	0.5355	-0.1101	0.4199
Rel. with development agencies	0.4583	0.3529	0.457
Rel. with NGOs	0.4178	-0.3551	0.5257

Kaiser-Meyer-Olkin measure of sampling adequacy

Variable	kmo
Rel. with input suppliers	0.6631
Rel. with credit providers	0.6472
Rel. with extension officers	0.6714
Rel. with development agencies	0.7129
Rel. with NGOs	0.7535
Overall	0.6870





Test for univariate normality

Variable	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
Rel. with input suppliers	0.0000	0.0473	17.56	0.0002
Rel. with credit providers	0.0000	0.0032	66.48	0.0000
Rel. with extension officers	0.2066	.	.	.
Rel. with development agencies	0.0000	0.0000	.	0.0000
Rel. with NGOs	0.0000	0.3351	41.43	0.0000

Doornik-Hansen test for bivariate normality

Pair of variables		chi2	Df	Prob>chi2
relinput~rhh	relcredi~rhh	925.89	4	0.0000
	relexten~rhh	105.86	4	0.0000
	reldevel~rhh	322.40	4	0.0000
	relngos_~rhh	482.49	4	0.0000
relcredi~rhh	relexten~rhh	892.05	4	0.0000
	reldevel~rhh	1010.83	4	0.0000

Pair of variables		chi2	Df	Prob>chi2
relngos_~rhh		1412.77	4	0.0000
relexten~rhh	reldevel~rhh	300.24	4	0.0000
relngos_~rhh		526.91	4	0.0000
reldevel~rhh	relngos_~rhh	769.48	4	0.0000

Test for multivariate normality

Mardia mSkewness =	6.544799	chi2(35) = 337.068	Prob>chi2 = 0.0000
Mardia mKurtosis =	34.53275	chi2(1) = 0.238	Prob>chi2 = 0.6258
Henze-Zirkler =	13.59917	chi2(1) = 1661.269	Prob>chi2 = 0.0000
Doornik-Hansen		chi2(10) = 1317.926	Prob>chi2 = 0.0000

Structural bonding social capital index

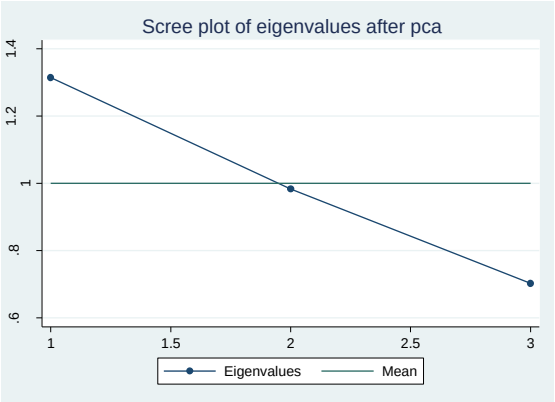
Principal components/correlation			Number of obs =	305
			Number of comp. =	2
			Trace =	3
Rotation: (unrotated = principal)			Rho =	0.7657
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1 |	1.31425	0. 331443	0.4381	0.4381
Comp2 |	0.982804	0.279854	0.3276	0.7657
Comp3 |	0.702949	.	0.2343	1.0000

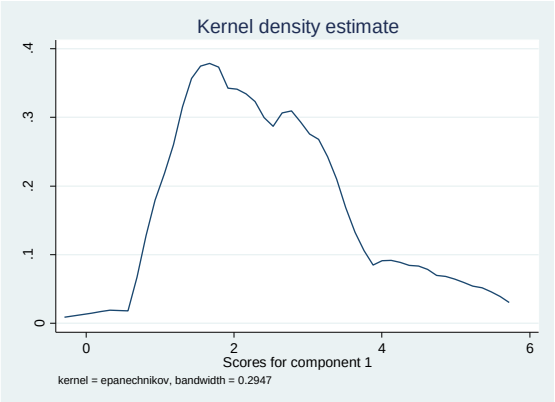
Principal components (eigenvectors)

Variable	Comp1	Comp2	Unexplained
Rel. other farmers	0.5061	0.7084	0.1701
Rel. FO	0.6971	-0.0002	0.3614
Rel. social network	-0.5078	0.7058	0.1715

Kaiser-Meyer-Olkin measure of sampling adequacy

Variable	kmo
Rel. other farmers	0.4932
Rel. FO	0.4966
Rel. social network	0.4933
Overall	0.4949





Test for univariate normality

Variable	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
Rel. other farmers	0.0000	0.0001	30.11	0.0000
Rel. FO	0.0036	.	.	.
Rel. social network	0.0000	0.5281	41.33	0.0000

Doornik-Hansen test for bivariate normality

Pair of variables		chi2	Df	Prob>chi2
relo~s_strhh	relfo_strhh	174.39	4	0.0000
socnetDall		535.70	4	0.0000
relfo_strhh	socnetDall	579.91	4	0.0000

Test for multivariate normality

Mardia mSkewness = 2.88246	chi2(10) = 148.695	Prob>chi2 = 0.0000
Mardia mKurtosis = 15.18893	chi2(1) = 0.091	Prob>chi2 = 0.7633
Henze-Zirkler = 21.01848	chi2(1) = 364.696	Prob>chi2 = 0.0000
Doornik-Hansen	chi2(6) = 582.163	Prob>chi2 = 0.0000

Cognitive social capital index

Principal components/correlation — Number of obs = 305; Number of comp. = 2; Trace = 5; Rotation: (unrotated = principal); Rho = 0.6560

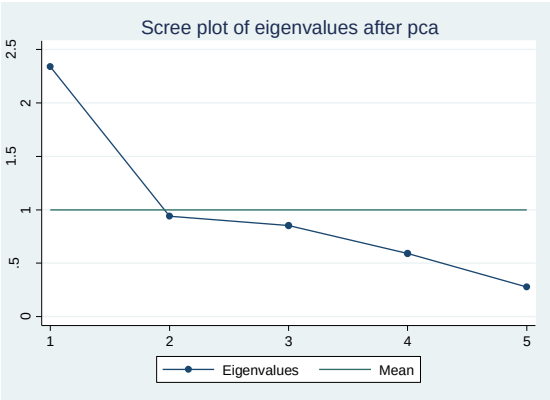
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.33959	1.39935	0.4679	0.4679
Comp2	0.940235	0.0880816	0.1880	0.6560
Comp3	0.852154	0.260945	0.1704	0.8264
Comp4	0.591209	0.314392	0.1182	0.9446
Comp5	0.276817	.	0.0554	1.0000

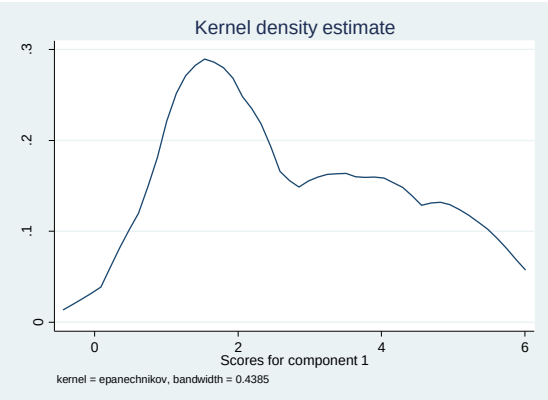
Principal components (eigenvectors)

Variable	Comp1	Comp2	Unexplained
Trust input suppliers	0.2858	0.8072	0.1963
Trust extension officers	0.4609	0.2839	0.4273
Trust development agencies	0.5435	-0.1965	0.2725
Trust FO	0.5608	-0.2188	0.2192
Trust other farmers	0.3099	-0.4258	0.6048

Kaiser-Meyer-Olkin measure of sampling adequacy

Variable	kmo
Trust input suppliers	0.7520
Trust extension officers	0.7987
Trust development agencies	0.6538
Trust FO	0.6362
Trust other farmers	0.8488
Overall	0.6905





Test for univariate normality

Variable	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
Trust input suppliers	0.0000	0.0164	34.12	0.0000
Trust extension officers	0.2174	.	.	.
Trust development agencies	0.0000	0.0000	.	0.0000
Trust FO	0.0097	.	.	.
Trust other farmers	0.0000	0.0000	45.41	0.0000

Doornik-Hansen test for bivariate normality

Pair of variables		chi2	Df	Prob>chi2
trustinput~h	trustexten~h	178.87	4	0.0000
	trustdevel~h	385.76	4	0.0000
	trustfohh	279.53	4	0.0000
	trustoth~shh	126.77	4	0.0000
trustexten~h	trustdevel~h	270.58	4	0.0000
	trustfohh	174.16	4	0.0000
	trustoth~shh	141.54	4	0.0000

Pair of variables		chi2	Df	Prob>chi2
trustdevel~h	trustfohh	107.17	4	0.0000
	trustoth~shh	324.22	4	0.0000
trustfohh	trustoth~shh	207.17	4	0.0000

Test for multivariate normality

Mardia mSkewness = 5.906812	chi2(35) = 304.210	Prob>chi2 = 0.0000
Mardia mKurtosis = 37.89869	chi2(1) = 9.153	Prob>chi2 = 0.0025
Henze-Zirkler = 13.36953	chi2(1) = 1640.389	Prob>chi2 = 0.0000
Doornik-Hansen	chi2(10) = 278.085	Prob>chi2 = 0.0000

Appendix 3.3. Full estimation results

Basic model

Table 1 Determinants of adoption - Probit results

Dep. var=mango adoption (0/1) VARIABLES		(A1) Adoption mfx	(A2) Adoption mfx	(A3) Adoption mfx	(A4) Adoption mfx	(A5) Adoption mfx	(A6) Adoption mfx	(A7) Adoption mfx
Age head[1]	Years	**-0.004***	**-0.006****	**-0.006****	**-0.005***	**-0.005****	**-0.006****	-0.001
		(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Male head	(0/1)	**0.172***	**0.203*****	**0.181***	**0.139*****	**0.140****	**0.140*****	**0.181*****
		(0.094)	(0.076)	(0.096)	(0.050)	(0.055)	(0.051)	(0.062)
Higher education	(0/1)	**0.118****	0.045	0.048	0.020	0.035	0.043	-0.003
		(0.059)	(0.070)	(0.076)	(0.067)	(0.069)	(0.064)	(0.013)
Farm labour[1]	#	**-0.024*****	**-0.018***	-0.024	-0.030	**-0.028***	**-0.029****	-0.017
		(0.005)	(0.011)	(0.017)	(0.020)	(0.016)	(0.014)	(0.022)
Farm size[1]	Acres		**0.013****	**0.012***	**0.011****	**0.013****	**0.013****	**0.013****
			(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Land ownership	(0/1)		**0.145***	**0.173****	**0.203*****	**0.189****	**0.226*****	**0.230*****
			(0.080)	(0.068)	(0.064)	(0.090)	(0.083)	(0.063)
Production other cash crops	(0/1)		-0.026	**-0.057***	-0.047	-0.088	-0.083	**-0.091*****
			(0.027)	(0.031)	(0.043)	(0.057)	(0.054)	(0.035)
Livestock ownership	#			0.001	0.001	0.001	0.001	0.001
				(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Access to non-farm income	(0/1)			0.060	0.058	0.049	0.055	**0.064***
				(0.040)	(0.040)	(0.040)	(0.046)	(0.038)
Access to credit	(0/1)			0.153	0.159	0.174	**0.195***	0.112
				(0.104)	(0.114)	(0.113)	(0.106)	(0.085)
Ownership of tractor	(0/1)				**-0.302*****	**-0.258****	**-0.317*****	**-0.346*****
					(0.098)	(0.130)	(0.118)	(0.066)
Ownership of mobile	(0/1)				0.110	0.099	**0.102***	0.087
					(0.077)	(0.065)	(0.060)	(0.118)
Ownership of radio	(0/1)				**-0.120*****	**-0.123*****	**-0.140*****	**-0.093*****
					(0.044)	(0.043)	(0.048)	(0.027)
Ownership of bicycle	(0/1)				0.123	0.053	0.037	**0.057****
					(0.076)	(0.070)	(0.079)	(0.026)
Ownership of motorcycle	(0/1)				0.069	0.062	0.071	0.006
					(0.059)	(0.068)	(0.074)	(0.053)
Ownership of car	(0/1)				**0.120*****	**0.105*****	**0.110*****	**-0.032*****
					(0.020)	(0.003)	(0.012)	(0.009)
Road conditions	#					**-0.043*****	**-0.047*****	**-0.035****
						(0.008)	(0.006)	(0.018)
Moderate risk averse	(0/1)						**0.157*****	**0.123*****
							(0.038)	(0.036)
No risk averse	(0/1)						0.006	0.034
							(0.068)	(0.078)
Impatient	(0/1)						0.041	-0.022
							(0.041)	(0.064)
Experience in farming[1]	Years							**-0.012*****
								(0.002)
Training	(0/1)							**0.503*****
								(0.112)
Observations		305	305	305	305	305	305	305

[1] Values at the time of adoption for mango farmers; current values for non-mango farmers
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 2 Determinants of time of adoption - absolute cut off

Dep. var=later adoption (0/1) *Cut-off=2006* VARIABLES		(A1) Time adoption-abs mfx	(A2) Time adoption-abs mfx	(A3) Time adoption-abs mfx	(A4) Time adoption-abs mfx	(A5) Time adoption-abs mfx	(A6) Time adoption-abs mfx	(A7) Time adoption-abs mfx
Age head[1]	Years	-0.002	0.001	0.000	0.001	0.001	0.001	-0.001
		(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Male head	(0/1)	-0.051	-0.105	-0.128	-0.139	-0.135	-0.121	-0.074
		(0.301)	(0.288)	(0.290)	(0.284)	(0.273)	(0.268)	(0.252)
Higher education	(0/1)	**-0.202***	**-0.085***	-0.069	-0.091	**-0.102****	**-0.100***	**-0.080****
		(0.123)	(0.044)	(0.047)	(0.061)	(0.048)	(0.053)	(0.039)
Farm labour[1]	#	**0.116*****	**0.129*****	**0.137*****	**0.144*****	**0.146*****	**0.144*****	**0.147*****
		(0.012)	(0.024)	(0.014)	(0.022)	(0.022)	(0.020)	(0.012)
Farm size[1]	Acres		**-0.013*****	**-0.013*****	**-0.013*****	**-0.013*****	**-0.014*****	**-0.014*****
			(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Land ownership	(0/1)		**-0.203*****	**-0.182****	**-0.214***	**-0.216***	**-0.220***	-0.206
			(0.078)	(0.075)	(0.119)	(0.113)	(0.119)	(0.139)
Production other cash crops	(0/1)		**-0.095****	**-0.115*****	**-0.127*****	**-0.121*****	**-0.115*****	**-0.101*****
			(0.045)	(0.022)	(0.043)	(0.044)	(0.031)	(0.007)
Livestock ownership	#			-0.000	-0.000	**-0.001***	**-0.000***	-0.001
				(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Access to non-farm income	(0/1)			0.002	0.003	0.007	0.002	0.011
				(0.033)	(0.021)	(0.021)	(0.023)	(0.023)
Access to credit	(0/1)			0.159	0.164	0.158	0.171	0.154
				(0.147)	(0.144)	(0.149)	(0.133)	(0.137)
Ownership of mobile	(0/1)				0.067	0.085	0.085	0.085
					(0.186)	(0.160)	(0.156)	(0.169)
Ownership of radio	(0/1)				**0.177*****	**0.169****	**0.156*****	**0.137*****
					(0.068)	(0.069)	(0.046)	(0.032)
Ownership of bicycle	(0/1)				-0.028	-0.015	-0.021	-0.040
					(0.141)	(0.125)	(0.142)	(0.114)
Ownership of motorcycle	(0/1)				-0.086	-0.083	-0.078	-0.068
					(0.160)	(0.158)	(0.158)	(0.142)
Ownership of car	(0/1)				-0.011	-0.005	-0.005	0.028
					(0.090)	(0.099)	(0.095)	(0.093)
Road conditions	#					0.018	0.018	0.020
						(0.029)	(0.028)	(0.032)
Moderate risk averse	(0/1)						0.040	0.042
							(0.084)	(0.065)
No risk averse	(0/1)						-0.009	-0.033
							(0.111)	(0.078)
Impatient	(0/1)						-0.064	-0.060
							(0.089)	(0.095)
Experience in farming[1]	Years							0.006
								(0.005)
Training	(0/1)							-0.043
								(0.221)
Observations		196	196	196	196	196	196	196

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3 Determinants of time of adoption - relative cut off

Dep. var=later adoption (0/1) *Cut-off=regional median* VARIABLES		(A1) Time adoption-rel mfx	(A2) Time adoption-rel mfx	(A3) Time adoption-rel mfx	(A4) Time adoption-rel mfx	(A5) Time adoption-rel mfx	(A6) Time adoption-rel mfx	(A7) Time adoption-rel Heck-mfx
Age head[1]	Years	-0.002	-0.001	-0.002	-0.001	-0.001	-0.001	-0.003
		(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	0.005
Male head	(0/1)	-0.112	-0.134	-0.146	-0.136	-0.127	-0.120	IV
		(0.158)	(0.140)	(0.144)	(0.139)	(0.132)	(0.141)	
Higher education	(0/1)	-0.103	-0.023	-0.006	-0.018	-0.047	-0.046	-0.013
		(0.087)	(0.035)	(0.036)	(0.056)	(0.038)	(0.044)	0.070
Farm labour[1]	#	**0.098*** **	**0.108*** **	**0.115*** **	**0.120*** **	**0.122*** **	**0.122*** **	**0.134*** **
		(0.021)	(0.022)	(0.017)	(0.014)	(0.010)	(0.012)	0.015
Farm size[1]	Acres		**-0.008*** **	**-0.008*** **	**-0.008*** **	**-0.009*** **	**-0.009*** **	**-0.021*** **
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	0.007
Land ownership	(0/1)		-0.079	-0.056	-0.089	-0.091	-0.088	IV
			(0.087)	(0.081)	(0.130)	(0.121)	(0.136)	
Production other cash crops	(0/1)		0.027	0.009	-0.001	0.017	0.020	**0.087***
			(0.059)	(0.031)	(0.052)	(0.062)	(0.051)	0.046
Livestock ownership	#			-0.001	-0.001	-0.001	-0.001	**-0.001***
				(0.001)	(0.001)	(0.001)	(0.001)	0.001
Access to non-farm income	(0/1)			-0.004	0.000	0.010	0.006	0.008
				(0.030)	(0.024)	(0.032)	(0.038)	0.027
Access to credit	(0/1)			0.137	0.141	0.123	0.131	0.112
				(0.134)	(0.123)	(0.135)	(0.128)	0.134
Ownership of mobile	(0/1)				0.094	0.138	0.134	0.132
					(0.185)	(0.152)	(0.147)	0.149
Ownership of radio	(0/1)				0.124	0.106	0.098	IV
					(0.141)	(0.163)	(0.149)	
Ownership of bicycle	(0/1)				-0.050	-0.016	-0.021	-0.050
					(0.126)	(0.116)	(0.126)	0.116
Ownership of motorcycle	(0/1)				-0.118	-0.113	-0.110	-0.107
					(0.152)	(0.145)	(0.142)	0.150
Ownership of car	(0/1)				-0.033	-0.018	-0.012	0.052
					(0.065)	(0.072)	(0.073)	0.060
Road conditions	#					0.045	**0.045***	**0.053***
						(0.029)	(0.027)	0.030
Moderate risk averse	(0/1)						0.024	IV
							(0.059)	
No risk averse	(0/1)						-0.031	IV
							(0.122)	
Impatient	(0/1)						-0.027	0.005
							(0.073)	0.077
Experience in farming[1]	Years							0.010**
								0.004
Training	(0/1)							-0.200*
								0.112
Observations		196	196	196	196	196	196	196

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4 Determinants of intensity of adoption

Dep var=ln(n. trees)		(A1) Intensity	(A2) Intensity	(A3) Intensity	(A4) Intensity	(A5) Intensity	(A6) Intensity	(A7) Intensity
VARIABLES		OLS	OLS	OLS	OLS	OLS	OLS	OLS
Age head[1]	Years	0.002	0.002	0.002	0.002	0.002	0.002	0.004
		(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Male head	(0/1)	**0.818****	**0.644****	**0.588****	**0.539****	**0.523****	**0.573****	**0.421***
		(0.323)	(0.286)	(0.272)	(0.263)	(0.257)	(0.258)	(0.254)
Higher education	(0/1)	**0.653****	**0.503****	**0.542****	**0.499****	**0.475****	**0.470****	**0.372***
		(0.253)	(0.209)	(0.212)	(0.203)	(0.206)	(0.200)	(0.195)
Farm labour[1]	#	-0.004	-0.045	-0.044	-0.046	-0.045	-0.052	-0.063
		(0.073)	(0.061)	(0.065)	(0.064)	(0.064)	(0.061)	(0.055)
Farm size[1]	Acres		**0.038*****	**0.036*****	**0.031*****	**0.030*****	**0.029*****	**0.029*****
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Land ownership	(0/1)		-0.229	-0.174	-0.166	-0.112	-0.197	-0.133
			(0.259)	(0.250)	(0.248)	(0.245)	(0.227)	(0.216)
Production other cash crops	(0/1)		**-0.341***	**-0.374***	-0.268	-0.263	-0.229	-0.311
			(0.205)	(0.204)	(0.198)	(0.199)	(0.200)	(0.199)
Livestock ownership	#			**0.004*****	**0.003***	0.002	0.002	0.002
				(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Access to non-farm income	(0/1)			0.068	0.055	0.072	0.071	0.089
				(0.093)	(0.093)	(0.095)	(0.096)	(0.101)
Access to credit	(0/1)			0.270*	0.234	0.205	0.200	0.143
				(0.155)	(0.149)	(0.152)	(0.154)	(0.160)
Ownership of tractor	(0/1)				0.156	0.145	0.208	0.042
					(0.561)	(0.567)	(0.584)	(0.535)
Ownership of mobile	(0/1)				-0.165	-0.133	-0.112	-0.154
					(0.126)	(0.128)	(0.125)	(0.126)
Ownership of radio	(0/1)				**0.302***	**0.309****	**0.274***	**0.324****
					(0.155)	(0.154)	(0.163)	(0.146)
Ownership of bicycle	(0/1)				-0.019	-0.011	0.008	0.139
					(0.157)	(0.158)	(0.160)	(0.156)
Ownership of motorcycle	(0/1)				**0.469*****	**0.450*****	**0.468*****	**0.415*****
					(0.134)	(0.133)	(0.134)	(0.130)
Ownership of car	(0/1)				**0.444****	**0.474****	**0.451****	**0.386****
					(0.211)	(0.212)	(0.206)	(0.194)
Road conditions	#					0.051	0.057	0.056
						(0.034)	(0.037)	(0.037)
Moderate risk averse	(0/1)						-0.020	-0.080
							(0.153)	(0.138)
No risk averse	(0/1)						0.177	0.123
							(0.237)	(0.224)
Impatient	(0/1)						**-0.272***	**-0.270****
							(0.142)	(0.136)
Experience in farming[1]	(0/1)							-0.009
								(0.005)
Training	(0/1)							**0.619*****
								(0.186)
Constant		4.139***	4.251***	4.034***	3.969***	3.672***	3.780***	3.398***
		(0.447)	(0.492)	(0.458)	(0.463)	(0.480)	(0.472)	(0.444)
Observations		196	196	196	196	196	196	196
R-squared		0.141	0.443	0.472	0.531	0.535	0.548	0.589

[1] Values at the time of adoption for mango farmers; current values for non-mango farmers
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Basic model and bridging social capital

Table 5 Determinants of adoption with bridging social capital

Dep. var=mango adoption (0/1) VARIABLES		(A7) Adoption mfx	(A8) Adoption mfx	(A9) Adoption mfx
Age head[1]	Years	-0.001	-0.001	-0.001
		(0.003)	(0.002)	(0.002)
Male head	(0/1)	**0.181*** **	**0.109**	**0.149** **
		(0.062)	(0.074)	(0.065)
Higher education	(0/1)	-0.003	**0.022*** **	0.008
		(0.013)	(0.008)	(0.014)
Farm labour[1]	#	-0.017	**-0.030** **	-0.015
		(0.022)	(0.014)	(0.013)
Farm size[1]	Acres	**0.013** **	**0.006** *	0.005
		(0.005)	(0.003)	(0.003)
Land ownership	(0/1)	**0.230*** **	**0.225*** **	**0.249*** **
		(0.063)	(0.038)	(0.014)
Production other cash crops	(0/1)	**-0.091*** **	-0.037	**-0.038** *
		(0.035)	(0.043)	(0.022)
Livestock ownership	#	0.001	0.000	0.000
		(0.001)	(0.001)	(0.001)
Access to non-farm income	(0/1)	**0.064** *	**0.072*** **	**0.059*** **
		(0.038)	(0.012)	(0.012)
Access to credit	(0/1)	0.112	**0.221*** **	0.139
		(0.085)	(0.078)	(0.116)
Ownership of tractor	(0/1)	**-0.346*** **	**-0.205*** **	**-0.143*** **
		(0.066)	(0.068)	(0.037)
Ownership of mobile	(0/1)	0.087	0.137	**0.129** *
		(0.118)	(0.097)	(0.070)
Ownership of radio	(0/1)	**-0.093*** **	-0.031	-0.026
		(0.027)	(0.029)	(0.044)
Ownership of bicycle	(0/1)	**0.057** **	0.032	0.028
		(0.026)	(0.071)	(0.047)
Ownership of motorcycle	(0/1)	0.006	0.013	0.007
		(0.053)	(0.074)	(0.069)
Ownership of car	(0/1)	**-0.032*** **	-0.017	-0.053
		(0.009)	(0.081)	(0.087)
Road conditions	#	**-0.035** **	**-0.038*** **	**-0.034** **
		(0.018)	(0.006)	(0.015)
Moderate risk averse	(0/1)	**0.123*** **	**0.079*** **	**0.062*** **
		(0.036)	(0.012)	(0.009)
No risk averse	(0/1)	0.034	**0.077** **	0.059
		(0.078)	(0.038)	(0.043)
Impatient	(0/1)	-0.022	-0.039	-0.034
		(0.064)	(0.069)	(0.047)
Experience in farming[1]	Years	**-0.012*** **	**-0.012*** **	**-0.012*** **
		(0.002)	(0.001)	(0.002)
Training	(0/1)	**0.503*** **	0.149	0.109
		(0.112)	(0.091)	(0.111)
Relationship with input suppliers	(0/1)		**0.383*** **	
			(0.148)	
Relationship with credit providers	(0/1)		**-0.433** **	
			(0.217)	
Relationship with extension officers	(0/1)		**0.144*** **	
			(0.035)	
Relationship with Dev Agencies	(0/1)		**0.454*** **	
			(0.052)	
Relationship with NGOs	(0/1)		0.084	
			(0.057)	
Strength of relationship with input suppliers	(1/5)			**0.046*** **
				(0.017)
Strength of relationship with credit providers	(1/5)			-0.059
	(1/5)			(0.056)
Strength of relationship with extension officers	(1/5)			0.025
	(1/5)			(0.018)
Strength of relationship with Dev Agencies	(1/5)			**0.177*** **
	(1/5)			(0.021)
Strength of relationship with NGOs	(1/5)			0.026
				(0.018)
Observations		305	305	305

[1] Values at the time of adoption for mango farmers; current values for non-mango farmers

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6 Determinants of time of adoption with bridging social capital - absolute cut-off

Dep. var=later adoption (0/1)		(A7)	(A8)	(A9)
Cut-off=2006		Time adoption-abs	Time adoption- abs	Time adoption- abs
VARIABLES		mfx	mfx	mfx
Age head[1]	Years	-0.001	-0.001	-0.001
		(0.005)	(0.005)	(0.006)
Male head	(0/1)	-0.074	-0.040	-0.055
		(0.252)	(0.256)	(0.275)
Higher education	(0/1)	**-0.080****	**-0.117****	-0.116
		(0.039)	(0.047)	(0.072)
Farm labour[1]	#	**0.147*****	**0.156*****	**0.153*****
		(0.012)	(0.007)	(0.005)
Farm size[1]	Acres	**-0.014*****	**-0.016*****	**-0.016*****
		(0.002)	(0.002)	(0.003)
Land ownership	(0/1)	-0.206	-0.089	-0.147
		(0.139)	(0.087)	(0.097)
Production other cash crops	(0/1)	**-0.101*****	**-0.046*****	**-0.055*****
		(0.007)	(0.009)	(0.008)
Livestock ownership	#	-0.001	**-0.001****	**-0.001***
		(0.000)	(0.000)	(0.001)
Access to non-farm income	(0/1)	0.011	-0.001	0.004
		(0.023)	(0.022)	(0.011)
Access to credit	(0/1)	0.154	0.148	**0.240****
		(0.137)	(0.129)	(0.120)
Ownership of mobile	(0/1)	0.085	0.055	0.074
		(0.169)	(0.146)	(0.186)
Ownership of radio	(0/1)	**0.137*****	**0.177*****	**0.160*****
		(0.032)	(0.055)	(0.027)
Ownership of bicycle	(0/1)	-0.040	-0.046	-0.057
		(0.114)	(0.134)	(0.129)
Ownership of motorcycle	(0/1)	-0.068	-0.100	-0.098
		(0.142)	(0.159)	(0.139)
Ownership of car	(0/1)	0.028	0.065	0.066
		(0.093)	(0.096)	(0.105)
Road conditions	#	0.020	0.019	0.020
		(0.032)	(0.033)	(0.028)
Moderate risk averse	(0/1)	0.042	0.018	0.029
		(0.065)	(0.061)	(0.048)
No risk averse	(0/1)	-0.033	**-0.077*****	-0.022
		(0.078)	(0.029)	(0.050)
Impatient	(0/1)	-0.060	-0.077	-0.093
		(0.095)	(0.074)	(0.077)
Experience in farming[1]	Years	0.006	**0.007****	**0.008*****
		(0.005)	(0.003)	(0.003)
Training	(0/1)	-0.043	-0.022	-0.024
		(0.221)	(0.258)	(0.223)
Relationship with input suppliers	(0/1)		**-0.428*****	
			(0.068)	
Relationship with credit providers	(0/1)		**-0.087***	
			(0.047)	
Relationship with extension officers	(0/1)		0.070	
			(0.102)	
Relationship with Dev Agencies	(0/1)		0.093	
			(0.260)	
Relationship with NGOs	(0/1)		**-0.217*****	
			(0.083)	
Strength of relationship with input suppliers	(1/5)			**-0.062****
				(0.031)
Strength of relationship with credit providers	(1/5)			**-0.048*****
	(1/5)			(0.014)
Strength of relationship with extension officers	(1/5)			0.030
	(1/5)			(0.037)
Strength of relationship with Dev Agencies	(1/5)			0.024
	(1/5)			(0.066)
Strength of relationship with NGOs	(1/5)			**-0.063***
				(0.037)
Observations		196	196	196

[1] Values at the time of adoption for mango farmers; current values for non-mango farmers
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7 Determinants of time of adoption with bridging social capital - relative cut-off

Dep. var=later adoption (0/1)		(A7)	(A8)	(A9)
Cut-off=regional median		Time adoption-rel	Time adoption- rel	Time adoption- rel
VARIABLES		Heck-mfx	Heck-mfx	Heck-mfx
Age head[1]	Years	-0.003	-0.003	-0.004
		(0.005)	(0.005)	(0.005)
Male head	(0/1)	IV	IV	IV
Higher education	(0/1)	-0.013	-0.037	-0.012
		(0.070)	(0.105)	(0.138)
Farm labour[1]	#	**0.134*** **	**0.136*** **	**0.133*** **
		(0.015)	(0.006)	(0.004)
Farm size[1]	Acres	**-0.021*** **	**-0.014*** **	**-0.012*** **
		(0.007)	(0.003)	(0.004)
Land ownership	(0/1)	IV	IV	IV
Production other cash crops	(0/1)	**0.087***	**0.104***	0.085
		(0.046)	(0.054)	(0.056)
Livestock ownership	#	**-0.001***	**-0.001*** **	**-0.001** **
		(0.001)	(0.000)	(0.001)
Access to non-farm income	(0/1)	0.008	-0.011	-0.008
		(0.027)	(0.031)	(0.027)
Access to credit	(0/1)	0.112	0.132	**0.180*** **
		(0.134)	(0.108)	(0.058)
Ownership of mobile	(0/1)	0.132	0.123	0.074
		(0.149)	(0.146)	(0.154)
Ownership of radio	(0/1)	IV	IV	IV
Ownership of bicycle	(0/1)	-0.050	-0.058	-0.071
		(0.116)	(0.161)	(0.147)
Ownership of motorcycle	(0/1)	-0.107	-0.127	-0.122
		(0.150)	(0.126)	(0.123)
Ownership of car	(0/1)	0.052	0.041	0.065
		(0.060)	(0.042)	(0.051)
Road conditions	#	**0.053***	**0.068*** **	**0.062** **
		(0.030)	(0.023)	(0.025)
Moderate risk averse	(0/1)	IV	IV	IV
No risk averse	(0/1)	IV	IV	IV
Impatient	(0/1)	0.005	-0.000	-0.012
		(0.077)	(0.084)	(0.080)
Experience in farming[1]	Years	**0.010** **	**0.013*** **	**0.013*** **
		(0.004)	(0.003)	(0.004)
Training	(0/1)	**-0.200***	**-0.185** **	**-0.163***
		(0.112)	(0.091)	(0.084)
Relationship with input suppliers	(0/1)		dropped	
Relationship with credit providers	(0/1)		-0.004	
			(0.124)	
Relationship with extension officers	(0/1)		**0.139** **	
			(0.064)	
Relationship with Dev Agencies	(0/1)		-0.081	
			(0.222)	
Relationship with NGOs	(0/1)		-0.146	
			(0.111)	
Strength of relationship with input suppliers	(1/5)			**-0.099*** **
				(0.020)
Strength of relationship with credit providers	(1/5)			-0.032
	(1/5)			(0.023)
Strength of relationship with extension officers	(1/5)			**0.050***
	(1/5)			(0.027)
Strength of relationship with Dev Agencies	(1/5)			-0.041
	(1/5)			(0.046)
Strength of relationship with NGOs	(1/5)			-0.031
				(0.034)
Observations		196	196	196

[1] Values at the time of adoption for mango farmers; current values for non-mango farmers
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 8 Determinants of intensity of adoption with bridging social capital

Dep var=ln(n. trees)		(A7) Intensity	(A8) Intensity	(A9) Intensity
VARIABLES		OLS	OLS	OLS
Age head[1]	Years	0.004	0.003	0.003
		(0.005)	(0.005)	(0.005)
Male head	(0/1)	**0.421***	**0.506****	**0.517****
		(0.254)	(0.248)	(0.248)
Higher education	(0/1)	0.372*	0.265	0.221
		(0.195)	(0.195)	(0.195)
Farm labour[1]	#	-0.063	-0.052	-0.054
		(0.055)	(0.050)	(0.049)
Farm size[1]	Acres	**0.029*****	**0.026*****	**0.024*****
		(0.004)	(0.004)	(0.004)
Land ownership	(0/1)	-0.133	-0.053	-0.081
		(0.216)	(0.224)	(0.218)
Production other cash crops	(0/1)	-0.311	-0.274	-0.269
		(0.199)	(0.188)	(0.184)
Livestock ownership	#	0.002	**0.002***	**0.002***
		(0.001)	(0.001)	(0.001)
Access to non-farm income	(0/1)	0.089	0.072	0.084
		(0.101)	(0.103)	(0.101)
Access to credit	(0/1)	0.143	0.028	0.050
		(0.160)	(0.218)	(0.210)
Ownership of tractor	(0/1)	0.042	0.226	0.352
		(0.535)	(0.490)	(0.483)
Ownership of mobile	(0/1)	-0.154	-0.134	-0.113
		(0.126)	(0.137)	(0.137)
Ownership of radio	(0/1)	**0.324****	0.251	0.256
		(0.146)	(0.182)	(0.182)
Ownership of bicycle	(0/1)	0.139	0.212	0.217
		(0.156)	(0.151)	(0.146)
Ownership of motorcycle	(0/1)	**0.415*****	**0.432*****	**0.422*****
		(0.130)	(0.124)	(0.126)
Ownership of car	(0/1)	**0.386****	**0.326***	0.303
		(0.194)	(0.185)	(0.184)
Road conditions	#	0.056	0.026	0.027
		(0.037)	(0.036)	(0.034)
Moderate risk averse	(0/1)	-0.080	-0.070	-0.064
		(0.138)	(0.136)	(0.132)
No risk averse	(0/1)	0.123	0.034	0.074
		(0.224)	(0.224)	(0.220)
Impatient	(0/1)	**-0.270****	**-0.309****	**-0.318****
		(0.136)	(0.134)	(0.136)
Experience in farming[1]	Years	-0.009	-0.007	-0.008
		(0.005)	(0.006)	(0.006)
Training	(0/1)	**0.619*****	**0.468****	**0.428****
		(0.186)	(0.190)	(0.188)
Relationship with input suppliers	(0/1)		-0.079	
			(0.134)	
Relationship with credit providers	(0/1)		-0.008	
			(0.167)	
Relationship with extension officers	(0/1)		-0.140	
			(0.170)	
Relationship with Dev Agencies	(0/1)		**0.570*****	
			(0.178)	
Relationship with NGOs	(0/1)		-0.152	
			(0.123)	
Strength of relationship with input suppliers	(1/5)			-0.009
				(0.040)
Strength of relationship with credit providers	(1/5)			-0.003
	(1/5)			(0.048)
Strength of relationship with extension officers	(1/5)			-0.028
	(1/5)			(0.041)
Strength of relationship with Dev Agencies	(1/5)			**0.164*****
	(1/5)			(0.042)
Strength of relationship with NGOs	(1/5)			-0.035
				(0.037)
Constant		3.398***	3.643***	3.555***
		(0.444)	(0.445)	(0.481)
Observations		196	196	196
R-squared		0.589	0.629	0.634

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Basic model and bonding social capital

Table 9 Determinants of adoption with bonding social capital

Dep. var=mango adoption (0/1) VARIABLES		(A7) Adoption mfx	(A10) Adoption mfx	(A11) Adoption mfx	(A12) Adoption mfx	(A13) Adoption mfx
Age head[1]	Years	-0.001	-0.001	-0.001	-0.002	-0.001
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Male head	(0/1)	**0.181*** **	0.119	**0.196*** **	0.145	**0.190*** **
		(0.062)	(0.105)	(0.059)	(0.103)	(0.056)
Higher education	(0/1)	-0.003	0.032	-0.014	0.010	-0.004
		(0.013)	(0.030)	(0.029)	(0.019)	(0.013)
Farm labour[1]	#	-0.017	-0.019	-0.014	-0.015	-0.013
		(0.022)	(0.021)	(0.021)	(0.019)	(0.021)
Farm size[1]	Acres	**0.013** **	**0.011** **	**0.013** **	**0.012** **	**0.013** **
		(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Land ownership	(0/1)	**0.230*** **	**0.265*** **	**0.220*** **	**0.262*** **	**0.255*** **
		(0.063)	(0.037)	(0.079)	(0.040)	(0.064)
Production other cash crops	(0/1)	**-0.091*** **	**-0.097***	**-0.097*** **	**-0.096***	**-0.088** **
		(0.035)	(0.057)	(0.032)	(0.051)	(0.038)
Livestock ownership	#	0.001	0.001	0.001	0.001	0.001
		(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Access to non-farm income	(0/1)	**0.064***	**0.056** **	0.051	**0.058** **	0.061
		(0.038)	(0.022)	(0.049)	(0.024)	(0.038)
Access to credit	(0/1)	0.112	0.095	0.117	0.078	0.099
		(0.085)	(0.071)	(0.089)	(0.072)	(0.086)
Ownership of tractor	(0/1)	**-0.346*** **	**-0.257*** **	**-0.349*** **	**-0.263*** **	**-0.326*** **
		(0.066)	(0.056)	(0.077)	(0.059)	(0.058)
Ownership of mobile	(0/1)	0.087	0.071	0.084	0.075	0.102
		(0.118)	(0.115)	(0.118)	(0.117)	(0.127)
Ownership of radio	(0/1)	**-0.093*** **	**-0.117*** **	**-0.096*** **	**-0.115*** **	**-0.108*** **
		(0.027)	(0.037)	(0.029)	(0.036)	(0.030)
Ownership of bicycle	(0/1)	**0.057** **	**0.059***	**0.057***	**0.060***	**0.052** **
		(0.026)	(0.034)	(0.029)	(0.037)	(0.023)
Ownership of motorcycle	(0/1)	0.006	-0.008	0.016	-0.017	0.000
		(0.053)	(0.076)	(0.056)	(0.079)	(0.058)
Ownership of car	(0/1)	**-0.032*** **	0.025	-0.015	0.019	**-0.029*** **
		(0.009)	(0.017)	(0.018)	(0.021)	(0.005)
Road conditions	#	**-0.035** **	-0.024	**-0.040** **	-0.026	**-0.037** **
		(0.018)	(0.021)	(0.017)	(0.021)	(0.018)
Moderate risk averse	(0/1)	**0.123*** **	**0.081***	**0.138*** **	**0.077***	**0.119*** **
		(0.036)	(0.045)	(0.027)	(0.046)	(0.038)
No risk averse	(0/1)	0.034	-0.002	0.026	0.007	0.024
		(0.078)	(0.069)	(0.091)	(0.069)	(0.078)
Impatient	(0/1)	-0.022	-0.045	-0.047	-0.031	-0.022
		(0.064)	(0.071)	(0.069)	(0.070)	(0.066)
Experience in farming[1]	Years	**-0.012*** **	**-0.013*** **	**-0.013*** **	**-0.013*** **	**-0.013*** **
		(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Training	(0/1)	**0.503*** **	**0.339*** **	**0.491*** **	**0.364*** **	**0.499*** **
		(0.112)	(0.082)	(0.091)	(0.086)	(0.120)
Relationship with other farmers	(0/1)		*dropped*	*dropped*	*dropped*	*dropped*
Relationship with FO	(0/1)		**0.317*** **			
			(0.084)			
Strength of relationship with other farmers	(1/5)			0.056		
				(0.055)		
Membership in FO	(1/5)				**0.275*** **	
					(0.095)	
Social network(ln)	#					**-0.161***
						(0.088)
Observations		305	305	305	305	305

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 10 Determinants of time of adoption with bonding social capital - absolute cut-off

Dep. var=later adoption (0/1) *Cut-off=2006* VARIABLES		(A7) Time adoption-abs mfx	(A10) Time adoption- abs mfx	(A11) Time adoption- abs mfx	(A12) Time adoption- abs mfx	(A13) Time adoption- abs mfx
Age head[1]	Years	-0.001	-0.002	-0.001	-0.002	-0.001
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Male head	(0/1)	-0.074	-0.084	-0.052	-0.091	-0.074
		(0.252)	(0.240)	(0.248)	(0.235)	(0.251)
Higher education	(0/1)	**-0.080****	**-0.082****	**-0.087****	**-0.082*****	**-0.080****
		(0.039)	(0.035)	(0.037)	(0.032)	(0.031)
Farm labour[1]	#	**0.147*****	**0.150*****	**0.148*****	**0.150*****	**0.147*****
		(0.012)	(0.012)	(0.012)	(0.011)	(0.017)
Farm size[1]	Acres	**-0.014*****	**-0.014*****	**-0.015*****	**-0.015*****	**-0.014*****
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Land ownership	(0/1)	-0.206	-0.182	-0.197	-0.177	-0.207
		(0.139)	(0.135)	(0.136)	(0.131)	(0.162)
Production other cash crops	(0/1)	**-0.101*****	**-0.111*****	**-0.123*****	**-0.110*****	**-0.101*****
		(0.007)	(0.010)	(0.015)	(0.004)	(0.005)
Livestock ownership	#	-0.001	-0.001	-0.001	-0.001	-0.001
		(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Access to non-farm income	(0/1)	0.011	0.011	0.003	0.012	0.011
		(0.023)	(0.021)	(0.016)	(0.022)	(0.025)
Access to credit	(0/1)	0.154	0.148	0.149	0.142	0.156
		(0.137)	(0.136)	(0.139)	(0.140)	(0.169)
Ownership of mobile	(0/1)	0.085	0.085	0.078	0.091	0.083
		(0.169)	(0.164)	(0.160)	(0.157)	(0.148)
Ownership of radio	(0/1)	**0.137*****	**0.138*****	**0.156*****	**0.141*****	**0.137*****
		(0.032)	(0.027)	(0.026)	(0.026)	(0.032)
Ownership of bicycle	(0/1)	-0.040	-0.056	-0.057	-0.064	-0.039
		(0.114)	(0.114)	(0.103)	(0.112)	(0.121)
Ownership of motorcycle	(0/1)	-0.068	-0.077	-0.064	-0.080	-0.067
		(0.142)	(0.149)	(0.150)	(0.153)	(0.122)
Ownership of car	(0/1)	0.028	0.021	0.060	0.019	0.027
		(0.093)	(0.094)	(0.094)	(0.093)	(0.103)
Road conditions	#	0.020	0.025	0.010	0.030	0.020
		(0.032)	(0.037)	(0.032)	(0.041)	(0.032)
Moderate risk averse	(0/1)	0.042	0.029	0.071	0.018	0.042
		(0.065)	(0.066)	(0.083)	(0.063)	(0.061)
No risk averse	(0/1)	-0.033	-0.056	-0.035	-0.070	-0.032
		(0.078)	(0.065)	(0.072)	(0.061)	(0.079)
Impatient	(0/1)	-0.060	-0.065	-0.092	-0.065	-0.060
		(0.095)	(0.103)	(0.094)	(0.106)	(0.095)
Experience in farming[1]	Years	0.006	0.007	0.006	0.007	0.007
		(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Training	(0/1)	-0.043	-0.120	-0.047	-0.169	-0.042
		(0.221)	(0.199)	(0.221)	(0.180)	(0.210)
Relationship with other farmers	(0/1)		*dropped*	*dropped*	*dropped*	*dropped*
Relationship with FO	(0/1)		0.120			
			(0.085)			
Strength of relationship with other farmers	(1/5)			0.086		
				(0.074)		
Membership in FO	(0/1)				**0.194***	
					(0.103)	
Social network(ln)	#					0.017
						(0.233)
Observations		196	196	196	196	196

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 11 Determinants of time of adoption with bonding social capital - relative cut-off

Dep. var=later adoption (0/1) *Cut-off=2006* VARIABLES		(A7) Time adoption-rel Heck-mfx	(A10) Time adoption- rel Heck-mfx	(A11) Time adoption- rel mfx	(A12) Time adoption- rel Heck-mfx	(A13) Time adoption- rel Heck-mfx
Age head[1]	Years	-0.003	-0.003	-0.004	-0.003	-0.002
		(0.005)	(0.006)	(0.004)	(0.006)	(0.005)
Male head	(0/1)	IV	IV	-0.091	IV	IV
				(0.109)		
Higher education	(0/1)	-0.013	-0.029	-0.007	-0.022	-0.012
		(0.070)	(0.076)	(0.049)	(0.075)	(0.065)
Farm labour[1]	#	**0.134*** **	**0.133*** **	**0.131*** **	**0.133*** **	**0.124*** **
		(0.015)	(0.012)	(0.013)	(0.012)	(0.012)
Farm size[1]	Acres	**-0.021*** **	**-0.016*** **	**-0.009*** **	**-0.017*** **	**-0.020*** **
		(0.007)	(0.004)	(0.002)	(0.003)	(0.006)
Land ownership	(0/1)	IV	IV	-0.078	IV	IV
				(0.151)		
Production other cash crops	(0/1)	**0.087***	0.077	0.031	**0.083***	**0.082***
		(0.046)	(0.051)	(0.045)	(0.045)	(0.050)
Livestock ownership	#	**-0.001***	**-0.001****	-0.001	**-0.001***	**-0.001***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Access to non-farm income	(0/1)	0.008	0.008	0.007	0.007	0.006
		(0.027)	(0.027)	(0.033)	(0.028)	(0.028)
Access to credit	(0/1)	0.112	0.105	0.121	0.113	0.136
		(0.134)	(0.125)	(0.116)	(0.125)	(0.149)
Ownership of mobile	(0/1)	0.132	0.133	0.127	0.135	0.097
		(0.149)	(0.149)	(0.163)	(0.149)	(0.143)
Ownership of radio	(0/1)	IV	IV	0.077	IV	IV
				(0.130)		
Ownership of bicycle	(0/1)	-0.050	-0.042	-0.057	-0.046	-0.030
		(0.116)	(0.132)	(0.119)	(0.131)	(0.131)
Ownership of motorcycle	(0/1)	-0.107	-0.092	-0.100	-0.091	-0.092
		(0.150)	(0.136)	(0.130)	(0.139)	(0.123)
Ownership of car	(0/1)	0.052	0.006	0.027	0.010	0.029
		(0.060)	(0.089)	(0.072)	(0.090)	(0.074)
Road conditions	#	**0.053***	**0.050***	0.044	**0.051***	**0.054***
		(0.030)	(0.029)	(0.029)	(0.029)	(0.029)
Moderate risk averse	(0/1)	IV	IV	0.043	IV	IV
				(0.068)		
No risk averse	(0/1)	IV	IV	-0.052	IV	IV
				(0.122)		
Impatient	(0/1)	0.005	0.008	-0.024	0.006	0.010
		(0.077)	(0.085)	(0.070)	(0.082)	(0.063)
Experience in farming[1]	Years	**0.010****	**0.010****	**0.008****	**0.010****	**0.011****
		(0.004)	(0.005)	(0.003)	(0.005)	(0.005)
Training	(0/1)	**-0.200***	**-0.122*****	**-0.126****	**-0.137*****	**-0.158***
		(0.112)	(0.044)	(0.062)	(0.045)	(0.092)
Relationship with other farmers	(0/1)		dropped	dropped	dropped	dropped
Relationship with FO	(0/1)		-0.096			
			(0.092)			
Strength of relationship with other farmers	(1/5)			0.019		
				(0.037)		
Membership in FO	(0/1)				-0.090	
					(0.084)	
Social network(ln)	#					**0.234*****
						(0.077)
Observations		196	196	196	196	196

[1] Values at the time of adoption for mango farmers; current values for non-mango farmers
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 12 Determinants of intensity of adoption with bonding social capital

Dep var=ln(n. trees)		(A7) Intensity	(A10) Intensity	(A11) Intensity	(A12) Intensity	(A13) Intensity
VARIABLES		OLS	OLS	OLS	Heck-OLS	OLS
Age head[1]	Years	0.004	0.000	0.004	0.004	0.004
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Male head	(0/1)	**0.421***	0.407	**0.446***	0.190	**0.420***
		(0.254)	(0.247)	(0.249)	(0.238)	(0.254)
Higher education	(0/1)	**0.372***	**0.339***	**0.368***	**0.405*****	**0.374***
		(0.195)	(0.174)	(0.195)	(0.138)	(0.195)
Farm labour[1]	#	-0.063	-0.044	-0.061	-0.040	-0.065
		(0.055)	(0.048)	(0.055)	(0.045)	(0.054)
Farm size[1]	Acres	**0.029*****	**0.027*****	**0.028*****	**0.026*****	**0.029*****
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Land ownership	(0/1)	-0.133	-0.225	-0.152	IV	-0.131
		(0.216)	(0.190)	(0.211)		(0.217)
Production other cash crops	(0/1)	-0.311	**-0.429****	**-0.332***	**-0.307****	-0.309
		(0.199)	(0.174)	(0.196)	(0.135)	(0.199)
Livestock ownership	#	0.002	0.002	0.002	0.002	0.002
		(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Access to non-farm income	(0/1)	0.089	0.058	0.076	0.060	0.090
		(0.101)	(0.096)	(0.102)	(0.073)	(0.101)
Access to credit	(0/1)	0.143	0.112	0.139	0.088	0.148
		(0.160)	(0.147)	(0.157)	(0.134)	(0.171)
Ownership of tractor	(0/1)	0.042	0.100	0.074	0.313	0.037
		(0.535)	(0.527)	(0.528)	(0.465)	(0.534)
Ownership of mobile	(0/1)	-0.154	-0.157	-0.167	-0.162	-0.157
		(0.126)	(0.132)	(0.129)	(0.184)	(0.123)
Ownership of radio	(0/1)	**0.324****	**0.189**	**0.335****	**0.383***	**0.326****
		(0.146)	(0.158)	(0.145)	(0.202)	(0.148)
Ownership of bicycle	(0/1)	0.139	0.137	0.130	-0.062	0.138
		(0.156)	(0.146)	(0.154)	(0.130)	(0.155)
Ownership of motorcycle	(0/1)	**0.415*****	**0.416*****	**0.437*****	**0.320*****	**0.415*****
		(0.130)	(0.116)	(0.132)	(0.122)	(0.130)
Ownership of car	(0/1)	**0.386****	0.271	**0.402****	**0.438****	**0.385***
		(0.194)	(0.176)	(0.195)	(0.173)	(0.197)
Road conditions	#	0.056	0.045	0.040	**0.108*****	0.057
		(0.037)	(0.033)	(0.038)	(0.035)	(0.037)
Moderate risk averse	(0/1)	-0.080	-0.119	-0.038	IV	-0.080
		(0.138)	(0.130)	(0.132)		(0.138)
No risk averse	(0/1)	0.123	0.020	0.127	IV	0.124
		(0.224)	(0.225)	(0.224)		(0.224)
Impatient	(0/1)	**-0.270****	**-0.314****	**-0.304****	**-0.259****	**-0.268***
		(0.136)	(0.132)	(0.145)	(0.121)	(0.140)
Experience in farming[1]	Years	-0.009	-0.005	**-0.009***	0.000	-0.009
		(0.005)	(0.005)	(0.006)	(0.008)	(0.006)
Training	(0/1)	**0.619*****	**0.122**	**0.624*****	-0.078	**0.620*****
		(0.186)	(0.202)	(0.187)	(0.222)	(0.187)
Relationship with other farmers	(0/1)		*dropped*	*dropped*	dropped	*dropped*
Relationship with FO	(0/1)		**0.849*****			
			(0.197)			
Strength of relationship with other farmers	(1/5)			0.097		
				(0.066)		
Membership in FO	(1/5)				**0.430****	
					(0.170)	
Social network(ln)	#					0.031
						(0.229)
Constant		3.398***	3.948***	3.125***	3.939***	3.375***
		(0.444)	(0.415)	(0.487)	(0.416)	(0.512)
Observations		196	196	196	196	196
R-squared		0.589	0.644	0.592	0.645	0.589

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Basic model and cognitive social capital

Table 13 Determinants of adoption with cognitive social capital

Dep. var=later adoption (0/1)		(A14)	(A14)	(A14)	(A14)
Cut-off=2006		Adoption	Time adoption- abs	Time adoption- rel	Intensity
VARIABLES		mfx	mfx	Heck-mfx	coeff
Age head[1]	Years	-0.000	0.001	-0.003	0.001
		(0.003)	(0.005)	(0.004)	(0.005)
Male head	(0/1)	**0.093*** **	-0.081	IV	**0.508** **
		(0.034)	(0.276)		(0.242)
Higher education	(0/1)	**0.056*** **	-0.082	-0.031	0.237
		(0.018)	(0.069)	(0.099)	(0.183)
Farm labour[1]	#	-0.019	**0.155*** **	**0.128*** **	-0.038
		(0.024)	(0.019)	(0.016)	(0.046)
Farm size[1]	Acres	**0.006** **	**-0.016*** **	**-0.012*** **	**0.024*** **
		(0.002)	(0.002)	(0.003)	(0.004)
Land ownership	(0/1)	**0.297*** **	**-0.166** **	IV	-0.129
		(0.032)	(0.065)		(0.188)
Production other cash crops	(0/1)	-0.048	-0.065	0.095	**-0.361** **
		(0.050)	(0.058)	(0.061)	(0.169)
Livestock ownership	#	0.000	**-0.002*** **	**-0.001*** **	0.002
		(0.002)	(0.001)	(0.000)	(0.001)
Access to non-farm income	(0/1)	**0.044*** **	0.012	0.012	0.048
		(0.012)	(0.033)	(0.042)	(0.102)
Access to credit	(0/1)	0.126	**0.328*** **	**0.163*** **	0.102
		(0.119)	(0.018)	(0.011)	(0.222)
Ownership of tractor		**-0.098*** **	dropped	dropped	0.264
		(0.030)			(0.458)
Ownership of mobile	(0/1)	0.109	0.101	0.124	-0.143
		(0.075)	(0.133)	(0.137)	(0.138)
Ownership of radio	(0/1)	-0.044	**0.170*** **	IV	0.176
		(0.057)	(0.047)		(0.164)
Ownership of bicycle	(0/1)	0.031	-0.089	-0.062	0.156
		(0.050)	(0.091)	(0.123)	(0.141)
Ownership of motorcycle	(0/1)	0.007	-0.095	-0.132	**0.410*** **
		(0.090)	(0.178)	(0.141)	(0.128)
Ownership of car	(0/1)	0.027	0.081	0.029	0.270
		(0.048)	(0.089)	(0.073)	(0.167)
Road conditions	#	**-0.028*** **	0.014	0.054	0.015
		(0.007)	(0.036)	(0.033)	(0.032)
Moderate risk averse	(0/1)	**0.056*** **	0.072	IV	-0.095
		(0.012)	(0.055)		(0.133)
No risk averse	(0/1)	0.047	-0.002	IV	-0.025
		(0.049)	(0.041)		(0.220)
Impatient	(0/1)	-0.071	**-0.143** *	-0.011	**-0.368** **
		(0.074)	(0.083)	(0.088)	(0.142)
Experience in farming[1]	Years	**-0.012*** **	**0.006** *	**0.011*** **	-0.005
		(0.001)	(0.003)	(0.004)	(0.005)
Training	(0/1)	0.091	-0.085	**-0.160** **	0.115
		(0.105)	(0.234)	(0.069)	(0.192)
Trust in input suppliers	(1/3)	**0.091** *	**-0.145** **	**-0.224*** **	0.082
		(0.051)	(0.060)	(0.040)	(0.057)
Trust in credit providers	(1/3)	-0.064	**-0.103*** **	-0.052	-0.020
		(0.076)	(0.033)	(0.034)	(0.059)
Trust in extension officers	(1/3)	0.038	**0.083*** **	**0.086*** **	-0.011
		(0.033)	(0.030)	(0.009)	(0.057)
Trust in FO	(1/3)	**0.072** **	-0.014	-0.045	**0.270*** **
		(0.029)	(0.040)	(0.043)	(0.082)
Trust in Development Agencies	(1/3)	**0.192*** **	0.040	-0.008	**0.152** **
		(0.028)	(0.115)	(0.094)	(0.071)
Trust in NGOs	(1/3)	0.016	-0.070	-0.021	**-0.087** *
		(0.046)	(0.047)	(0.049)	(0.048)
Trust in other farmers	(1/3)	-0.006	**0.312*** **	**0.152*** **	-0.059
		(0.041)	(0.109)	(0.035)	(0.145)
Observations		305	196	196	196

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Basic model and aggregate measures of social capital

Table 14 Determinants of adoption with aggregates measure of social capital

Dep. var=mango adoption (0/1) VARIABLES		(A7) Adoption mfx	(A15) Adoption mfx	(A16) Adoption mfx	(A17) Adoption mfx	(A18) Adoption mfx	(A19) Adoption mfx	(A20) Adoption mfx	(A21) Adoption mfx	(A22) Adoption mfx	(A23) Adoption mfx
Age head[1]	Years	-0.001	-0.002	-0.001	-0.001	-0.000	-0.001	-0.000	-0.001	-0.001	-0.001
		(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Male head	(0/1)	**0.181*** **	**0.152*** **	**0.190*** **	**0.105** **	0.069	**0.108** **	0.080	0.077	**0.107** **	**0.101***
		(0.062)	(0.030)	(0.064)	(0.047)	(0.061)	(0.052)	(0.050)	(0.054)	(0.047)	(0.052)
Higher education	(0/1)	-0.003	-0.014	-0.011	**0.053*** **	**0.050** **	**0.023** **	**0.082*** **	**0.059** **	**0.029*** **	**0.070*** **
		(0.013)	(0.020)	(0.013)	(0.016)	(0.024)	(0.009)	(0.026)	(0.027)	(0.007)	(0.015)
Farm labour[1]	#	-0.017	-0.025	-0.008	-0.027	-0.032*	-0.021	-0.025	-0.025	-0.015	-0.017
		(0.022)	(0.022)	(0.023)	(0.023)	(0.018)	(0.022)	(0.021)	(0.016)	(0.020)	(0.017)
Farm size[1]	Acres	**0.013** **	**0.009***	**0.012** **	**0.009** **	**0.010** **	**0.009***	**0.011*** **	**0.008** **	**0.007***	**0.009*** **
		(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)
Land ownership	(0/1)	**0.230*** **	**0.212*** **	**0.281*** **	**0.302*** **	**0.305*** **	**0.335*** **	**0.375*** **	**0.228*** **	**0.255*** **	**0.283*** **
		(0.063)	(0.046)	(0.032)	(0.027)	(0.057)	(0.036)	(0.017)	(0.040)	(0.027)	(0.018)
Production other cash crops	(0/1)	**-0.091*** **	**-0.090*** **	**-0.096***	-0.069	**-0.081***	**-0.090** **	-0.069	**-0.117*** **	**-0.135*** **	**-0.103***
		(0.035)	(0.023)	(0.053)	(0.072)	(0.049)	(0.038)	(0.058)	(0.045)	(0.044)	(0.058)
Livestock ownership	#	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Access to non-farm income	(0/1)	**0.064***	**0.076** **	0.038	**0.048***	**0.076*** **	**0.058** **	**0.056*** **	**0.062*** **	**0.043** **	**0.046** **
		(0.038)	(0.038)	(0.043)	(0.026)	(0.013)	(0.025)	(0.020)	(0.013)	(0.020)	(0.019)
Access to credit	(0/1)	0.112	-0.012	0.086	0.075	-0.027	-0.046	-0.011	0.080	0.069	0.086
		(0.085)	(0.140)	(0.068)	(0.072)	(0.082)	(0.103)	(0.070)	(0.078)	(0.079)	(0.070)
Ownership of tractor	(0/1)	**-0.346*** **	**-0.278*** **	**-0.281*** **	**-0.190*** **	**-0.222*** **	**-0.205*** **	**-0.156*** **	**-0.165*** **	**-0.138*** **	**-0.147*** **
		(0.066)	(0.055)	(0.050)	(0.008)	(0.075)	(0.070)	(0.033)	(0.060)	(0.047)	(0.011)
Ownership of mobile	(0/1)	0.087	0.046	0.110	0.057	0.042	0.041	0.039	0.008	0.013	0.016
		(0.118)	(0.100)	(0.128)	(0.111)	(0.091)	(0.092)	(0.093)	(0.088)	(0.083)	(0.095)
Ownership of radio	(0/1)	**-0.093*** **	**-0.050***	**-0.130*** **	**-0.080*** **	-0.074	**-0.062***	**-0.078***	-0.089	**-0.082** **	**-0.100** **
		(0.027)	(0.029)	(0.049)	(0.030)	(0.054)	(0.035)	(0.042)	(0.057)	(0.040)	(0.042)
Ownership of bicycle	(0/1)	0.057**	0.044**	0.046*	0.032	0.033	0.023	0.012	0.045	0.027	0.025
		(0.026)	(0.021)	(0.025)	(0.043)	(0.037)	(0.031)	(0.027)	(0.050)	(0.044)	(0.040)
Ownership of motorcycle	(0/1)	0.006	-0.004	0.005	-0.004	-0.000	0.004	-0.002	-0.023	-0.009	-0.015
		(0.053)	(0.054)	(0.074)	(0.083)	(0.057)	(0.067)	(0.067)	(0.065)	(0.078)	(0.073)
Ownership of car	(0/1)	**-0.032*** **	-0.022	0.016	**0.089*** **	**0.032*** **	**0.037*** **	**0.062*** **	**0.031*** **	**0.043*** **	**0.054*** **
		(0.009)	(0.014)	(0.012)	(0.011)	(0.006)	(0.008)	(0.013)	(0.004)	(0.008)	(0.003)
Road conditions	#	**-0.035** **	**-0.031***	**-0.040** **	-0.027	-0.015	**-0.024***	-0.020	-0.022	**-0.034** **	**-0.027***
		(0.018)	(0.018)	(0.018)	(0.019)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.016)
Moderate risk averse	(0/1)	**0.123*** **	**0.165*** **	**0.115*** **	**0.124***	**0.111*** **	**0.122*** **	**0.108** **	**0.093*** **	**0.114*** **	**0.112** **
		(0.036)	(0.032)	(0.043)	(0.064)	(0.027)	(0.040)	(0.053)	(0.032)	(0.033)	(0.054)
No risk averse	(0/1)	0.034	0.063	-0.012	0.059	0.037	0.014	0.046	0.036	0.023	0.050

[1] Values at the time of adoption for mango farmers; current values for non-mango farmers

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Dep. var=mango adoption (0/1) VARIABLES		(A7) Adoption mfx	(A15) Adoption mfx	(A16) Adoption mfx	(A17) Adoption mfx	(A18) Adoption mfx	(A19) Adoption mfx	(A20) Adoption mfx	(A21) Adoption mfx	(A22) Adoption mfx	(A23) Adoption mfx
		(0.078)	(0.061)	(0.092)	(0.045)	(0.035)	(0.039)	(0.029)	(0.041)	(0.033)	(0.040)
Impatient	(0/1)	-0.022	-0.030	-0.063	-0.102	-0.053	-0.066	-0.080	-0.045	-0.054	-0.079
		(0.064)	(0.047)	(0.078)	(0.097)	(0.067)	(0.068)	(0.077)	(0.065)	(0.062)	(0.080)
Experience in farming[1]	Years	**-0.012*** **	**-0.011*** **	**-0.015*** **	**-0.013*** **	**-0.013*** **	**-0.013*** **	**-0.013*** **	**-0.012*** **	**-0.012*** **	**-0.013*** **
		(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Training	(0/1)	**0.503*** **	**0.256** *	**0.406*** **	0.153	**0.183** **	0.137	0.161	0.078	0.059	0.103
		(0.112)	(0.142)	(0.089)	(0.115)	(0.085)	(0.103)	(0.117)	(0.104)	(0.115)	(0.133)
Structural Bridging Index	#		**0.167*** **								
			(0.027)								
Structural Bonding Index	#			**0.126*** **							
				(0.043)							
Cognitive Index	#				**0.214*** **						
					(0.049)						
Diversity social capital	#					**0.159*** **					
						(0.012)					
Intensity of diversity of social capital	#						**0.046*** **				
							(0.006)				
General trust	#							**0.063*** **			
								(0.012)			
Diversity of selected change agents	#								**0.228*** **		
									(0.021)		
Intensity of diversity of selected change agents	#									**0.066*** **	
										(0.010)	
Trust in selected change agents	#										**0.084*** **
											(0.016)
Observations		305	305	305	305	305	305	305	305	305	305

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 15 Determinants of time of adoption with aggregates measure of social capital - absolute cut-off

Dep. var=later adoption (0/1) *Cut-off=2006*		(A7) Time adoption-abs	(A15) Time adoption- abs	(A16) Time adoption- abs	(A17) Time adoption- abs	(A18) Time adoption- abs	(A19) Time adoption- abs	(A20) Time adoption-abs	(A21) Time adoption- abs	(A22) Time adoption- abs	(A23) Time adoption- abs
VARIABLES		mfx	mfx	mfx	mfx	mfx	mfx	mfx	mfx	mfx	mfx
Age head[1]	Years	-0.001	-0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Male head	(0/1)	-0.074	-0.068	-0.071	-0.077	-0.071	-0.072	-0.085	-0.071	-0.072	-0.087
		(0.252)	(0.267)	(0.244)	(0.224)	(0.270)	(0.264)	(0.250)	(0.268)	(0.263)	(0.252)
Higher education	(0/1)	**-0.080****	**-0.084****	**-0.085*****	**-0.076*****	**-0.081****	**-0.081****	**-0.071****	**-0.082****	**-0.080****	**-0.072****
		(0.039)	(0.035)	(0.028)	(0.028)	(0.038)	(0.040)	(0.033)	(0.037)	(0.039)	(0.034)
Farm labour[1]	#	**0.147*****	**0.147*****	**0.151*****	**0.150*****	**0.147*****	**0.147*****	**0.148*****	**0.147*****	**0.147*****	**0.148*****
		(0.012)	(0.010)	(0.018)	(0.016)	(0.012)	(0.013)	(0.015)	(0.012)	(0.014)	(0.015)
Farm size[1]	Acres	**-0.014*****	**-0.014*****	**-0.014*****	**-0.014*****	**-0.014*****	**-0.014*****	**-0.014*****	**-0.014*****	**-0.014*****	**-0.014*****
		(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Land ownership	(0/1)	-0.206	-0.211	-0.185	-0.149	-0.209	-0.212	-0.170	-0.207	-0.209	-0.183
		(0.139)	(0.151)	(0.174)	(0.143)	(0.132)	(0.149)	(0.138)	(0.136)	(0.146)	(0.135)
Production other cash crops	(0/1)	**-0.101*****	**-0.107*****	**-0.109*****	**-0.094*****	**-0.102*****	**-0.102*****	**-0.095*****	**-0.100*****	**-0.100*****	**-0.104*****
		(0.007)	(0.007)	(0.014)	(0.007)	(0.005)	(0.008)	(0.005)	(0.018)	(0.013)	(0.006)
Livestock ownership	#	-0.001	-0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Access to non-farm income	(0/1)	0.011	0.006	0.010	0.016	0.010	0.010	0.017	0.011	0.011	0.015
		(0.023)	(0.021)	(0.019)	(0.023)	(0.024)	(0.025)	(0.025)	(0.023)	(0.024)	(0.024)
Access to credit	(0/1)	0.154	0.199	0.142	0.147	0.159	0.160	0.130	0.155	0.155	0.153
		(0.137)	(0.147)	(0.154)	(0.125)	(0.136)	(0.152)	(0.129)	(0.138)	(0.141)	(0.125)
Ownership of mobile	(0/1)	0.085	0.104	0.091	0.078	0.086	0.087	0.076	0.087	0.087	0.076
		(0.169)	(0.164)	(0.148)	(0.161)	(0.164)	(0.172)	(0.165)	(0.162)	(0.172)	(0.163)
Ownership of radio	(0/1)	**0.137*****	**0.130*****	**0.139*****	**0.156*****	**0.135*****	**0.135*****	**0.153*****	**0.136*****	**0.137*****	**0.143*****
		(0.032)	(0.044)	(0.029)	(0.032)	(0.051)	(0.046)	(0.046)	(0.040)	(0.037)	(0.033)
Ownership of bicycle	(0/1)	-0.040	-0.033	-0.053	-0.073	-0.037	-0.036	-0.063	-0.036	-0.037	-0.062
		(0.114)	(0.111)	(0.128)	(0.127)	(0.127)	(0.130)	(0.133)	(0.125)	(0.132)	(0.129)
Ownership of motorcycle	(0/1)	-0.068	-0.052	-0.076	-0.093	-0.066	-0.066	-0.084	-0.066	-0.066	-0.081
		(0.142)	(0.152)	(0.134)	(0.157)	(0.151)	(0.142)	(0.154)	(0.151)	(0.142)	(0.156)
Ownership of car	(0/1)	0.028	0.057	0.037	0.033	0.029	0.029	0.034	0.033	0.031	0.023
		(0.093)	(0.065)	(0.102)	(0.099)	(0.087)	(0.086)	(0.099)	(0.077)	(0.076)	(0.094)
Road conditions	#	0.020	0.020	0.019	0.023	0.019	0.020	0.023	0.019	0.020	0.022
		(0.032)	(0.030)	(0.032)	(0.037)	(0.037)	(0.033)	(0.036)	(0.035)	(0.032)	(0.036)
Moderate risk averse	(0/1)	0.042	0.031	0.042	0.036	0.042	0.041	0.037	0.043	0.041	0.035
		(0.065)	(0.057)	(0.068)	(0.063)	(0.063)	(0.067)	(0.066)	(0.062)	(0.066)	(0.066)
No risk averse	(0/1)	-0.033	-0.022	-0.044	-0.069	-0.031	-0.031	-0.049	-0.030	-0.031	-0.055
		(0.078)	(0.055)	(0.082)	(0.063)	(0.066)	(0.067)	(0.071)	(0.058)	(0.063)	(0.063)
Impatient	(0/1)	-0.060	-0.084	-0.069	-0.081	-0.061	-0.061	-0.065	-0.063	-0.061	-0.064
		(0.095)	(0.068)	(0.100)	(0.122)	(0.089)	(0.091)	(0.109)	(0.079)	(0.088)	(0.108)

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Dep. var=later adoption (0/1) *Cut-off=2006* VARIABLES		(A7) Time adoption-abs mfx	(A15) Time adoption- abs mfx	(A16) Time adoption- abs mfx	(A17) Time adoption- abs mfx	(A18) Time adoption- abs mfx	(A19) Time adoption- abs mfx	(A20) Time adoption-abs mfx	(A21) Time adoption- abs mfx	(A22) Time adoption- abs mfx	(A23) Time adoption- abs mfx
Experience in farming[1]	Years	0.006	0.006	0.006	0.007	0.006	0.006	0.007	0.006	0.006	0.007
		(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Training	(0/1)	-0.043	0.071	-0.075	-0.176	-0.029	-0.027	-0.117	-0.016	-0.024	-0.142
		(0.221)	(0.187)	(0.188)	(0.169)	(0.192)	(0.157)	(0.179)	(0.216)	(0.131)	(0.173)
Structural Bridging Index	#		-0.075								
			(0.057)								
Structural Bonding Index	#			0.032							
				(0.067)							
Cognitive Index	#				0.078						
					(0.050)						
Diversity social capital	#					-0.006					
						(0.051)					
Intensity of diversity of social capital	#						-0.002				
							(0.009)				
General trust	#							0.013			
								(0.015)			
Diversity of selected change agents	#								-0.013		
									(0.091)		
Intensity of diversity of selected change agents	#									-0.003	
										(0.016)	
Trust in selected change agents	#										0.020
											(0.026)
Observations		196	196	196	196	196	196	196	196	196	196

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 16 Determinants of time of adoption with aggregates measure of social capital - relative cut-off

Dep. var=later adoption (0/1) *Cut-off=regional median* VARIABLES		(A7) Time adoption-rel Heck-mfx	(A15) Time adoption- rel Heck- mfx	(A16) Time adoption- rel Heck- mfx	(A17) Time adoption- rel mfx	(A18) Time adoption- rel Heck- mfx	(A19) Time adoption- rel Heck- mfx	(A20) Time adoption-rel mfx	(A21) Time adoption- rel Heck- mfx	(A22) Time adoption- rel mfx	(A23) Time adoption- rel mfx
Age head[1]	Years	-0.003	-0.002	-0.003	-0.004	-0.003	-0.003	-0.004	-0.003	-0.004	-0.004
		(0.005)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
Male head	(0/1)	IV	IV	IV	-0.099	IV	IV	-0.101	IV	-0.087	-0.107
					(0.110)			(0.126)		(0.130)	(0.126)
Higher education	(0/1)	-0.013	-0.041	-0.015	-0.004	-0.047	-0.036	-0.002	-0.050	-0.007	0.001
		(0.070)	(0.086)	(0.060)	(0.044)	(0.086)	(0.074)	(0.044)	(0.087)	(0.049)	(0.044)
Farm labour[1]	#	**0.134*** **	**0.138*** **	**0.122*** **	**0.132*** **	**0.134*** **	**0.127*** **	**0.132*** **	**0.134*** **	**0.130*** **	**0.132*** **
		(0.015)	(0.009)	(0.013)	(0.013)	(0.016)	(0.012)	(0.013)	(0.011)	(0.010)	(0.014)
Farm size[1]	Acres	**-0.021*** **	**-0.019*** **	**-0.014** **	**-0.009*** **	**-0.016*** **	**-0.014*** **	**-0.009*** **	**-0.015*** **	**-0.009*** **	**-0.009*** **
		(0.007)	(0.002)	(0.007)	(0.002)	(0.005)	(0.005)	(0.001)	(0.004)	(0.001)	(0.001)
Land ownership	(0/1)	IV	IV	IV	-0.062	IV	IV	-0.066	IV	-0.083	-0.068
					(0.138)			(0.143)		(0.155)	(0.143)
Production other cash crops	(0/1)	**0.087***	**0.087*** **	0.067	0.039	0.079*	0.074	0.040	0.083	0.036	0.036
		(0.046)	(0.034)	(0.066)	(0.043)	(0.046)	(0.057)	(0.039)	(0.055)	(0.050)	(0.046)
Livestock ownership	#	**-0.001***	**-0.001***	**-0.001***	-0.001	**-0.001***	-0.001	-0.001	**-0.001** **	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Access to non-farm income	(0/1)	0.008	0.001	0.014	0.011	0.006	0.011	0.011	0.011	0.008	0.011
		(0.027)	(0.040)	(0.027)	(0.035)	(0.034)	(0.030)	(0.037)	(0.035)	(0.034)	(0.037)
Access to credit	(0/1)	0.112	0.152	0.114	0.120	0.134	0.131	0.113	0.092	0.123	0.122
		(0.134)	(0.121)	(0.135)	(0.107)	(0.138)	(0.132)	(0.105)	(0.129)	(0.118)	(0.106)
Ownership of mobile	(0/1)	0.132	0.162	0.102	0.128	0.161	0.147	0.126	0.166	0.130	0.125
		(0.149)	(0.123)	(0.133)	(0.159)	(0.145)	(0.142)	(0.162)	(0.134)	(0.169)	(0.159)
Ownership of radio	(0/1)	IV	IV	IV	0.077	IV	IV	0.079	IV	0.072	0.075
					(0.142)			(0.153)		(0.140)	(0.138)
Ownership of bicycle	(0/1)	-0.050	-0.048	-0.024	-0.064	-0.030	-0.029	-0.063	-0.041	-0.049	-0.066
		(0.116)	(0.118)	(0.144)	(0.124)	(0.139)	(0.140)	(0.133)	(0.141)	(0.134)	(0.127)
Ownership of motorcycle	(0/1)	-0.107	-0.095	-0.091	-0.109	-0.093	-0.091	-0.107	-0.093	-0.098	-0.108
		(0.150)	(0.137)	(0.117)	(0.141)	(0.145)	(0.130)	(0.141)	(0.142)	(0.130)	(0.141)
Ownership of car	(0/1)	0.052	0.075	0.007	0.023	0.019	0.014	0.025	0.011	0.027	0.020
		(0.060)	(0.069)	(0.080)	(0.072)	(0.080)	(0.076)	(0.074)	(0.077)	(0.062)	(0.072)
Road conditions	#	**0.053***	**0.063*** **	**0.052** **	**0.047**	**0.051***	**0.052** **	**0.047**	**0.055** **	**0.047***	0.048
		(0.030)	(0.023)	(0.026)	(0.029)	(0.026)	(0.022)	(0.030)	(0.027)	(0.028)	(0.031)
Moderate risk averse	(0/1)	IV	IV	IV	0.036	IV	IV	0.035	IV	0.034	0.033
					(0.064)			(0.065)		(0.064)	(0.066)
No risk averse	(0/1)	IV	IV	IV	-0.063	IV	IV	-0.059	IV	-0.051	-0.066
					(0.117)			(0.117)		(0.115)	(0.114)
Impatient	(0/1)	0.005	-0.009	0.019	-0.027	-0.002	0.001	-0.021	-0.006	-0.018	-0.022
		(0.077)	(0.068)	(0.068)	(0.099)	(0.071)	(0.072)	(0.090)	(0.061)	(0.081)	(0.091)
Experience in farming[1]	Years	**0.010** **	**0.010*** **	**0.010** **	**0.008** **	**0.011** **	**0.011** **	**0.008*** **	**0.011** **	**0.008*** **	**0.008** **

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Dep. var=later adoption (0/1) *Cut-off=regional median* VARIABLES		(A7) Time adoption-rel Heck-mfx	(A15) Time adoption- rel Heck- mfx	(A16) Time adoption- rel Heck- mfx	(A17) Time adoption- rel mfx	(A18) Time adoption- rel Heck- mfx	(A19) Time adoption- rel Heck- mfx	(A20) Time adoption-rel mfx	(A21) Time adoption- rel Heck- mfx	(A22) Time adoption- rel mfx	(A23) Time adoption- rel mfx
		(0.004)	(0.004)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)
Training	(0/1)	**-0.200***	**-0.083*****	**-0.102**	**-0.169*****	**-0.060****	**-0.059*****	**-0.155*****	**-0.063**	**-0.101*****	**-0.181****
		(0.112)	(0.024)	(0.098)	(0.061)	(0.029)	(0.022)	(0.058)	(0.079)	(0.035)	(0.074)
Structural Bridging Index	#		**-0.080****								
			(0.035)								
Structural Bonding Index	#			**-0.054****							
				(0.023)							
Cognitive Index	#				0.027						
					(0.044)						
Diversity social capital	#					-0.055					
						(0.043)					
Intensity of diversity of social capital	#						**-0.014***				
							(0.008)				
General trust	#							0.005			
								(0.014)			
Diversity of selected change agents	#								-0.059		
									(0.071)		
Intensity of diversity of selected change agents	#									-0.004	
										(0.013)	
Trust in selected change agents	#										0.013
											(0.022)
Observations		196	196	196	196	196	196	196	196	196	196

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 17 Determinants of intensity of adoption with aggregates measure of social capital

Dep var=ln(n. trees)		(A7) Intensity	(A15) Intensity	(A16) Intensity	(A17) Intensity	(A18) Intensity	(A19) Intensity	(A20) Intensity	(A21) Intensity	(A22) Intensity	(A23) Intensity
VARIABLES		OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Age head[1]	Years	0.004	0.004	0.003	0.003	0.004	0.003	0.004	0.003	0.003	0.004
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Male head	(0/1)	**0.421***	0.418	**0.470***	**0.436***	0.386	0.397	0.394	0.386	0.403	0.382
		(0.254)	(0.254)	(0.249)	(0.234)	(0.252)	(0.248)	(0.243)	(0.256)	(0.247)	(0.244)
Higher education	(0/1)	**0.372***	**0.369***	**0.326***	**0.330***	**0.362***	**0.348***	**0.365***	**0.376****	**0.346***	**0.370***
		(0.195)	(0.196)	(0.185)	(0.185)	(0.196)	(0.195)	(0.193)	(0.190)	(0.189)	(0.189)
Farm labour[1]	#	-0.063	-0.062	-0.034	-0.051	-0.061	-0.054	-0.057	-0.059	-0.050	-0.058
		(0.055)	(0.055)	(0.053)	(0.050)	(0.053)	(0.052)	(0.051)	(0.052)	(0.051)	(0.051)
Farm size[1]	Acres	**0.029*****	**0.028*****	**0.027*****	**0.024*****	**0.027*****	**0.026*****	**0.026*****	**0.027*****	**0.025*****	**0.025*****
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Land ownership	(0/1)	-0.133	-0.135	-0.185	-0.216	-0.166	-0.136	-0.164	-0.207	-0.193	-0.218
		(0.216)	(0.219)	(0.203)	(0.208)	(0.226)	(0.217)	(0.219)	(0.223)	(0.216)	(0.217)
Production other cash crops	(0/1)	-0.311	-0.314	**-0.380****	**-0.390****	-0.331	**-0.329***	**-0.346***	**-0.375***	**-0.374***	**-0.385****
		(0.199)	(0.201)	(0.186)	(0.189)	(0.202)	(0.197)	(0.201)	(0.199)	(0.191)	(0.195)
Livestock ownership	#	0.002	**0.002***	0.002	0.001	**0.002***	**0.002***	0.002	**0.002***	0.002	0.002
		(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Access to non-farm income	(0/1)	0.089	0.092	0.056	0.076	0.098	0.088	0.094	0.089	0.078	0.086
		(0.101)	(0.102)	(0.101)	(0.098)	(0.105)	(0.102)	(0.102)	(0.102)	(0.100)	(0.099)
Access to credit	(0/1)	0.143	0.129	0.064	0.120	0.072	0.064	0.066	0.137	0.136	0.142
		(0.160)	(0.171)	(0.152)	(0.160)	(0.187)	(0.175)	(0.178)	(0.163)	(0.161)	(0.162)
Ownership of tractor	(0/1)	0.042	0.066	0.190	0.275	0.131	0.168	0.184	0.186	0.283	0.256
		(0.535)	(0.532)	(0.515)	(0.458)	(0.498)	(0.486)	(0.472)	(0.482)	(0.474)	(0.472)
Ownership of mobile	(0/1)	-0.154	-0.160	-0.130	**-0.223***	-0.180	-0.190	**-0.202***	**-0.194**	**-0.208***	**-0.213***
		(0.126)	(0.123)	(0.126)	(0.130)	(0.121)	(0.123)	(0.122)	(0.126)	(0.126)	(0.127)
Ownership of radio	(0/1)	**0.324****	**0.326****	**0.257***	0.219	**0.317****	**0.326****	**0.294****	**0.280***	**0.278***	0.240
		(0.146)	(0.146)	(0.152)	(0.144)	(0.152)	(0.145)	(0.147)	(0.154)	(0.147)	(0.151)
Ownership of bicycle	(0/1)	0.139	0.138	0.139	0.171	0.125	0.118	0.134	0.130	0.120	0.145
		(0.156)	(0.157)	(0.148)	(0.148)	(0.158)	(0.155)	(0.154)	(0.154)	(0.151)	(0.151)
Ownership of motorcycle	(0/1)	0.415***	0.409***	0.440***	0.420***	0.410***	0.408***	0.413***	0.414***	0.418***	0.423***
		(0.130)	(0.129)	(0.127)	(0.120)	(0.128)	(0.126)	(0.125)	(0.125)	(0.123)	(0.124)
Ownership of car	(0/1)	**0.386****	**0.375***	**0.377****	**0.315***	**0.354***	**0.345***	**0.360***	0.307	0.300	**0.314***
		(0.194)	(0.199)	(0.184)	(0.172)	(0.198)	(0.195)	(0.192)	(0.195)	(0.190)	(0.185)
Road conditions	#	0.056	0.056	0.025	0.023	0.055	0.048	0.043	0.053	0.040	0.039
		(0.037)	(0.036)	(0.038)	(0.033)	(0.035)	(0.035)	(0.034)	(0.034)	(0.034)	(0.033)
Moderate risk averse	(0/1)	-0.080	-0.075	-0.048	-0.052	-0.073	-0.049	-0.068	-0.086	-0.047	-0.076
		(0.138)	(0.138)	(0.133)	(0.133)	(0.138)	(0.136)	(0.138)	(0.136)	(0.132)	(0.136)
No risk averse	(0/1)	0.123	0.118	0.088	0.031	0.109	0.099	0.083	0.092	0.097	0.058
		(0.224)	(0.224)	(0.216)	(0.207)	(0.222)	(0.220)	(0.218)	(0.218)	(0.214)	(0.212)
Impatient	(0/1)	**-0.270****	**-0.264***	**-0.338****	**-0.368*****	**-0.274****	**-0.277****	**-0.302****	**-0.259***	**-0.273****	**-0.305****
		(0.136)	(0.139)	(0.147)	(0.137)	(0.136)	(0.136)	(0.134)	(0.136)	(0.135)	(0.136)

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Dep var=ln(n. trees)			(A7) Intensity OLS	(A15) Intensity OLS	(A16) Intensity OLS	(A17) Intensity OLS	(A18) Intensity OLS	(A19) Intensity OLS	(A20) Intensity OLS	(A21) Intensity OLS	(A22) Intensity OLS	(A23) Intensity OLS
VARIABLES												
Experience in farming[1]		Years	-0.009	-0.009	**-0.009***	-0.006	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008
			(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
Training		(0/1)	**0.619*** **	**0.577*** **	**0.469** **	0.213	**0.426** **	**0.394** **	**0.402** **	0.289	0.252	0.301
			(0.186)	(0.197)	(0.187)	(0.186)	(0.193)	(0.188)	(0.177)	(0.201)	(0.207)	(0.195)
Structural Bridging Index	#			0.029								
				(0.054)								
Structural Bonding Index	#				**0.195** **							
					(0.075)							
Cognitive Index	#					**0.279*** **						
						(0.060)						
Diversity social capital	#						**0.094***					
							(0.055)					
Intensity of diversity of social capital	#							**0.029** **				
								(0.013)				
General trust	#								**0.045*** **			
									(0.017)			
Diversity of selected change agents	#									**0.178*** **		
										(0.062)		
Intensity of diversity of selected change agents	#										**0.055*** **	
											(0.017)	
Trust in selected change agents	#											**0.076*** **
												(0.023)
Constant			3.398***	3.355***	3.341***	3.393***	3.278***	3.284***	3.355***	3.354***	3.395***	3.473***
			(0.444)	(0.448)	(0.446)	(0.415)	(0.434)	(0.436)	(0.429)	(0.443)	(0.434)	(0.434)
Observations			196	196	196	196	196	196	196	196	196	196
R-squared			0.589	0.589	0.610	0.628	0.596	0.600	0.602	0.604	0.612	0.610

[1] *Values at the time of adoption for mango farmers; current values for non-mango farmers*

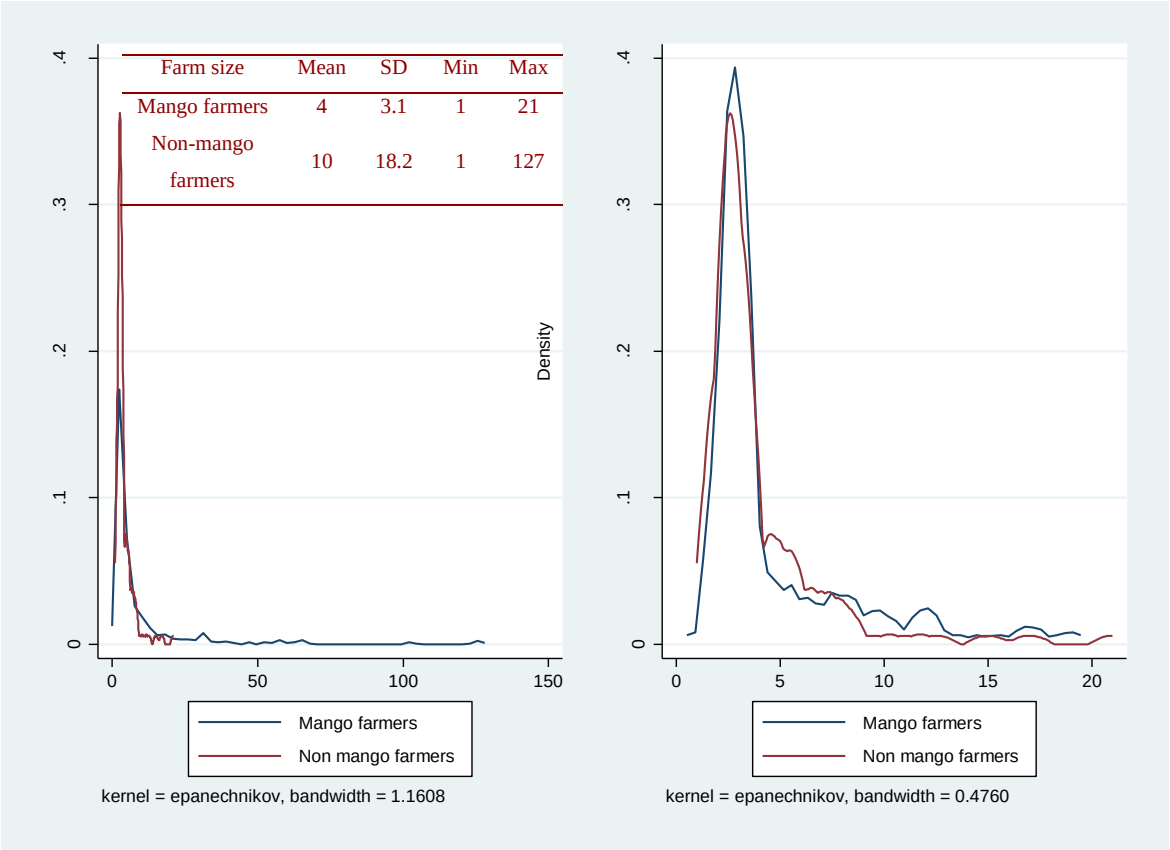
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix 3.4. Estimation without large farmers

In order to validate the robustness of the results I have also run additional estimations on a subset of farmers. One of the main differences between adopters and non-adopters highlighted in Section 3 was the size of the cultivated farm. Adopters, early adopters as well as more intense adopters were observed to have consistently higher farm size that the respective comparison group. These differences might have been driven by the existence in the sample of very big mango farmers. The exploratory analysis suggests that among non-mango farmers the biggest farm size is about 21 acres while among mango farmers the largest farm is 127 acres (Figure 6). In order to reduce the systematic difference in farm endowments between adopters and non-adopters I have run the analysis of the adoption and its dimensions on the subset of farmers with similar farm size (with 21 or less acres). As a result of this selection, 20 mango farmers were excluded from the analysis. Using this sample, I have re-run the basic model as in Table 6 and the model with social capital variables as in Table 7. The results in Table 18 show that the estimations discussed above do not change much when the biggest farmers are dropped from the analysis. The size, the significance as well as the direction of the coefficients estimated in the full model remain very similar also in these estimations. However, some differences can be pointed out.

First, farm size becomes not significant in the discrete decision to adopt mango. This result is, however, expected as, in this sample, mango and non-mango farmers are more similar in terms of farm endowment (right graph in Figure 6).

Figure 6 Farm size, by adoption status



More differences can be noticed for the time of adoption. In these analyses, land ownership becomes not significant, suggesting that when similar size farms are compared, owning land increases the probability to adopt earlier than others. Moreover, the production of other cash crops also becomes not significant for both analyses of the time of adoption. This result might be explained with the fact that the production of other cash crops is more evenly distributed between early (earlier) and late (later) adopters (85 farmers vs 88 farmers compared to 103 farmers vs 93 farmers in the case of the full sample).

In the analysis of the intensity of adoption, higher education and gender of the head of the household becomes not significant while the ownership of tractor and experience in farming become now statistically relevant. These changes might suggest that for relatively similar farmers in terms of land cultivated, the intensity of adoption is more affected by farm assets and skills than human capital characteristic. More specifically, these results tend to indicate that, although the majority of the estimation results are quite robust to the different sample specification, when reducing the differences in terms of farm size, farm assets and farm related skills might become more important for the adoption decision.

The robustness of the previous estimations is also confirmed by the result of the model which includes social capital variables (Table 19). Overall, the results do not change much with regards to the majority of the measures of social capital, regardless of what dimension of the adoption decision is analysed. The only difference that can be pointed out is the higher importance for farmers of similar farm size of having a relationship with input or credit providers, which are found to be positively associated with early adoption. Extension services are still found to increase the time of adoption also for this group of farmers. Nonetheless, both cognitive and social capital associations with adoption decision and its dimensions do not change much suggesting that the presence of big farmers in the previous estimations did not significantly affects the results. A similar story is observed for the majority of the aggregate measures of social capital.

Table 18 Determinants of adoption, basic model (no large mango farmers)

VARIABLES		(A24) Adoption Probit mfx	(A25) Time adoption Absolute cut-off[119] Probit mfx	(A27) Time adoption Relative cut-off[120] Probit mfx	(A28) Intensity OLS coeff.
Age head[121]	Years	-0.002	0.001	-0.003	0.001
		(0.003)	(0.007)	(0.005)	(0.005)
Male head	(0/1)	**0.197*** **	-0.067	-0.117	0.400
		(0.071)	(0.266)	(0.095)	(0.252)
Higher education	(0/1)	0.007	-0.054	0.010	0.182
		(0.009)	(0.079)	(0.084)	(0.196)
Farm labour[14]	#	-0.012	**0.114*** **	**0.106*** **	-0.041
		(0.021)	(0.022)	(0.008)	(0.049)
Farm size[14]	Acres	-0.001	**-0.040*** **	**-0.029*** **	**0.089*** **
		(0.010)	(0.005)	(0.007)	(0.019)
Land ownership	(0/1)	**0.277*** **	**-0.237*** **	**-0.125** **	-0.097
		(0.058)	(0.059)	(0.058)	(0.229)
Production other cash crops	(0/1)	**-0.081***	-0.082	**0.093*** **	**-0.525** **
		(0.042)	(0.059)	(0.016)	(0.201)
Livestock ownership	#	0.001	-0.001	-0.001	**0.003** **
		(0.002)	(0.001)	(0.002)	(0.002)
Access to non-farm income	(0/1)	**0.080** **	0.057	0.015	0.086
		(0.037)	(0.058)	(0.056)	(0.109)
Access to credit	(0/1)	0.120	0.148	0.146	0.167
		(0.091)	(0.143)	(0.121)	(0.168)
Ownership of tractor	(0/1)	**-0.369*** **	*dropped*	*dropped*	**0.903*** **
		(0.049)			(0.324)
Ownership of mobile	(0/1)	0.091	0.131	0.161	-0.178
		(0.127)	(0.156)	(0.144)	(0.132)
Ownership of radio	(0/1)	**-0.095*** **	**0.148*** **	0.087	**0.296** **
		(0.034)	(0.025)	(0.109)	(0.144)
Ownership of bicycle	(0/1)	0.063**	-0.051	-0.071	0.078
		(0.029)	(0.109)	(0.125)	(0.147)
Ownership of motorcycle	(0/1)	-0.005	-0.030	-0.029	**0.262***
		(0.053)	(0.199)	(0.192)	(0.136)
Ownership of car	(0/1)	**-0.044*** **	0.081	0.102	**0.457** **
		(0.002)	(0.099)	(0.075)	(0.221)
Road conditions	#	**-0.031**	0.026	0.050**	**0.066***
		(0.020)	(0.036)	(0.025)	(0.036)
Moderate risk averse	(0/1)	**0.145*** **	0.043	0.025	-0.034
		(0.035)	(0.068)	(0.073)	(0.128)
No risk averse	(0/1)	0.063	0.028	-0.013	0.055
		(0.082)	(0.092)	(0.122)	(0.243)
Impatient	(0/1)	-0.015	-0.056	-0.020	**-0.311** **
		(0.072)	(0.105)	(0.078)	(0.134)
Experience in farming[1]	Years	**-0.013*** **	**0.009** **	**0.011*** **	**-0.014** **
		(0.002)	(0.004)	(0.003)	(0.006)
Training	(0/1)	**0.531*** **	-0.064	**-0.152** **	**0.510*** **
		(0.116)	(0.229)	(0.059)	(0.180)
Constant					3.246***
					(0.450)
Observations		285	176	176	176

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[119] =1 if late adopter; = 0 if early adopter. Cut-off year=2006

[120] =1 if later adopter; =0 if earlier adopter. Cut-off year= regional median of year of adoption

[121] At the time of adoption for mango farmers; current for non-mango farmers.

Table 19 Social capital (no large mango farmers)

Basic model and social capital		(A28) Adoption	(A30) Time adoption Absolute cut-off[122]	(A31) Time adoption Relative cut-off[123]	(A32) Intensity
VARIABLES		Probit mfx	Heck/Probit mfx	Heck/Probit mfx	Heck/ OLS coeff
Structural bonding social capital					
Relationship with FO	(0/1)	**0.352*** **	0.164	-0.047	**0.715*** **
		(0.084)	(0.118)	(0.095)	(0.204)
Strength of relationship with other farmers	(0/1)	0.060	0.091	0.024	0.075
		(0.061)	(0.079)	(0.040)	(0.065)
Membership in FO	(0/1)	**0.303*** **	0.178	0.056[124]	**0.766*** **
		(0.096)	(0.117)	(0.334)	(0.190)
Social network	#	**-0.198***	0.104	**0.327** **	-0.076
		(0.109)	(0.213)	(0.136)	(0.220)
Structural bridging social capital					
Relationship with input suppliers	(0/1)	**0.411*** **	**-0.406*** **	*dropped*	-0.001
		(0.145)	(0.039)		(0.119)
Relationship with credit providers	(0/1)	**-0.460** **	-0.190***	**-0.660*** **[24]	0.099
		(0.209)	(0.044)	(0.252)	(0.179)
Relationship with extension officers	(0/1)	**0.164*** **	0.039	**0.521** *[24]	-0.262
		(0.037)	(0.110)	(0.204)	(0.174)
Relationship with Dev Agencies	(0/1)	**0.505*** **	0.109	0.477[24]	**0.333***
		(0.062)	(0.252)	(0.649)	(0.181)
Relationship with NGOs	(0/1)	0.085	**-0.195** **	-0.293[24]	-0.211
		(0.080)	(0.087)	(0.178)	(0.128)
Strength of relationship with input suppliers	(1/5)	**0.058** **	-0.030	**-0.053*** **	-0.009
		(0.023)	(0.030)	(0.012)	(0.039)
Strength of relationship with credit providers	(1/5)	-0.075	**-0.071*** **	**-0.073*** **	0.019
		(0.066)	(0.016)	(0.018)	(0.048)
Strength of relationship with extension officers	(1/5)	0.030	0.008	0.041	-0.044
		(0.023)	(0.029)	(0.030)	(0.040)
Strength of relationship with Dev Agencies	(1/5)	**0.220*** **	0.030	0.009	**0.103** **
		(0.028)	(0.066)	(0.057)	(0.045)
Strength of relationship with NGOs	(1/5)	0.027	-0.064	-0.031	-0.060
		(0.024)	(0.040)	(0.036)	(0.038)
Cognitive social capital					
Trust in input suppliers	(1/3)	**0.117***	**-0.117** **	**-0.199*** **	0.094[24]
		(0.066)	(0.048)	(0.044)	(0.072)
Trust in credit providers	(1/3)	-0.080	**-0.136*** **	**-0.103*** **	-0.010[24]
		(0.086)	(0.052)	(0.009)	(0.074)
Trust in extension officers	(1/3)	0.043	**0.069*** **	**0.102*** **	-0.075[24]
		(0.040)	(0.023)	(0.019)	(0.052)
Trust in FO	(1/3)	**0.093*** **	0.001	-0.050	**0.227*** **[24]
		(0.036)	(0.049)	(0.046)	(0.060)
Trust in Development Agencies	(1/3)	**0.232*** **	0.039	0.035	0.091[24]
		(0.030)	(0.115)	(0.093)	(0.057)
Trust in NGOs	(1/3)	0.005	-0.067	-0.013	-0.056[24]
		(0.058)	(0.044)	(0.040)	(0.051)
Trust in other farmers	(1/3)	-0.005	**0.307*** **	**0.166*** **	-0.061[24]
		(0.052)	(0.117)	(0.049)	(0.124)
Aggregates					
Structural Bridging Index	#	**0.179*** **	-0.077	-0.046	-0.046
		(0.031)	(0.059)	(0.046)	(0.053)
Structural Bonding Index	#	**0.144*** **	0.028	-0.061	**0.177** **
		(0.044)	(0.075)	(0.048)	(0.072)
Cognitive Index	#	**0.246*** **	0.082	0.018	**0.223*** **
		(0.055)	(0.060)	(0.045)	(0.061)
Diversity social capital	#	**0.175*** **	0.000	-0.029	0.043
		(0.009)	(0.054)	(0.051)	(0.057)
Intensity of diversity of social capital	#	**0.052*** **	-0.001	-0.009	0.016
		(0.007)	(0.009)	(0.008)	(0.012)
General trust	#	**0.073*** **	0.013	-0.000	**0.036** **

[122] =1 if late adopter; = 0 if early adopter. Cut-off year=2006

[123] =1 if later adopter; =0 if earlier adopter. Cut-off year= regional median of year of adoption

[124] Heckman corrected

Basic model and social capital		(A28) Adoption Probit	(A30) Time adoption Absolute cut-off[122] Heck/Probit	(A31) Time adoption Relative cut-off[123] Heck/Probit	(A32) Intensity Heck/ OLS
VARIABLES		mfx	mfx	mfx	coeff
		(0.014)	(0.015)	(0.015)	(0.016)
Diversity of selected change agents	#	**0.252*** **	-0.000	0.090[24]	**0.166***
		(0.023)	(0.099)	(0.260)	(0.087)
Intensity of diversity of selected change agents	#	**0.074*** **	-0.001	-0.008	**0.033** **
		(0.011)	(0.018)	(0.013)	(0.015)
Trust in selected change agents	#	**0.096*** **	0.023	0.009	**0.056** **
		(0.018)	(0.028)	(0.022)	(0.022)

Appendix 3.5. The role of social capital in reducing barriers to adoption

Table 20 Sub-sample by type of change agents

VARIABLES	(A33) Adoption Input suppliers	(A34) Adoption Extension officers	(A35) Adoption Development agencies	(A36) Adoption FO	(A37) Intensity Development agencies	(A38) Intensity FO	(A39) Time adoption - abs Input suppliers	(A40) Time adoption - abs Credit providers	(A41) Time adoption - abs NGOs	(A42) Time adoption - abs FO	(A43) Time adoption-rel Input suppliers	(A44) Time adoption-rel Extension officers
Age head[1]	-0.001	-0.001	-0.000	-0.002***	0.001	-0.001	-0.001	0.000	0.001	-0.007	-0.004	-0.009***
	(0.003)	(0.003)	(0.000)	(0.000)	(0.008)	(0.007)	(0.005)	(0.000)	(0.006)	(0.008)	(0.003)	(0.002)
Male head	0.124**	0.093	0.999***	0.035	1.028***	0.641*	-0.100	-0.000	-0.021	-0.160	-0.108	0.020
	(0.061)	(0.093)	(0.001)	(0.021)	(0.279)	(0.346)	(0.256)	(0.000)	(0.305)	(0.293)	(0.116)	(0.227)
Higher education	-0.022	-0.102***	*dropped*	-0.007	0.923***	0.626***	-0.074**	*dropped*	0.206*	-0.147***	0.008	-0.009
	(0.014)	(0.029)		(0.024)	(0.340)	(0.236)	(0.034)		(0.111)	(0.051)	(0.053)	(0.059)
Farm labour[1]	-0.030	-0.007	-0.000	0.001	0.046	-0.022	0.150***	-0.000	0.127***	0.125***	0.143***	0.150***
	(0.027)	(0.027)	(0.000)	(0.002)	(0.062)	(0.047)	(0.011)	(0.000)	(0.026)	(0.013)	(0.012)	(0.031)
Farm size[1]	0.011*	0.011***	-0.000	0.001	0.023***	0.028***	-0.014***	-0.000	-0.019***	-0.015***	-0.009***	-0.008***
	(0.006)	(0.003)	(0.000)	(0.002)	(0.004)	(0.004)	(0.002)	(0.000)	(0.002)	(0.004)	(0.002)	(0.002)
Land ownership	0.219**	0.054**	-0.564***	0.027	0.213	-0.087	-0.156	-0.149**	-0.326*	-0.143	-0.034	-0.152**
	(0.088)	(0.022)	(0.063)	(0.022)	(0.331)	(0.194)	(0.134)	(0.072)	(0.189)	(0.199)	(0.154)	(0.064)
Production other cash crops	-0.060	-0.063***	*dropped*	-0.010	-0.215	-0.735**	-0.091***	-1.000***	0.048	-0.137	0.030	0.142***
	(0.039)	(0.002)		(0.013)	(0.408)	(0.288)	(0.009)	(0.000)	(0.041)	(0.215)	(0.054)	(0.036)
Livestock ownership	-0.000	0.001	0.000	0.000**	0.002	0.002	-0.001	-0.000	-0.004	-0.002*	-0.001	-0.002
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)
Access to non-farm income	0.054*	0.023	-0.000	0.009	-0.165	-0.022	0.004	0.000	0.101*	0.031	-0.004	-0.043
	(0.032)	(0.029)	(0.000)	(0.006)	(0.126)	(0.088)	(0.030)	(0.000)	(0.052)	(0.071)	(0.038)	(0.043)
Access to credit	0.052	0.076	*dropped*	0.004	0.350	0.144	0.124	*dropped*	*dropped*	0.173	0.087	0.207***
	(0.066)	(0.059)		(0.005)	(0.215)	(0.150)	(0.121)			(0.153)	(0.111)	(0.056)
Ownership of tractor	-0.428***	*dropped*	*dropped*		0.263	-0.230	*dropped*	*dropped*	*dropped*			
	(0.061)				(0.596)	(0.576)						
Ownership of mobile	0.114	0.094	0.000	-0.013**	-0.257	-0.043	0.040	0.000	-0.497***	0.172	0.083	0.369**
	(0.122)	(0.171)	(0.000)	(0.006)	(0.177)	(0.121)	(0.141)	(0.000)	(0.162)	(0.217)	(0.145)	(0.157)
Ownership of radio	-0.055***	-0.059	0.000	-0.010	0.300*	0.157	0.163***	0.765***	-0.083	0.239***	0.094	-0.017
	(0.018)	(0.045)	(0.000)	(0.012)	(0.159)	(0.144)	(0.046)	(0.084)	(0.110)	(0.031)	(0.159)	(0.218)
Ownership of bicycle	0.055	0.008	-0.000	0.000	0.086	-0.062	-0.027	-0.117*	0.014	-0.037	-0.056	0.016
	(0.042)	(0.045)	(0.000)	(0.005)	(0.216)	(0.182)	(0.127)	(0.061)	(0.114)	(0.228)	(0.146)	(0.171)
Ownership of motorcycle	-0.014	-0.019	0.000	-0.001	0.654***	0.467***	-0.067	-0.020***	0.155	-0.140	-0.121	-0.104
	(0.052)	(0.039)	(0.000)	(0.004)	(0.152)	(0.121)	(0.148)	(0.005)	(0.209)	(0.182)	(0.131)	(0.128)
Ownership of car	0.066***	0.080**			0.565*	0.430*	0.032	0.179**	0.173	-0.028	0.046	-0.039
	(0.019)	(0.038)			(0.302)	(0.228)	(0.093)	(0.081)	(0.140)	(0.085)	(0.077)	(0.043)
Road conditions	-0.027	-0.024**	-0.000	0.005	0.100	0.068	0.021	-0.000	-0.036	0.041	0.049*	0.063***

VARIABLES	(A33) Adoption Input suppliers	(A34) Adoption Extension officers	(A35) Adoption Development agencies	(A36) Adoption FO	(A37) Intensity Development agencies	(A38) Intensity FO	(A39) Time adoption - abs Input suppliers	(A40) Time adoption - abs Credit providers	(A41) Time adoption - abs NGOs	(A42) Time adoption - abs FO	(A43) Time adoption-rel Input suppliers	(A44) Time adoption-rel Extension officers
	(0.017)	(0.010)	(0.000)	(0.005)	(0.062)	(0.046)	(0.031)	(0.000)	(0.027)	(0.029)	(0.029)	(0.019)
Moderate risk averse	0.151***	0.171***	*dropped*	0.039***	-0.140	-0.205	0.011	0.758***	-0.076	0.067	0.002	0.046
	(0.040)	(0.049)		(0.011)	(0.211)	(0.176)	(0.070)	(0.096)	(0.064)	(0.158)	(0.067)	(0.171)
No risk averse	0.053	0.078	*dropped*	0.008	-0.112	-0.196	-0.029	0.010	-0.024	-0.010	-0.110	-0.028
	(0.059)	(0.064)		(0.009)	(0.284)	(0.237)	(0.065)	(0.008)	(0.068)	(0.148)	(0.106)	(0.234)
Impatient	-0.006	-0.077**	-0.002**	-0.049	-0.382**	-0.175	-0.030	0.000	0.187	-0.167	-0.005	-0.014
	(0.040)	(0.032)	(0.001)	(0.040)	(0.164)	(0.124)	(0.092)	(0.000)	(0.246)	(0.120)	(0.077)	(0.095)
Experience in farming[1]	-0.012***	-0.008***	-0.000	-0.001**	-0.006	-0.001	0.005	-0.000	0.011***	0.005	0.008***	0.008*
	(0.002)	(0.002)	(0.000)	(0.000)	(0.006)	(0.005)	(0.004)	(0.000)	(0.003)	(0.010)	(0.002)	(0.005)
Training	0.507***	0.244***	*dropped*	0.908***	*dropped*	-0.063	-0.047	*dropped*	0.046	0.132	-0.112	-0.146***
	(0.058)	(0.063)		(0.060)		(0.356)	(0.215)		(0.150)	(0.270)	(0.070)	(0.035)
Observations	276	188	32	117	103	123	186	38	69	123	186	153

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21 Social capital interactions (Bridging Social Capital)

VARIABLES	(A1) Adoption mfx	(A45) Adoption mfx	(A2) Time adoption - abs mfx	(A46) Time adoption - abs mfx	(A3) Time adoption - rel mfx	(A47) Time adoption - rel mfx	(A4) Intensity coeff	(A48) Intensity coeff
Farm size	**0.013****	**0.009***	**-0.014*****	**-0.015*****	**-0.009*****	**-0.008*****	**0.029*****	**0.028*****
	(0.005)	(0.006)	(0.002)	(0.004)	(0.002)	(0.001)	(0.004)	(0.004)
Land ownership	**0.230*****	**0.213*****	-0.206	-0.259*	-0.080	-0.086	-0.133	-0.104
	(0.063)	(0.052)	(0.139)	(0.157)	(0.150)	(0.159)	(0.216)	(0.216)
Radio	**-0.093*****	**-0.065*****	**0.137*****	**0.096****	0.073	0.050	**0.324****	**0.339****
	(0.027)	(0.023)	(0.032)	(0.048)	(0.136)	(0.127)	(0.146)	(0.145)
Access to credit	0.112	0.078	0.154	-0.254	0.122	0.220	0.143	0.375
	(0.085)	(0.141)	(0.137)	(0.479)	(0.114)	(0.324)	(0.160)	(0.412)
Road conditions	**-0.035****	**-0.075*****	0.020	**0.202*****	0.046	**0.121*****	0.056	0.009
	(0.018)	(0.010)	(0.032)	(0.067)	(0.029)	(0.040)	(0.037)	(0.084)
Moderate risk aversion	**0.123*****	**-0.123***	0.042	**0.346*****	0.035	0.014	-0.080	0.183
	(0.036)	(0.070)	(0.065)	(0.062)	(0.063)	(0.144)	(0.138)	(0.323)
No risk aversion	0.034	-0.110	-0.033	-0.108	-0.053	**0.088***	0.123	-0.490
	(0.078)	(0.131)	(0.078)	(0.131)	(0.125)	(0.050)	(0.224)	(0.726)
Structural Bridging Index		0.020		0.139		0.054		0.023
		(0.020)		(0.123)		(0.102)		(0.126)
i_roads1		0.020		**-0.064*****		-0.027		0.018
		(0.016)		(0.019)		(0.017)		(0.026)
i_credit1		-0.022		0.135		-0.031		-0.066
		(0.018)		(0.120)		(0.073)		(0.107)
i_riskMOD1		**0.138*****		**-0.112*****		0.006		-0.094
		(0.040)		(0.019)		(0.062)		(0.104)
i_riskNO1		**0.079****		0.034		-0.044		0.170
		(0.039)		(0.063)		(0.046)		(0.200)
i_farm1		**0.009*****		**-0.007*****		**0.003****		-0.001
		(0.002)		(0.002)		(0.001)		(0.004)
i_land1		**-0.086****		-0.105		-0.075		0.097
		(0.042)		(0.138)		(0.097)		(0.096)
i_radio1		-0.119		-0.003		-0.070		-0.131
		(0.143)		(0.038)		(0.045)		(0.146)

Table 22 Social capital interactions (Bonding Social Capital)

VARIABLES	(A1) Adoption mfx	(A49) Adoption mfx	(A2) Time adoption - abs mfx	(A50) Time adoption - abs mfx	(A3) Time adoption - rel mfx	(A51) Time adoption - rel mfx	(A4) Intensity coeff	(A52) Intensity coeff
Farm size	**0.013****	**0.011***	**-0.014*****	**-0.014*****	**-0.009*****	**-0.009*****	**0.029*****	**0.027*****
	(0.005)	(0.007)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
Land ownership	**0.230*****	**0.286*****	-0.206	-0.193	-0.080	-0.104	-0.133	-0.176
	(0.063)	(0.033)	(0.139)	(0.180)	(0.150)	(0.187)	(0.216)	(0.204)
Radio	**-0.093*****	**-0.134****	**0.137*****	**0.154*****	0.073	0.106	**0.324****	**0.263***
	(0.027)	(0.054)	(0.032)	(0.020)	(0.136)	(0.111)	(0.146)	(0.147)
Access to credit	0.112	**-0.138****	0.154	-0.046	0.122	-0.009	0.143	0.486
	(0.085)	(0.059)	(0.137)	(0.161)	(0.114)	(0.152)	(0.160)	(0.370)
Road conditions	**-0.035****	**-0.063**	0.020	0.015	0.046	0.079	0.056	-0.024
	(0.018)	(0.056)	(0.032)	(0.081)	(0.029)	(0.075)	(0.037)	(0.088)
Moderate risk aversion	**0.123*****	-0.094	0.042	0.189	0.035	-0.137	-0.080	0.066
	(0.036)	(0.199)	(0.065)	(0.212)	(0.063)	(0.259)	(0.138)	(0.300)
No risk aversion	0.034	0.034	-0.033	-0.270	-0.053	**-0.567****	0.123	-0.059
	(0.078)	(0.160)	(0.078)	(0.361)	(0.125)	(0.238)	(0.224)	(0.676)
Structural Bonding Index		0.004		0.046		-0.073		0.205
		(0.063)		(0.103)		(0.101)		(0.141)
i_roads2		0.011		0.002		-0.013		0.018
		(0.031)		(0.024)		(0.021)		(0.032)
i_credit2		**0.092****		0.062		0.045		-0.133
		(0.044)		(0.098)		(0.093)		(0.092)
i_riskMOD2		0.098		-0.062		0.061		-0.034
		(0.081)		(0.099)		(0.106)		(0.107)
i_riskNO2		-0.010		0.068		0.200		0.051
		(0.081)		(0.155)		(0.157)		(0.225)
i_farm2		0.001		**-0.016*****		**-0.004***		-0.002
		(0.003)		(0.001)		(0.003)		(0.002)
i_land2		-0.050		0.094		-0.081		0.103
		(0.114)		(0.075)		(0.058)		(0.126)
i_radio2		**-0.032****		**0.194*****		**0.311****		-0.031
		(0.015)		(0.028)		(0.126)		(0.090)

Table 23 Social capital interactions (Cognitive Social Capital)

VARIABLES	(A1) Adoption mfx	(A53) Adoption mfx	(A2) Time adoption - abs mfx	(A54) Time adoption - abs mfx	(A3) Time adoption - rel mfx	(A55) Time adoption - rel mfx	(A4) Intensity coeff	(A56) Intensity coeff
Farm size	**0.013****	**0.009****	**-0.014*****	**-0.015*****	**-0.009*****	**-0.009*****	**0.029*****	**0.025*****
	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)	(0.004)
Land ownership	**0.230*****	**0.320*****	-0.206	-0.187	-0.080	-0.086	-0.133	-0.211
	(0.063)	(0.026)	(0.139)	(0.169)	(0.150)	(0.156)	(0.216)	(0.220)
Radio	**-0.093*****	**-0.096*****	**0.137*****	**0.145*****	0.073	0.053	**0.324****	0.228
	(0.027)	(0.027)	(0.032)	(0.041)	(0.136)	(0.133)	(0.146)	(0.142)
Access to credit	0.112	-0.082	0.154	**-0.276****	0.122	0.054	0.143	0.317
	(0.085)	(0.145)	(0.137)	(0.134)	(0.114)	(0.102)	(0.160)	(0.377)
Road conditions	**-0.035****	**-0.083*****	0.020	0.124	0.046	**0.124***	0.056	0.054
	(0.018)	(0.028)	(0.032)	(0.088)	(0.029)	(0.067)	(0.037)	(0.083)
Moderate risk aversion	**0.123*****	-0.067	0.042	0.242	0.035	0.030	-0.080	0.160
	(0.036)	(0.057)	(0.065)	(0.201)	(0.063)	(0.236)	(0.138)	(0.273)
No risk aversion	0.034	0.102	-0.033	**0.185*****	-0.053	0.086	0.123	-0.369
	(0.078)	(0.070)	(0.078)	(0.043)	(0.125)	(0.093)	(0.224)	(0.671)
Cognitive Index		**0.066***		**0.211****		0.102		**0.341*****
		(0.037)		(0.100)		(0.092)		(0.094)
i_roads3		0.024		**-0.031***		**-0.024****		-0.008
		(0.019)		(0.016)		(0.012)		(0.021)
i_credit3		**0.066****		**0.119*****		0.015		-0.047
		(0.031)		(0.039)		(0.042)		(0.075)
i_riskMOD3		**0.087*****		-0.081		-0.001		-0.064
		(0.026)		(0.072)		(0.082)		(0.069)
i_riskNO3		-0.012		**-0.079*****		-0.041		0.095
		(0.054)		(0.014)		(0.031)		(0.164)
i_farm3		-0.001		**-0.016*****		**-0.002****		-0.005
		(0.004)		(0.001)		(0.001)		(0.004)
i_land3		-0.056		-0.057		**-0.100***		0.116
		(0.058)		(0.082)		(0.057)		(0.096)
i_radio3		-0.009		**0.113***		0.119		-0.089
		(0.072)		(0.061)		(0.079)		(0.082)

Table 24 Social capital interaction (Diversity Social Capital)

VARIABLES	(A1) Adoption mfx	(A57) Adoption mfx	(A2) Time adoption - abs mfx	(A58) Time adoption - abs mfx	(A3) Time adoption - rel mfx	(A59) Time adoption - rel mfx	(A4) Intensity coeff	(A60) Intensity coeff
Farm size	**0.013****	**0.011*****	**-0.014*****	**-0.014*****	**-0.009*****	**-0.008*****	**0.029*****	**0.027*****
	(0.005)	(0.004)	(0.002)	(0.003)	(0.002)	(0.001)	(0.004)	(0.004)
Land ownership	**0.230*****	**0.349*****	-0.206	**-0.256***	-0.080	-0.103	-0.133	-0.129
	(0.063)	(0.048)	(0.139)	(0.149)	(0.150)	(0.162)	(0.216)	(0.246)
Radio	**-0.093*****	**-0.074****	**0.137*****	**0.132****	0.073	0.039	**0.324****	**0.336****
	(0.027)	(0.037)	(0.032)	(0.056)	(0.136)	(0.152)	(0.146)	(0.155)
Access to credit	0.112	-0.203	0.154	**-0.458*****	0.122	**0.194***	0.143	0.595
	(0.085)	(0.210)	(0.137)	(0.143)	(0.114)	(0.111)	(0.160)	(0.495)
Road conditions	**-0.035****	**-0.131*****	0.020	**0.125***	0.046	**0.115****	0.056	-0.045
	(0.018)	(0.017)	(0.032)	(0.076)	(0.029)	(0.057)	(0.037)	(0.108)
Moderate risk aversion	**0.123*****	-0.144	0.042	0.233	0.035	-0.046	-0.080	0.089
	(0.036)	(0.174)	(0.065)	(0.174)	(0.063)	(0.243)	(0.138)	(0.360)
No risk aversion	0.034	0.157	-0.033	**0.177****	-0.053	-0.019	0.123	0.076
	(0.078)	(0.149)	(0.078)	(0.076)	(0.125)	(0.089)	(0.224)	(0.802)
Diversity social capital		0.017		0.059		0.025		0.069
		(0.030)		(0.090)		(0.073)		(0.109)
i_roads4		**0.033*****		**-0.022*****		**-0.014*****		0.020
		(0.006)		(0.007)		(0.005)		(0.020)
i_credit4		0.038		**0.124*****		-0.014		-0.091
		(0.035)		(0.021)		(0.017)		(0.076)
i_riskMOD4		0.073		-0.046		0.017		-0.033
		(0.052)		(0.048)		(0.060)		(0.070)
i_riskNO4		-0.033		-0.039		-0.005		0.001
		(0.053)		(0.026)		(0.027)		(0.138)
i_farm4		0.003		**-0.008*****		**0.001*****		-0.001
		(0.005)		(0.001)		(0.000)		(0.003)
i_land4		-0.109		**-0.218***		**-0.176****		0.106
		(0.077)		(0.115)		(0.072)		(0.069)
i_radio4		-0.090		**0.088*****		0.131		-0.034
		(0.127)		(0.025)		(0.104)		(0.086)

Table 25 Social capital interactions (Intensity)

VARIABLES	(A1) Adoption mfx	(A61) Adoption mfx	(A2) Time adoption - abs mfx	(A62) Time adoption - abs mfx	(A3) Time adoption - rel mfx	(A63) Time adoption - rel mfx	(A4) Intensity coeff	(A64) Intensity coeff
Farm size	**0.013****	**0.009****	**-0.014*****	**-0.015*****	**-0.009*****	**-0.008*****	**0.029*****	**0.027*****
	(0.005)	(0.004)	(0.002)	(0.003)	(0.002)	(0.001)	(0.004)	(0.004)
Land ownership	**0.230*****	**0.354*****	-0.206	-0.256	-0.080	-0.100	-0.133	-0.109
	(0.063)	(0.045)	(0.139)	(0.158)	(0.150)	(0.167)	(0.216)	(0.223)
Radio	**-0.093*****	**-0.081*****	**0.137*****	**0.121****	0.073	0.042	**0.324****	**0.352****
	(0.027)	(0.031)	(0.032)	(0.047)	(0.136)	(0.139)	(0.146)	(0.147)
Access to credit	0.112	-0.188	0.154	-0.247	0.122	0.236	0.143	0.412
	(0.085)	(0.154)	(0.137)	(0.283)	(0.114)	(0.181)	(0.160)	(0.416)
Road conditions	**-0.035****	**-0.096*****	0.020	**0.131***	0.046	**0.119****	0.056	-0.006
	(0.018)	(0.003)	(0.032)	(0.074)	(0.029)	(0.051)	(0.037)	(0.101)
Moderate risk aversion	**0.123*****	-0.107	0.042	**0.273***	0.035	-0.025	-0.080	0.268
	(0.036)	(0.147)	(0.065)	(0.154)	(0.063)	(0.206)	(0.138)	(0.316)
No risk aversion	0.034	**0.188*****	-0.033	-0.034	-0.053	-0.063	0.123	-0.113
	(0.078)	(0.057)	(0.078)	(0.078)	(0.125)	(0.097)	(0.224)	(0.773)
Intensity of diversity of social capital		**0.015***		0.023		0.010		0.032
		(0.009)		(0.016)		(0.014)		(0.027)
i_roads5		**0.006*****		**-0.007*****		**-0.005*****		0.003
		(0.001)		(0.002)		(0.001)		(0.006)
i_credit5		0.010		**0.021****		-0.007		-0.017
		(0.010)		(0.010)		(0.005)		(0.018)
i_riskMOD5		0.020		-0.015		0.004		-0.019
		(0.013)		(0.011)		(0.014)		(0.017)
i_riskNO5		**-0.015***		-0.000		0.001		0.009
		(0.009)		(0.008)		(0.007)		(0.038)
i_farm5		0.001		**-0.002*****		**0.000***		-0.001
		(0.001)		(0.000)		(0.000)		(0.001)
i_land5		-0.011		-0.027		-0.028		0.028
		(0.016)		(0.029)		(0.017)		(0.019)
i_radio5		-0.029		**0.022*****		0.033		-0.032
		(0.032)		(0.007)		(0.025)		(0.021)

Table 26 Social capital interactions (General trust)

VARIABLES	(A1) Adoption mfx	(A65) Adoption mfx	(A2) Time adoption - abs mfx	(A66) Time adoption - abs mfx	(A3) Time adoption - rel mfx	(A67) Time adoption - rel mfx	(A4) Intensity coeff	(A68) Intensity coeff
Farm size	**0.013****	**0.011*****	**-0.014*****	**-0.014*****	**-0.009*****	**-0.009*****	**0.029*****	**0.026*****
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)	(0.004)
Land ownership	**0.230*****	**0.394*****	-0.206	-0.223	-0.080	-0.094	-0.133	-0.146
	(0.063)	(0.019)	(0.139)	(0.169)	(0.150)	(0.168)	(0.216)	(0.235)
Radio	**-0.093*****	**-0.092*****	**0.137*****	**0.161****	0.073	0.057	**0.324****	**0.305****
	(0.027)	(0.033)	(0.032)	(0.065)	(0.136)	(0.159)	(0.146)	(0.152)
Access to credit	0.112	**-0.302*****	0.154	**-0.408*****	0.122	-0.010	0.143	0.411
	(0.085)	(0.084)	(0.137)	(0.153)	(0.114)	(0.117)	(0.160)	(0.411)
Road conditions	**-0.035****	**-0.083*****	0.020	0.122	0.046	**0.122****	0.056	0.021
	(0.018)	(0.004)	(0.032)	(0.081)	(0.029)	(0.061)	(0.037)	(0.085)
Moderate risk aversion	**0.123*****	-0.039	0.042	**0.334***	0.035	0.110	-0.080	0.027
	(0.036)	(0.072)	(0.065)	(0.191)	(0.063)	(0.264)	(0.138)	(0.287)
No risk aversion	0.034	**0.162***	-0.033	**0.393*****	-0.053	**0.217*****	0.123	-0.174
	(0.078)	(0.094)	(0.078)	(0.045)	(0.125)	(0.047)	(0.224)	(0.637)
General trust		0.022		**0.055****		0.030		0.047
		(0.015)		(0.028)		(0.027)		(0.030)
i_roads6		**0.008*****		**-0.008****		**-0.006****		0.002
		(0.002)		(0.004)		(0.003)		(0.006)
i_credit6		**0.026*****		**0.042*****		0.008		-0.023
		(0.005)		(0.013)		(0.012)		(0.022)
i_riskMOD6		**0.018***		**-0.032***		-0.008		-0.007
		(0.010)		(0.019)		(0.024)		(0.019)
i_riskNO6		-0.017		**-0.039*****		**-0.024****		0.018
		(0.022)		(0.008)		(0.009)		(0.041)
i_farm6		0.001		**-0.005*****		0.000		-0.001
		(0.002)		(0.000)		(0.000)		(0.001)
i_land6		-0.012		**-0.047***		**-0.053*****		0.026
		(0.025)		(0.028)		(0.020)		(0.024)
i_radio6		-0.030		**0.021***		0.026		-0.023
		(0.043)		(0.011)		(0.025)		(0.023)

Table 27 Social capital interaction (Diversity - selected agents)

VARIABLES	(A1) Adoption mfx	(A69) Adoption mfx	(A2) Time adoption - abs mfx	(A69) Time adoption - abs mfx	(A3) Time adoption - rel mfx	(A70) Time adoption - rel mfx	(A4) Intensity coeff	(A71) Intensity coeff
Farm size	**0.013****	**0.009*****	**-0.014*****	**-0.015*****	**-0.009*****	**-0.009*****	**0.029*****	**0.027*****
	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.004)	(0.004)
Land ownership	**0.230*****	**0.245*****	-0.206	-0.258	-0.080	-0.100	-0.133	-0.170
	(0.063)	(0.032)	(0.139)	(0.162)	(0.150)	(0.173)	(0.216)	(0.228)
Radio	**-0.093*****	**-0.091****	**0.137*****	**0.114*****	0.073	0.034	**0.324****	**0.314****
	(0.027)	(0.044)	(0.032)	(0.041)	(0.136)	(0.122)	(0.146)	(0.155)
Access to credit	0.112	-0.006	0.154	**-0.430*****	0.122	0.161	0.143	0.491
	(0.085)	(0.175)	(0.137)	(0.118)	(0.114)	(0.106)	(0.160)	(0.432)
Road conditions	**-0.035****	**-0.093*****	0.020	**0.174****	0.046	**0.128****	0.056	0.036
	(0.018)	(0.030)	(0.032)	(0.083)	(0.029)	(0.063)	(0.037)	(0.097)
Moderate risk aversion	**0.123*****	-0.112	0.042	0.145	0.035	-0.171	-0.080	0.046
	(0.036)	(0.099)	(0.065)	(0.116)	(0.063)	(0.144)	(0.138)	(0.338)
No risk aversion	0.034	-0.059	-0.033	-0.106	-0.053	-0.075	0.123	-0.591
	(0.078)	(0.174)	(0.078)	(0.167)	(0.125)	(0.109)	(0.224)	(0.807)
Diversity of selected change agents		0.048		0.108		0.032		0.175
		(0.059)		(0.147)		(0.133)		(0.134)
i_roads7		**0.033****		**-0.047*****		**-0.025***		0.006
		(0.015)		(0.014)		(0.014)		(0.026)
i_credit7		0.042		**0.182*****		-0.015		-0.095
		(0.071)		(0.023)		(0.010)		(0.105)
i_riskMOD7		**0.100****		-0.038		0.066		-0.042
		(0.040)		(0.047)		(0.061)		(0.101)
i_riskNO7		0.052		0.022		0.010		0.184
		(0.041)		(0.057)		(0.041)		(0.212)
i_farm7		0.006		**-0.009*****		**0.002***		-0.001
		(0.005)		(0.001)		(0.001)		(0.003)
i_land7		**-0.158****		**-0.254****		**-0.226*****		**0.185***
		(0.064)		(0.122)		(0.082)		(0.095)
i_radio7		-0.115		**0.193*****		**0.205***		-0.099
		(0.122)		(0.025)		(0.116)		(0.155)

Table 28 Social capital interactions (Intensity - selected agents)

VARIABLES	(A1) Adoption mfx	(A72) Adoption mfx	(A2) Time adoption - abs mfx	(A73) Time adoption - abs mfx	(A3) Time adoption - rel mfx	(A74) Time adoption - rel mfx	(A4) Intensity coeff	(A75) Intensity coeff
Farm size	**0.013****	**0.007***	**-0.014*****	**-0.015*****	**-0.009*****	**-0.009*****	**0.029*****	**0.026*****
	(0.005)	(0.004)	(0.002)	(0.003)	(0.002)	(0.001)	(0.004)	(0.004)
Land ownership	**0.230*****	**0.259*****	-0.206	-0.246	-0.080	-0.091	-0.133	-0.168
	(0.063)	(0.029)	(0.139)	(0.158)	(0.150)	(0.162)	(0.216)	(0.215)
Radio	**-0.093*****	**-0.092*****	**0.137*****	**0.103*****	0.073	0.040	**0.324****	**0.301****
	(0.027)	(0.033)	(0.032)	(0.033)	(0.136)	(0.123)	(0.146)	(0.143)
Access to credit	0.112	0.040	0.154	-0.193	0.122	0.218	0.143	0.460
	(0.085)	(0.162)	(0.137)	(0.232)	(0.114)	(0.173)	(0.160)	(0.384)
Road conditions	**-0.035****	**-0.080*****	0.020	**0.167****	0.046	**0.128****	0.056	0.064
	(0.018)	(0.004)	(0.032)	(0.081)	(0.029)	(0.057)	(0.037)	(0.094)
Moderate risk aversion	**0.123*****	-0.042	0.042	0.206	0.035	-0.117	-0.080	0.236
	(0.036)	(0.096)	(0.065)	(0.184)	(0.063)	(0.182)	(0.138)	(0.325)
No risk aversion	0.034	0.092	-0.033	**-0.237****	-0.053	-0.163	0.123	-0.431
	(0.078)	(0.087)	(0.078)	(0.095)	(0.125)	(0.126)	(0.224)	(0.723)
Intensity of diversity of selected change agents		**0.032****		0.040		0.014		**0.076****
		(0.013)		(0.030)		(0.027)		(0.037)
i_roads8		**0.006****		**-0.013*****		**-0.007****		-0.002
		(0.002)		(0.004)		(0.003)		(0.008)
i_credit8		0.006		**0.027*****		-0.009		-0.024
		(0.021)		(0.010)		(0.006)		(0.025)
i_riskMOD8		**0.021***		-0.015		0.014		-0.025
		(0.011)		(0.016)		(0.017)		(0.027)
i_riskNO8		-0.007		**0.016***		0.009		0.037
		(0.011)		(0.009)		(0.008)		(0.053)
i_farm8		**0.002****		**-0.002*****		**0.001***		-0.001
		(0.001)		(0.000)		(0.000)		(0.001)
i_land8		-0.019		-0.038		**-0.041****		0.043
		(0.014)		(0.027)		(0.016)		(0.029)
i_radio8		-0.017		**0.051*****		**0.056****		-0.041
		(0.022)		(0.003)		(0.025)		(0.035)

Table 29 Social capital interactions (General trust - selected agents)

VARIABLES	(A1) Adoption mfx	(A76) Adoption mfx	(A2) Time adoption - abs mfx	(A77) Time adoption - abs mfx	(A3) Time adoption - rel mfx	(A78) Time adoption - rel mfx	(A4) Intensity coeff	(A79) Intensity coeff
Farm size	**0.013****	**0.010*****	**-0.014*****	**-0.014*****	**-0.009*****	**-0.009*****	**0.029*****	**0.026*****
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)	(0.004)
Land ownership	**0.230*****	**0.295*****	-0.206	-0.228	-0.080	-0.090	-0.133	-0.202
	(0.063)	(0.016)	(0.139)	(0.164)	(0.150)	(0.163)	(0.216)	(0.226)
Radio	**-0.093*****	**-0.108*****	**0.137*****	**0.120*****	0.073	0.042	**0.324****	**0.252***
	(0.027)	(0.038)	(0.032)	(0.038)	(0.136)	(0.122)	(0.146)	(0.150)
Access to credit	0.112	-0.066	0.154	**-0.325****	0.122	0.053	0.143	0.396
	(0.085)	(0.137)	(0.137)	(0.145)	(0.114)	(0.073)	(0.160)	(0.375)
Road conditions	**-0.035****	**-0.076*****	0.020	**0.147***	0.046	**0.122***	0.056	0.060
	(0.018)	(0.007)	(0.032)	(0.090)	(0.029)	(0.071)	(0.037)	(0.083)
Moderate risk aversion	**0.123*****	-0.033	0.042	0.261	0.035	-0.005	-0.080	0.076
	(0.036)	(0.049)	(0.065)	(0.218)	(0.063)	(0.259)	(0.138)	(0.296)
No risk aversion	0.034	0.025	-0.033	**0.214***	-0.053	**0.140***	0.123	-0.450
	(0.078)	(0.145)	(0.078)	(0.112)	(0.125)	(0.082)	(0.224)	(0.641)
Trust in selected change agents		0.028		0.085		0.040		**0.091****
		(0.018)		(0.055)		(0.052)		(0.041)
i_roads9		**0.009****		**-0.015****		**-0.009***		-0.002
		(0.004)		(0.006)		(0.005)		(0.008)
i_credit9		0.029		**0.056*****		0.006		-0.026
		(0.020)		(0.019)		(0.015)		(0.031)
i_riskMOD9		**0.027*****		-0.036		0.004		-0.018
		(0.010)		(0.031)		(0.036)		(0.032)
i_riskNO9		0.007		**-0.035****		**-0.023***		0.052
		(0.020)		(0.015)		(0.013)		(0.066)
i_farm9		**0.003***		**-0.006*****		0.000		-0.001
		(0.002)		(0.001)		(0.000)		(0.001)
i_land9		-0.020		**-0.064****		**-0.065*****		0.043
		(0.014)		(0.031)		(0.018)		(0.039)
i_radio9		-0.028		**0.043*****		0.044		-0.037
		(0.045)		(0.012)		(0.033)		(0.038)

CHAPTER 4: APPENDICES

Appendix 4.1. Brief review of poverty measures

The poverty measurements have been widely analysed across the literature. The aim of these measures is to capture as much accurately as possible the socio-economic status of the unit of observation. Household's income and household's expenditures, per capita or per adult equivalent, are the most common candidates for this type of analysis and several practitioners and scholars have pointed out their advantages (Deaton and Zaidi, 2002).

However, the estimation of poverty using these measures is not as straightforward. Measurement errors, understatement, and difficulties in obtaining good estimates of earnings from some types of self-employment or the value of some housing services are only some of the challenges in measuring poverty using income and consumption data. Although consumption if often preferred to income indicators, collecting expenditure data could pose similar difficulties to the income measurement, because households, especially in developing countries, tend to understate their expenses in what they consider to be luxury goods, such as alcohol or sweets, or in illegal items and services, such as drugs and prostitution, or because their consumption level could not be as stable as it is expected, due to the limited access to credit. Furthermore, the length and the depth of the survey investigation required by the collection of accurate information on expenditures on both food and non-food items, durable and non-durable goods, and so on, pose serious financial and organisational difficulties in the case of small surveys.

In addition, consumption and income measures of poverty have been also widely criticised for the inner inability to provide a comprehensive measure of well-being that goes beyond the monetary definition of welfare. The multi-dimensions of poverty has been inspired and supported by this school of thoughts and informed the establishment of analysis based on human and physical assets endowment as well as studies on subjective poverty (Ravallion, 2012). In addition, consumption and income poverty measures are usually more volatile than other measures of poverty based, for example, on asset endowment.

A measure of poverty based on asset endowments is often believed to provide a better measure of the households' poverty than the standard data on consumption or income for small and short surveys (Filmer and Prichett, 2001). However, many scholars claim that even this measure still provides an income-focused perspective of welfare and poverty (Stevenson and Wolfers, 2008; Ravallion, 2012) and support the use of happiness and subjective well-being for the estimation of poverty profiles.

The first studies on happiness were done by psychologists in the 1960s and one of the first attempts to quantify happiness in the economics framework dates back to 1965, when Cantril forged the idea of "ladder of life". Nowadays, the main subjective measures of well-being and poverty are collected using the following survey tools: the" Economic ladder" question, whereby the respondent is asked the put him/herself on a step of a ladder of relative socio-economic status; "the minimum income" question, where respondents are asked to quantify the monetary value for accomplishing their minimum needs; "income evaluation and/or consumption adequacy" questions, that rate the income or consumption on a scale from 1 (very bad) to 5 (very good) and finally the "satisfaction with life" question, which rates the satisfaction from 1 (lowest) to 5 (highest).

The main ideas of subjective measures of well-being and poverty is to provide a more comprehensive perspective of the socio-economic status that includes also non income dimension of well-being, that contextualizes the concept of welfare and attempts to capture those fundamental social functioning capabilities conceived by Sen.

Although highly correlated with the objective measures of income, subjective measures have been found essential in the testing, calibrating or complementing classical income -focused welfare and poverty analyses (Stevenson and Wolfers, 2008; Ravallion at al., 2013). First of all, subjective measures favoured the emergence of a relative conceptualization of poverty. Several studies have argued that "relative deprivation" can substantially affect the perception of our own socio-economic status at any given income. And this is proved to be especially true for relatively richer countries where the concepts of rich and poor are mainly relative ideas. However, this phenomenon is not completely absent in developing countries, either (Ravallion and Loshkin, 2010).

Furthermore, the use of subjective measures has also highlighted the importance of perceptions, expectations and aspirations in poverty analysis. For example, Ravallion and Lokshin in 2002 found that past income increases current subjective measures of welfare through the expectation of higher future income. Similarly, in a study of rural poverty in China, Knight et al. (2009) argue that future and past income can affect the perception of current economic status. On the other hand, Knight and Gunatilaka (2012) find that aspirations on future income could also decrease the current subjective perception of welfare and they propose the idea of the "hedonic treadmill", whereby the access to a higher income does not current increase happiness or subjective well-being if the level of aspired income is not reached yet.

Finally, the comparison between objective and subjective measures provided new insights in drawing poverty profiles. For example, household's size which is one of the main determinants of the objective poverty, is argued to play a smaller role in the subjective poverty. Thus, when using subjective measures of wealth bigger households are not necessarily the poorer among the others, as usually argued when income or consumption data are analysed, and this can be explained by the exploitation of economies of scale in consumption (Posel and Rogan, 2014).

Appendix 4.2. The construction of the wealth index

Main results

Table 1 Full PCA estimation results

Principal components/correlation	Number	of	obs	=	305
	Number	of	comp.	=	1
	Trace			=	8
Rotation: (unrotated = principal)	Rho			=	0.3613
	Component	Eigenvalue	Difference	Proportion	Cumulative
	Comp1	2.89056	1.77799	0.3613	**0.3613**
	Comp2	1.11257	0.199911	0.1391	0.5004
	Comp3	0.912659	0.072147	0.1141	0.6145
	Comp4	0.840511	0.113176	0.1051	0.7195
	Comp5	0.727335	0.099742	0.0909	0.8105
	Comp6	0.627593	0.146784	0.0784	0.8889
	Comp7	0.480809	0.072843	0.0601	0.949
	Comp8	0.407965	.	0.051	1

Table 2 Kaiser-Meyer-Olkin measure of sampling adequacy

Variable (standardised)	kmo
Farm size (acres)	0.7507
Drinking water (0/1)	0.7655
Private toilet (0/1)	0.7602
Tractor (0/1)	0.5488
Motorbicycle (0/1)	0.7827
Car (0/1)	0.8235
Fridge (0/1)	0.7990
Generator (0/1)	0.7812
Overall	**0.7683**

Table 3 Internal coherence

	Rich top 20%	**Poor bottom 40%**	
	Mean	Mean	pvalue
Farm size (acres)	20.99	3.42	0.000***
Drinking water (0/1)	0.73	0.00	0.000***
Private toilet (0/1)	0.84	0.00	0.000***
Tractor (0/1)	0.08	0.00	0.001***
Motorbicycle (0/1)	0.58	0.00	0.000***
Car (0/1)	0.48	0.00	0.000***
Fridge (0/1)	0.83	0.00	0.000***
Generator (0/1)	0.14	0.00	0.000***
N	64	127	

From the estimation of the PCA above, the choice of the first component is supported by the quite satisfactory variance explained by this component (36%) and both by the graphic examination and by the value of the sample adequacy obtained running the KMO test (0.76). The best set of variables proved to be the one without the number of livestock which provided a lower value of the combined variance explained by the first

component (33%) and a lower value of sample adequacy (0.72). As a consequence this variable was not included in the final estimation.

Methodology

The seminal work by Filmer and Prichett (2001) was the first study that implemented the principal component analysis, whose main intuition is to identify a set of households', farm, transport's assets, etc that could be a good indicator of the household's welfare, in absence of income or consumption data. The principal component analysis attributes different weights to each variables in the set as a measure of their relevance with respect to the outcome, in this case the wealth of the household. As a consequence the choice of the set of variables to include in the analysis proves to be crucial.

Two main problems can arise from the mis-choice of the variables or wealth "determinants". These problems are what McKenzie (2003) calls clumping and truncation. Clumping or clustering occurs when households in the sample are naturally grouped in a small number of cluster, while truncation refers to the case when the distribution of the combination of assets across the sample is too skewed, suggesting a high degree of similarity between households and making it very difficult to distinguish between poor and non-poor. These problems are likely to hold in my sample[125]. Nonetheless, to minimize the effect of clumping and truncation the choice of the variables needs to careful aim to the stability of the index, whereby the identification of poor and non-poor households should not be affected by the choice of the variable themselves. In other words, the assets used for the calculation of the index should aim to provide indication of welfare which is as close as possible to the reality.

Asset indices for poverty analysis usually include a selection of farm assets, livestock, household's assets and transport assets. For the choice of this selected set, different methods have been proposed in the literature (Vyas and Kumaranayake, 2006). The following are some of the criteria for the choice of the variables for a stable index through the PCA:

1. Variables with high standard deviation should be included

PCA is known to work best when the assets are correlated and also when the distribution varies across the sample, for which PCA will give more weight (McKenzie, 2003). A way to identify a low and high standard deviation is to calculate the coefficient of variation, whereby the standard deviation is normalised and so comparable across variables[126]. A coefficient higher than one is considered to reflect high standard deviation, while a coefficient lower than one is indicative of lower standard deviation. Using this procedure the following variables can be identified out of the entire range of assets available[127] in the dataset:

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[125] My sample is mainly composed of very small farmers with a farm size less than three acres. They are indeed likely to own a similar composition of assets which could complicate the computation of the wealth index, which is likely to be left skewed. However, these groups of households represent 60% of the sample. The remaining 40% should allow for the discrimination between poor and non-poor households.

[126] The coefficient of variation is calculated dividing the standard deviation by the mean of the same variable.

[127] The full list of assets in the dataset is the following: Farm assets (water management tools, land management tools, tractor, wheel barrow, saws, spray pump, spray hose for tractors, micro - sprinklers, animal plough, weighing machine, simple tools (hoes, cutlass, etc); Transport assets (cart, bicycle, motorbicycle, car, open truck, refrigerated truck); Livestock (cow, oxen, donkey, goats, sheep, poultry); Household assets (fridge, radio, tv, computer, landline, mobile phone, washing machine, sewing machine, generator, ownership of households, drinking water, number of rooms, electric lighting, private toilet).

Table 4 Asset index components

	Mean	Standard deviation	Min	Max	Coefficient of Variation
Farm size (acres)	7.833	14.992	1	127	1.914
Drinking water (0/1)	0.200	0.401	0	1	2.003
Private toilet (0/1)	0.340	0.473	0	1	1.403
Tractor (0/1)	0.020	0.139	0	1	7.071
Motorbicycle (0/1)	0.266	0.442	0	1	1.666
Car (0/1)	0.115	0.319	0	1	2.782
Fridge (0/1)	0.256	0.437	0	1	1.709
Generator (0/1)	0.030	0.170	0	1	5.744
Number of livestock (#)	22.518	33.021	0	276	1.466
N	305				

2. Related to one, variables with no variation should be dropped

PCA will attribute no weight to those variables with no variation across the sample. Hence, these variables should be a priori excluded from the choice[128]. None of the variables listed in table 1 has no variation.

3. Variables with missing values should be excluded.

This criterion aims to maintain a wide variation in the distribution of the assets across the entire sample of households[129]. However, this procedure could induce to a reduction of the sample size itself and could generate a bias towards to better off households because of the higher likelihood to have missing values for poor households (Cortinovis et al. 1993, Vyas and Kumaranayake, 2006). Luckily, no variables listed in table 1 have any missing value[130].

After implementing these criteria, there is one more test that needs to be implemented before the estimation of the PCA. This is a test of multivariate normality, whereby you assess that the underlying assumption of the PCA is not rejected. If not rejected the estimation of the PCA can be run with the favourite set of variables. It is worth noting that if variables with different scales are included in the chosen set, PCA will attribute a higher weight to those variables such as farm size or a categorical variable compared to, for example, dummy variables. To minimize this issue, variables needs to be standardised before the computation of the PCA. The following table shows the variables summary statistics after the standardization.

Using this procedure the distribution of each variable is expanded or reduced, depending to the original standard deviation, around the zero mean and standard deviation of one. For example, farm size and number of livestock had a very high standard deviation with a scale well above the range of values of the other variables (Table 5). If used with these scales in the computation of the asset index, by construction the PCA would over-weighted farm size and livestock in the wealth composition with respect to the other assets.

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[128] The condrop program in STATA can implement this task.

[129] Cortinovis et al. (1993) excluded households with at least one missing value from their analysis to develop socio-economic groups. Gwatkin et al. (2000) replaced missing values with the mean value for that variable.

[130] An additional criteria would be to include those variables that are significantly correlated with expenditure data. As mentioned before, this data is not available in my dataset. However, the literature uses these criteria to minimize the impact of clumping and truncation with the inclusion in the PCA index of as many variables as possible.

Table 5 Asset index components, standardised

Variable	Mean	Standard Deviation	Min	Max
Farm size (acres)	0	1	-0.456	7.948
Drinking water (0/1)	0	1	-0.499	1.997
Private toilet (0/1)	0	1	-0.713	1.398
Tractor (0/1)	0	1	-0.141	7.048
Motorbicycle (0/1)	0	1	-0.600	1.660
Car (0/1)	0	1	-0.359	2.772
Fridge (0/1)	0	1	-0.359	2.773
Generator (0/1)	0	1	-0.585	1.703
Number of livestock (#)	0	1	-0.174	5.725
N	305			

Before interpreting the results, another important decision to be taken is the choice of the component of the estimated PCA to retain for the computation of the wealth index. Although the researcher could potentially choose any number of components which follows the rule of thumb of having eigenvalues greater than one, there is a wide consensus in the literature that the first component is a representative measure of the economic status and that the addition of other components does not improve the stability of the index (Houweling et al. 2003; McKenzie, 2003; Vyas and. Kumaranayake, 2006; Filmer and Prichett, 2001). Nonetheless, two main tests can be used for the choice of the components: 1. Graphical examination using the screeplot command in Stata. 2. Kaiser-Meyer-Olkin measure of sampling adequacy. These tests will provide information on the variance explained by the first component, the index predicted and will evaluate ex-post the fitness of the asset variables chosen for the estimation.

If the first component is chosen, the aim of the two tests mentioned is to achieve the highest possible variance explained by that component and several trials with different sets of variables included and excluded in to the PCA estimation should be implemented, during which variables previously selected should be discarded in favour of those that provide support for the choice of the first component.

As mentioned above, the list of assets included in the PCA estimates provided the highest cumulative variance and the highest KMO measure when the first component was selected.

Appendix 4.3. Objective poverty thresholds, sensitivity checks

Figure 1 Sensitivity checks, objective poverty threshold

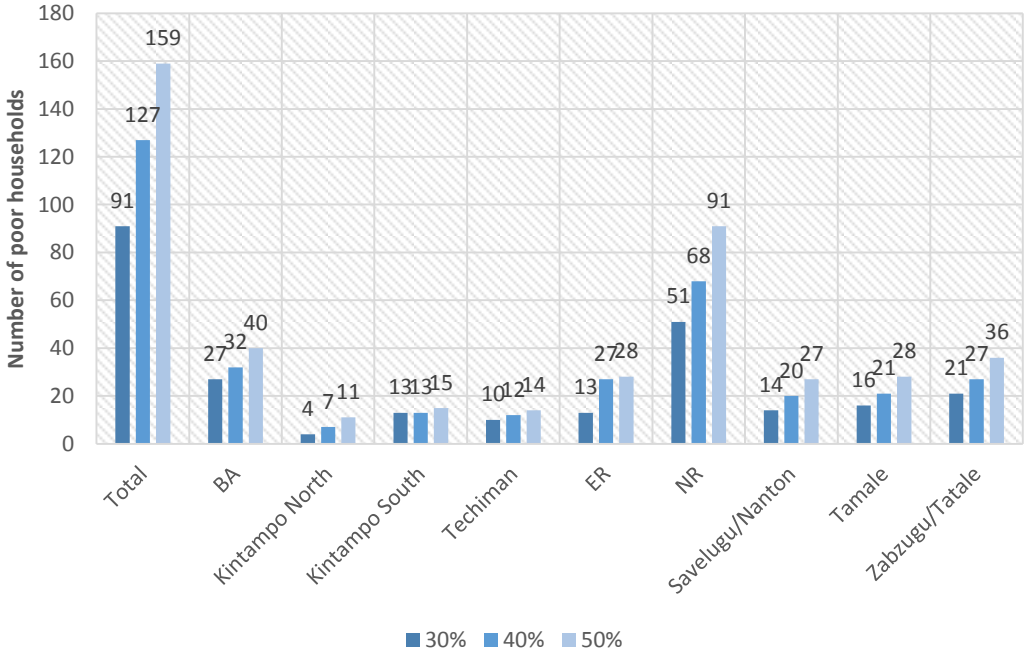


Table 6 Poverty ranking, by district

District Poverty ranking					
30%		40%		50%	
1st	Tamale	1st	Tamale	1st	Tamale
2nd	Zabzugu/Tatale	2nd	Zabzugu/Tatale	2nd	Zabzugu/Tatale
3rd	Savelugu/Nanton	3rd	Savelugu/Nanton	3rd	Savelugu/Nanton
4th	Kintampo South	4th	Yilo Krobo	4th	Yilo Krobo
5th	Yilo Krobo	5th	Kintampo South	5th	Kintampo South
6th	Techiman	6th	Techiman	6th	Kintampo North
7th	Kintampo North	7th	Kintampo North	7th	Techiman

Appendix 4.4. Subjective poverty, sensitivity checks

The "Minimum Income", the "Income evaluation" and "Consumption Adequacy" questions, although slightly different measures of subjective well-being, can help verifying the stability of the subjective poverty definition.

The Minimum Income question was formulated as follows: *"Living where you do now, what is the smallest income you and your family would need (after deductions) to make ends meet each month?".* Finally the Income and Consumption Adequacy questions: *"How would you evaluate your income for reaching your needs?"* and *"Concerning your food consumption, which of the following is true?",* both of them using the following scale:*"1=Very bad; 2 =Bad 3=Moderate;4=Good; 5=Very good"*[131].

Table 7 shows that the median threshold used for defining poor and non-poor household according to the relative economic ladder could be appropriate in this analysis. Hence, subjective poor households defined using this threshold are observed to be relatively poorer also according to the Minimum Income and Consumption Adequacy question. More specifically, the subjective poor households are observed to need a lower minimum income than non-poor households and they consider their current and past income and consumption worse than non-poor households.

Table 7 Assessment internal coherence, subjective poverty

	Subjective non poor	Subjective Poor	p-value
Minimum income (Ghc/month)	271.83	202.92	0.009***
Income evaluation (current; 1-5)	3.34	2.81	0.000***
Income evaluation (12 months ago; 1-5)	3	2.78	0.016**
Food consumption adequacy (current; 1-5)	3.53	3.09	0.000***
Food consumption adequacy (12 months ago; 1-5)	3.30	3.02	0.000***
N	192	113	

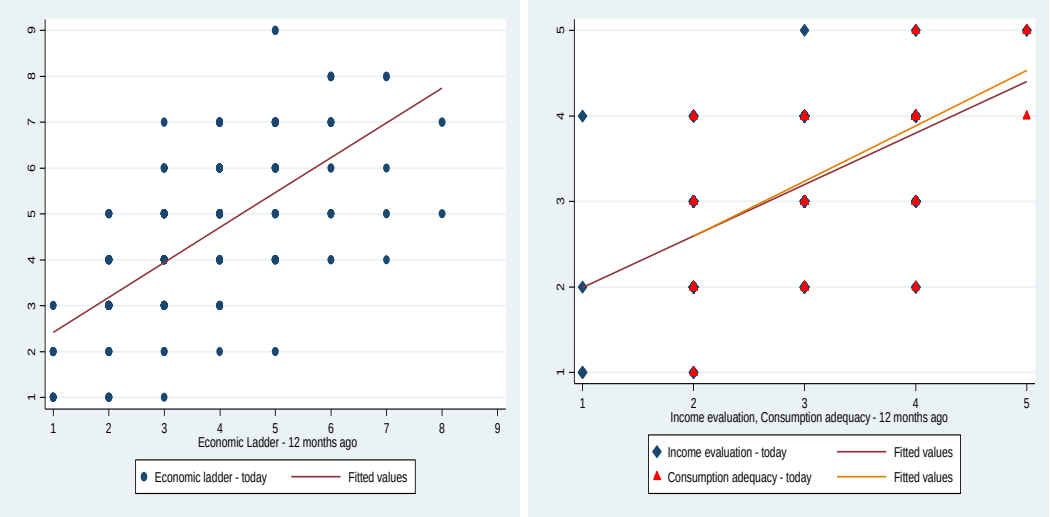
Nonetheless, although generally poorer than other households, subjective poor households are observed to have experienced a more positive trend in their wealth than non-poor households in the previous 12 months (Income Evaluation questions). In order to see whether this is the case I plot the current and past values (12 months) for each of the subjective poverty measures.

Figure 2 shows that there is a positive correlation between the current and past socio-economic status for lower values and negative for higher values, suggesting that poorer households are indeed feeling better off than non-poor households compared to the past[132].

[131] As for the Economic ladder question, the adequacy questions were asked for current and past (12 months before the survey) values of income and consumption respectively.

[132] Also, if this is the case and poorer households are expecting to be better off in the future, we could expect subjective measures of well – being to be higher than actual objective measures of welfare in this case the asset index, at any given level of actual wealth. This could be supported by the fact that using subjective poverty measures identifies as poor a smaller number HHs than when using objective measures (113 HHs compared to 127 HHs). This

Figure 2 Subjective poverty measures today and 12 months ago



result suggest that these subjective measures could be useful in calibrating the poverty analysis based on the asset index.

Appendix 4.5. Correlation between objective and subjective measures of poverty

Figure 3 Correlation objective and subjective measures

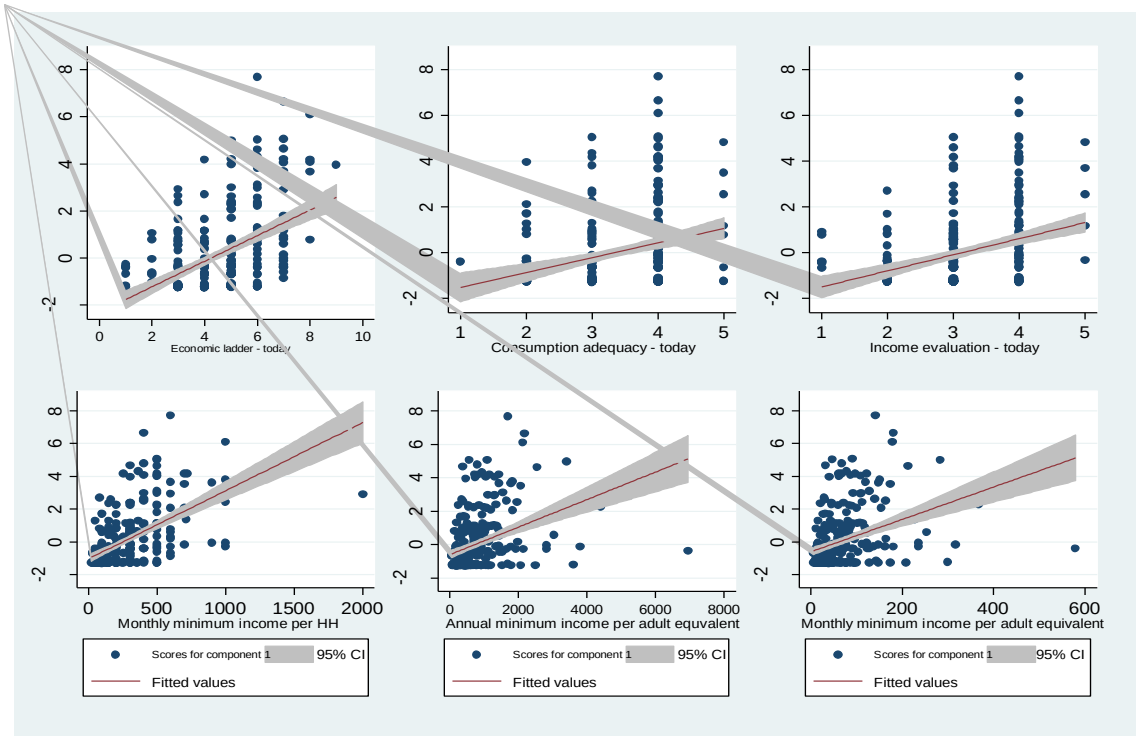


Table 8 Poverty ranking, by objective and subjective measures of poverty

Regional Poverty ranking			
Objective poverty		Subjective poverty	
1st	Northern region	1st	Brong Ahafo region
2nd	Eastern region	2nd	Northern region
3rd	Brong ahafo region	3rd	Eastern region

District Poverty ranking			
Objective poverty		Subjective poverty	
1st	Tamale	1st	Kintampo South
2nd	Zabzugu/Tatale	2nd	Zabzugu/Tatale
3rd	Savelugu/Nanton	3rd	Kintampo North
4th	Yilo Krobo	4th	Techiman
5th	Kintampo South	5th	Savelugu/Nanton
6th	Techiman	6th	Yilo Krobo
7th	Kintampo North	7th	Tamale

Appendix 4.6. The poverty profile

Using these definitions of poverty the following paragraphs describe main differences in household, farm and livelihood characteristics between poor and non-poor farmers. Table 9 reports some selected summary statistics by poverty status of the households in the sample.

Overall, regardless of the measure of poverty used, poor farmers live in similar size household, with on average few members of the household engaged in non-farm employment. The dependency ratio is significantly higher for subjective poor compared to both non-poor (subjective) and objective poor households[133]. Moreover, education level of poor household is generally lower than non-poor households, although the difference is only statistically significant for objective poor and non-poor households.

Overall, poorer households are poorly endowed in farm and transport assets. While this is expected in the case of objective poverty measurements, which by constructions discriminate poverty status according to asset endowments, also subjective poor households are found to own less assets than non-poor households[134]. More specifically, non-poor farmers usually farm about 10 acres of land while poor farmers only cultivate 3.4 acres (5 acres in the case of subjective poor), they usually own land and own several assets such as fridge, radio, TV or motorbicycle and cars. The main source of livelihood does not change much according to the poverty status. The majority of the households in the sample are involved in farming activities, which provides on average 70% of the total household income. However, although the number of crops produced does not differ between non-poor and poor household, the type of crops that feeds into the household's crop portfolio is found to differ considerably depending on the poverty status.

Figure 4 shows that poor households tend to have a very scarcely differentiated portfolio with respect to non-poor households, with 85% (108 households) of the objective poor households and 70% (78 households) of the subjective poor households producing only food crops (or food crops associated with mango) and only very few of them producing other cash crops, such as banana, cashew, palm oil, or pineapple.

Furthermore, poor households tend to consume more of the crops produced and sell less and the differences are highly statistically significant. Aside for a lower market participation, poor households are also observed to participate in different marketing channels. Poor households mostly sell their produce to market women and to neighbours while non poor farmers tend to use a more diversified set of marketing channels. Nonetheless home, farm and local markets are the main selling points for the majority of the farmers regardless of their poverty status (Figure 5 and Figure 6).

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[133] This difference is mainly driven by the higher number of elderly people in the households, whose mean is 0.34 for subjective poor household compared to 0.18 (subjective non-poor), 0.22 and 0.25 for objective poor and objective non-poor, respectively.

[134] A major exception of this trend regards to ownership of a bicycle, which is observed to be more common in the case of objectively poorer households. This finding is in line with the common field observations that ownership of a bicycle does not necessarily links to better well-being and economic status.

Table 9 Selected summary statistics

	Objective poverty Wealth index			Subjective poverty Economic ladder		
	Non poor	Poor		Non poor	Poor	
	Mean	Mean	p-value	Mean	Mean	p-value
HH size (#)	6.11	5.64	0.074*	5.91	5.93	0.933
Dependency ratio (%)	74.58	72.94	0.848	66.26	86.87	0.017**
N. HH members with secondary education (%)	13.16	6.130	0.000***	12	8	0.037**
N. HH members with higher education (%)	10.32	5.33	0.003***	9	7	0.218
N. HH members with non-farm employment (%)	14.29	12.85	0.422	14.1	13.00	0.549
Fridge (0/1)	0.44	0.00	0.000***	0.32	0.16	0.003***
Radio (0/1)	0.93	0.87	0.049**	0.92	0.88	0.194
TV (0/1)	0.66	0.22	0.000***	0.56	0.34	0.000***
Computer (0/1)	0.10	0.00	0.000***	0.08	0.02	0.018**
Telephone (0/1)	0.45	0.00	0.016**	0.04	0.88	0.144
Mobile (0/1)	0.89	0.76	0.003***	0.87	0.78	0.040**
Sewing machine (0/1)	0.25	0.06	0.000***	0.19	0.12	0.116
Generator (0/1)	0.05	0.00	0.010**	00.5	0.00	0.019**
Electric lighting (0/1)	0.72	0.44	0.000***	0.65	0.52	0.029**
Drinking water (0/1)	0.34	0.00	0.000***	0.45	0.12	0.010**
Private toilet (0/1)	0.58	0.00	0.000***	0.36	0.31	0.284
Farm size (acres)	0.11	0.03	0.000***	0.10	0.49	0.009***
Land ownership (0/1)	0.68	0.51	0.003***	0.62	0.61	0.825
Tractor (0/1)	0.03	0.00	0.037**	0.03	0.00	0.058*
N. Livestock (#)	0.26	0.18	0.028**	0.28	0.14	0.000***
Bicycle (0/1)	0.62	0.74	0.033**	0.70	0.63	0.212
Motorbicycle (0/1)	0.46	0.00	0.000***	0.34	0.14	0.000***
Car (0/1)	0.20	0.00	0.000***	0.15	0.06	0.026**
Farm income (% total income)	65.53	71.88	0.009***	67.19	69.84	0.287
N. crops produced (#)	2.67	2.55	0.346	2.61	2.65	0.783
Harvest consumed (% total harvest)	17.87	31.51	0.000***	22.01	26.16	0.112
Harvest sold (% total harvest)	73.26	58.52	0.000***	70.32	61.69	0.005***
Distance to market (Km)	4.59	4.06	0.257	4.05	4.92	0.071*
Shocks – Pests (0/1)	0.69	0.55	0.012**	0.64	0.63	0.902
Training (0/1)	0.65	0.52	0.021**	0.68	0.46	0.000***
Certification (0/1)	0.15	0.06	0.023**	0.16	0.04	0.001***
N	178	127		192	113	

Figure 4 Crop portfolio

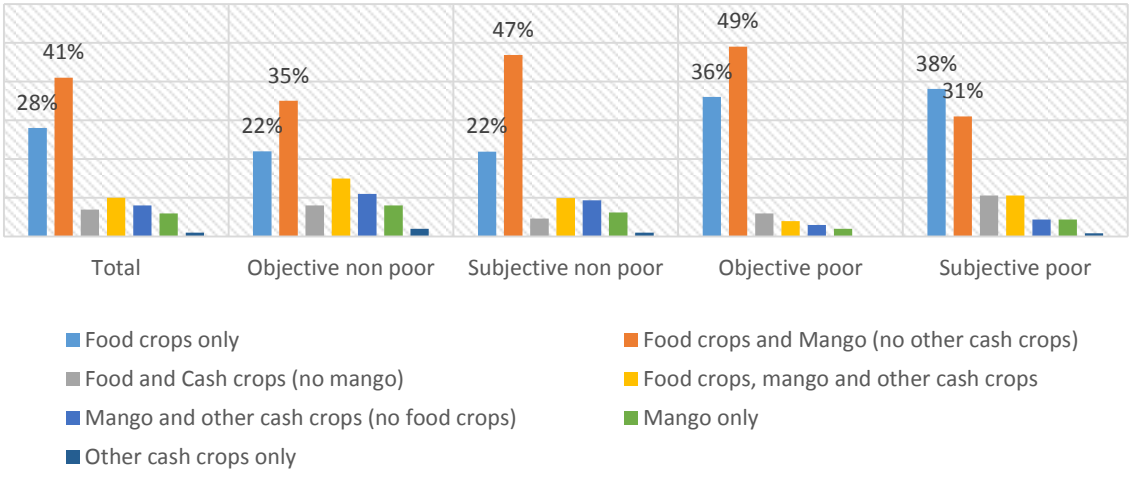


Figure 5 Marketing channels, objective poverty

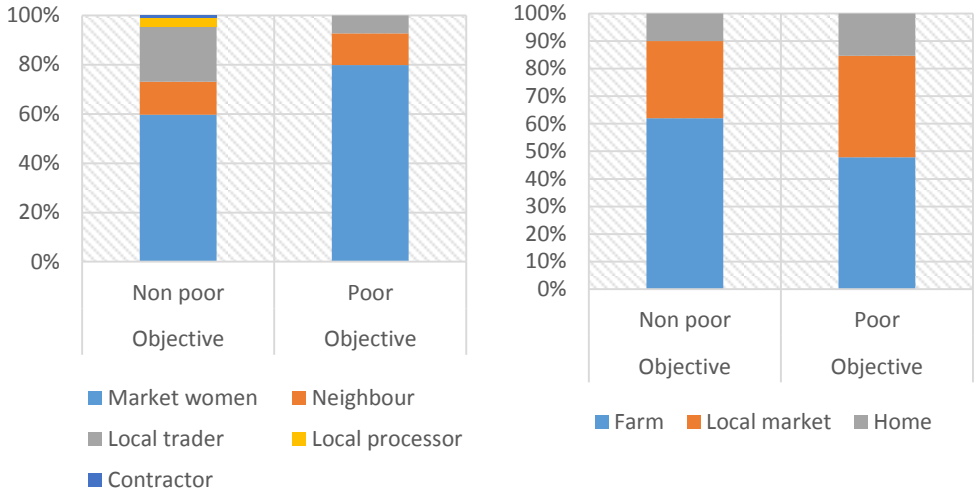
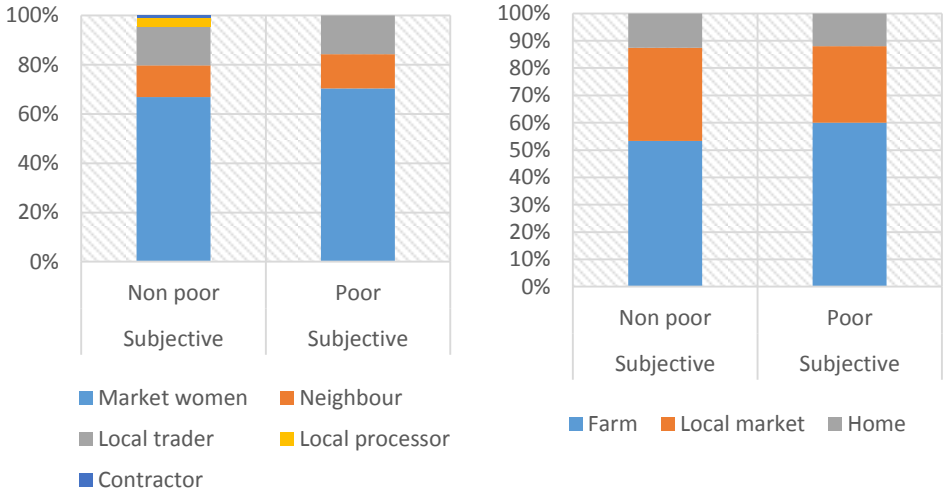


Figure 6 Marketing channels, subjective poverty



Appendix 4.7. Summary statistics by mango adoption (subjective poverty)

Table 10 Summary statistics - mango adoption (subjective poverty)

		Subjective non poor			Subjective poor		
		Non mango	Mango		Non mango	Mango	
		Mean	Mean	p-value	Mean	Mean	p-value
Male head	(0/1)	0.87	0.94	0.086*	0.84	0.91	0.243
Age head	Years	44.15	50.29	0.001***	49.25	50.26	0.697
Primary education head	(0/1)	0.08	0.06	0.793	0.11	0.05	0.289
Higher education head	(0/1)	0.28	0.32	0.589	0.21	0.39	0.047**
No risk aversion	(0/1)	0.13	0.12	0.856	0.13	0.09	0.524
Impatience	(0/1)	0.53	0.39	0.081*	0.55	0.51	0.637
HH size	#	5.42	6.09	0.078*	5.68	6.18	0.216
Dependency ratio	(%)	67.11	65.93	0.900	88.97	84.80	0.812
N. Married	#	1.94	2.27	0.049**	1.75	2.16	0.030**
N. Male adults	#	1.75	2.16	0.047**	1.88	1.84	0.881
N. HH members with higher education	(%)	0.34	0.60	0.062*	0.27	0.49	0.060*
N. HH members with non-farm employment	(%)	12.74	14.61	0.452	9.94	16.01	0.037**
Fridge	(0/1)	0.05	0.26	0.002***	0.23	0.35	0.113
Radio	(0/1)	0.89	0.86	0.596	0.91	0.93	0.607
TV	(0/1)	0.23	0.44	0.020**	0.45	0.60	0.059*
Mobile	(0/1)	0.71	0.84	0.104	0.81	0.89	0.139
Sewing machine	(0/1)	0.09	0.16	0.272	0.13	0.22	0.190
Drinking water	(0/1)	0.07	0.18	0.095*	0.06	0.32	0.000***
Bicycle	(0/1)	0.50	0.75	0.005***	0.75	0.68	0.292
Car	(0/1)	0.08	0.17	0.089*	0.04	0.09	0.255
Farm size	(acres)	3.93	11.68	0.008***	4.02	5.83	0.103
Farm size[1]	(acres)	3.93	10.33	0.022**	4.02	5.15	0.276
Land ownership	(0/1)	0.47	0.67	0.012**	0.55	0.65	0.304
N. Livestock	#	25.85	28.37	0.678	12.41	15.07	0.503
Hired	#	6.64	10.96	0.057*	4.45	10.00	0.000***
Tractor	(0/1)	0.04	0.03	0.751	0.00	0.00	.
Cash crops production	(0/1)	0.21	0.27	0.404	0.23	0.30	0.431
Training	(0/1)	0.23	0.85	0.000***	0.29	0.63	0.000***
FO	(0/1)	0.17	0.70	0.000***	0.13	0.46	0.000**
N. visits extension off.	#	1.38	4.96	0.011**	1.00	1.67	0.095*
Innovation	#	0.66	0.24	0.001***	0.09	0.18	0.242
N		53	139		56	57	

[1]At the time of adoption for mango farmers; current for non-mango farmers

Appendix 4.8. Common Support based on matching criteria from economic model

Table 11 Matching variables from Economic model

Variable	Description
Age head*	Years*
Gender head	=1 if head is a man; 0 otherwise
Higher education	=1 if head awarded secondary or higher education; 0 otherwise
Farm labour	Number of HH members working on own farm
Farm size*	Acres*
Land ownership	=1 if any land is owned; 0 otherwise
Production of other cash crops	=1 if other cash crops are produced; 0 otherwise
Livestock ownership	Number of livestock owned
Access to credit	=1 if any HH member had access to credit in the past 12 months; 0 otherwise
Ownership of tractor	=1 if a tractor is owned; 0 otherwise
Ownership of mobile	=1 if a mobile phone is owned; 0 otherwise
Ownership of radio	=1 if a radio is owned; 0 otherwise
Ownership of bicycle	=1 if a bicycle is owned; 0 otherwise
Ownership of motorbicycle	=1 if a motorbicycle is owned; 0 otherwise
Ownership of car	=1 if a car is owned; 0 otherwise
Roads condition	Number of months of impassable roads
Moderate risk aversion	=1 if head is moderately risk averse; 0 otherwise [Base= extreme risk aversion]
No risk aversion	=1 if head is no risk averse; 0 otherwise [Base= extreme risk aversion]
Impatience	= 1 if head is impatient; 0 otherwise
Experience in farming*	Number of years of experience in farming
Training	= 1 if any HH member received any training; 0 otherwise
Social capital	See variables in Chapter 3

Figure 7 Common support

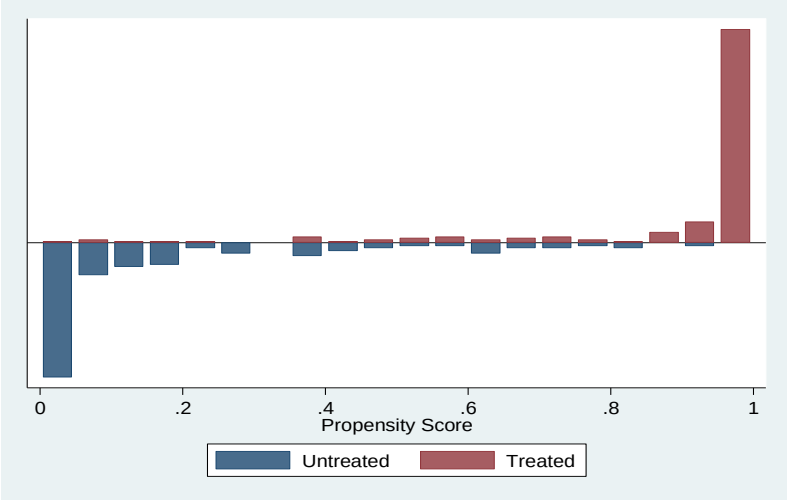
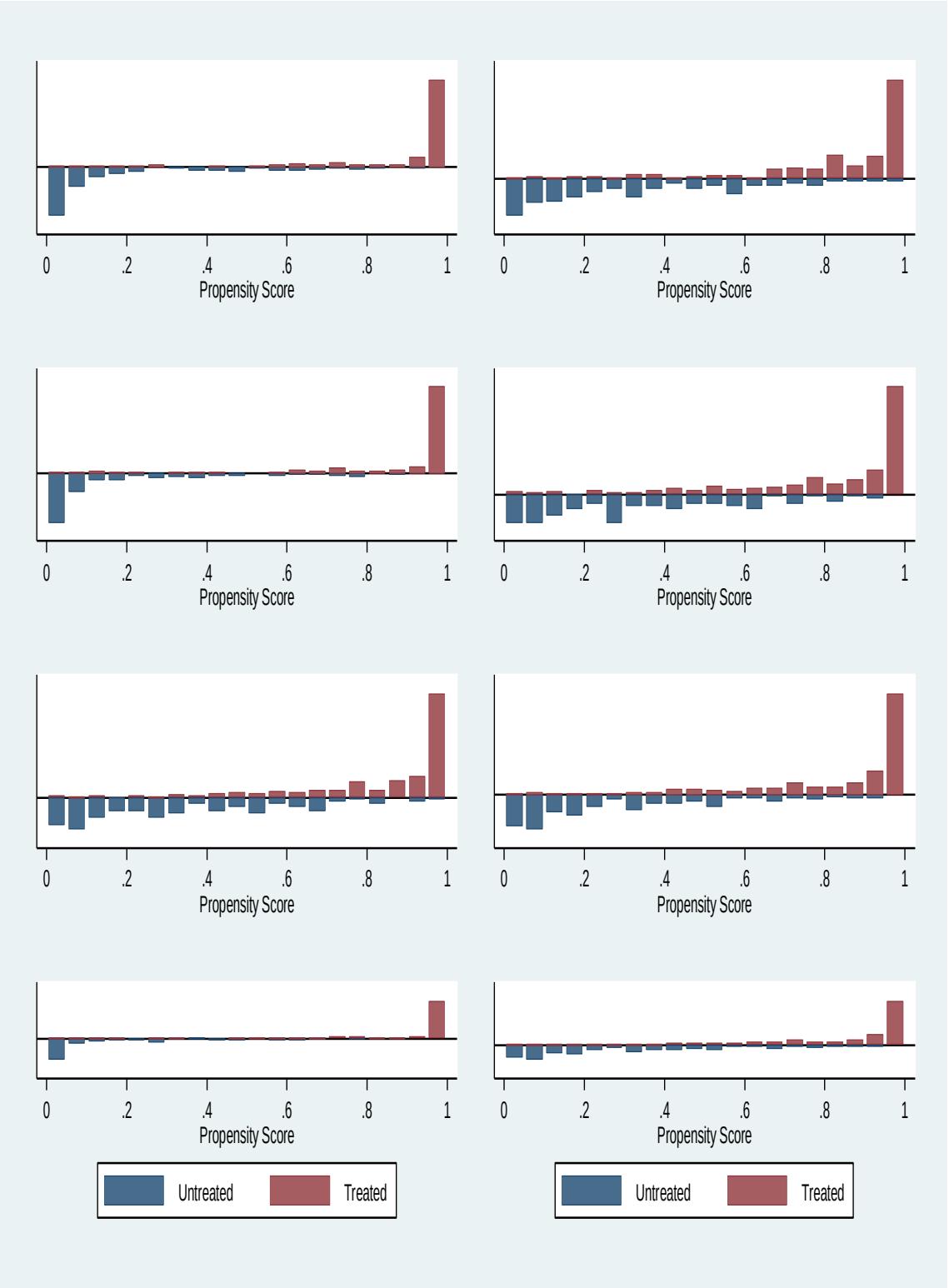


Figure 8 Common support, different specification economic model



Appendix 4.9. Indicators of matching quality

Table 12 ATET - additional results

		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	Pseudo Rsquare before matching	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090
	Pseudo Rsquare after matching	0.024	0.025	0.007	0.010	0.023	0.024	0.023	0.023	0.004	0.019	0.018	0.019	0.039
M1	LRT p-value	0.083	0.105	0.992	0.990	0.109	0.082	0.149	0.149	1.000	0.774	0.864	0.774	0.124
	Median bias before matching	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197
	Median bias after matching	6.344	5.798	**1.907**	5.513	7.500	8.629	5.949	5.949	**3.162**	**4.571**	**4.683**	**4.571**	**4.255**
	Pseudo Rsquare before matching	0.093	0.093	0.093	0.093	0.093	0.093	0.093	0.093	0.093	0.093	0.093	0.093	0.093
	Pseudo Rsquare after matching	0.027	0.023	0.007	0.014	0.027	0.030	0.027	0.027	0.009	0.026	0.015	0.026	0.052
M2	LRT p-value	0.047	0.183	0.995	0.978	0.053	0.028	0.079	0.079	0.993	0.582	0.941	0.582	0.031
	Median bias before matching	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736
	Median bias after matching	7.927	6.805	**3.124**	**4.681**	7.065	6.460	5.586	5.586	**2.407**	8.590	**3.574**	8.590	5.562
	Pseudo Rsquare before matching	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095
	Pseudo Rsquare after matching	0.028	0.031	0.009	0.027	0.024	0.026	0.021	0.021	0.010	0.031	0.011	0.031	0.076
M3	LRT p-value	0.060	0.047	0.994	0.687	0.130	0.093	0.298	0.302	0.994	0.438	0.994	0.438	0.001
	Median bias before matching	21.557	21.557	21.557	21.557	21.557	21.557	21.557	21.557	21.557	21.557	21.557	21.557	21.557
	Median bias after matching	9.297	5.933	**2.325**	**4.318**	7.960	8.410	6.782	6.759	**3.905**	7.563	**4.107**	7.563	8.065
	Pseudo Rsquare before matching	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114
	Pseudo Rsquare after matching	0.045	0.047	0.015	0.040	0.025	0.025	0.035	0.035	0.007	0.057	0.025	0.057	0.062
M4	LRT p-value	0.002	0.003	0.935	0.428	0.195	0.206	0.050	0.050	1.000	0.050	0.870	0.050	0.026
	Median bias before matching	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736	22.736
	Median bias after matching	11.340	12.052	**3.951**	7.795	8.273	7.976	10.666	10.666	**3.131**	7.111	**4.267**	7.111	8.803
	Pseudo Rsquare before matching	0.132	0.132	0.132	0.132	0.132	0.132	0.132	0.132	0.132	0.132	0.132	0.132	0.132
	Pseudo Rsquare after matching	0.034	0.027	0.016	0.029	0.032	0.036	0.030	0.030	0.009	0.031	0.015	0.031	0.069
M5	LRT p-value	0.032	0.224	0.933	0.837	0.052	0.020	0.151	0.151	0.999	0.612	0.992	0.612	0.010
	Median bias before matching	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197	23.197
	Median bias after matching	**4.533**	**4.398**	**4.516**	**4.411**	7.801	8.766	5.553	5.553	**4.387**	5.479	5.098	5.479	9.802

Appendix 4.10. Additional ATET estimations

Table 13 Average treatment effect on the treated, cash crop adoption

Cash crops adoption		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	**-0.252*** **	**-0.254** **	**-0.034**	**-0.160***	**-0.205*** **	**-0.185** **	**-0.201** **	**-0.201** **	**-0.192*** **	**-0.252*** **	**-0.202** **	**-0.252** **	**-0.233*** **
M1	ATET subjective	**-0.198** **	**-0.194** **	**-0.170** **	**-0.240*** **	**-0.177** **	**-0.193** **	**-0.204** **	**-0.204** **	**-0.182** **	**-0.198** **	**-0.210** **	**-0.198** **	**-0.149** **
	N. On support	290	289	176	163	290	290	289	289	290	290	289	290	290
	ATET objective	**-0.170***	**-0.178***	**-0.068***	-0.139	**-0.167** **	**-0.167** **	**-0.185** **	**-0.185***	**-0.180** **	**-0.170***	**-0.196** **	**-0.170***	**-0.210** **
M2	ATET subjective	**-0.250*** **	**-0.239*** **	**-0.182** **	-0.111	**-0.219*** **	**-0.224*** **	**-0.241*** **	**-0.241*** **	**-0.221*** **	**-0.250** **	**-0.262*** **	**-0.250*** **	**-0.175** **
	N. On support	288	285	176	160	288	288	285	285	288	288	285	288	288
	ATET objective	**-0.239*** **	**-0.246** **	-0.102	-0.093	**-0.180** **	**-0.169** **	**-0.185** **	**-0.185***	**-0.183** **	**-0.239*** **	**-0.193** **	**-0.239** **	**-0.199** **
M3	ATET subjective	**-0.239*** **	**-0.231** **	**-0.182** **	-0.067	**-0.222*** **	**-0.227*** **	**-0.238*** **	**-0.238*** **	**-0.217*** **	**-0.239*** **	**-0.232** **	**-0.239** **	**-0.214*** **
	N. On support	289	287	176	163	289	289	287	287	289	289	287	289	289
	ATET objective	-0.141	-0.138	-0.023	-0.070	**-0.142***	**-0.136***	-0.110	-0.110	**-0.143***	-0.141	-0.121	-0.141	**-0.157** **
M4	ATET subjective	-0.108	-0.099	**-0.148***	-0.099	**-0.190** **	**-0.196** **	-0.128	-0.128	**-0.171** **	-0.108	-0.124	-0.108	**-0.178** **
	N. On support	273	269	176	159	273	273	269	269	273	273	269	273	273
	ATET objective	-0.105	-0.085	-0.034	-0.074	**-0.195** **	**-0.175** **	-0.144	-0.144	**-0.169** **	-0.105	-0.138	-0.105	**-0.209** **
M5	ATET subjective	-0.152	-0.131	**-0.136***	**-0.265*** **	**-0.216*** **	**-0.192** **	**-0.183***	**-0.183** **	**-0.168** **	-0.152	**-0.174** **	-0.152	**-0.147***
	N. On support	274	264	176	156	279	279	264	264	279	279	264	279	279

*Note: NN=nearest neighbour; Caliper 01= nearest neighbour with caliper width of 0.01; NN_Norep= nearest neighbour, no replacement; NN_Norepcal= nearest neighbour, no replacement with caliper width of 0.01; NN 10= nearest 10 neighbours; NN 20= nearest 20 neighbours; NN 10 cal= nearest 10 neighbours with caliper width of 0.01; NN 20 cal= nearest 20 neighbours with caliper width of 0.01; Kepan= kernel; Knorm=kernel normal; Kbw01=kernel with bandwidth of 0.01; Knormbw01=kernel normal with bandwidth of 0.01

Table 14 Average treatment effect on the treated, late vs early adopters (abs)

Early vs later (196 Households)		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	0.088	0.116	**0.188****	0.073	**0.173****	**0.198****	0.113	0.113	0.103	0.088	0.103	0.088	**0.200****
	ATET subjective	**0.188***	**0.188***	**0.138***	**0.200***	**0.166****	**0.171****	**0.199****	**0.199****	**0.179****	**0.188****	**0.196***	**0.188***	**0.225*****
M1	N. On support	183	172	183	158	183	183	172	172	183	183	172	183	183
	ATET objective	0.039	0.127	**0.208*****	0.100	**0.175***	**0.204*****	0.158	0.156	0.110	0.039	0.159	0.039	**0.208****
	ATET subjective	0.156	0.127	**0.130***	0.140	**0.168****	**0.151***	0.118	0.118	**0.184****	0.156	0.124	**0.156***	**0.221****
M2	N. On support	180	166	180	153	180	180	166	166	180	180	166	180	180
	ATET objective	0.038	0.106	**0.192****	0.130	**0.181****	**0.198****	0.125	0.125	0.116	0.038	0.149	0.038	**0.205****
	ATET subjective	0.141	0.106	0.128	**0.167***	**0.178****	**0.149****	0.130	0.130	**0.180****	0.141	0.120	0.141	**0.205****
M3	N. On support	181	169	181	157	181	181	169	169	181	181	169	181	181
	ATET objective	0.159	0.159	**0.183****	0.109	0.129	**0.188****	0.098	0.098	0.127	0.159	0.126	0.159	0.122
	ATET subjective	0.171	0.130	0.110	0.043	**0.179****	0.124	0.126	0.126	**0.178****	0.171	0.134	**0.171***	0.146
M4	N. On support	185	172	185	149	185	185	172	172	185	185	172	185	185
	ATET objective	0.125	0.047	**0.175****	0.021	0.090	**0.173***	0.042	0.042	0.102	0.125	0.033	0.125	0.150
	ATET subjective	**0.188***	0.188	0.100	0.128	**0.135***	0.121	0.188	0.188	**0.170***	**0.188***	0.187	**0.188***	0.138
M5	N. On support	183	167	183	150	183	183	167	167	183	183	167	183	183

Table 15 Average treatment effect on the treated, later vs earlier (rel)

Later vs Earlier (196 Households)		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	0.107	0.110	0.103	0.067	0.128	**0.139***	0.145	0.145	0.074	0.107	0.123	0.107	0.054
M1	ATET subjective	**0.196****	0.154	0.103	0.050	0.138	**0.148***	0.141	0.140	**0.164****	**0.196***	0.116	**0.196****	**0.196*****
	N. On support	190	169	156	138	190	190	169	169	190	190	169	190	190
	ATET objective	0.009	0.033	0.090	-0.054	0.106	**0.136***	0.079	0.079	0.090	0.009	0.080	0.009	0.084
M2	ATET subjective	**0.206****	**0.176***	0.090	0.071	**0.152***	**0.156****	0.149	0.149	**0.187****	**0.206****	0.151	**0.206****	**0.178****
	N. On support	185	169	156	134	185	185	169	169	185	185	169	185	185
	ATET objective	0.093	0.144	0.090	0.036	0.124	**0.128***	0.096	0.096	0.087	0.093	0.108	0.093	0.075
M3	ATET subjective	**0.187***	0.144	0.077	0.109	**0.172***	**0.151***	0.136	0.136	**0.185****	**0.187***	0.134	**0.187****	**0.159****
	N. On support	185	168	156	133	185	185	168	168	185	185	168	185	185
	ATET objective	0.118	0.140	0.103	0.000	0.113	0.107	0.111	0.111	0.106	0.118	0.120	0.118	0.029
M4	ATET subjective	0.147	0.128	0.077	0.059	0.114	0.104	**0.159***	0.159	0.145	0.147	0.164	0.147	0.108
	N. On support	180	164	156	129	180	180	164	164	180	180	164	180	180
	ATET objective	0.058	0.058	0.103	0.020	0.102	0.106	0.070	0.070	0.102	0.058	0.058	0.058	0.049
M5	ATET subjective	**0.184***	0.174	0.077	0.082	0.110	0.099	0.174	0.174	**0.145****	0.184	0.174	0.184	0.049
	N. On support	181	164	156	127	181	181	164	164	181	181	164	181	181

*Note: NN=nearest neighbour; Caliper 01= nearest neighbour with caliper width of 0.01; NN_Norep= nearest neighbour, no replacement; NN_Norepcal= nearest neighbour, no replacement with caliper width of 0.01; NN 10= nearest 10 neighbours; NN 20= nearest 20 neighbours; NN 10 cal= nearest 10 neighbours with caliper width of 0.01; NN 20 cal= nearest 20 neighbours with caliper width of 0.01; Kepan= kernel; Knorm=kernel normal; Kbw01=kernel with bandwidth of 0.01; Knormbw01=kernel normal with bandwidth of 0.01

Table 16 Average treatment effect on the treated, small farmers (3 or less acres)

Small farmers (189 Households)		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	0.064	0.030	0.107	0.103	0.072	0.057	0.065	0.065	0.094	0.064	0.059	0.064	0.055
M1	ATET subjective	-0.018	-0.030	-0.040	-0.086	-0.106	-0.123	-0.098	-0.098	-0.083	-0.018	-0.105	-0.018	-0.064
	N. On support	184	175	150	133	184	184	175	175	184	184	175	184	184
	ATET objective	0.084	0.093	0.053	0.096	0.092	0.060	0.098	0.098	0.099	0.084	0.094	0.084	0.103
M2	ATET subjective	-0.131	-0.103	-0.040	-0.077	-0.136	-0.125	-0.096	-0.096	-0.131	-0.131	-0.095	-0.131	-0.056
	N. On support	182	172	150	127	182	182	172	172	182	182	172	182	182
	ATET objective	0.092	0.071	0.053	0.060	0.078	0.051	0.058	0.058	0.089	0.092	0.056	0.092	0.110
M3	ATET subjective	-0.064	-0.040	-0.040	-0.140	-0.144	-0.115	-0.110	-0.110	-0.130	-0.064	-0.092	-0.064	-0.064
	N. On support	184	174	150	125	184	184	174	174	184	184	174	184	184
	ATET objective	**0.227***	0.200	0.027	0.091	0.119	0.064	0.154	0.154	0.141	**0.227***	0.177	**0.227***	0.073
M4	ATET subjective	-0.118	-0.067	-0.093	-0.182	-0.125	-0.096	-0.112	-0.112	**-0.179***	-0.118	-0.108	-0.118	-0.036
	N. On support	185	165	150	119	185	185	165	165	185	185	165	185	185
	ATET objective	0.067	0.038	-0.013	0.026	0.038	0.023	0.065	0.065	0.074	0.067	0.065	0.067	0.000
M5	ATET subjective	-0.095	-0.165	-0.107	-0.132	-0.073	-0.091	-0.147	-0.147	-0.039	-0.095	-0.143	-0.095	-0.105
	N. On support	180	154	150	113	180	180	154	154	180	180	154	180	180

Table 17 Average treatment effect on the treated, large farmers (More than 3 acres)

Big farmers (116 Households)		NN	caliper_01	NN_norep	NN_norepcal	NN10	NN20	NN10cal	NN20cal	Kepan	Knorm	Kbw01	Knormbw01	mahalanobis
	ATET objective	**-0.304***	**-0.415***	**-0.235****	**-0.438***	**-0.338****	**-0.318*****	**-0.435***	**-0.435***	**-0.371****	**-0.304***	**-0.420***	**-0.304***	**-0.362*****
M1	ATET subjective	**-0.536*****	**-0.488****	**-0.441*****	**-0.688*****	**-0.375*****	**-0.451*****	**-0.439***	**-0.439***	**-0.381****	**-0.536*****	**-0.456****	**-0.536*****	**-0.391****
	N. On support	103	75	68	50	103	103	75	75	103	103	75	103	103
	ATET objective	-0.301*	-0.256	-0.235**	-0.313	-0.334***	-0.299**	-0.233	-0.233	**-0.318****	**-0.301***	-0.243	**-0.301***	**-0.315****
M2	ATET subjective	**-0.438****	**-0.442***	**-0.441*****	**-0.375***	**-0.396*****	**-0.440*****	-0.395	-0.395	**-0.322****	**-0.438****	-0.405	**-0.438****	**-0.479*****
	N. On support	107	77	68	50	107	107	77	77	107	107	77	107	107
	ATET objective	**-0.443****	**-0.409****	**-0.265****	-0.333	**-0.350*****	**-0.316****	-0.360	**-0.360***	**-0.373****	**-0.443****	-0.376	**-0.443****	**-0.371*****
M3	ATET subjective	**-0.314***	**-0.409***	**-0.471*****	**-0.600*****	**-0.414*****	**-0.446*****	**-0.424***	-0.424	**-0.339***	-0.314	**-0.423***	-0.314	**-0.471*****
	N. On support	104	78	68	49	104	104	78	78	104	104	78	104	104
	ATET objective	-0.114	-0.074	-0.176	-0.133	-0.232	-0.248*	-0.148	-0.148	-0.211	-0.114	-0.111	-0.114	**-0.341*****
M4	ATET subjective	**-0.364***	-0.222	**-0.412*****	-0.400	**-0.318****	**-0.399*****	-0.259	-0.259	**-0.346***	**-0.364***	-0.246	**-0.364***	**-0.432*****
	N. On support	78	61	68	49	78	78	61	61	78	78	61	78	78
	ATET objective	-0.250	-0.320	-0.147	-0.231	-0.184	**-0.225***	-0.300	-0.300	-0.228	-0.250	-0.304	-0.250	**-0.295****
M5	ATET subjective	-0.227	-0.120	-0.441***	-0.308	**-0.393****	**-0.380*****	-0.160	-0.160	-0.293	-0.227	-0.151	-0.227	**-0.341****
	N. On support	78	59	68	47	78	78	59	59	78	78	59	78	78

*Note: NN=nearest neighbour; Caliper 01= nearest neighbour with caliper width of 0.01; NN_Norep= nearest neighbour, no replacement; NN_Norepcal= nearest neighbour, no replacement with caliper width of 0.01; NN 10= nearest 10 neighbours; NN 20= nearest 20 neighbours; NN 10 cal= nearest 10 neighbours with caliper width of 0.01; NN 20 cal= nearest 20 neighbours with caliper width of 0.01; Kepan= kernel; Knorm=kernel normal; Kbw01=kernel with bandwidth of 0.01; Knormbw01=kernel normal with bandwidth of 0.01