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MASTER THESIS

Social learning among Ghanaian cocoa farmers: Choosing the optimal amounts of inputs

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Declaration of Authorship

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Signature

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Abstract

In this thesis I inspect learning about adoption of technologies among cocoa farmers in Ghana, which are represented by non-labor inputs, particularly by fertilizer and hybrid seeds. Earlier research focused mainly on learning about returns associated with adoption of such innovative inputs. However, it is not clear whether the adopters learn about these returns or rather about what are the optimal amounts of these inputs. Therefore the focus of this thesis is to examine how do the farmers choose and learn about optimal amounts of inputs. Cocoa farming is very labor intensive, and thus this thesis concentrates on learning about both non-labor and labor inputs, which are closely connected. Similar research carried out in India suggests that heterogeneous returns among farmers might cause that the farmers rely rather on their own considerations than on observation of behavior of their village neighbors, i.e. social learning. The heterogeneous returns are also present among the Ghanaian cocoa farmers, which suggest that these farmers should similarly prefer individual learning over the social one. Using a model developed for estimation of the prevailing type of learning about the optimal amount of inputs, I show that the farmers do tend to prefer individual learning in case of the non-labor inputs but rather rely on social learning in case of the labor inputs.

JEL Classification	C21, C23, Q12, Q16
Keywords	Cocoa Abrabopa Association, Ghana, Agricultural technology, Fertilizer, Hybrid seeds, Agricultural inputs

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Abstrakt

Tato práce zkoumá, jakými způsoby se farmáři pěstující kakao v Ghaně učí o možnostech využití nových technologií. Těmito technologiemi jsou zde myšleny technické vstupy, zejména hnojiva a hybridní semena. Dosavadní výzkum se zabýval převážně způsoby, kterými se farmáři učí o výnosech spjatých s využitím těchto inovativních vstupů. Nicméně, není zcela jasné, zda se farmáři učí spíše o těchto výnosech, nebo o tom, jaké množství těchto vstupů je optimální použít. Tato práce se proto zabývá způsobem, jakým se farmáři rozhodují a učí o tom jaké je jejich optimální množství těchto vstupů. Pěstování kakaa vyžaduje využití značného množství lidské síly. Tato práce proto zkoumá způsoby učení se o nejen technických, ale i o lidských vstupech. Podobný výzkum z farem v Indii naznačuje, že vysoké rozdíly ve výnosech mezi farmáři způsobují, že se farmáři spoléhají spíše na vlastní úsudek, než na pozorování chování sousedních farmářů z jejich vesnice, tj. takzvané sociální učení. Mezi farmáři kakaa v Ghaně existují tyto velké rozdíly ve výnosech, což naznačuje, že se tito farmáři pravděpodobně řídí spíše vlastním úsudkem, než vypozorovaným chováním ostatních farmářů ze své vesnice. Využití ekonometrického modelu, který odhaduje převládající formu učení se o optimálním množství vstupů, ukazuje, že farmáři kakaa v Ghaně se opravdu spoléhají převážně na svůj úsudek v případě technických vstupů, nicméně v případě lidských vstupů se řídí spíše vypozorovaným chováním sousedních farmářů ze své vesnice.

Klasifikace	C21, C23, Q12, Q16
Klíčová slova	Cocoa Abrabopa Association, Ghana, Zemědělská technologie, Hnojivo, Hybridní semena, Zemědělské vstupy

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Master Thesis Proposal

Author:	Bc. David Švenka
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Defense Planned:	June 2013

Proposed Topic:

The effects of microfinance on the productivity of Ghanaian cocoa farmers

Topic Characteristics:

Adoption of a new technology can be a significant production booster if the new technology implementation turns out to be successful. Therefore it seems only logical to stick to such innovative technology and to likely permanently change previous manners of production. Nevertheless, it might also be the case that some part of the new adopters of such commonly successful technology decides not to use it in the consecutive period of production. To be more specific, there are various evidences from rural Africa showing such trend. And there are also various authors trying to explain this phenomenon.

In this thesis, I will focus on such research conducted by a team of researchers led by Andrew Zeitlin. Particularly, I plan to build on several papers written by these authors and mainly on their rich panel dataset compiled from questionnaires related to a program ran by the Cocoa Abrabopa Association (CAA) spanning several years. Based on Caria et al. (2009), the CAA program provides a package of inputs – fertilizer, insecticide, and fungicide – to groups of farmers on a seasonal credit basis. Therefore the program has some important microfinance features such that the credit is not provided to individuals but to farmer groups of between 5 and 15 members formed for purpose of participation.

The goal of the thesis will be to inspect the role of social learning on individual farmer's decision to adopt a new technology. There has already been done some research on this topic using the above mentioned dataset, namely by Zeitlin (2011) and Caria et al. (2010), however I intend to use a bit different approach based mainly on several papers written by Conley et al. (2001, 2004) and by Foster and Rosenzweig (2010). In contrast to part of the research conducted by Conley et al. (2001, 2004) and by Foster and Rosenzweig (2010), the nature of the CAA program has the already mentioned microfinance features which I expect to help me to overcome various assumptions related to the extent of knowledge possessed by a farmer about other members of his group.

Hypotheses:

1. Adoption of a new technology (i.e. fertilizer) by an individual farmer is affected (positively or negatively) by the extent of prior adoption by his „neighbors".
2. Adoption of a new technology (i.e. fertilizer) by an individual farmer is affected (positively or negatively) by social learning, i.e. by learning of his peers' or "neighbors' " performance

Methodology:

As introduced above.
1. I will use one main source of data: The CAA program multi-year panel dataset
2. I intend to base my theoretical framework predominantly on previous research conducted by Zeitlin,Conley et al., and by Foster and Rosenzweig

Outline:

1. Introduction
2. Theoretical framework
3. Empirical part
    3.1. Data description
    3.2. Model
    3.3. Discussion of the results
4. Conclusion

Core Bibliography:

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Author **Supervisor**

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Acronyms

CAA	Cocoa Abrabopa Association
CAGR	Compound Annual Growth Rate
CSAE	Center for the Study of African Economies (Oxford)
CRIG	Cocoa Research Institute of Ghana
HYV	High-Yielding Varieties
ICCO	The International Cocoa Organization
IFDC	International Fertilizer Development Center
JSS	Junior Secondary School
LBC	Licensed Buying Companies
OLS	Ordinary least squares
VM	Village Mean

1 INTRODUCTION

The economy of many developing countries is built around agriculture which is a crucial part of income of major part of their populations. However, various evidences from these countries show that agricultural technologies could be significantly improved and that the outcomes of many farmers are often far from their production potential. Therefore there are many programs and initiatives promoting adoption of new technologies, such as fertilizer or hybrid seed varieties, in these countries. Overall, various research presents evidence showing that adoption of such technologies has on average very positive results and allows many farmers to boost production of their farms closer to its actual potential. Nevertheless, at the same time, the adoption rates are not very high and there are many farmers who do not sustain utilization of such new technologies in the following production period despite its overall positive impact on production in their area. Therefore it is important to study the factors which influence and determine adoption of such new technologies.

Among the programs facilitating access to such new technologies, namely to fertilizer, is Cocoa Abrabopa Association (CAA) whose members are cocoa farmers in Ghana. The goal of this thesis is thus to examine learning about utilization of such technologies among the Ghanaian cocoa farmers. In particular, since the technologies are represented mainly by fertilizer and hybrid seed varieties here, the aim of this thesis is to study how do the farmers learn and choose the optimal amounts of these inputs. Specifically, whether the farmers are more influenced by individual or social learning.

To do this, the thesis is built on methodology developed by Munshi (2004) which is slightly adjusted in order to enable estimations using panel data methods. This approach is different from previous research of the cocoa farmers in Ghana and should allow for better understanding of factors influencing learning of the farmers. Furthermore, the methodology appears to be also suitable for inspecting learning about labor inputs which are closely connected to the non-labor inputs representing the technology in this thesis. Therefore the aim of this thesis is to describe the learning mechanism through several case studies, each representing learning about different input, and to compare how do the farmers learn about non-labor and labor inputs. Furthermore, the results are compared to those of Munshi's (2004), whose results from Indian wheat and rice farmers are used as a benchmark for the Ghanaian cocoa farmers inspected in this thesis.

The thesis is structured as follows: Chapter 2 describes Ghanaian cocoa sector, the CAA program and overview of research related to the CAA and adoption of new technology among Ghanaian cocoa farmers. Chapter 3 begins with a review of research related to social learning, followed by details of the methodology, main hypothesis and description of the sample used in the empirical analysis further in the thesis. Chapter 4 presents results of the empirical analysis, and the final chapter 5 covers summary of the results and conclusions.

2 BACKGROUND

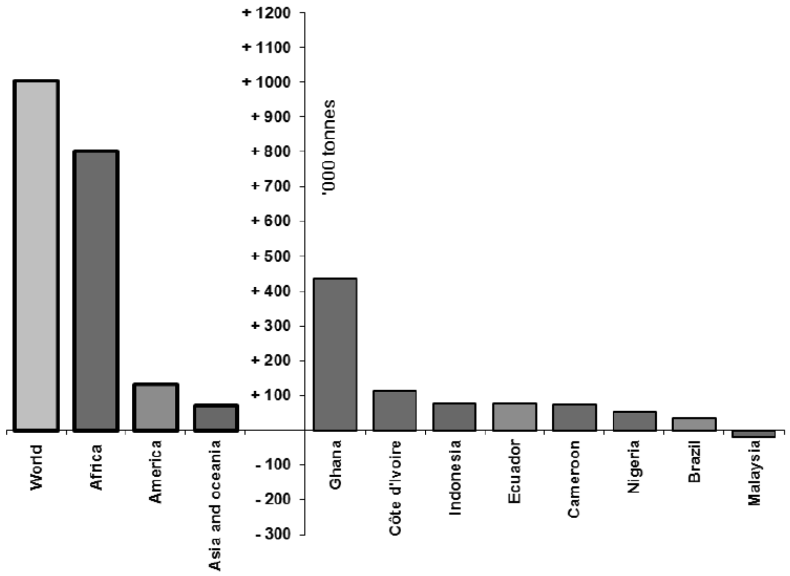
The following chapter begins with description of current state of and challenges to cocoa production in Ghana, followed by a brief description of the CAA program and summary of research, related to evaluation of CAA and adoption of a new technology, carried out on data collected with assistance of the CAA.

2.1 Cocoa production in Ghana

Ghana is one of the fastest growing cocoa producers in the world (see figure 1), growing by 6.1% p.a. between 1990 and 2007 (Gilbert, 2009). In 2010, Ghana exported 88% of its cocoa production and generated USD 2.2 billion which made cocoa its second[1] most important source of export earnings (ICCO, 2012). Ghana has a great comparative advantage in quality of cocoa and over 95% of sold Ghanaian cocoa production is of grade 1 (Gilbert, 2009). Kolavalli & Vigneri (2011) describes that the important characteristics, crucial for the quality of cocoa butter and cocoa liquor[2], are determined mainly by the size of beans, moisture and fat content and fat quality. Supreme level of these features ensures Ghanaian cocoa a great reputation which allows Ghana to earn a substantially higher premium (between 2.75% and 5%) over all other African cocoa producers (Gilbert, 2009).

[1] First was gold.
[2] Two ingredients that add texture, aroma, color and flavor to chocolate. (Kolavalli & Vigneri, 2011)

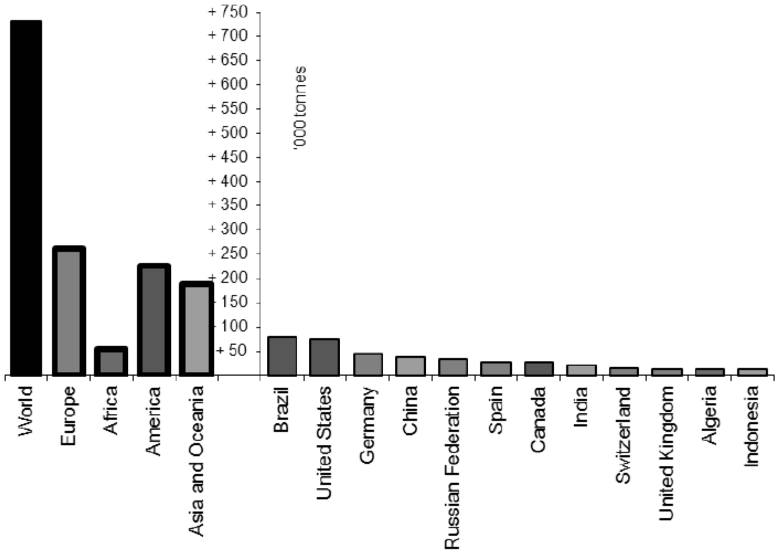
FIGURE 1: Changes in Production of Cocoa Beans – 2002/2003 to 2011/2012 (three-year average)



Source: ICCO (2012)

From the consumption perspective, figure 2 shows that the global consumption increased by almost 750,000 tones between 2002/2003 and 2010/2011. This increase can be attributed mainly to traditional European cocoa consumers, whose consumption grew by 262,000 tones (up by 17%), and then to consumers from the Americas, whose consumption increased by 227,000 tones (up by 22%), together accounting for ca. 65% of the global increase. (ICCO, 2012)

FIGURE 2: Changes in Apparent Consumption of Cocoa 2002/2003 and 2010/2011 (Bean equivalent)



Source: ICCO (2012)

Nevertheless, as Kolavalli & Vigneri (2011) pointed out, the cocoa industry in Ghana faces several challenges:

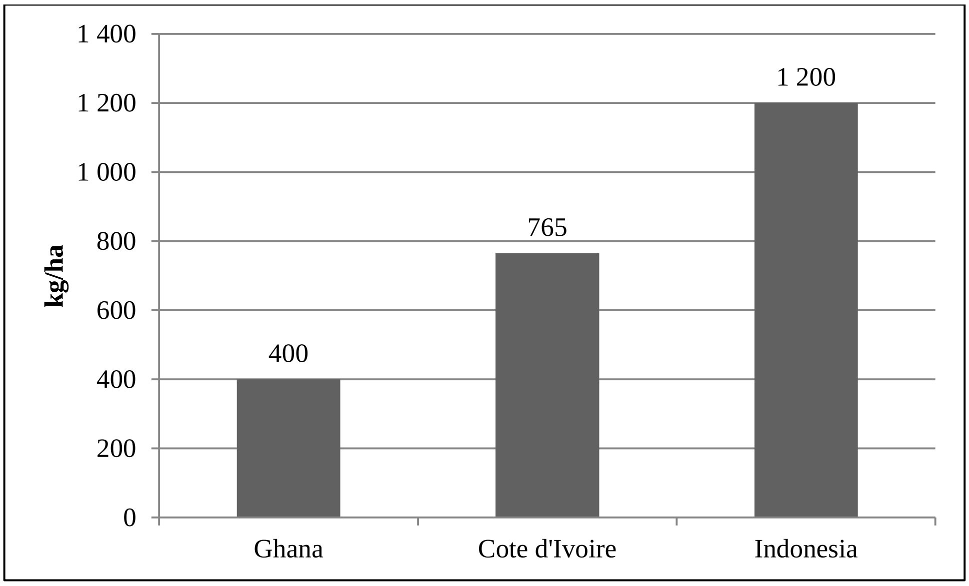
- Threat of disappearance of the supreme Ghanaian cocoa quality advantage over the years
- Lower productivity in comparison to other countries
- Competitiveness of cocoa needs to endure the cocoa households change
- The impact of current farming practices on the environment will soon constraint further production expansion

Preservation of the supreme quality advantage is crucial for Ghana. The two main threats to this comparative advantage are that the processors are nowadays technically capable to compensate for differences in quality through substitution of origins of cocoa and consumers, which leads to lower dependence on traditional

origin parameters, and that some of the processors may not be willing to pay the premium for the supreme quality over time. (Kolavalli & Vigneri , 2011)
Nevertheless, Ghanaian cocoa is currently very attractive for large consumers (e.g. Cadburys) due to the thorough quality control processes which ensure some minimal parameters crucial for the large consumers. (Kolavalli & Vigneri , 2011)

Second important challenge is increasing the current productivity. In comparison to other countries producing cocoa, Caria et al. (2009) estimated that the Ghanaian cocoa farms yields are significantly lower than in the neighboring Cote d’Ivoire and several times lower in comparison to Indonesia (see figure 3). The gap between the observed and achievable yields is estimated to be between 50 to 80 percent, depending on cultivation practices adopted by farmers. **(**Kolavalli & Vigneri, 2011) Fertilizer application seems to be one of the possible ways to improve the productivity, as at least the evidence from experimental farms show that yields of young trees can threefold when the fertilizer is applied. (Kolavalli and Vigneri, 2011) Therefore the key factor to increase the productivity could be presence of a program, such as the CAA one described in the following sub-chapter, facilitating the access to and promoting the higher utilization of fertilizer and other related inputs.

FIGURE 3: Comparison of cocoa farm yields (estimated from 2007 data)



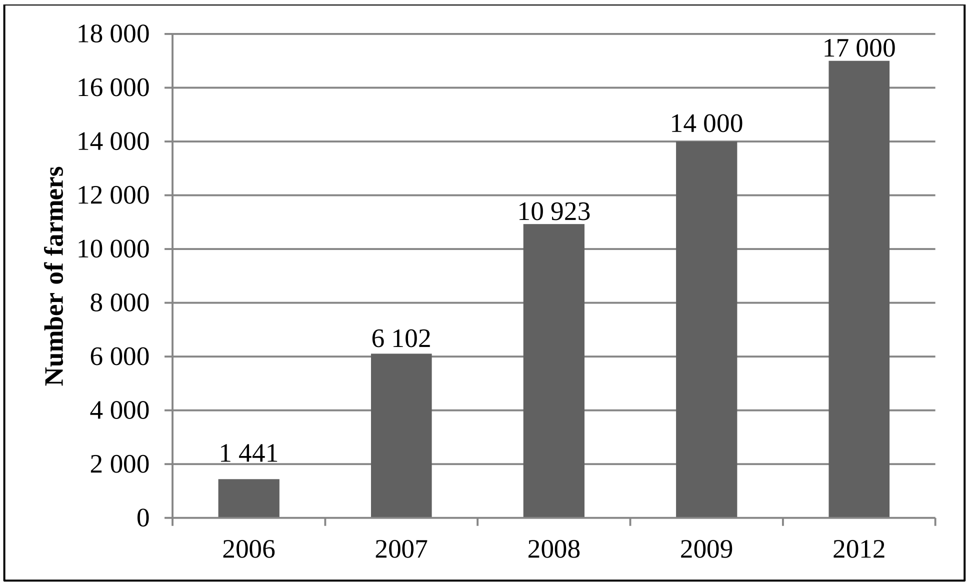
Source: Adapted from Zeitlin (2011)

2.2 Brief CAA program description

The data examined in this thesis were collected on cocoa farmers in Ghana who were offered a package of fertilizer, insecticide, and fungicide. The package was developed by the Cocoa Research Institute of Ghana (CRIG) and provided by Cocoa Abrabopa Association (CAA, a non-profit subsidiary of Wienco Ghana Limited. Besides that, the farmers are trained by the International Fertilizer Development Center (IFDC) in integrated Soil Fertility Management. The main goal of the CAA project is to improve access to agro-inputs and improve the cocoa quality and environment in Ghana. (IFDC 2012)

The first "version" of the package was provided already in 2002, but the CAA program has started in the 2006/07 season with 1,440 farmers and quickly expanded to about 17,000 in 2012. (Caria et al., 2009) The CAA has a maximum target of 50,000 members at maximum credit assistance of 5 acres per farmer. (CAA, 2009)

FIGURE 4: CAA expansion



Source: Adapted from Caria et al. (2009) and IFDC 2012

Based on CAA (2009):

The minimum requirements for the CAA membership are:

- Be a healthy and strong cocoa farmer between 18 and 65 years of age,
- Have a mature cocoa farms of a minimum of 5 acres which is not located near hillsides and water bodies,
- Have a farm plan showing the size and location of farm,
- Be in the possession of a valid Ghanaian voters ID,

The group registration requirements are:

- Form a group of 8-12 good members including yourself,
- Open a group bank account at a bank nearby,
- Collect group dues to operate group bank account.

The package[3] is offered on a seasonal credit basis to a group of farmers of between 8 and 12 members. The usual schedule is following: in March, the groups enter into a contract, receive the package of inputs which are typically applied in April and May. The harvest starts in October and continues to the following year. However, the CAA loans are to be repaid by December 15, as it is estimated that the farmers have harvested approximately three quarters of their annual production by this time. (Caria et al., 2009)

The groups' formation process has two stages. First, a village is selected and the program is advertised through local leaders, cocoa sales outlets, and general meetings. Second, farmers who are able to demonstrate production rights to over 5 acres of land[4] form groups and receive the CAA package. (Caria et al., 2009)

Besides providing credit to the groups instead of individuals, the CAA program has at least two other microfinance features – joint liability and dynamic incentives.

The impact of these features is that the groups that failed to repay the CAA loan would be suspended for at least one year, while the groups that managed to

[3] The original CAA package contains inputs for two acres of cocoa

[4] i.e. the qualified farmers

successfully repay the loan are eligible to obtain four acres' worth of inputs in the following year[5]. (Zeitlin et. Al., 2010) The result and impact of the CAA program are described in the following sub-chapter.

2.3 Evaluation of the CAA program and learning about a new technology

It is important to mention former research using panel data from the CAA because it provides a better picture about farmers inspected in this thesis. There are four publicly available papers written using this dataset until today. In particular, the majority of the research, relevant for this thesis, has been so far focused on two main problems, evaluation of the CAA program and the factors influencing farmers' decisions about adoption of a new technology, i.e. learning about a new technology.

Evaluation of the CAA program

Caria et al. (2009) used an experimental design to evaluate the impact of the CAA program, particularly by measuring the returns to participation in the program. Via comparing outcomes from those that received the inputs with those who have formed groups and have joined the CAA but have not yet received the inputs at the time of their survey, Caria et al. (2009) found that the farmers involved in the CAA program have managed to almost threefold the return on the loan. The positive impact of the CAA program has been also confirmed by findings of Zeitlin (2012) which show that adopter of the CAA program has been on average positively impacted by the program; and by Zeitlin et al. (2010) who found that the farmers whose village was reached by the CAA program and who adopted the offered treatment at the first year they were reached had on average significantly higher returns than other farmers.

[5] In the first year, the farmers are offered two acres' worth of inputs.

Caria et al. (2009) further looked into whether the gains might have been influenced by the possibility that the CAA loans altered the use of other inputs on the farm. Particularly, they found that the program farmers reduced their fertilizer consumption by ca. 1 bag, but increased the number of daily wage laborers, and the number of *nnoboa*[6] laborers, employed on the farms. However, these changes in input demand are not sufficient to alter the cost benefit implication of the program.

Nevertheless, even though these results appear to be very positive for the CAA program, Zeitlin et al. (2010) showed that the high average returns in fact hide persistent heterogeneity[7] in realized returns. And more importantly Caria et al. (2009) found that there is a 10% non-repayment rate and over 30% drop-out rate among farmers who were CAA members on the 2007/08 season. Therefore, the key question for the CAA management is what the main causes of these negative figures are. Specifically, are these problems with retention, drop-out rate and non-repayments caused rather by low returns of some farmers or by repayment problems?

Caria et al. (2009) looked into the low returns explanation, i.e. whether the drop-outs could have been caused by heterogeneity in realized returns. They found that farmers experiencing low returns are actually both economically and statistically substantially less likely to remain within the program. In particular, they found that, out of the farmers they observed, only three farmers who experienced a negative change in cocoa output after joining the CAA program remained in the program. On the other hand, based on their findings, every farmer who experienced a rise in log cocoa output of more than 0.5 stayed in the program.

Based on Zeitlin et. al. (2010), the problems with repaying the CAA loans, which are caused by changes in output, are estimated to result in 70 percent decline in the probability of renewed membership. Furthermore, from the group point of view, if one or more fellow members of the same group fails to repay, his other group members are by approximately 45 percent less likely to sustain their membership

[6] Caria et al. (2009) describes Nnoboa as a labor-sharing arrangement common in this part of Ghana.

[77] Zeitlin et. al. (2010) define the persistent heterogeneity as a situation when returns vary among farmers and are not known with certainty. This might lead to a situation when farmers update their beliefs about their idiosyncratic returns to adoption on the basis of these realizations.

into the following season. (Zeitlin et. al., 2010) Last but not least, individuals appear to have higher probability of joining a group with more individuals of different ethnicity. (Zeitlin, 2011)

Factors influencing farmers' decisions about adoption of a new technology

Important part of the previous research on the CAA farmers is devoted to factors influencing adoption of a new technology. To be more specific, by new technology is meant mainly adoption of fertilizer which is part of the CAA package.

Zeitlin (2011) inspected how can characteristics of individual farmer's peers, such as differences in farm size between the farm size of an individual and the mean farm size of his peer group, directly influence individual's propensity to adopt a new technology. He found that group peers' decision about adoption of a fertilizer is quite influential. To be more specific, when a farmer, who was one season in a group where no peer decided to adopt fertilizer, moves to a group where all peers decide to adopt a fertilizer in the following season, his probability to adopt fertilizer increases by 27 percent. Among other factors positively influencing the decision to adopt fertilizer are the group size, the size of farmer's plot and an exogenous increase in the fraction of farmer's peers using fertilizer.[8] Furthermore, when group size imposes a congestion cost then the relatively uninformed farmers (other things equal, which are less likely to adopt in any given period) are most likely to be observed affiliated with "experts", who have high priors and are likely to adopt, other things equal. Last but not least, no significant evidence of sex or education impact on the adoption probabilities was found. (Zeitlin, 2011)

Besides these above mentioned factors, Zeitlin (2012) focused on two possible mechanisms influencing the farmer's decision to adopt a new technology. The first one is precautionary savings. Zeitlin (2012) describes it as prudence, i.e. building a

[8] Zeitlin (2011) found specifically that an exogenous 10 percent increase in the fraction of farmers's peers using fertilizer means a 21 percent increase in the probability that a farmer will adopt fertilizer himself.

buffer stock in anticipation of the adoption of risky technologies. However, farmers could be discouraged to create this buffer stock when there are low realized returns to adoption because it affects the farmers’ ability to insure themselves against adverse events in the future.

The second mechanism is learning, i.e. updating of each farmer’s beliefs about the distribution of outcomes that he faces based on these realizations. (Zeitlin, 2012)

Both learning and precautionary savings connect outcomes from experimentation with the new technology and the decision to keep using this technology in the following seasons. However, in most cases, each of these mechanisms has opposite implications for the association between adoption of new technologies and yields realized under traditional technologies used in the previous seasons. (Zeitlin, 2012) In particular, the learning mechanism, on the contrary to the precautionary savings mechanism, drives the observed relationship between realized returns and subsequent adoption decisions.

Last but not least, the above mentioned persistent heterogeneity in realized returns is another very important factor influencing adoption of new technology because Zeitlin (2012) found that a farmer who has any signals of low returns is less likely to sustain using the technology. To be more specific, his findings show that, in terms of distribution of returns, the bottom quarter of the distribution appears to have a zero economic return from using the new technology.

All of these findings above have very important implication for programs such as the CAA because they imply that when persistent heterogeneity is quantitatively important, policymakers will need to be cautious in promoting widespread adoption of such technologies. (Zeitlin, 2012)

3 THEORETICAL FRAMEWORK

There is a substantial amount of literature dealing with the social learning. Apart from the above mentioned research using the panel data, it is important to also briefly map other research in this area in order to formulate the theoretical framework in this thesis. Therefore, this part begins with a brief overview of such former research.

3.1 Previous research of social learning

It is good to start with definition of social learning. Among others, Bandiera & Rasul (2006) noticed that the diffusion of new agricultural technologies has been studied since the first research done by Griliches (1957). However, most of the earlier literature solely recognized the importance of social learning in agriculture, without attempting to identify the effects of learning separately from other determinants of adoption (Bandiera & Rasul, 2006).

Nevertheless, there is probably not any widely accepted general definition of social learning and most authors use the term rather as an "umbrella" for their own specific definition. For instance Bandiera & Rasul (2006) define it as "*estimation of farmer propensity to adopt sunflower as a function of the number of adopters among their family and friends"*.

However, even though it is hard to find a generally acceptable definition, Conley & Udry (2001) got very close to it by demonstrating social learning on a very simple example:

Imagine a village, which consists of farmers who are collectively experimenting. Each farmer in the village observes the activities (related to farming) of each of his neighbors. Therefore, when any farmer decides to adopt a new technology, his village neighbors observe impact of the adoption and update their opinions regarding this technology. These neighbors then use the new information to make decisions regarding cultivation for the next season, and the learning process continues. (Conley & Udry, 2001)

However, for the purposes of this thesis, I build on a simple definition formulated by Munshi (2004), which defines Social learning as a description of a "*process by which an individual learns from his neighbors' experiences (their previous decisions and outcomes) about a new technology."*

It is obvious that the transmission of information about the new technologies is crucial for the process of learning. However it is very hard to measure the actual amount of knowledge the farmers possess about each other. For example Conley and Udry (2001) discovered that farmers in their survey often do not know about the actual output, i.e. harvest, of the other farmers in their village and more importantly, regarding the new technology adoption, they were usually lacking sufficient information about the inputs that were used by the other farmers.
This problem was noticed by other authors too. Foster & Rosenzweig (2010) concluded that apart from them, Conley & Udry (2001) and Bandiera & Rasul (2006) all had to make an assumption that information about a new technology is largely non-specific, at least within the village

Apart from these authors, Zeitlin (2011) examined a "shop talk" form of the social influence among the CAA farmers. To be more specific, by "shop talk" are meant social interactions between farmers and cocoa sales' outlets called Licensed Buying Companies (LBCs). Based on this examination, he observed that it is a question whether farmers are learning about returns associated with adoption of new technologies or rather about optimal inputs. Therefore, the aim of this thesis is to closer inspect the learning about optimal inputs.

3.2 Methodology

In this thesis, the goal is to inspect how the Ghanaian cocoa farmers learn about the optimal amount of labor and non-labor inputs for their cocoa farm. In particular, in case of the labor inputs, I examine Household labor days, Paid labor days and Nnoboa[9] labor days, and in case of the non-labor inputs I focus on fertilizer and the share of hybrid trees.

In general, I will assume that the cocoa farmers can learn either from their own experience, or from their neighbors in the village, or by some combination of these two.

In order to examine the way of learning among the Ghanaian cocoa farmers, I build on methodology introduced by Munshi (2004).

Munshi has developed this approach for the purposes of his research of social learning in India, particularly for data from Indian wheat and rice farms, where he was inspecting how these two groups of farmers learn about high-yielding varieties (HYVs) of wheat and rice[10]. Using this methodology, he has shown that the social learning is weaker in a heterogeneous population. Specifically, when there is a sensitivity of performance of a new technology to unobserved (or imperfectly observed) individual characteristics, which causes that farmers are not able to account for differences between their own and their neighbors' characteristics when they are learning from their neighbors' experiences. (Munshi 2004)

Munshi (2004) has observed that the rice farmers in India are representing such heterogeneous population, unlike the Indian wheat farmers. The results of his social learning research are consistent with this observation and show that the social learning was significantly more present among the wheat farmers. I presume that the Ghanaian cocoa farmers are rather similar to the Indian rice firmest, therefore I will use Munshi's research as a benchmark for the models in this thesis.

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[9] Caria et al. (2009) describes Nnoboa as a labor-sharing arrangement common in this part of Ghana.

[10] Specifically, how these farmers learn about the optimal acreage of their fields that they devote to the HYVs

3.2.1 Learning about optimal amount of inputs

It was already mentioned that the farmers can learn about the optimal amounts of inputs either from their own past experience, or from the past actions of their neighbors in the village.

However, the optimal amount of an input is such amount that maximizes the expected yield, i.e. the expected amount of sold cocoa. Therefore, it is reasonable to assume that the farmers also account for the expected yield when they decide about optimal amounts of the inputs.

Nevertheless, it is important to distinguish between the situation when this expected yield is known with certainty and when it is not. Munshi (2004) therefore distinguishes between two possible worlds - with perfect and with imperfect information. The assumption of perfect information is, of course, far from reality but this differentiation helped Munshi to develop this model and led to three important conclusions:

1. **Optimal input choice with perfect information:**

   With perfect information about the new technology, the [farmer] *arrives at his optimal amount of input immediately and there is no role for social learning.* (Munshi, 2004)

2. **Optimal input choice with imperfect information:**

   i. **Constant expected yield across farmers**

   When expected yields are constant in the village, the grower's … decision [about optimal amount of input] *is determined by his lagged decision and the mean of his neighbors' previous decisions and yield realizations.* (Munshi, 2004)

ii. Expected yield dependent on farmers' characteristics

> *The grower will choose individual learning if the population is heterogeneous and the yield is sufficiently sensitive to unobserved characteristics; otherwise, he will prefer to learn from his neighbors.* (Munshi, 2004)

It was already mentioned that Zeitlin et. al. (2010) found that high average returns of the CAA program in fact hide persistent heterogeneity in realized returns. Therefore, based on the above mentioned three conclusions from Munshi (2004), I hypothesize that the Ghanaian cocoa farmers, similarly to the Indian rice farmers, will prefer individual learning over the social one.

3.3 Empirical specification

The technology is represented by fertilizer and share of hybrid trees, i.e. the non-labor inputs, in this thesis. However, cocoa production is very labor intensive, and thus changes in adoption of these non-labor inputs are associated with changes in labor inputs. Therefore, since the following model is in general constructed to estimate the impact of learning type on the optimal amount of input, it should be also suitable to estimate this impact on the labor inputs, i.e. the Household labor days, Paid labor days and Nnoboa labor days. Among these inputs, the share of hybrid trees is the one most similar to the HYV used by Munshi (2004), thus I anticipate that results of the model inspecting this input will be best comparable to the Munshi's results.

I expect that time-invariant variables such as age, gender, farm size and other similar variables will be important explanatory variables. Therefore, in order to inspect their impact, it is necessary that their effect on the dependent variable is not absorbed by the intercept (Torres-Reyna, 2013). Thus, given the panel nature of the data, the most suitable method is the random-effects model. However, it must be noted that in all of the following models, the Hausman test[11] rejects the random-effects model in favor of the fixed-effects model. Nevertheless, based on Baum (2006), this test rejects the random-effects model quite often[12], and thus the model should be chosen mainly based on appropriateness given the inspected data. Therefore, since the random-effects model appears to be more appropriate for the purposes of this thesis, it will be used in all of the following models. In addition to the random-effects, each model is also estimated using the OLS method, as this estimation method was used by Munshi (2004), and thus involving these estimates should allow for better comparability with Munshi's results. In order to compare the accuracy of random-effects and OLS estimates, the Breusch-Pagan Lagrange Multiplier test is used in each model[13] (Torres-Reyna, 2013). I will use the model based on Munshi (2004) to test the following hypothesis:

"*There will be individual learning effect present and either very weak or none social learning effect among the Ghanaian cocoa farmers.*"

In other words, that the Ghanaian cocoa farmers will be similar to the Indian rice farmers and will prefer the individual learning over the social one.

[11] This test is commonly used in order to decide between fixed and random effects model, i.e. rejection of the null hypothesis of this test normally suggests that the fixed-effects should be used for the analysis (see e.g. Baum (2006) for reference)
[12] And also is not very reliable when used in small samples, though this should not be a problem in this thesis.
[13] The null hypothesis in this test is that variance across entities is zero. Therefore, non-rejection of the null hypothesis means that there is no significant difference across units (i.e. no panel effect) and thus that the OLS estimates are better. (see Torres-Reyna (2013 for reference)

The model developed by Munshi (2004), slightly adjusted for the purposes of this thesis, is specified as follows:

$$A_{jt} = \beta_0 + \beta_1 A_{jt-1} + \beta_2 \bar{A}_{t-1} + \beta_3 \bar{y}_{t-1} + \sum_{n=4}^{N} \beta_n Z_i + \varepsilon_i \qquad (1)$$

, where:

β_i ………are the estimated regression coefficients

A_{jt} ……...is the optimal amount of input[14] used by a farmer *j* in year *t*

A_{jt-1} ……is the amount of input used by a farmer *j* in year *t-1*

$\bar{A}_{t-1}$ …….is the mean amount of input used by a farmer *j*'s village in year *t-1*

$\bar{y}_{t-1}$ …….is the mean yield, in terms of cocoa sold, in farmer *j*'s village in year *t-1*

Z_i ……….are control variables related to each farmer's individual characteristics and to each farmer's plot characteristics

, and where, in case of random effects estimation, $\varepsilon_i = \mu_j + \omega_{vt}$, where $\mu_j \sim IID(0, \sigma_\mu^2)$ represents individual characteristics of farmer *j*, and $\omega_{vt} \sim IID(0, \sigma_\omega^2)$ is village-specific effect of village *v* in year *t*.

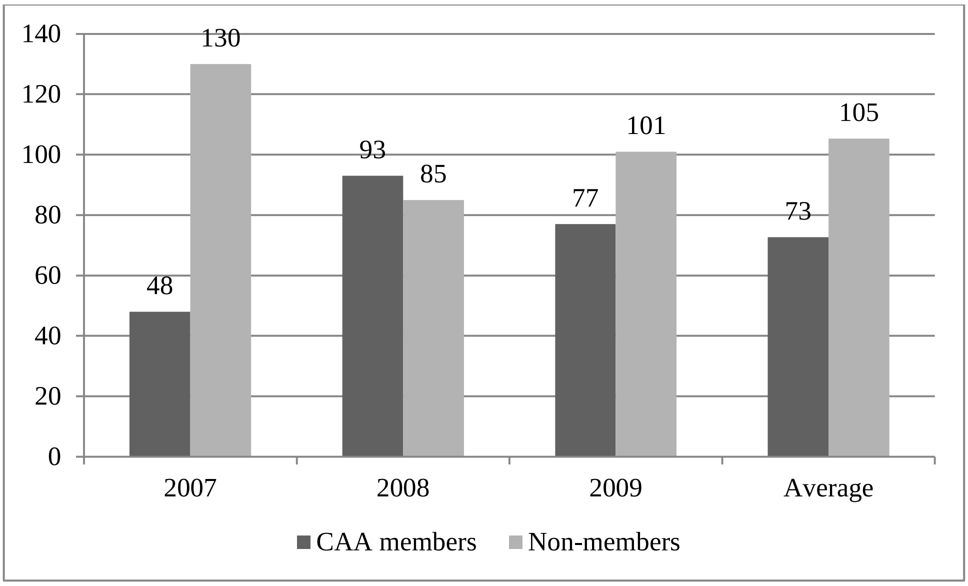
Munshi (2004) has shown that if the social learning is present, β_2 and β_3 , representing the village and the yield effect respectively, should be significantly high. If not, β_1 , representing the individual effect, should be significantly high. He has demonstrated these results on the difference in the estimation between the wheat and the rice growers. He has particularly found that there was a strong yield effect for wheat growers ($\beta_3 > 0$), while these effects were absent among the rice growers ($\beta_3 = 0$).

3.4 Sample

The available dataset consists of data from 534 farmers spanning over three seasons: 2007/2008, 2008/2009 and 2009/2010, i.e. 178 farmers in each season.

Figure 5 shows that the number of farmers who became the CAA members, has significantly increased between the 2007/2008 and 2009/20010 seasons. Nevertheless, on average, the sample consists of more non-members.

FIGURE 5: CAA membership



Source: author's computations.

Nevertheless, table 1 shows that only 20 percent of farmers who were members of the CAA in 2007/2008 season sustained their membership in 2008/2009 season. However, the retention has improved in the following season when 43 percent of farmers who were members of the CAA in 2008/2010 season remained members in 2009/2010 season. Furthermore, there was 33 percent increase of CAA member in 2008/2009 season in comparison to negligible less than percent increase in 2009/2010 season. Therefore, it is possible to conclude that the number of members has substantially grown between the 2007/2008 and 2009/2010 season, however, the sample shows that the retention of the membership can be very dynamic.

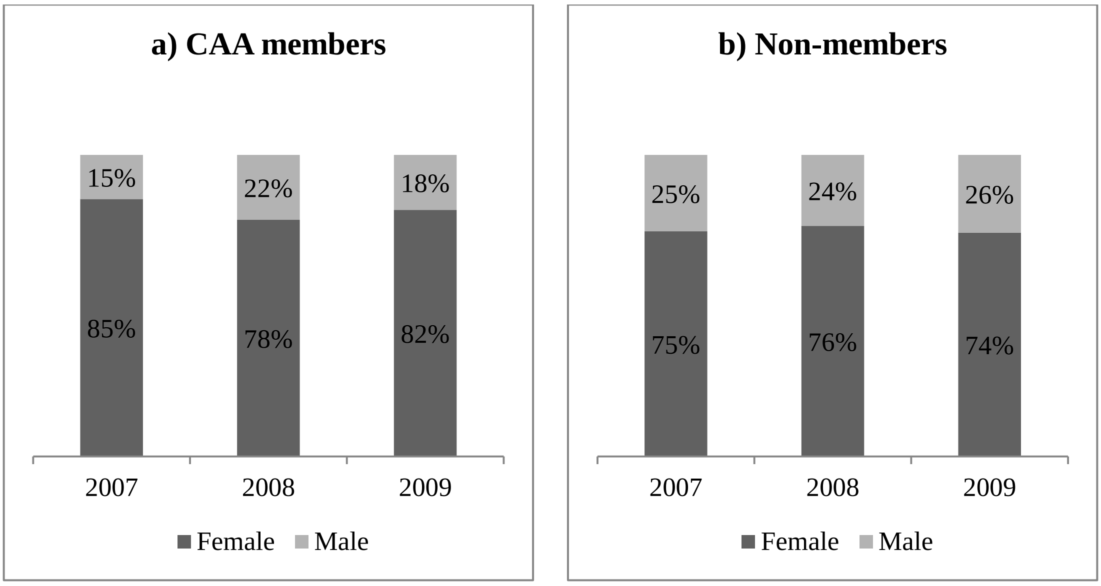
TABLE 1: Transitions in CAA membership across seasons

		2008/2009	
		Y	*N*
2007/2008	*Y*	35 (0.20)	13 (0.07)
	N	58 (0.33)	72 (0.40)
	*(N=178)		
	2009/2010		
		Y	*N*
2008/2009	*Y*	76 (0.43)	17 (0.10)
	N	1 (0.01)	84 (0.47)
	*(N=178)		

Notes: Matrices give numbers of individuals transiting from adoption state (Y;N) on left to adoption state (Y;N) in subsequent year. Parentheses contain the fraction of peers in the particular adoption state on the observed sample.
Source: author's computations.

The gender distribution across farmers in the sample is very uneven. Figure 6 displays that female farmers form almost 80% of the sample. Furthermore, the female farmers seem to be more often CAA members than the male farmer.

FIGURE 6: Gender distribution

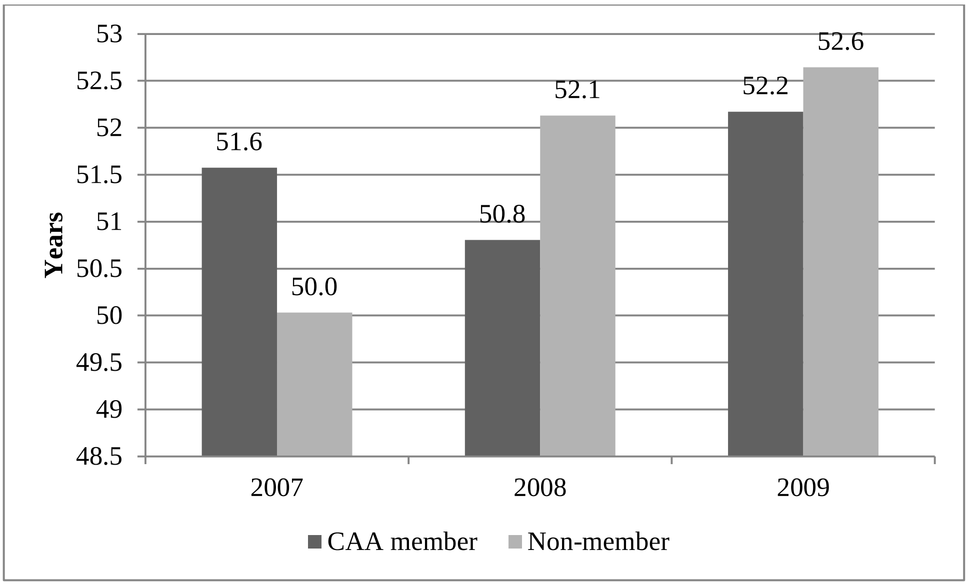


Source: author's computations.

On the other hand, the CAA membership most probably is not dependent on the age of the farmers[15], as there is not any significant difference between the mean age of the CAA members and the non-members (see figure 7).

[15] The CAA registration requirments are:" Be a healthy and strong cocoa farmer between 18 and 65 years of age" (CAA newsletter, 2011)

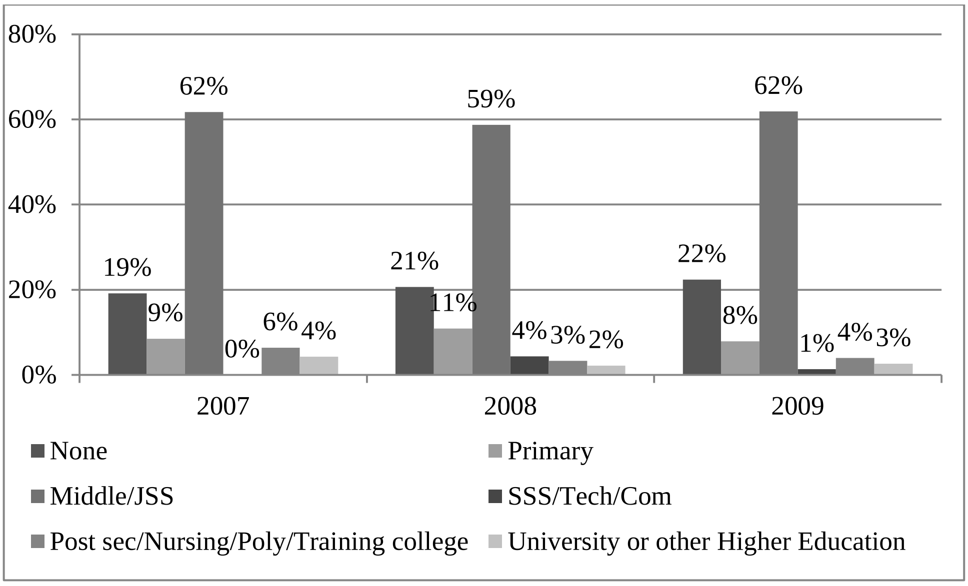
FIGURE 7: Mean age of farmers



Source: author's computations.

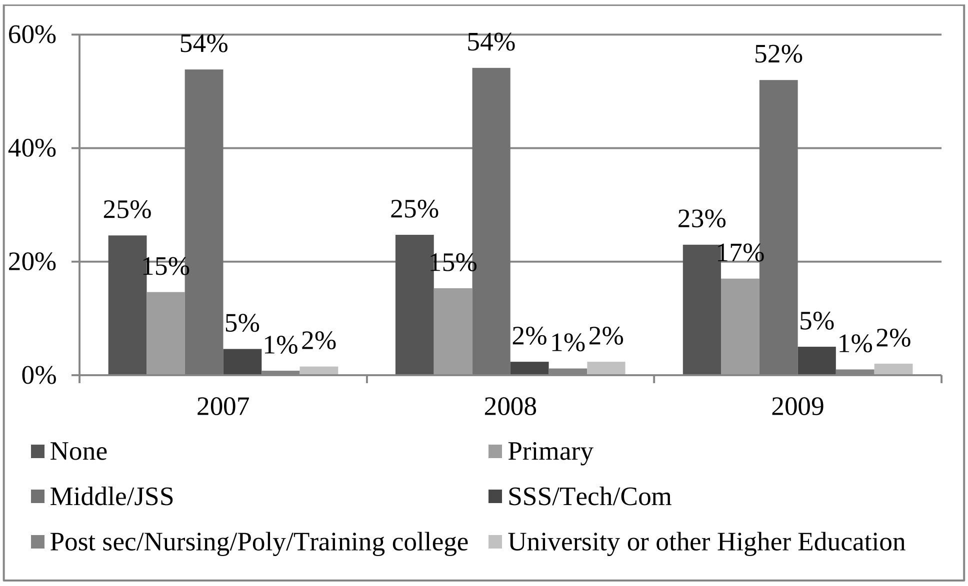
Education of the farmers should be an important factor when learning about the optimal amount of used inputs. Figures 8 and 9 show that majority of the farmers have middle school or JSS. However, closer look at the distribution of the education reveals that the CAA members tend to be more educated than the non-members, as there is substantially less farmers with none or primary education, and significantly larger share of farmers with post-secondary and tertiary education among the CAA members. In other words, the more educated the farmer is, the more likely she is to join the CAA program.

FIGURE 8: Education of CAA members



Source: author's computations.

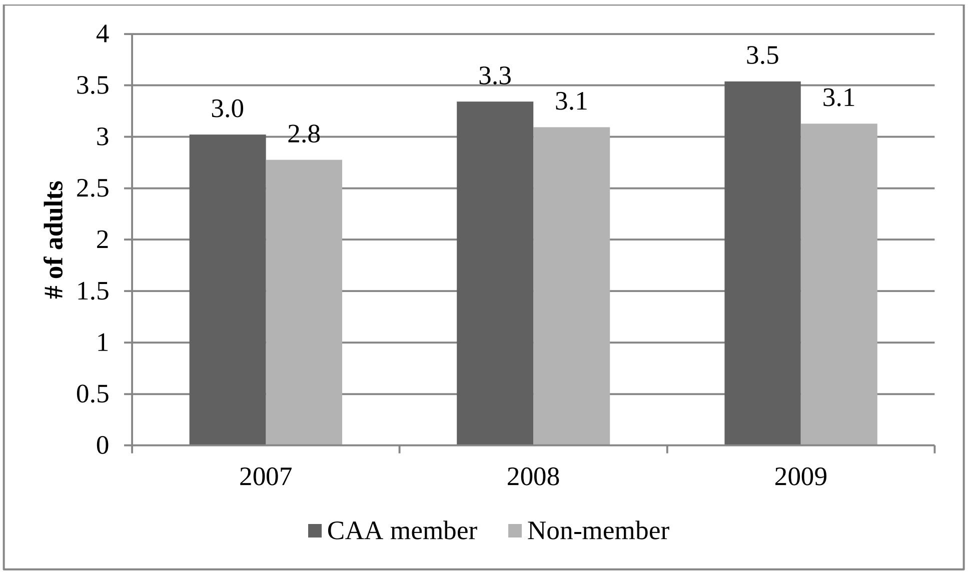
FIGURE 9: Education of non-members



Source: author's computations.

The household size of the farmers in the sample is on average 3 adults and Figure 10 displays that the household size probably does not have any substantial influence on the farmer's decision about the CAA membership.

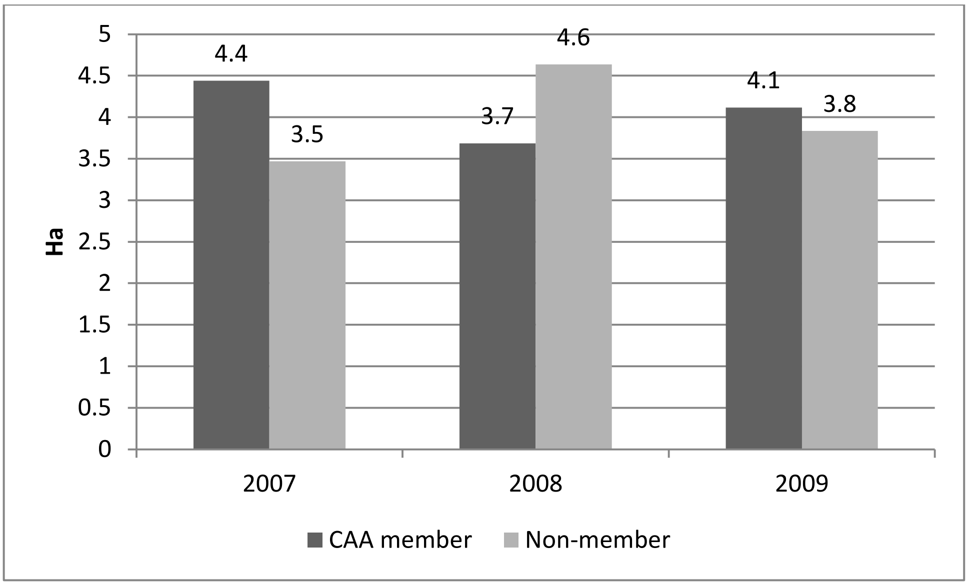
FIGURE 10: Household size



Source: author's computations.

The farm size is another factor which might be crucial for the decision of adopting a new technology and choosing the optimal amounts of both labor and non-labor inputs. Figure 11 shows that the average farmer in the sample was cultivating approximately 4 ha and that there is not any significant, clearly visible, difference between the CAA members and the non-members. When we take a look at the farm sizes in a greater detail, it is apparent that the farm size is quite heterogeneous, as the largest farm had ca. 16ha, the smallest farm ca. 0.4 ha and the median farms was ca. 3.2 ha.

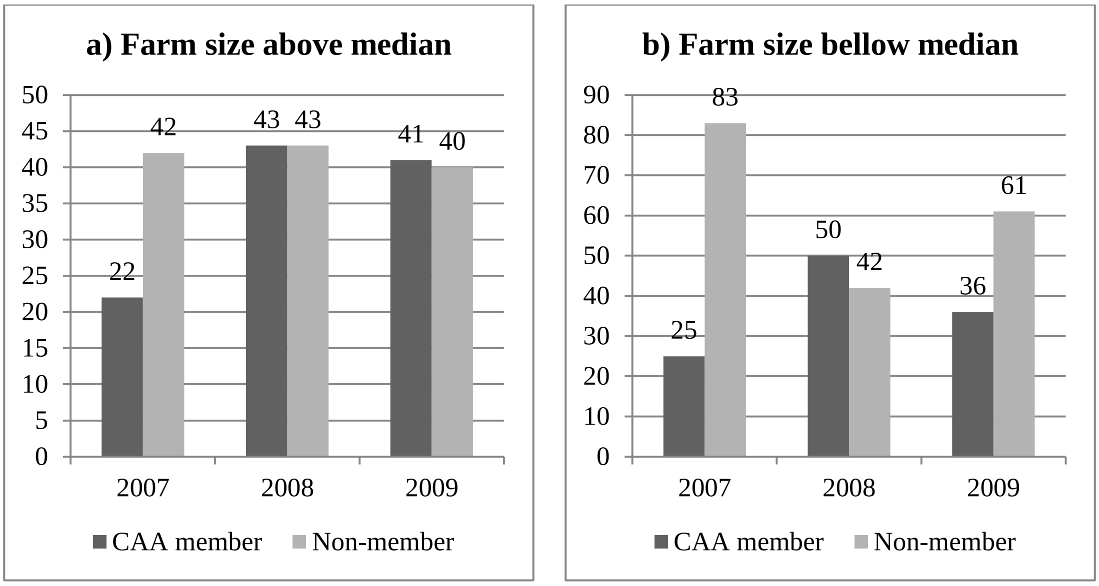
FIGURE 11: Farm size (in ha)



Source: author's computations.

It is interesting to inspect whether there is any connection between this heterogeneity in the farm size and the CAA membership. Figure 12 a, b demonstrates that majority (on average ca. 60%) of the non-members of the CAA program in the sample tend to have smaller farms, i.e. their farm size is bellow ca. 3.2ha (median).

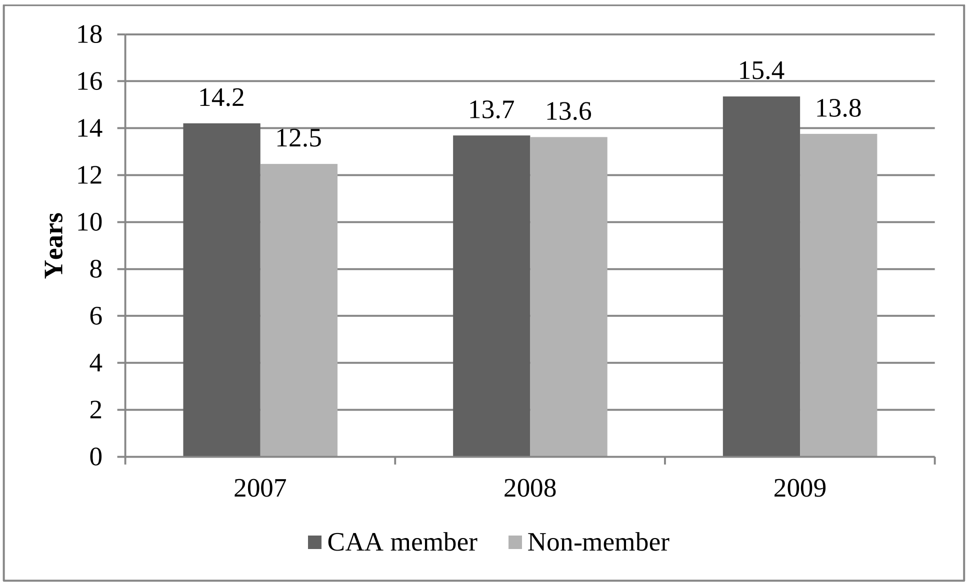
FIGURE 12: CAA membership by farm size (# of farmers)



Source: author's computations.

Similarly to the farm size, the age of the cocoa trees might be another important factor when farmers decide about adopting a new technology and choose the optimal amounts of both labor and non-labor inputs. Figure 13 displays that the CAA members in the sample had on average slightly older trees. The mean in the whole sample age was 13.7 years.

FIGURE 13: Mean cocoa tree age

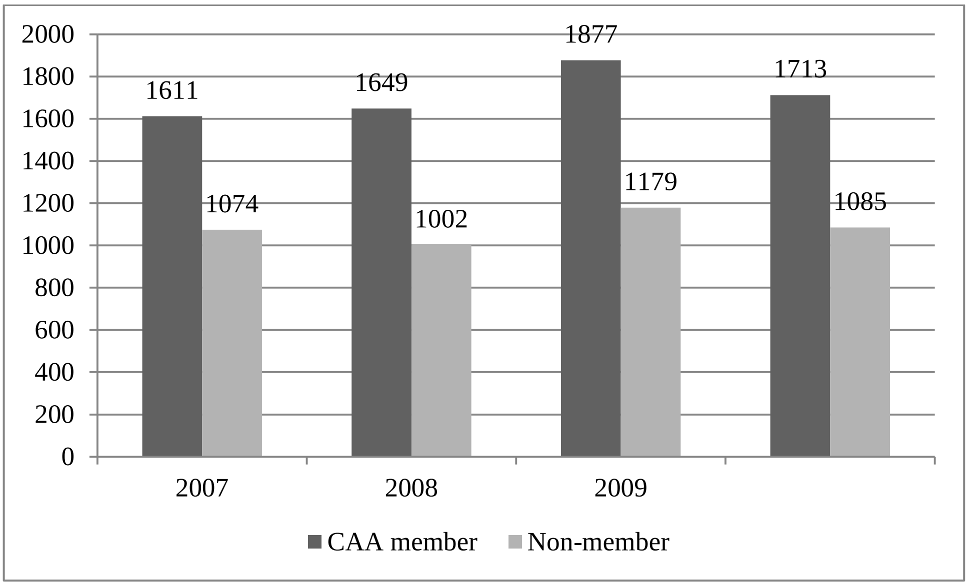


Source: author's computations.

Finally, it is very important to closer examine the cocoa yields of the farmers in the sample. Figure 14 shows that the CAA members in the sample have substantially larger cocoa yields per acre. In particular, the CAA members yielded on average by over 600 kg per acre more than the non-members between the 2006/2007 and 2009/2010 seasons. Furthermore, the cocoa yields are very heterogeneous as the maximum yield per acre was 13,750kg, the smallest was 5kg and the median 937.5kg. This finding supports the hypothesis that the Ghanaian cocoa farmers are similar to the Indian rice farmers and thus, based on the theoretical framework above, will prefer the individual learning over the social one.

Furthermore, there is a 0.4 correlation between the farm size and the cocoa yields, which suggests that the CAA members achieve to sell more cocoa, as they are more often owners of the farms with size above the median.

FIGURE 14: Mean cocoa yield per acre



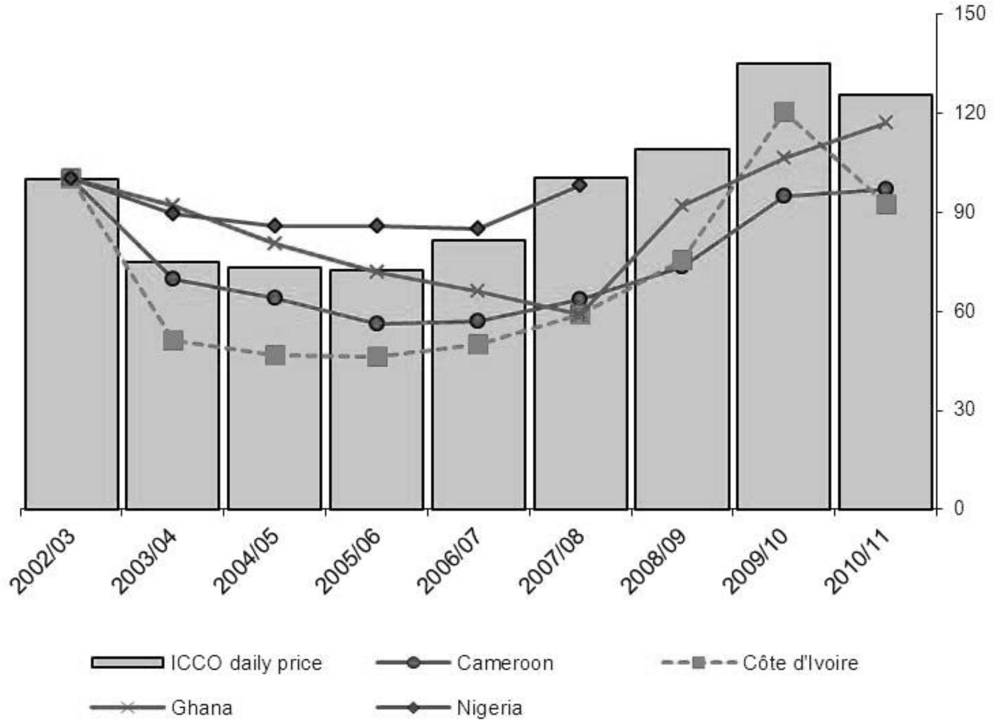
Source: author's computations.

4 EMPIRICAL ANALYSIS

Before we proceed with the estimation of the models, it is important to begin with a discussion about why should the optimal amounts of inputs differ every year, and thus why should the farmers learn about which amount is optimal. The demand for inputs of the non-members of the CAA program is realized on the market, and thus it is reasonable to believe that it is influenced by multiple factors such as the change in the market price of each input (as shown on figure 15) and the size of the farm output (mainly in case of the labor inputs). The budget and credit constraints of the farmers are without a doubt influenced by the amount of cocoa yield[16] in a given year and therefore it is meaningful to consider these constraints variable throughout the years. Therefore, assuming that both the input prices and the farm outputs are not constant, these constraints play definitely an important role when choosing the optimal amount of inputs, and thus push the farmers to reconsider the optimal amounts of inputs every year based on their historical performance and their current situation. Furthermore, the non-labor inputs and the labor inputs are, to some extent, complements to each other and some of the labor inputs could be substitutes to each other. Therefore, it is meaningful to believe that, in general, the change in the optimal amount of one input will influence the optimal amounts of the other inputs and thus creates another incentive for the farmers to reconsider the optimal amounts on a regular basis.

[16] Because the revenues from sales of the cocoa represent large share of households' income , i.e. cocoa is the major source of income for farmers (Vigneri, 2008)

FIGURE 15: ICCO DAILY PRICES AND FARM GATE PRICES IN CONSTANT TERMS, 2002/2003 = 100
CAMEROON, CÔTE D'IVOIRE, GHANA, and NIGERIA



Source: ICCO 2012

However, the situation is slightly more complicated in case of the CAA members as they cannot influence the amount of some non-labor inputs that they receive as part of the package of inputs from the CAA[17]. It was already mentioned that this package is provided to cover approximately 2 ha in the first year and, in case of successful repayment in the first year, 4 ha in the following years. Nevertheless, the median farm size is ca. 3.2 ha and 38% of the observed farms were larger than 4 ha between 2006 and 2010. Therefore, it is reasonable to believe that at least some of the CAA members will be interested in buying additional non-labor inputs to cover more than 2 or 4 ha. Furthermore, the CAA program should offer the inputs for more attractive

[17] In this thesis this holds for the fertilizer

prices than the other market providers, and thus it can be assumed that it improves the budget and credit constraints of the farmers, and thus allows for greater demand for both labor and non-labor inputs. Therefore, apart from those CAA members specific factors, the optimal amounts of inputs should be influenced by the same factors as in case of the non-members.

The rest of this chapter is dedicated to the estimation of the model for each input and the discussion of results and impacts of each model. The model is first estimated for the non-labor inputs, i.e. fertilizer and the share of hybrid trees, and then for the labor inputs, i.e. Household labor days, Paid labor days and Nnoboa labor days.
Each model is first estimated in a “pure” version, i.e. without the control variables, followed by “full” version estimation, i.e. with all variables. Some of the control variables[18] are included in a lagged form, (t-1), as the farmers could observe only their state or amounts from previous season when they were learning about the optimal amount of the further examined inputs for the upcoming season.

4.1 Non - labor inputs

The increased use of fertilizer, the adoption of hybrid cocoa varieties, and greater control of pests and diseased trees are the three most noticeable changes that have taken place in the technology of production in Ghana from 1990 onwards. (Kolavalli & Vigneri, 2011) Therefore the two non-labor inputs inspected in this thesis are fertilizer and hybrid trees, as these two are available in the used dataset. It is important to point out that fertilizer, unlike the hybrid trees, is provided as part of the CAA package which might be an important factor for, at least partly, revealing the influence of the CAA program on learning. Furthermore, each of these inputs is probably used in a different frequency, i.e. the fertilizer is used on a regular basis and

[18] those that are assumed to change every season

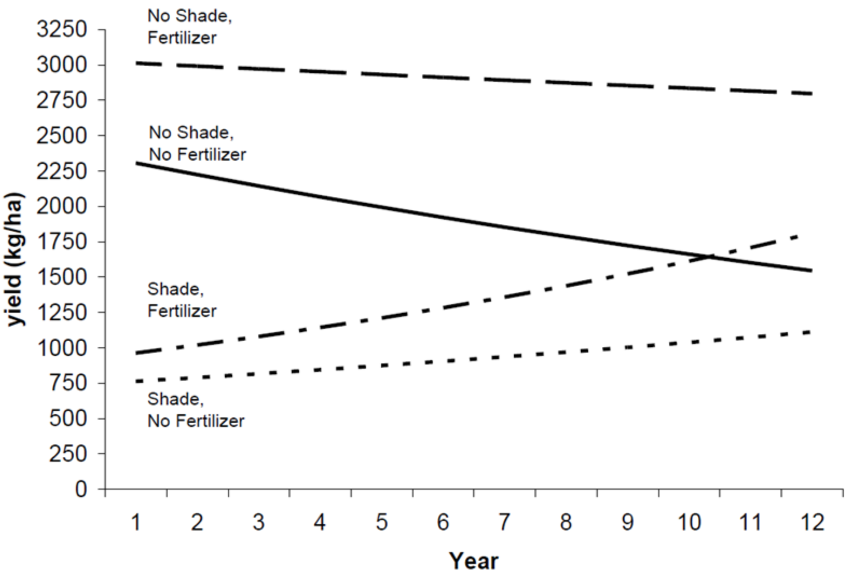
thus its optimal amount will be most probably much more stable than that of the hybrid trees on a year-to-year basis.

4.1.1 Fertilizer

When we take a look at Ghana on aggregate, the use of fertilizer has extended since the 1990, especially in the last decade. (Kolavalli & Vigneri, 2011) In particular, Vigneri (2008) describes that between 1992 and 1997 there was quite a large number of farmers using mostly low amounts of fertilizer. However, after 1997, the input subsidies were removed in Ghana[19], which has caused a turn in the previous trend, i.e. less farmers using larger quantity of fertilizer. (Vigneri, 2008) Nevertheless, this trend has changed again after 2001 when, as Vigneri (2008) reported, both number of farmers applying fertilizer and the amount of used fertilizer started to increase. In terms of yields, Edwin & Masters (2005) found that use of fertilizer is associated with approximately 19 % higher cocoa yield per 50 kilo bag of fertilizer in Ghana. Furthermore, Gockowski (2007) showed that the impact of fertilizer application can significantly improve the cocoa yields in shaded areas. The estimated proportion of cocoa area with no shade is 13% in the Ashanti region, 14% in the Brong Ahafo region, 27% in the western region and 7% in the eastern region. (Gockowski, 2007) Figure 16 shows that application of fertilizer can slow down the decrease of cocoa yields in the areas with no shade and conversely substantially increase the cocoa yields in shaded areas.

[19] Due to the liberalization of input markets in 1996/97 which eliminated the subsidies but improved private distribution (Kolavalli & Vigneri, 2011)

FIGURE 16: The Productive Potential of Full Sun Systems: The CRIG Shade-No Shade fertilizer trial, 1958 to1969



Source: Gockowski (2007)

When we take a look at farmers in our sample, Figure 17 shows that the CAA members were on average using almost three times more fertilizer than the non-members. The straightforward explanation for this gap between the two groups of the farmers is that the CAA program is quite successful in fulfilling its goal of improving access to fertilizer and other inputs, which is also supported by Caria et al. (2009) who found that the CAA members reduce their autonomous consumption of fertilizer by one bag. Kolavalli & Vigneri (2011) found that approximately half of the farmers in his sample were applying over five 50 Kilo bags of fertilizer in the three main regions[20] of cocoa production around 2003. Figure 17 displays that the CAA members in the examined sample were on average using eleven 50 kilo bags and the non-members four bags. Furthermore, 35 percent of farmers adopted fertilizer in the 2008/2009 season and 63 percent of farmers were using fertilizer in this and also in the subsequent 2009/2010 season (See table 2).

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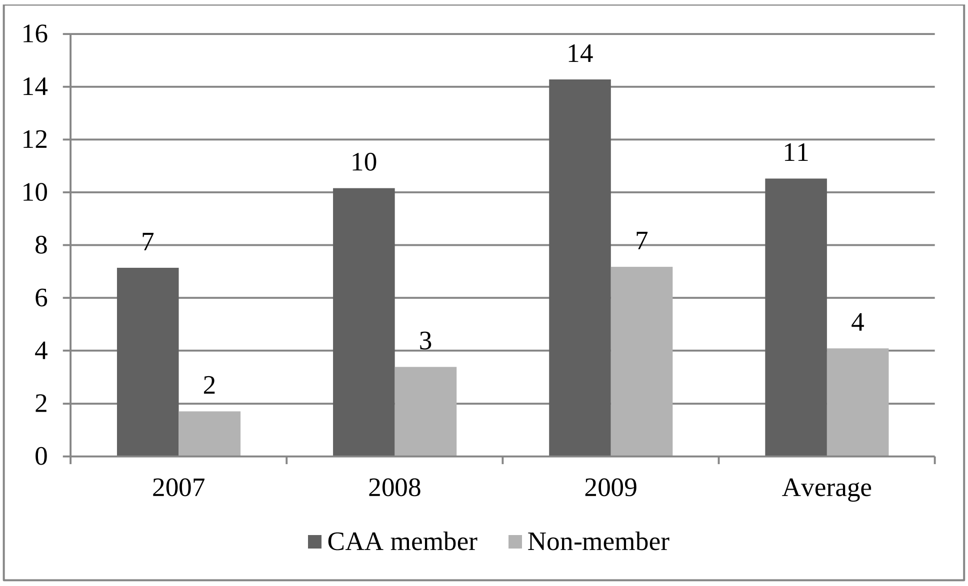
[20] Ashanti, Brong and Ahafo

FIGURE 17: Average use of fertilizer (50kg bags)



Source: author's computations.

TABLE 2: Transitions in individual fertilizer use across seasons

	2008/2009		
		Y	*N*
2007/2008	*Y*	60 (0.34)	15 (0.08)
	N	63 (0.35)	40 (0.22)
	*(N=178)		
	2009/2010		
		Y	*N*
2008/2009	*Y*	112 (0.63)	11 (0.06)
	N	14 (0.08)	41 (0.23)
	*(N=178)		

Notes: Matrices give numbers of individuals transiting from adoption state (Y;N) on left to adoption state (Y;N) in subsequent year. Parentheses contain the fraction of peers in the particular adoption state on the observed sample.
Source: author's computations.

Both, the OLS and the random-effects models show that the farmers choose the optimal quantity of 50 kilo fertilizer bags based on both the amount of fertilizer applied by them and by their village in the previous year, which is suggesting that there is a combination of individual and social learning about the optimal amount of fertilizer present (see Table 3). Adding the control variables to the models reveal that especially the farm size and number of adults in each farmer's household are other important factors when choosing the optimal amount of fertilizer (see Table 4). However, the Breusch-Pagan test implies that the OLS estimates are more accurate.

The importance of the farm size is not very surprising, as it obviously holds that the larger the farm, the higher the needed quantity of fertilizer. The significance (although slightly less important) of household size most probably lies in the fact that the utilization of fertilizer has quite high labor costs and family members represent the cheapest and most important source of labor in cocoa farming in Ghana. (Suri, 2006; Vigneri, 2008) On the other hand, given the gap between the CAA members and non-members shown on figure 17, it is quite surprising that the membership in the CAA is not significant in the model. I believe that the reason for this may be that the farmers in the CAA program in fact choose only the quantity above that provided in the CAA package and thus, when they need more fertilizer than the CAA provides, they are not influenced by the CAA membership and determine the optimal amount in a similar fashion as the non-members.

Nevertheless, even though both models show that the social learning is slightly more significant[21], the more accurate[22] OLS estimates suggest that the estimated coefficient representing the individual learning and those representing the social learning[23] are very similar and thus that the farmers learn about optimal amount of fertilizer through a combination of individual and social learning.

[21] i.e. the estimated coefficient of the village mean of the quantity of used fertilizer in the previous season is higher than the individual farmer's quantity of used fertilizer in the previous season

[22] Based on the Breusch-Pagan test

[23] Represented by the village effect in this case

TABLE 3: Optimal amount of fertilizer (Pure model)

Model:	*Random-effects*			*OLS*		
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*	
Intercept	1.3075	0.8922		1.3295	1.0986	
Fertilizer (t-1)	0.7106	0.0624	***	0.7361	0.1202	***
Fertilizer VM (t-1)	0.7341	0.1872	***	0.7203	0.2370	***
Cocoa VM (t-1)	-0.0012	0.0012		-0.0012	0.0017	

Note: Random-effects (GLS) and Pooled OLS with robust standard errors (R-squared 0.51), both models using 344 observations (Included 176 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

TABLE 4: Optimal amount of fertilizer (Full model)

Model:	*Random-effects*			*OLS*		
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*	
Intercept	-3.4975	2.8534		-2.5883	2.3965	
Fertilizer (t-1)	0.5901	0.0757	***	0.7167	0.1434	***
Fertilizer VM (t-1)	0.9039	0.2145	***	0.8548	0.2426	***
Cocoa VM (t-1)	-0.0019	0.0014		-0.0021	0.0018	
CAA member (t-1)	-0.7114	0.9416		-1.1912	1.0517	
Tree age	0.0414	0.0666		0.0481	0.0620	
HH size	0.4119	0.2434	*	0.5510	0.2351	**
Female	-0.1494	1.1695		-0.2445	0.7788	
Age	-0.0006	0.0376		-0.0082	0.0279	
Education	0.4256	0.4541		0.3325	0.3529	
Farm size	0.7035	0.1640	***	0.6159	0.1573	***
Hybrid share (t-1)	-0.5388	0.9584		-0.7703	0.8961	
Nnoboa days (t-1)	-0.0119	0.0089		-0.0049	0.0102	
HH days (t-1)	0.0036	0.0039		0.0017	0.0052	
Paid days (t-1)	-0.0006	0.0029		-0.0022	0.0035	

Note: Random-effects (GLS) and Pooled OLS with robust standard errors (R-squared 0.55), both models using 338 observations (Included 175 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

4.1.2 Share of hybrid trees

Hybrid cocoa varieties were first introduced[24] in 1984 and have been used ever since in Ghana. The benefits of hybrid trees are mainly production of more pods per tree and bearing fruit in shorter time[25]. (Kolavalli & Vigneri, 2011) To be more specific, Edwin & Masters (2005) show that the hybrid varieties are associated with at least 42% higher yields and furthermore that they do not differ in their response to fertilizer, pesticide use or labor, and also that the yield advantage of the new hybrid varieties did not decline over 17-year age span of their observed sample from Ghana. Nevertheless, in order to achieve the above mention performance, optimal weather conditions and complementary farming practices such as the application of chemical inputs, the adoption of new planting procedures, pruning and spraying are necessary. (Kolavalli & Vigneri, 2011) Furthermore, the hybrid trees require more harvest rounds at the beginning and at the end of the season, which can cause problems to farmers when carried out on a regular basis, as it may conflict with other farming or trading activities. (Kolavalli & Vigneri, 2011)

However, hybrid trees currently represent majority (57%) of the cocoa trees in the three main regions of cocoa production in Ghana and may have completely replaced the traditional trees on fields planted after 1995. (Kolavalli & Vigneri, 2011)

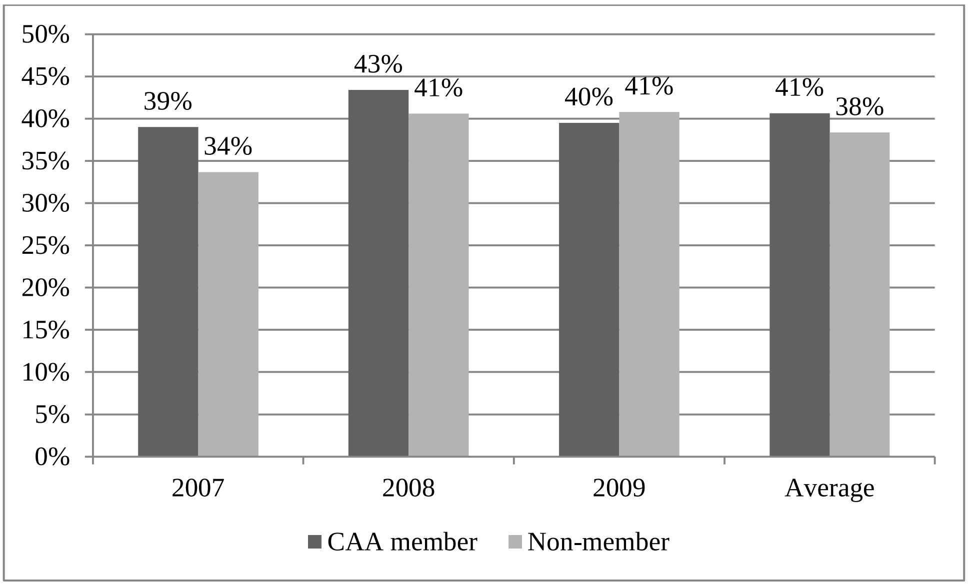
Figure 18 displays that, in the observed sample, on average 41% of the CAA members' farms and 38% of the non-members' farms were formed by the hybrid trees between the 2006/07 and 2009/10 seasons. However, closer look at the number

[24] though the government's Cocoa Rehabilitation Project (CRP)

[25] Particularly in three years in compare to the "traditional" seeds which usually bear fruits in five years

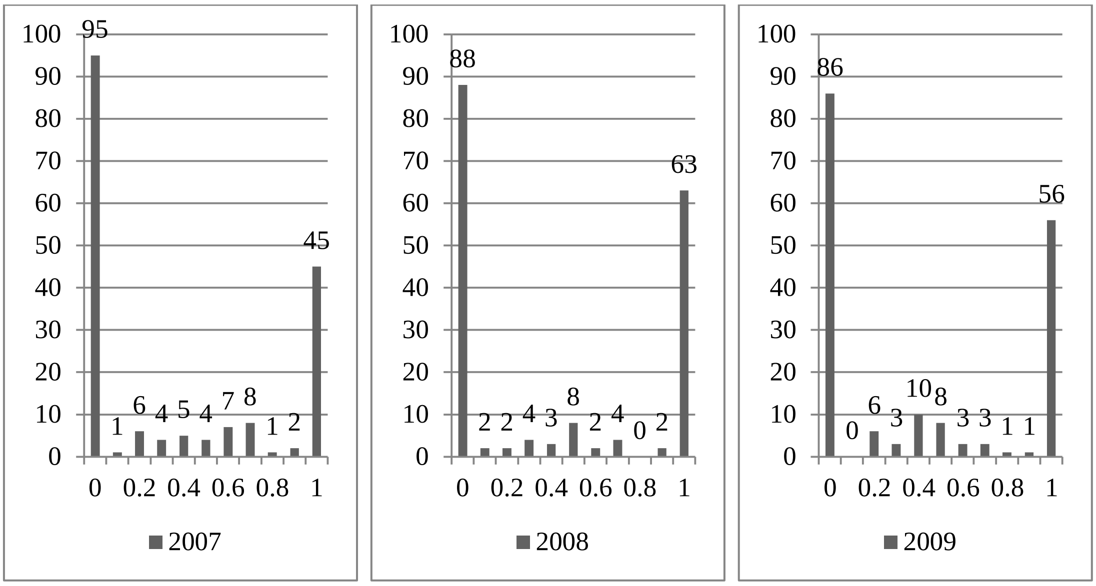
of farmers per share of hybrid trees reveals that most of the farmers had none or 100% of hybrid trees on their farms during the three observed seasons (as shown on figure 19). In 2008, 75% and 42% in 2009 of the observed farmers adjusted the share of hybrid trees on their farms. On average, farmers increased the share of hybrid trees by 5% during these two years, in particular, the CAA members by 6% and the non-members by 3%.

FIGURE 18: Average share of hybrid trees



Source: author's computations.

FIGURE 19: Distribution of hybrid trees (# of farmers per share of hybrid trees)



Source: author’s computations.

The random-effects model suggests that, similarly to fertilizer, farmers adjust the optimal share of hybrid trees based on both, their own and the village’s proportion of the hybrid trees from the previous year’s season, i.e. combination of individual and social learning. Nevertheless, the OLS estimation indicates that the village proportion of the hybrid trees from the previous year’s season is not significant, and thus that the individual learning prevails (see table 5 for both above mentioned models). Adding the control variables (see table 6) does not change the significance of these estimates and both models further reveal not very surprising significance of the tree age, as it is obviously more risky[26] and costly[17] to replace the older traditional trees with the hybrid ones. Nevertheless, the estimated coefficient of the tree age is close to zero and thus this relation is not very influential for the actual choice of share of hybrid trees. On the other hand, given the above mentioned findings of Edwin & Masters (2005), it is slightly surprising that the models do not

[26] In terms of changes to farm output

reveal that the decision of changing the share of hybrid trees is associated with either change in the amount of used fertilizer or with change in the amount of any labor input.

It was already mentioned that each of the two models suggests presence of different types of learning about the optimal share of hybrid trees. However, the Breusch-Pagan test implies that the OLS model is more accurate. Therefore, based on the OLS estimates, it is possible to conclude that the farmers are mainly influenced by their own individual considerations when they learn the optimal share of hybrid trees.

TABLE 5: Optimal share of hybrid trees (Pure model)

Model:	*Random-effects*			*OLS*		
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*	
Intercept	0.0135	0.0631		0.1125	0.0522	**
Hybrid share (t-1)	0.2892	0.0480	***	0.6089	0.0491	***
Hybrid share VM (t-1)	0.7045	0.1212	***	0.1525	0.0969	
Cocoa VM (t-1)	0.0000	0.0000		0.0000	0.0000	

Note: Random-effects (GLS) and Pooled OLS with robust standard errors (R-squared 0.37), both models using 356 observations (Included 178 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

TABLE 6: Optimal share of hybrid trees (Full model)

Model:	*Random-effects*			*OLS*		
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*	
Intercept	0.3392	0.1556	**	0.3263	0.1236	***
Hybrid share (t-1)	0.1828	0.0486	***	0.5810	0.0498	***
Hybrid share VM (t-1)	0.7275	0.1400	***	0.0298	0.1030	
Cocoa VM (t-1)	0.0000	0.0000		0.0000	0.0000	
CAA member (t-1)	-0.0677	0.0413		-0.0732	0.0445	
Tree age	-0.0096	0.0031	***	-0.0161	0.0031	***
HH size	0.0008	0.0113		0.0074	0.0098	
Female	-0.0308	0.0651		-0.0166	0.0534	
Age	-0.0021	0.0022		0.0012	0.0014	
Education	-0.0214	0.0255		-0.0147	0.0208	
Farm size	0.0060	0.0079		0.0087	0.0068	
Nnoboa days (t-1)	0.0001	0.0004		0.0004	0.0006	
HH days (t-1)	0.0001	0.0002		0.0000	0.0002	
Paid days (t-1)	0.0001	0.0001		0.0001	0.0002	
Fertilizer (t-1)	0.0005	0.0034		-0.0011	0.0037	

Note: Random-effects (GLS) and Pooled OLS with robust standard errors (R-squared 0.44), both models using 340 observations (Included 176 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

4.1.3 Non-labor inputs results and benchmark

The estimates of the models for the non-labor inputs do not unambiguously confirm the hypothesis that the Ghanaian farmers are similar to the Indian rice farmers in terms of learning, i.e. that the individual learning univocally prevails and that there is very small or none social learning effect. Nevertheless, it was already mentioned that, out of the inputs examined in this thesis, the share of hybrid trees is the most similar input to the HYVs inspected by Munshi (2004). The more accurate estimation of the OLS model, in case of this input, suggests that both village and yield effects are not present and that the individual learning prevails among the observed farmers. This finding thus supports the hypothesis that, in terms of learning, the Ghanaian cocoa farmers are similar to the Indian rice farmers, i.e. that the prevailing type of learning is the individual one. On the other hand, the results of both models estimating the prevailing type of learning about optimal amount of fertilizer indicate presence of combination of social[27] and individual learning and thus do not unambiguously support the above mentioned hypothesis. However, this finding does not necessarily implies that the observed cocoa farmers are therefore more similar to the India wheat farmers inspected by Munshi (2004), as his results show that the social learning is represented mainly by the yield effect, meanwhile my results show rather the village effect and, similarly to the Indian rice farmers, zero influence of the yield effect. Nevertheless, non-prevalence of the hypothesized individual learning is still quite surprising finding given the substantial heterogeneity of cocoa output among farmers. Munshi (2004) has defined heterogeneity among farmers, which creates the conditions for prevalence of the individual learning, as a sensitivity of a new technology to unobserved or imperfectly observed individual characteristics. Assuming that this sensitivity is the main cause for the Indian rice farmers for non-prevalence of the social learning, it appears that one of the possible explanations for the results of the models could be that the heterogeneous outputs of the Ghanaian cocoa farmers are not that much attributable to the unobserved or imperfectly

[27] Represented by the village effect

observed characteristics of the farmers but rather to some different factors. In other words, based on this framework, it seems that, in case of fertilizer, the Ghanaian cocoa farmers are to some extent quite well able to observe the reasons for different farm outputs of their neighbors. This assumption could be further supported by the presence of the CAA, which has an important role in fertilizer distribution, as it may to some extent function as an information intermediary through for instance the trainings it provides to the farmers and also possibly through the pressure to monitor which it creates among peer farmers in each group that obtains the package of inputs on credit. Therefore the CAA could play an important role in decreasing the heterogeneity[28] among the farmers. However, assuming that the above mentioned function of the CAA holds, it is important to discuss why the CAA membership is not significant for the choice of optimal amount of either input in the models above. This could be possibly explained by a positive externality, in terms of improved flow of information among farmers, arising from the CAA presence in the villages. In other words, regardless whether the farmers are members of the CAA or not, the CAA presence in the villages might improve the overall foreknowledge about the individual characteristics that the farmers have about each other and which are important for the decision about optimal amount of fertilizer. Therefore the CAA membership may not be that much important when choosing the optimal amounts of fertilizer and the optimal share of hybrid trees.

4.2 Labor inputs

Cocoa farming is a labor intensive industry and the total amount of labor used on cocoa farms has significantly increased across all Ghanaian regions during the last decades. (Vigneri, 2008) The most important labor input in Ghana is the family members, particularly spouses and children. Nevertheless, Vigneri (2008) found that

[28] as defined by Munshi

behind the overall increase in the amount of used labor inputs is in fact a decline of hired labor[29] and a substantial grow of the utilized household labor. Furthermore, this increase of the amount of labor working on the cocoa farms combined with the rise of the output of the farms caused the labor productivity to decline by 58%. (Vigneri, 2008)

Another important factor shaping labor utilization is gender. Vigneri (2008) explains that male labor is used for the physically demanding tasks such as cutting down trees and clearing the land, meanwhile the female labor is usually used for lighter tasks such as weeding and harvesting. This division of tasks causes that female-headed households are less probable to have acquired land through forest clearance[30] and, given the task carried out by female labor, also creates larger demand for female labor in Ghana. (Quisumbing et al., 2001) These gender specifics are very important for this analysis, as females form majority of the observed sample[31].

Looking at the length of labor contracts, Vigneri (2008) describes that annual labor is a relatively cost-efficient way to keep up a farm because it is possible to defer the payment for this labor until harvest. Nevertheless, the uncertain outputs of the farms causes many farmers to prefer more costly shorter-term contracts such as the most often used daily wage contracts, i.e. the labor is contracted for specific tasks and allows greater flexibility as farmers can hire labor as long as they are able to pay for it[32]. (Vigneri, 2008)

All of the labor inputs inspected in this thesis are measured in terms of number of work days, i.e. not in terms of number of workers. This type of measurement should provide better insight into the work extent of each labor input used. The first two examined labor inputs are the nnoboa and household labor days which are explicitly

[29] Vigneri (2008) estimated this decline to 18%

[30] Nevertheless it is important to mention that women can and do hire male laborers to clear the forest for them, however the female heads of household typically have less access to the resources to do so. (Quisumbing et al., 2001)

[31] See figure 6 for more details

[32] Daily wage laborers have higher wages than the minimum wages and are more costly than the annual laborers. (Vigneri, 2008)

supported and recommended by the CAA[33] because they are the most cost-efficient inputs available, and thus it is reasonable to closer analyze them in this thesis. The third inspected labor input is the paid labor days which was also used by Zeitlin (2012), and should represent the usage of more costly labor inputs.

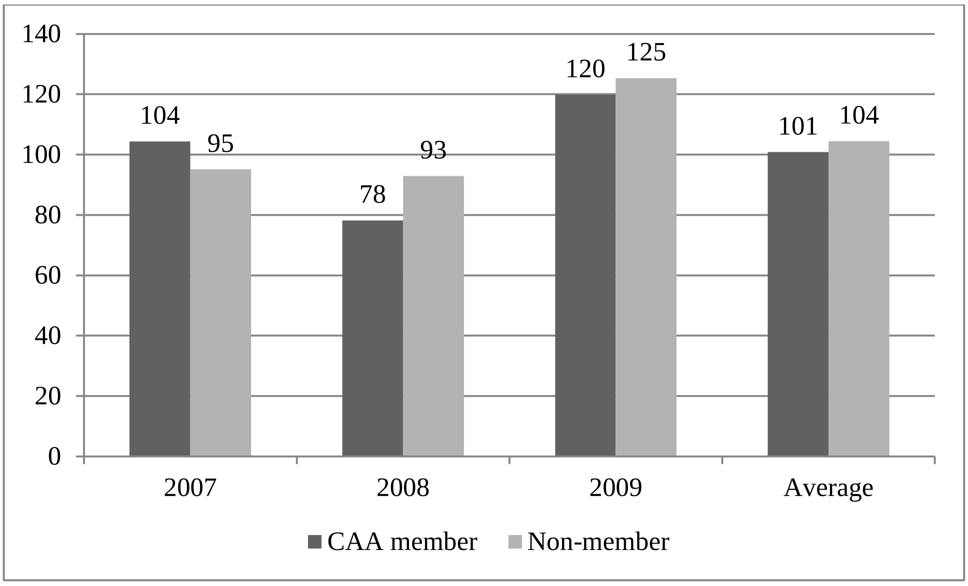
In terms of farm size and labor type used, the correlation between the farms size and paid labor (0.36) is significantly higher than that of the farm size and either the household (0.23) or the nnoboa (0.10) labor days. Therefore, the paid labor is more likely to be hired by farmers cultivating larger portions of land.

4.2.1 Household labor days

It was already mentioned that household labor is the most important labor input for cocoa production. Average household in the observed sample consists of three adults[34], however, the household labor is formed by both adults and children and given that the majority of the examined sample are female farmers and that there is on average four[35] children born per women in Ghana, an average household could consist of around seven members. On average, the observed farmers utilized 33.5 household labor days per hectare, which is almost twice more than in case of paid labor days and almost five times more than in the case of nnoboa days. Furthermore, the amount of used household labor days grew by 9% p.a.[36] between the 2006/2007 and 2009/2010 seasons. Figure 20 shows that the CAA members and the non-members used on average almost the same amount of this labor input. Nevertheless, the quantity of used household labor days grew by 2% p.a.[28] faster in case of the non-members than in case of the CAA members during the observed period.

[33] See Caria et al. (2009) for reference
[34] See figure 10
[35] Source: CIA world factbook
[36] CAGR

FIGURE 20: Average household labor days



Source: author's computations.

The pure random-effects and OLS models suggest that the farmers choose the optimal amount of household labor days based on how did they and their village utilize this input in the previous season, meaning that the optimal amount is determined based on a combination of individual and social learning (see table 7). However, adding the control variables reveals prevalence of the village effect, i.e. of the social learning (see table 8). The estimates of the random-effects and OLS models with control variables are very similar; however, the Breusch-Pagan test implies that the OLS estimates are more accurate.

Both models further disclose that the household size is a very important factor for choosing the optimal amount of household labor days, as the optimal amount of used household labor days grows with the household size. Another important significant variable is the farm size because the greater the farm, the more labor needed and, since household labor is the cheapest and the most frequently used type of labor, it is not very surprising that its utilized quantity increases with the farm size.

Furthermore, the model implies that the amount of fertilizer used in the previous season is another significant variable. It was already mentioned above that increasing the amount of used fertilizer increases the demand for labor and also the output of the farms, and thus when farmers need more labor for application of fertilizer, cultivation of the farms and harvesting, it is reasonable that they choose the most cost-efficient type of labor, i.e. the household labor. Furthermore, the models show an interesting substantial negative impact of education of the farmers on the choice of the optimal amount of household labor days. Specifically, it seems that the more educated the farmers are, the less household labor days they use. It should be noted that the household labor is the only labor input influenced by education[37]. There might be at least two possible explanations of this relation. First, that the more educated farmers realize the above mentioned decline in labor productivity caused by the increased use of labor, and thus they are able to do the necessary amount of work with less household labor days or by hiring some substitute labor input such as the nnoboa labor[38]. And second, that there might be an "externality" in the form that the more educated farmers may want the other members of their household to also have higher level of education and thus there might be less labor available in these household, as some members of these household might spend longer time studying and/or choose to work in different industries than the cocoa production.

Finally, neither model shows any impact of gender on the choice of the amount of household labor days and, more importantly, nor any influence of the utilized amounts of nnoboa or paid labor days.

[37] As i tis shown further in the text

[38] However, this hypothesis is not supported by the estimation of the model on the nnoboa labor days, as it does not reveal any impact of education on this type of labor. (see table 10 for more details)

TABLE 7: Optimal amount of household labor days (Pure model)

Model:	*Random-effects*			*OLS*		
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*	
Intercept	-1.4825	20.9880		-1.3988	20.2228	
HH days (t-1)	0.1309	0.0578	**	0.1384	0.0712	*
HH days VM (t-1)	0.7820	0.2036	***	0.7738	0.1915	***
Cocoa VM (t-1)	0.0101	0.0083		0.0102	0.0104	

Note: Random-effects (GLS) and Pooled OLS with robust standard errors (R-squared 0.09), both models using 356 observations (Included 178 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

TABLE 8: Optimal amount of household labor days (Full model)

Model:	*Random-effects*			*OLS*		
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*	
Intercept	-4.1383	41.9586		-3.3716	41.3042	
HH days (t-1)	0.0735	0.0615		0.0854	0.0650	
HH days VM (t-1)	0.6822	0.2165	***	0.6710	0.2127	***
Cocoa VM (t-1)	-0.0067	0.0097		-0.0066	0.0103	
CAA member (t-1)	-14.6622	13.9487		-14.8279	14.1006	
Tree age	0.9841	0.9864		0.9860	0.9603	
HH size	8.7128	3.5752	**	8.6537	3.2625	***
Female	6.5472	16.2463		6.2829	14.9687	
Age	-0.1715	0.5082		-0.1681	0.4866	
Education	-16.2591	6.3030	**	-16.1902	5.3048	***
Farm size	8.1126	2.3817	***	7.9708	2.6250	***
Paid days (t-1)	0.0105	0.0441		0.0105	0.0451	
Fertilizer (t-1)	3.3191	1.1153	***	3.3101	1.3574	**
Hybrid share (t-1)	12.3218	13.8741		11.6534	13.9812	
Nnoboa days (t-1)	-0.1693	0.1346		-0.1668	0.1018	

Note: Random-effects (GLS) and Pooled OLS with robust standard errors (R-squared 0.20), both models using 340 observations (Included 176 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

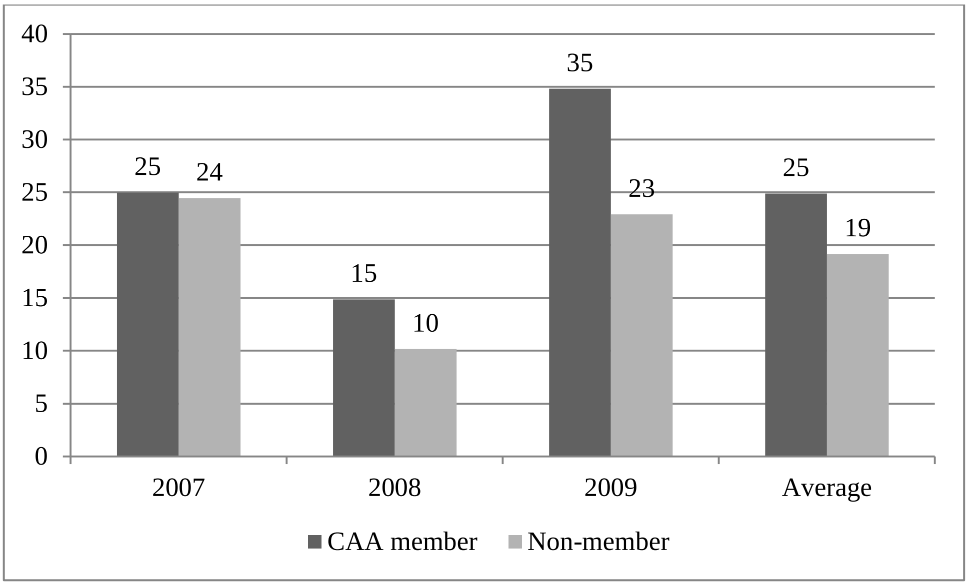
4.2.2 Nnoboa labor days

The word nnoboa literally means mutual assistance in weeding. (Funk & Salifu, 2012) To be more specific, it is a customary arrangement that provides reciprocal labor exchange for farm work among the Akan speaking communities in Southern Ghana. The nnoboa system is voluntary and temporary, i.e. the group of participating workers disbands after completing the task it was assembled for. The most frequent reasons for joining the nnoboa groups were exchange of labor, gaining access to credit and procuring mechanization and other services. (see Funk & Salifu, 2012, for references for all the text above)

It was already mentioned that the CAA encourages its members to use this type of labor. As a result, as displayed on Figure 21, the observed CAA members were on average using by 6 more nnoboa labor days than the non-members between the 2006/2007 and 2009/2010 seasons. Furthermore, there is a very low correlation (0.10) between the nnoboa labor days and the farm size thus it appears that the nnoboa labor is hired across farmers with various farms. Average farmer from the sample was using 7 nnoboa labor days per hectare, the CAA member 7.5 and the non-member 6.6 during the observed time period. In comparison to household days and the paid labor days, these are the least numbers of labor days per hectare, i.e. this labor input is the least used out of the three inspected labor inputs. In overall, the use of nnoboa labor days grew by 5% p.a.[39] between the 2006/2007 and 2009/2010 seasons, nevertheless, there is a huge difference in growth of this labor input among farmers, as it rose by 18% p.a.[30] in case of the CAA members and decreased by 3%p.a.[30] in case of the non-members.

[39] CAGR

FIGURE 21: Average nnoboa labor days



Source: author's computations.

Both random-effect and OLS pure models suggest prevalence of social learning about the optimal amount of nnoboa labor days, as the only significant variable is the village mean of the previous season's amount of nnoboa labor days (see table 9). However, adding the control variables reveals that the random effects most probably give imprecise estimates (see table 10), as the estimated coefficient of the previous season's amount of nnoboa labor days is negative, which seems to be slightly odd[40]. The suspicion that the random-effects estimates are not accurate is further supported by the Breusch-Pagan test which indicates that the OLS estimates (see table 10), which do not estimate this odd relation, are more precise. Therefore, based on the OLS model, it can be concluded that there is a prevailing village effect, meaning that the farmers seem to be influenced mainly by the social learning when they decide about optimal nnoboa labor days. Nevertheless, this conclusion must be taken with caution, because the r-squared of the OLS model is only 0.09, which suggests that even the OLS model most probably does not have very high explanatory power.

[40] Because this estimate suggests that the more nnoboa labor days were used in the previous season, the less nnoboa labor days will be used this season.

Both models further reveal that the paid labor days were significant when choosing the optimal amount of nnoboa labor. The positive relation with the nnoboa labor suggests that nnoboa labor is a complement to the more expensive paid labor.

TABLE 9: Optimal amount of Nnoboa labor days (Pure model)

Model:	*Random-effects*			*OLS*		
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*	
Intercept	3.0938	6.2477		3.0938	6.2477	
Nnoboa days (t-1)	0.0281	0.0655		0.0281	0.0655	
Nnoboa days VM (t-1)	0.8513	0.2699	***	0.8513	0.2699	***
Cocoa VM (t-1)	-0.0014	0.0048		-0.0014	0.0048	

Note: Random-effects (GLS) and Pooled OLS (R-squared 0.05), both models using 356 observations (Included 178 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

TABLE 10: Optimal amount of Nnoboa labor days (Full model)

Model:	*Random-effects*			*OLS*		
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*	
Intercept	-9.6016	27.1808		0.1065	19.2210	
Nnoboa days (t-1)	-0.1855	0.0605	***	-0.0269	0.0687	
Nnoboa days VM (t-1)	1.0839	0.4152	***	0.8047	0.2819	***
Cocoa VM (t-1)	-0.0038	0.0080		-0.0060	0.0054	
CAA member (t-1)	-1.3077	7.8415		0.7991	6.9081	
Tree age	0.1386	0.4689		0.2607	0.4826	
HH size	2.7662	1.7411		1.4877	1.7561	
Female	5.5599	11.6322		5.3753	7.7625	
Age	-0.2054	0.3722		-0.2165	0.2477	
Education	0.8159	4.4915		-0.5816	2.9905	
Farm size	0.5175	1.2460		0.6602	1.1610	
Hybrid share (t-1)	3.9587	7.0000		7.5907	6.8377	
HH days (t-1)	0.0030	0.0263		-0.0155	0.0294	
Paid days (t-1)	0.0563	0.0212	***	0.0563	0.0218	**
Fertilizer (t-1)	0.3846	0.4589		0.5264	0.5462	

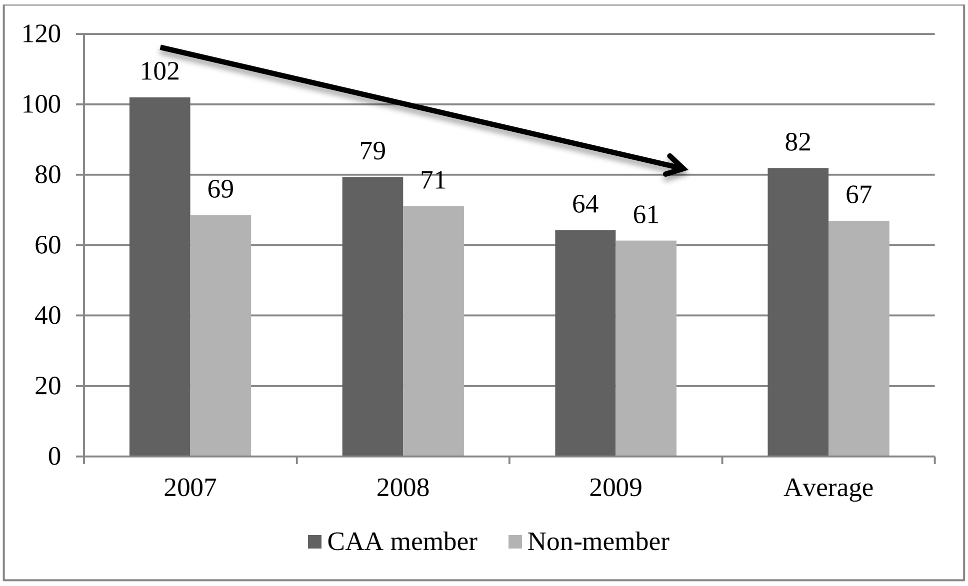
Note: Random-effects (GLS) and Pooled OLS (R-squared 0.09), both models using 340 observations (Included 176 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

4.2.3 Paid labor days

It was already mentioned that Vigneri (2008) found that despite the overall increase in total labor, the hired labor is actually decreasing. This is supported by the farmers observed in our sample, as figure 22 clearly shows a decreasing trend in the amount of used paid labor. Furthermore, the correlation between the quantity of sold cocoa and paid labor (0.41) is almost twice as high as that of the amount of sold cocoa and either the household (0.21) or the nnoboa (0.22) labor days. This, together with the above mentioned correlations with farm size, shows that the paid labor is more often hired by richer farmers with greater cocoa outputs. Figure 22 further displays that the amount of paid labor used by the CAA members is converging to that of the non-members. On average, the CAA members used by 15 paid labor days more than the non-members during the observed period. However, the amount of used paid labor days per hectare was decreasing by 18% p.a.[41], specifically, by 19% p.a.[33] in case of the CAA members and by 17% p.a.[33] in case of the non-members. Compared to the household and nnoboa labor, the average amount of paid labor days per hectare (ca. 19) was somewhere in the middle between the other two labor inputs. Nevertheless, the CAA members were using approximately 18 paid labor days per hectare which is by ca. 2 less than the non-members, who utilized around 20 paid labor days per hectare.

[41] CAGR

FIGURE 22: Average paid labor days



Source: author's computations.

The random-effects model without the control variables estimates that the farmers learn about the optimal amount of paid labor days mainly through the social learning, as the only significant variable is the village mean of the previous season's amount of paid labor days, and thus the village effects prevails. However, the pure OLS model estimates indicate that none of the variables is significant (see table 11 for both models). After adding the control variables, both models indicate prevalence of the yield effect, i.e. the social learning (see table 12). However, similarly to the random-effect model estimates in case of nnoboa labor, the estimated coefficient of the yield effect is negative. This relation is suspicious because this result suggests that the greater the yield per hectare in the previous season, the less paid labor days will be used this season. This finding is therefore not very consistent with the above mentioned hypothesis that the paid labor is more often hired by richer farmers with greater cocoa yields, i.e. that the farmers decide about the optimal amount of this labor input mainly based on the expected cocoa yield which is the most important determinant of their income. Therefore, I believe that these estimates are most probably not very accurate and to some extent biased. The Breusch-Pagan test implies that the OLS estimates are more accurate but given the above mention suspicious results, even the OLS estimates are most probably imprecise. I believe that the estimates could be to some extent biased here by the overall trend of decreasing amount of paid labor, which was found in Ghana, and is clearly present in the observed sample.

The control variables are not very helpful here, as for instance the significance of farm size, indicating that the larger the farm, the more paid labor days used, is rather supporting the above mentioned hypothesis. Furthermore, similarly to the case of the household labor days, the optimal amount of paid labor rises with the amount of utilized fertilizer, as it is a very labor intensive technology.

Ignoring the direction of the estimated yield effect, the significance of this variable could at least indicate a weak suggestion that the social learning might be more important in case of this input, however, since both random-effects and OLS models estimate the coefficient of the yield effect to be very close to zero, it is not possible to draw conclusions about which type of learning is prevailing in case of the paid labor days.

TABLE 11: Optimal amount of paid labor days (Pure model)

Model:	*Random-effects*			*OLS*	
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*
Intercept	21.1606	17.6887		20.1924	16.7896
Paid days (t-1)	-0.0195	0.0490		0.0651	0.0494
Paid days VM (t-1)	0.3595	0.2157	*	0.3046	0.2050
Cocoa VM (t-1)	0.0159	0.0136		0.0149	0.0129

Note: Random-effects (GLS) and Pooled OLS (R-squared 0.03), both models using 356 observations (Included 178 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

TABLE 12: Optimal amount of paid labor days (Full model)

Model:	*Random-effects*			*OLS*		
	Coefficient	*Std. Error*		*Coefficient*	*Std. Error*	
Intercept	-8.8460	28.6183		-9.7773	27.7422	
Paid days (t-1)	0.0239	0.0326		0.0386	0.0324	
Paid days VM (t-1)	0.1803	0.1230		0.1673	0.1189	
Cocoa VM (t-1)	-0.0149	0.0084	*	-0.0144	0.0082	*
CAA member (t-1)	-7.7827	10.1263		-6.6786	10.0572	
Tree age	0.3851	0.7107		0.4431	0.7023	
HH size	2.1979	2.5867		2.3225	2.5495	
Female	-14.2774	11.6224		-13.7289	11.2229	
Age	0.2592	0.3745		0.2557	0.3614	
Education	2.6913	4.5015		2.4194	4.3433	
Fertilizer (t-1)	1.8305	0.8205	**	1.6411	0.8132	**
Hybrid share (t-1)	2.6884	10.0467		3.1567	9.8818	
Farm size	11.2053	1.7165	***	11.1756	1.6847	***
Nnoboa days (t-1)	-0.0177	0.0983		-0.0249	0.0977	
HH days (t-1)	0.0085	0.0432		0.0076	0.0429	

Note: Random-effects (GLS) and Pooled OLS (R-squared 0.20), both models using 340 observations (Included 176 cross-sectional units). VM stands for village mean. Symbols *; **; *** denote p-values less than .1, .05, and .01

4.2.4 Labor inputs results and benchmark

The estimates of the models for the labor inputs do not confirm the hypothesis that the Ghanaian farmers are similar to the Indian rice farmers in terms of learning, i.e. that the individual learning prevails and that there is very small or none social learning effect. In fact, the labor inputs show exactly the opposite and even greater prevalence of the social learning about the optimal amounts of inputs than in case of fertilizer in the previous sub-chapter related to the non-labor inputs. At first glance, these results thus shift the Ghanaian cocoa farmers even closer to the Indian wheat farmers described by Munshi (2004). However, similarly to the results of the non-labor inputs, there is dominant village effect among the inspected farmers, meanwhile Munshi (2004) observed rather prevalence of the yield effect. Therefore, it is possible to conclude that the results suggest that the Ghanaian cocoa farmers are not similar to the Indian rice farmers, however, this does not necessarily imply that they are very much like the Indian wheat farmers (in terms of learning).

Another important finding is the linkage of labor inputs and utilization of fertilizer, which shows that there are some indirect costs connected to the CAA program. However, Caria et al. (2009) did a cost-benefit analysis of the CAA program and found that the increased costs for the additional labor inputs are not sufficiently high to alter the cost-benefit merit of the program.

Nevertheless, it must be noted that most of the models examining the labor inputs have probably quite low explanatory power. In particular, except for the household labor models estimates which seem to be more or less reliable, the estimates of the nnoboa days models appear to be much less accurate and the paid labor days models give probably imprecise results so that it was not even possible to assess the prevailing learning type here.

5 RESULTS AND CONCLUSIONS

Adoption of a new technology can be a significant production booster if the new technology implementation turns out to be successful. Therefore, it appears to be reasonable to sustain adoption of such innovative technology and to permanently change previous manners of production. Nevertheless, it might also be the case that some part of the new adopters of such commonly[42] successful technology decides not to use it in the consecutive period of production. To be more specific, there are various evidences from rural Africa showing such trend. Therefore, it is important to ask how do the adopters learn and decide about adoption of such new technologies. More specifically, the key question asked in this thesis is: Are the adopters' decisions based mainly on their own considerations (individual learning) or do they rather rely on observation of behavior of their village neighbors (social learning)?

The technology is represented by fertilizer and hybrid seed varieties and the examined adopters are Ghanaian cocoa farmers in this thesis. Therefore it is possible to further specify the question above by asking how do the farmers learn and choose optimal amounts of these non-labor inputs. However, adoption of these non-labor inputs is usually associated with changes in amounts of used labor inputs. Therefore it is important to inspect how the farmers learn about both nob-labor and labor inputs.

Former research from India suggests that heterogeneity, in terms of sensitivity of the optimal amounts of inputs to the unobserved characteristics determining the farm's yields, among farmers is a key factor influencing the prevailing form of learning about optimal usage of high yielding varieties among wheat and rice farmers. In particular, the research shows that the more heterogeneous the population is, the more inclining towards the individual learning it should be. The Ghanaian cocoa farmers, observed in this thesis, appear to be such heterogeneous population.

[42] i.e. on average

Therefore the main hypothesis in this thesis is that the Ghanaian cocoa farmers prefer the individual learning over the social one.

The evidence presented in this thesis does not unambiguously confirm this hypothesis. To be more specific, as shown in table 13, the evidence suggests that there is a significant difference between how the observed farmers learn about non-labor and labor inputs.

TABLE 13: Types of learning by input

Input		**Type of learning**		**Dominant effect**
		Individual	**Social**	
Non-labor	**Fertilizer**	◐	◐	Individual and village effect
	Share of hybrid trees	●	-	Individual effect
Labor	**Household labor**	-	●	Village effect
	Nnoboa labor	-	●	Village effect
	Paid labor	-	-	N/A (yield effect)

Source: author’s computations.

In particular, the observed farmers prefer the individual learning in case of the share of hybrid trees, which is the most similar input to the high yielding varieties inspected in the above mentioned research from India. However, the farmers seem to rely on a combination of individual and social learning in case of the other non-labor input examined in this thesis, i.e. fertilizer. On the other hand, the results suggest that the social learning is the dominant form of learning determining the optimal amount of labor inputs chosen by the farmers.

Therefore, the evidence shown in this thesis suggests that the farmers learn differently about non-labor and labor inputs and thus that the heterogeneity of the farmers’ population is most probably crucial mainly for determining the type of learning about the non-labor inputs.

However, the power of the models inspecting the labor inputs appears to be significantly lower than the power of the non-labor models. Increasing the size of the sample and including longer time period could possibly improve the power and accuracy of these models.

The contribution of the findings presented in this thesis is mainly in fostering programs such as the CAA one in the identification and understanding of the key factors determining adoption of a new technology, here represented by inputs. Furthermore, the evidence presented in this thesis suggests that the state of utilization of inputs in villages not yet reached by the CAA could be a relevant indicator of potential impact of the program in these villages, should they be considered to get involved in the program in the future.

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