Kiel

Working Papers

Kiel Institute for the World Economy

Organic Certification, Agro-Ecological Practices and Return on Investment: Farm Level Evidence from Ghana

by Linda Kleemann and Awudu Abdulai

No. 1816| December 2012

Web: www.ifw-kiel.de

Kiel Institute for the World Economy, Hindenburgufer 66, 24105 Kiel, Germany

Kiel Working Paper No. 1816| December 2012

Organic Certification, Agro-Ecological Practices and Return on Investment: Farm Level Evidence from Ghana*

Linda Kleemann and Awudu Abdulai

Abstract:

The recent empirical literature on economic sustainability of certified export crops shows that certification standards that enhance yields are important for improving farm revenues and farmer welfare. However, limited evidence exists on the impact of organic certification on the adoption of agro-ecological practices. In this study, we use unique farm-level data from Ghana to examine the impact of organic certification on the use of agro-ecological practices to improve environmental conditions, as well as how using these measures affect farm outcomes such as return on investment. In the former, we utilize an endogenous switching regression approach to account for selection bias due to unobservable factors. Our empirical results reveal that organic certification increases agro-ecological practice use, although from a very low starting point. Using a generalized propensity score approach, we show that there is a nonlinear relationship between the intensity of agro-ecological practice use and return on investment.

Keywords: organic agriculture, certification, agro-ecological practices, return on investment, impact assessment

JEL classification: O13, Q13, Q17, Q56

Linda Kleemann
Kiel Institute for the World Economy
24100 Kiel, Germany
Telephone: +49(0)431-8814-248
E-mail: linda.kleemann@ifw-kiel.de

*We would like to thank the Poverty Reduction, Equity and Growth Network (PEGNet) and the H.Wilhelm Schaumann Stiftung for financial support.

1 Introduction

Concerns over climate change and increasing pressure on land have resulted in increased promotion of sustainable production methods that increase yields, while protecting the environment as well as increasing the resilience of crops to climatic change (Kassam et al., 2012; Branca et al., 2011; FAO, 2011; Knowler and Bradshaw, 2007; Erenstein, 2002). Such agro-ecological practices form part of organic agriculture principles, but in practice, low-input production with none, or very little sustainable soil and water management practices are frequently certified as organic in many developing countries.

To encourage the adoption of sustainable production methods, national governments, NGOs and international donors have promoted the marketing of export crops through certified marketing channels, mostly through farmer-based groups, as an attractive business model for smallholders in developing countries (Beuchelt and Zeller, 2011). These sustainable certification schemes have become increasingly popular in many countries because they combine valued traits that are related to the environment, poverty alleviation, and health outcomes into a single commodity (Barham and Weber, 2012). Consumers generally show their preferences for such products by paying higher prices to support an environmentally healthy world. However, the success of these schemes depends to a large extent on prices received and incomes earned by the farmers.

The significance of these schemes in promoting sustainable farm practices and improving the incomes of smallholders in developing countries has attracted the attention of many policy analysts over the last few years. In particular, several studies have examined the impacts of certification schemes on farm outcomes such as farm revenues, profits, and household poverty (Pretty et al., 2003; Ninan and Sathyapalan, 2005; Bolwig et al., 2009; Valkila, 2009; Beuchelt and Zeller, 2011; Barham and Weber, 2012). Most researchers find modest positive impacts of organic certification on farm revenues and household income, using various measures and econometric approaches. They attribute the positive impacts of certification to price premiums that are paid at least for part of the crop sales (e.g. Valkila, 2009; Bolwig et al., 2009; ITC, 2011), although it is usually not clear whether the effect comes from certification, contract farming, or export market access. It is important to note that some researchers have been rather skeptical on the ability of certification to lift farmers out of poverty, given the usually low revenue increases. The main reasons for this skepticism are the high certification and investment costs involved in the process (Calo and Wise, 2005; Valkila, 2009; Beuchelt and Zeller, 2011).

Despite this increasing number of impact assessment studies, very few studies have considered the environmental outcomes of different certification programs (Barham and Weber, 2012). Philpott et al.'s (2007) study on Mexico examines environmental outcomes by analyzing the impact of certification on vegetation and ant, as well as bird diversity in coffee farms and forests. Rather surprisingly, their findings show no differences between in vegetation characteristics, ant or bird species richness, or fraction of forest fauna in farms based on certification. Pretty et al. (2006) conduct a review of 286 interventions to show that the use of sustainable agricultural practices increases productivity on developing country farms, albeit using best practices. Bolwig et al. (2009) studied the effect of organic contract farming and adoption of organic practices on 112 coffee producing smallholders and conclude there are somewhat higher revenues for farmers that adopt organic farming techniques, findings confirmed by Blackman and Naranjo (2010) who find that organic certified farmers in Costa Rica use less chemicals and adopt some environmental friendly management practices. However, they base their analysis on only 35 certified coffee farmers in Costa Rica.

With the notable exception of the study by Pretty et al. (2006), which includes countries from sub-Saharan Africa, we find no empirical evidence on the impacts of certification on environmental outcomes in sub-Saharan Africa. In particular, the dependence of the yield impact of organic certification on the intensity of agro-ecological practice use has hardly been studied in the existing literature. Some authors have argued that organic farming in Africa mostly implies the non-application of chemical inputs, without necessarily adopting alternative soil fertility management practices. This is particularly so for the many smallholders in Africa, who traditionally produce ”organically by default”, since they virtually use no external input. The smallholders who use no chemical inputs or very low levels of external inputs normally face lower entry barriers into organic certification programs, since they require small adjustments to meet certification requirements. Organic certification only requires abstaining from the use of chemical substances, but not the active use of alternative inputs. However, Barham and Weber (2012) suggest that improving productivity by means of agronomic practices may be more important than focusing on price increases by means of certification. On the other hand access to higher-priced organic markets may provide incentives to adopt (more) agro-ecological practices (Wollni et al., 2010).

This study contributes to the literature by examining the effect of organic certification on the extent to which agro-ecological practices are used, as well as the impact of the intensity of use on the return on investment (ROI). We employ data from a recent farm-level survey of 386 small-scale pineapple farmers in the Greater-Accra and Central Regions of Ghana. The study accounts for selection bias due to unobservable factors by using the framework of endogenous switching regression approach (Lee, 1978). The approach allows us to analyze the determinants and effects of the adoption decision of organic farming on the use of agro-ecological practices, separately for adopters and non-adopters among the sample of 386 pineapple farmers. In investigating the impact of agro-ecological practice on ROI, we use the generalized propensity score approach developed by Hirano and Imbens (2004) to control for selection bias.

As in many other developing countries, agricultural production in Ghana contributes to environmental damage such as underground water depletion, soil erosion, water and soil pollution, loss of biodiversity, deforestation, and global climate change. In particular, crops that are produced for export are usually intensively treated with pesticides to assure the required quality and uniformity. This is also the case for pineapple, the third most important agricultural export product of the country, after cocoa and palm oil. On the environmental side, climate change is expected to have negative effects on agricultural production, while population pressure will contribute to increased soil degradation and consequently lower crop yields (Diao and Sarpong, 2007). The Ghanaian government has attempted to address these problems through environmental protection (Government of Ghana, 2010) and has established an organic agriculture desk in the Ministry of Food and Agriculture (MOFA).

Our findings show that organic certification increases agro-ecological practice use, suggesting that certification already serves as a catalyst for the use of agro-ecological practices. We also find that the use of agro-ecological practices generally has a positive and nonlinear effect on the return on investment.

The remainder of the study is structured as follows: The next section gives an overview of the pineapple sector in Ghana and the data used in the analysis. It is followed by the presentation of the corresponding descriptive statistics. Subsequently, section 3 presents the conceptual framework and empirical strategy employed in the analysis. The empirical results are presented in section 4. The final section provides concluding remarks and implications.

2 Background and Data

2.1 Background

The agricultural sector in Ghana accounts for about 30% of gross domestic product (GDP) and employs over 50% of the Ghanaian working population (WDI, 2011). In recent years, non-traditional exports of horticultural products experienced significant growth. Exports of fresh fruits and vegetables, especially to Europe, are now the most important growth sector of Ghana's agriculture. The country began exporting pineapples in small quantities in the 1980s. Ghanaian pineapple farmers produce the varieties MD2, Smooth Cayenne, Sugar Loaf and Queen Victoria, where Sugar Loaf is mainly produced for the local market, or for processing, while Queen Victoria plays a minor role as a high-priced specialty product. Pineapple exports increased rapidly until 2004, after which it declined towards 2010, partly because of a change in varieties demanded on world markets, to which the Ghanaian pineapple sector reacted slowly. Many farmers gradually switched to the new world market variety (MD2), while some produced organic pineapples for export. According to estimates from the Ghanaian export promotion council (GEPC) and the Sea Freight Pineapple Exporters Association of Ghana (SPEG) about 31,000 tons of the estimated 75000 tons produced in the country were exported in 2009 (GEPC, 2010).

Actors in the Ghanaian Pineapple Sector

Pineapple farming in Ghana is largely located within a radius of 100 km north-west of the capital Accra in the regions of Greater Accra, and the Central and Eastern Region. The pineapple industry is driven by two dominant groups of producers that include few large or medium-sized producers, and a large number of small-scale farmers. The small-scale farmers mostly sell their fruits on the local market or to exporters. Among these smallholders, there are two clusters, traditional low-input "organic-by-default" producers and another group of farmers that strive to imitate large-scale high-input production. Smallholders prefer selling their fruits on the export market because of higher prices, but due to high quality requirements, fruits for export are also more expensive to produce (Suzuki et al., 2011). Pineapple export in Ghana is predominantly organized by export companies that are also engaged in pineapple production.

Organic Production

Certified organic products achieve price premia and access to new markets. According to Kleemann (2011), organic certified pineapples from Africa receive a price premium on the European market, which is normally passed on to the producers. About 0.19% of the agricultural land in Ghana is organic certified, with a presumably higher part in pineapples[1]. Organic certification refers to the standards in the EU regulations (EC) 834/2007 and (EC) 889/2008. It entails, among others, largely refraining from the use of synthetic inputs and the use of only stipulated inputs for flower induction. These requirements lead to a higher labor intensity of organic farming by way of more manual weeding, pest control and possibly own production of fertilizers. The resulting use of on-farm/local inputs in organic farming can be an advantage when markets are missing or do not function well. However, a major disadvantage of organic farming is potentially lower yields, in particular, when synthetic inputs are not replaced by organic inputs and when knowledge about soil nutrient and plant pest and disease management is not sufficient. Moreover, since organic production involves a long-term investment in soil fertility and sustainability, time lags between investment and returns may prove to be an entry barrier for small resource- constrained farmers in insecure environments. The Ministry of Food and Agriculture (MOFA), Agro Eco/Louis Bolk, West African Fair Fruit (WAFF) and the German International Cooperation are involved in the promotion of organic farming.

2.2 Data

The data used in the study come from a farm household survey that was conducted from January to March 2010 in six different districts[2] of the Central, Eastern and Greater Accra regions in southern Ghana, where pineapple cultivation is mostly located. Stratified random sampling in three stages was used. First, districts with significant amounts of smallholder pineapple production for export were selected, using information from development agencies and the Pineapple Exporters Association of Ghana. Next, lists of all pineapple farmer groups in the selected districts that are certified (organic or GlobalGAP if conventional) and producing for the export market certified were obtained. Finally, in each group, a percentage of farmers proportional to the total number of farmers in the group were selected randomly from the lists. The farmer answered a detailed questionnaire on the household's management of the pineapple farm, inputs into pineapple production, harvesting and marketing, the certification process, and relations with exporters. Besides, information on household characteristics, social capital and land disposition were requested, as well as data concerning non-income wealth indicators and perceptions of different statements about environmental values, organic farming techniques and the use of fertilizers and pesticides.

The dataset includes 386 households from 75 villages and 9 (organic) and 14 (conventional) different farmer associations. In total, 185 organic farmers and 201 conventional farmers were interviewed. All organic farmers sold part of their produce as organic certified to exporters or processors and part of it on the local market, without reference to the certification. Respectively, all conventional farmers sold their produce preferably to exporters or exporting processors, but also on the local market. In theory, there could be one-directional overlaps. This means that organic certified farmers could sell as organic certified (which has the highest price) as first preference, as conventional export produce as second preference and on the local market as last option. However, this is not the case in our sample. The opposite, i.e. conventional farmers trying to sell on the organic export market is not possible.

Descriptive Statistics of Sociodemographic Variables

The typical household in our sample has a similar income compared to the average in Ghana (country average 88.83 GHS per month, survey average: highest density in income groups 51-150 GHS per month), and a higher income share from agriculture (47.8% versus 67%; data from Ghana Living Standards Survey 5). All sociodemographic variables that are included in the estimations are presented in Table 1.

Organic farm household heads are older and less educated than conventional farm households. They have smaller farms, but are more specialized in pineapple farming. On average 39% of the organic farms, including the homesteads and 16% of the conventional farms are occupied with pineapple. They also seem to have fewer assets. However, the average organic household head received credit more often during the last five years, and stated a higher willingness to take risks in order to achieve success, as well as a greater openness to innovation.

Even though organic farming is supposedly more management intensive, organic farmers did not receive more training for improving farming techniques. The most likely reason is the lack of opportunities resulting from niche position of organic agriculture. Even with more labor needed for production, organic farmers more often recruit their workers from the family than hiring farm workers, which is reflected in the lower proportion of the production cost they spend on hired labor. Concerning location specific variables, organic farmers own a larger share of their land and grow pineapple on different soil types compared to conventional farmers. There is also a difference concerning the variety of pineapples planted: Organic farmers prefer Sugar Loaf, whereas conventional farmers favor Smooth Cayenne or MD2. To our knowledge this difference is caused by the buyers' preferences.

Of relevance to the adoption mechanism is the fact that organic farmers seem to have a stronger link to the local government and visit the capital more frequently. They are also more likely to have learned pineapple farming from friends or family members compared to in training courses or as laborers on large farms. Moreover, their certification process is more often organized by the farmer organization, compared to conventional farmers. The majority of farmers of both groups have been certified within the last two years and about 40 % have a written contract with an exporter, all others have an oral contract. The number of years that the farmers have been certified is slightly longer for organic farmers.

Descriptive Statistics of Economic Variables

Differences in economic characteristics of the farmers are presented in Table 2. Columns (2) and (3) of Table 2 show the average costs for each category per kilogram of pineapples. Kilogram is taken as a base factor instead of pieces to control for the fact that organic fruits are on average smaller than conventional fruits, they are on average 0.18 kg lighter than conventional fruit.

As expected, there are large differences in labor, equipment and input costs per Kg between organic and conventional pineapple production, and costs for land are similar for both groups. While organic farmers spent much more on labor - hired workers as well as household labor - conventional pineapple producers use more inputs and equipment[3]. We also observed that (not presented in the Table), organic farmers do not use any chemicals, and utilize very little organic fertilizers, spent a lot of time with manual removal of weeds and more often produce their own planting and mulching material, or exchange it with other farmers. Expenses for inputs like inorganic fertilizers, herbicides, fungicides and pesticides, as well as suckers (seedlings), are hence much higher for conventional farmers. In addition, they use chemicals to induce flowering more frequently (90% of conventional but only 30% of organic farmers) and spend more on plastic foil and safety equipment for their farm.

Certification costs are higher for conventional farmers, but in total they are small, because this Table shows only the part that the farmers themselves cover. A large part is often paid for by the exporter or a donor or NGO. Overall, these cost differences form the individual investment that each farmer makes in his production structure. For instance, for organic certification as such the farmer has to invest in certification, and potential changes in production.

Note that the production cycle on organic farms is on average longer than the production cycle on conventional farms, namely 18.72 month instead of 15.46 month. The different lengths of the production cycles do not affect the informative value of the returns on investment (ROI). However, it obviously affects other key figures such as yearly income from pineapple farming. The average ROI of certified organic farming is higher than of conventional farming, due to higher prices and lower production costs.

It is evident from Table 2 that conventional farmers sold 1.5 times as many pineapples as organic farmers. This is mainly because of the larger areas under conventional farming, as well as the higher yields obtained from this farming method.

As expected, export prices were in general higher than local prices for both groups. But organic pineapple achieved a price premium on both local and export markets, even though they were not marketed as certified locally. This suggests different marketing strategies by organic farmers, which seem to better match local preferences, a presumption for which we however do not have further information for verification. One hint is that the Sugar Loaf variety yielded the highest prices on the local (and export) market and was produced more frequently by organic than by conventional farmers.

Descriptive Statistics of Intensity of Agro-ecological Practice Use

To examine the impact of organic agricultural practices on the ROI we employ the framework proposed by Rigby et al (2001) to construct a variable that consists of the different organic cropping practices most relevant for pineapple production. The framework is based on a scoring system that range from 0 (technique not used) to 5 (highest frequency or intensity this technique was used, taking into account the type of material used). The practices considered include organic fertilizer, non-chemical weeding, mulching, manure, trash lines, infiltration ditches and crop rotation. The information on relevant practices was given by an agronomist and included in the questionnaire. Weeding seems to be an out of range at first sight; however it is very important in pineapple production. Since pineapple grow relatively small, apart from using herbicides or not, the weeding technique is relevant for soil water management and erosion control. Variables for organic pesticide use, cover crops, and leguminous residues use are zero when not used, and one when used[4]. All the variables were weighted according to the average importance of each practice for sustainability given by 13 Ghanaian agronomists. The variable used in the analysis (AGRECPRAC) was then constructed by adding up.

Table 3 shows the descriptive statistics for each method. Robustness checks were made by a) repeating the analysis without any weights and b) using an alternative weighting scheme which consisted in giving similar practice groups (fertilizers and fertilizing material, soil cover, and weeding and pesticides) the same overall weights, and c) by excluding weeding, since we cannot distinguish between weeding by hand (which is not strictly a sustainable practice) and weed prevention using e.g. beneficial organisms. For a), b) and c) all regressions were replicated.

Figure 1 presents kernel density estimates of the intensity of agro-ecological practices by the two categories of farmers. The estimates reveal that although conventional farmers also use sustainable farming methods, their intensity of use is generally less than that of their counterparts practicing organic farming. Moreover, it is clear from the results that there are hardly any organic farmers that do not employ these farming practices, whereas some conventional farmers never employed agro-ecological practices.

3 Conceptual Framework

The conceptual framework employed here is based on the assumption that farmers choose between adopting organic farming and practicing conventional farming. For analytical purposes, we assume here that farmers are risk neutral, and take into account the potential benefit derived from adopting organic farming or non-adoption in the decision making process. Farmers are therefore assumed to choose the technology that provides maximum benefits. Under these assumptions, let us represent the net benefits farmer i derives from adopting the technology as D_{iA} and the net benefits from non-adoption represented as D_{iN}. These two regimes can be can be specified as

$$D_{iA} = Z_i\beta_A + u_{iA} \quad (1)$$

$$D_{iN} = Z_i\beta_N + u_{iN} \quad (2)$$

Where $Z_i$is a vector of variable factor prices, fixed factors, as well as farm and household characteristics; β_A and β_N are vectors of parameters; u_{iA} and u_{iN} are iids. The farmer will normally choose the organic technology if the net benefits obtained by doing so are higher than that obtained by not choosing the technology, that is $D_{iA} > D_{iN}$.

The individual preferences of the farmers are normally unknown to the analysts, but the characteristics of the farmer and the attributes of the technology under consideration are observed during the survey period. Given the available information, net benefits can be represented by a latent variable D_i^*, which is not observed, but can be expressed as a function of the observed characteristics and attributes, denoted as Z, in a latent variable model as follows:

$$D_i^* = \beta Z_i + \mu_i, \quad D_i = 1[D_i^* > 0] \tag{3}$$

where D_i is a binary indicator variable that equals 1 for household i, in case of adoption of the technology and 0 otherwise, β is a vector of parameters to be estimated, Z_i is a vector of household and plot-level characteristics as defined earlier, and μ_i is an error term assumed to be normally distributed. The probability of adoption can then be expressed as

$$\Pr(D_i = 1) = \Pr(D_i^* > 0) = \Pr(\mu_i > -\beta Z X_i) = 1 - F(-\beta Z X_i)$$

(4)

where *F* is the cumulative distribution function for μ_i.

Impact of organic farming on agro-ecological practices

As indicated earlier, the intensity of use of agro-ecological practices vary between organic farm practices and conventional farm practices. To capture the effects of the different farm practices on the use of agro-ecological farm methods, we employ a specification from the impact assessment literature on outcomes to participation choice. Specifically, we hypothesize that adoption or non-adoption of organic technology, positively influences the use of agro-ecological farm practices. This may be expressed as

$$Y_i = X_i\beta + \delta D_i + \varepsilon_i \tag{5}$$

where Y_i represents the intensity of agro-ecological practices and D_i is the adoption dummy; X_i is a vector of farm-level and household-level characteristics, such as age and education of farmer, access to credit, social network variables, farm size, and soil quality variables. The coefficient δ in the specification captures the impact of adoption on the use of agro-ecological practices. The issue of self-selection is crucial here because the decision of households to adopt or not to adopt organic farming may be associated with the net benefits of adoption.

Selection bias arises if unobservable factors influence both the error term of the technology choice, μ_i, in equation (13) and the error term of the outcome specification (ε_i), in equation (5), resulting in correlation of both error terms. When the correlation between the two error terms is greater than zero, OLS regression techniques tend to yield biased estimates. To address these issues, we employ an endogenous switching regression model (ESR) to jointly examine the determinants of adoption and the impact of adoption on the intensity of agro-ecological practice use[5].

The parametric approach of the endogenous switching regression (ESR) model goes back to Lee (1978) and Maddala (1983), and accounts for self-selection and systematic differences across groups. Outcome equations are specified differently for each regime, conditional on the adoption decision, which is estimated by a probit model. Thus, if we define Y_{iA} and Y_{iN} as the intensity of agro-ecological practices for organic and non-organic farmers, we can specify the outcome equations as:

$$Y_{iA} = X_i'\beta_A + \xi_{iA} \quad \text{if } D_i = 1 \tag{6}$$

$$Y_{iN} = X_i'\beta_N + \xi_{iN} \quad \text{if } D_i = 0 \tag{7}$$

Although self-selection based on observables is taken into account in the above specification, unobservable factors could still create a correlation between μ_i and ξ_{iA}, ξ_{iN}.The endogenous switching regression model treats the sample selectivity problem as a missing variable problem, which can be estimated and plugged into the equations (6) and (7). Thus, after estimating a probit model in the first stage, the Mills ratios λ_0 and λ_1 and the covariances $\sigma_{\mu A} = Cov(\mu\xi_A)$ and $\sigma_{\mu N} = Cov(\mu\xi_N)$ can be computed and employed in the following second stage specification:

$$Y_{iA} = X_i'\beta_A + \sigma_A\lambda_{iA} + u_{iA} \quad \text{if } D_i = 1 \tag{8}$$

$$Y_{iN} = X_i'\beta_N + \sigma_N\lambda_{iN} + u_{iN} \quad \text{if } D_i = 0 \tag{9}$$

In these equations, the error terms u_{iA} and u_{iN} have conditional zero means. Following Lokshin and Sajaia (2004) we use the full information maximum likelihood method (FIML) to estimate this model, i.e. the selection equation and the outcome equations are estimated simultaneously.

When the correlation coefficients of μ and ξ_A ($\rho_{iA} = \sigma_{\mu A}/\sigma_{\mu}\sigma_A$) and of μ and ξ_N ($\rho_{iN} = \sigma_{\mu N}/\sigma_{\mu}\sigma_N$) are significant, the model has an endogenous switch, i.e. selection on unobservables is substantial. The coefficients obtained from the endogenous switching regression model can be employed to derive the average treatment effect (ATT) τ_{ATT}^{ESR} as:

$$\tau_{ATT}^{ESR} = E(Y_{iA}|D=1) - E(Y_{iN}|D=1) = X'(\beta_{iA} - \beta_{iN}) + (\sigma_{\mu A} - \sigma_{\mu N})\lambda_1 \qquad (10)$$

4. Empirical Results

4.1. Empirical Results for Adoption

The full information maximum likelihood estimates of the determinants of adoption of organic farming, as well as the impact of adoption on the intensity of use of agro-ecological practices are presented in Table 4. As mentioned earlier, identification of the model requires that there is at least one variable in the selection equation that does not appear in the outcome equation. The variable representing relation to the local government is used as identifying instrument, and as such dropped from the outcome equations. Quite interesting is the insignificance of the correlation coefficients presented in the Table. This finding indicates the absence of any endogenous switch, suggesting that there is no substantial selection on unobservables.

The selection equation, which can be interpreted as probit estimates of determinants of adoption generally indicate that farm-level and household characteristics do influence adoption decisions of farmers. The estimates of the impact of adoption on the intensity of use of agro-ecological practices show that the farm-level and household characteristics influence the behavior of adopters and non-adopters differently. In particular, education and wealth appear to have positive and significant effects on organic farmers using more agro-ecological practices, while no significant effect is observed for conventional farmers. Land ownership also appears to influence the intensity of use by organic farmers, but not by conventional farmers. Similarly, the number of years being certified positively and significantly influences the intensity of agro-ecological practices by organic farmers, but exerts a negative, *albeit* insignificant effect on conventional farmers.

The estimates for the average treatments effect (ATT), which shows the impact of organic certification on the use of agro-ecological practice was computed with equation (10). The results are presented in the first row in Table 5. Unlike the mean differences in the use of agro-ecological practices shown in Table 3, the ATT estimate accounts for selection bias arising from the fact that adopters and non-adopters may be systematically different. The estimated ATT is positive and highly significant, suggesting that organic certification does indeed act as a catalyst for the increased use of agro-ecological practices. Specifically, organic certification moves the farmer up 15-20% on the full range of possible intensities, or by about 80% taking the overall mean use as a reference point. It is interesting to note that when asked directly for changes in production methods after certification, 67% of organic and only 35% of conventional households claimed to have changed their use of agro-ecological practices. The robustness of the ESR is checked by estimating the same model, but using the three other specifications described in section 3.2. The estimates, which are also reported in the Table 5, also confirm the positive and highly significant impact of organic certification on the intensity of agro-ecological practices.

Given the absence of any endogenous switch, we also employed propensity score matching (PSM) approach to compute the ATT and compare with those from the ESR. PSM is basically a technique that mimicks an experiment *ex post*. The results, which are presented in the lower part of Table 5, show that the ATT ranges between 4.07 and 4.23, depending on the matching algorithm used. Overall, the results confirm the positive and significant impact of organic certification on the intensity of agro-ecological practices. The matching quality test conducted with the Rosenbaum and Rubin (1985) test shows that differences in the means of the covariates between the two groups vanish after matching. The sensitivity of the estimates to unobservables was also tested with the Rosenbaum (2002) bounds. Based on kernel matching, the critical value of $\Gamma(\Gamma^*)$ =1.35 indicates that the ATT would still be significant even if matched pairs differ in their odds of certification by the factor 1.35.

4.2. Impact of Intensity of Agro-ecological Practice Use on ROI

In this section, we examine the impact of agro-ecological practices on the return on investment (ROI), in order to ascertain whether using these practices tend to affect the economic viability of the farm. Given that the intensity of agro-ecological practices is a continuous variable, we employ the generalized propensity score (GPS) approach developed by Hirano and Imbens (2004). Thus, the analysis in this section considers the treatment variable as a continuous variable, and not a dichotomous decision variable as was assumed in the previous analyses.

In line with GPS approach, equation (5) can be re-specified as $Y_i = f(X_i T_i)$, where Y_i refers to the return on investment and T_i is the actual level of agro-ecological practice of the farm. Of significance is the average dose response function (DRF), which relates to each possible treatment level t_i, the unbiased potential outcome $Y_i(t)$ of the farmer i:

$$\theta(t) = E[Y_i(t)] \ \forall \ t \ in \ T \quad (11)$$

where θ represents the DRF. In line with Hirano and Imbens (2004), we presume that the assignment to the treatment is weakly unconfounded given the controls, i.e.

$$Y_i(t) \perp T_i \,|\, Y_i(t) \ \forall \ t \ in \ T \quad (12)$$

Thus, the treatment assignment process is supposed to be conditionally independent of each potential outcome, given the control variables. Hence, there is no systematic selection into specific levels of agro-ecological practice intensity caused by unobservable characteristics (Flores et al., 2009). Weak unconfoundedness implies that this independence only has to hold for each level of treatment t but not jointly for all potential outcomes. The generalized propensity score (GPS) suggested by Hirano and Imbens (2004) is defined as the conditional probability of a particular treatment given the observed covariates. When $r(T_i, X_i) = f_{T \perp X}(t \perp x)$ is the conditional density of potential treatment levels given specific covariates, then the GPS of a household i is given as $R_i = r(T_i, X_i)$. The GPS is a balancing score, i.e. within strata with the same value of $r\,(t, X)$ the probability that $T = t$ does not depend on the covariates X_i. Given this balancing property and weak unconfoundedness, Hirano and Imbens (2004) show that using the GPS to remove the selection bias allows the estimation of the average DRF of equation (11).

In the first step the conditional expectation of the outcome as a function of treatment T and GPS R is estimated as

$$\beta(t, r) = E(Y|T_i = t, R_i = r) \tag{13}$$

Then, the DRF at each level of treatment can be estimated by averaging the conditional expectation over the GPS at that treatment level:

$$\theta(t) = E[\beta(t, r(t, X_i))] \tag{14}$$

In our application, the GPS is estimated using a normal distribution of the logarithmic treatment given covariates X_i. The validity of the assumed normal distribution is assessed using the Kolomogorov-Smirnov test for normality. We followed Hirano and Imbens (2004) and took the logarithm of the treatment variable, because the distribution of the agro-ecological practices was skewed. This procedure yielded low skewness (0.090) and kurtosis (1.698) values and a positive Kolmogorov-Smirnov test for normality at the 5% level of significance. The balancing property of the estimated GPS is tested by employing the method proposed by Hirano and Imbens (2004). The common support condition, i.e. that households in one group have to match with comparable households in other treatment groups, is imposed by employing the method suggested by Flores et al. (2009). After estimating the GPS, the

DRF is estimated using a flexible polynomial function as in Bia and Mattei (2008). The average potential outcome at each treatment level is estimated using a quadratic approximation of the treatment variable and a linear one for the GPS. The specification is estimated using OLS regression for the ROI. Confidence bounds at 95% level are estimated using the bootstrapping procedure.

Results of Generalized Propensity Score Matching

The treatment variable is AGRECPRAC as indicated previously. The results of the maximum likelihood estimation of the GPS, which are presented in Table A.1 in the appendix, are not discussed here, since the estimates only serve to balance the observed distribution of covariates across the treated and untreated groups (Hirano and Imbens, 2004). It is however interesting to note that as in the regressions in the previous section, the organic certification dummy is again highly significant in the probit regression. Balancing tests indicate that the GPS has quite well balancing properties, i.e. the GPS eliminates bias in the estimates of the dose-response function[6]. Regarding the common support condition, 278 farmers were on support, which represents 87% of the initial 311 farmers for which we have sufficient data to calculate the ROI.

Figure 2 shows the dose response function of the impact of the use of agro-ecological practices on the return on investment in pineapple farming[7]. There is a non-linear hook shaped relationship, whereby the effect on the ROI is positive, but in different ways at different levels. The impact if high at very low levels of agro-ecological practice use, but declines at higher levels of use, before rising again, with increasing intensity. It is significant to note that in our analysis, a low level of the index implies very little use of agro-ecological practices and even a high level is still low compared to developed country agriculture. At the lowest point, the estimated ROI is just below the mean of the sample (2.265). While the impact of using agro-ecological practices is overall positive, relatively low and relatively high levels appear to perform better in terms of rate of return than a medium level of agro- ecological practice intensity. This implies that the motivation to increase the use may be low when farmers are unaware of the shape of this impact curve or have a high discount rate into the future. A look at the kernel density estimates in Figure 1 shows that most farmers are exactly in this impact dip.

To gain further insights into the differential behavior of the farmers, we also examined the composition of agro-ecological practices used at different intensities. Specifically, we divided the sample into several equally sized groups, according to the AGRECPRAC variable, involving those below and above the low impact dip. It was observed that at low levels of intensity, the average farmer restricts the use very few practices and first starts to use them more intensively, before adding different practices. Noteworthy is the fact that it is not the potentially costly organic fertilizers and pesticides that are used significantly less in the low-use groups, but rather manure, animal mulch, and cover crops. Since the farmers stated that they know what each practice is, the problem cannot be attributed to lack of information or knowledge, but rather economies of scale in transport cost.[8]

Robustness Checks

The large confidence bands at the ends of the distribution in Figure 2 suggest that the impacts are less clear among the non-users and the very intensive users. We therefore conducted a robustness check in which we excluded values of AGRECPRAC of over 13. The result obtained is shown in Figure A.1 in the appendix. It is slightly different at high values, with no flattening out, with the predicted impact higher at the right end. However, the shape of the curve, which is of primary interest, remains the same. As a further robustness check, we use different specifications of the agro-ecological practice index. The results, which are are presented in Figures A.2 (different weights described in section 3.2), A.3 (no weights), and A.4 (weeding excluded) in the appendix appear to be similar to the findings presented in Figure 2.

5 Concluding Remarks

Some concerns have been raised that organic certification and sustainable farming practices are insufficiently linked on farms in developing countries. Most farmers certified as organic producers have therefore been considered to be producing organic-by-default, with very little or no use of productivity-enhancing inputs and soil-improving measures, often resulting in low yields and unsustainable production.

In this paper we examine the impact of organic certification on the intensity of agro-ecological practice use, as well as the return on investment of such practices, using recent farm-level data from the Greater Accra and Central regions in Ghana. Our empirical results show that organic certification increases agro-ecological practice use, suggesting that certification already serves as a catalyst for the use of agro-ecological practices.

The estimates of the economic impacts of agro-ecological practices generally reveal a positive and nonlinear relationship between the rate of return and the intensity of agro-ecological practice use, indicating that more intensive use of agro-ecological practices is economically beneficial for farmers. This finding suggests that from an environmental policy perspective this link needs to be strengthened considerably, since the intensity of agro-ecological practice use is overall quite low. The low level of use is probably because of the nonlinear relationship, which suggests economic benefits at low levels and high levels. However, farmers need to surmount a low impact gap to attain high levels, including availability of organic material and high transport costs for organic material. Given that external inputs from cocoa production and juice factories are normally available for use, but at prohibitive transport costs for individual farmers, government agencies or certification agencies could organize intermediates to fill this gap by purchasing these organic materials from juice factories and cocoa producers and selling to farmers. Certification may therefore help ease the problem through high prices on the produce and the support by buyers.

Moreover, certification systems could also require the active use of organic soil fertility management methods to increase their intensity of use.

Overall, such a strategy could provide an alternative sustainable development strategy for parts of the rural population. If successfully managed, organic certification for the dominantly small farmers in Africa may provide two types of economic benefits. It may reduce rural poverty by providing market access and higher profits through a combination of high prices and better or more resilient yields, and it may provide environmental benefits for the local economy in the long term.

References

Abadie, A. and G.W. Imbens (2008). On the failure of the bootstrap for matching estimators. *Econometrica*, 76 (6), pp. 1537-1557.

Barham, B.L. and J.G. Weber (2012). The Economic Sustainability of Certified Coffee: Recent Evidence from Mexico and Peru. *World Development*, 40 (6), pp. 1269-1279.

Beuchelt, T. and M. Zeller (2011). Profits and poverty: Certification's troubled link for Nicaragua's organic and fairtrade coffee producers. *Ecological Economics*, 70 (7), pp. 1316-1324.

Bia, M. and A. Mattei (2008). A Stata package for the estimation of the dose response function through adjustment for the generalized propensity score. *The Stata Journal,* 8 (3), pp. 354-373.

Blackman, A. and M.A. Naranjo (2010). Does Eco-Certification Have Environmental Benefits? Organic Coffee in Costa Rica. Resources for the Future Discussion Paper, November 2010.

Bolwig, S., P. Gibbon, and S. Jones (2009). The Economics of Smallholder Organic Contract Farming in Tropical Africa. *World Development*, 37 (6), pp. 1094-1104.

Branca, G., N. McCarthy, L. Lipper, and M.C. Jolejole (2011). Climate Smart Agriculture: A Synthesis of Empirical Evidence of Food Security and Mitigation Benefits from Improved Cropland Management. FAO Working paper.

Caliendo, M. and S. Kopeinig (2008). Some Practical Guidance For The Implementation Of Propensity Score Matching. *Journal of Economic Surveys*, 22 (1), pp. 31-72.

Calo, M. and T.A. Wise (2005). Revaluing Peasant Coffee Production: Organic and Fair Trade Markets in Mexico. Global Development and Environment Institute Tufts University.

Diao, X. and D.B. Sarpong (2007). Cost Implications of Agricultural Land Degradation in Ghana. IFPRI Discussion Paper 00698.

Erenstein, O. (2002). Crop residue mulching in tropical and semi-tropical countries: An evaluation of residue availability and other technological implications. *Soil and Tillage Research*, 6 (2), pp. 115-33.

Flores, C.A., A. Flores-Lagunes, A. Gonzalez, and T.C. Neumann (2009). Estimating the Effects of Length of Exposure to Training Program: The Case of Job Corps. Working Papers 2010-3, University of Miami, Department of Economics.

Food and Agricultural Organization of the United Nations (FAO) (2011). Socio-economic analysis of conservation agriculture in southern Africa. Network Paper 2, FAO Rome.

Food and Agricultural Organization of the United Nations Statistics (FAOSTAT) (2011). Economic Growth Center Discussion Paper 984.

Ghana Export Promotion Council (GEPC) (2010). Ghana Pineapple Export Declines. Available at: http://www.gepcghana.com/news.php?news=196&pnm=Ghana Pineapple Export Declines, 11/29/2011.

Government of Ghana (2010). Medium-term national development policy framework: Ghana shared growth and development agenda, 2010-2013. Volume 1, Policy Framework.

Hirano, K. and G.W. Imbens (2004). The Propensity Score with Continuous Treatments. In: A. Gelman and X.-L. Meng (Eds.): *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives*. West Sussex, England: Wiley InterScience.

International Trade Center (ITC) (2011). The Impacts of Private Standards on Producers in Developing Countries. Literature Review Series on the Impacts of Private Standards, Part II, Geneva.

Kassam, A., T.Friedrich, R. Derpsch, R. Lahmar, R. Mrabet, G. Basch, E. Gonzalez-Sanchez, and R. Serraj (2012). Conservation agriculture in the dry Mediterranean climate. *Field Crops Research*, 132, pp. 7-17.

Kersting, Sarah and Meike Wollni (2012). New institutional arrangements and standard adoption: Evidence from small-scale fruit and vegetable farmers in Thailand. *Food Policy*, 37, pp. 452–462.

Kleemann, L. (2011). Organic Pineapple Farming in Ghana - A Good Choice for Smallholders? Kiel Working Paper 1671, Kiel Institute for the World Economy, Germany.

Knowler, D. and B. Bradshaw (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy*, 32 (1), pp. 25-48.

Lee, L.-F. (1978). Unionism and Wage Rates: A Simultaneous Equations Model with Qualitative and Limited Dependent Variables. *International Economic Review*, 19 (2), pp.415-433.

Lokshin, M. and Z. Sajaia (2004). Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, 4 (3), pp. 282-289.

Maddala, G.S. (1983). Limited-dependent and qualitative variables in econometrics. Cambridge University Press, Cambridge.

Ninan, K.N. and J. Sathyapalan (2005). The economics of biodiversity conservation: a study of a coffee growing region in the Western Ghats of India. *Ecological Economics*, 55 (1), pp. 61-72.

Philpott, S.M., P. Bichier, R. Rice, and R. Greenberg (2007). Field-Testing Ecological and Economic Benefits of Coffee Certification Programs. *Conservation Biology*, 21 (4), pp. 975–985.

Pretty, J.N., A.D. Noble, D. Bossio, J. Dixon, R.E. Hine, F.W.T. Penning de Vries, and J.I.L.Morison (2006). Resource-Conserving Agriculture Increases Yields in Developing Countries. *Environmental Science and Technology*, 40 (4), pp. 1114–1119.

Rigby, D., P. Woodhouse, T. Young, and M. Burton. (2001). Constructing a farm level indicator of sustainable agricultural practice. *Ecological Economics*, 39, pp. 463–478.

Rosenbaum, P.R. and D.B. Rubin (1985). Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *The American Statistician*, 39 (1), pp. 33-38.

Rosenbaum, P.R. (2002). Observational Studies. Springer, New York.

Suzuki, A., L.S. Jarvis, and R.J. Sexton (2011). Partial Vertical Integration, Risk Shifting, and Product Rejection in the High-value Export Supply Chain: The Ghana Pineapple Sector. *World Development*, 39 (9), pp. 1611-1623.

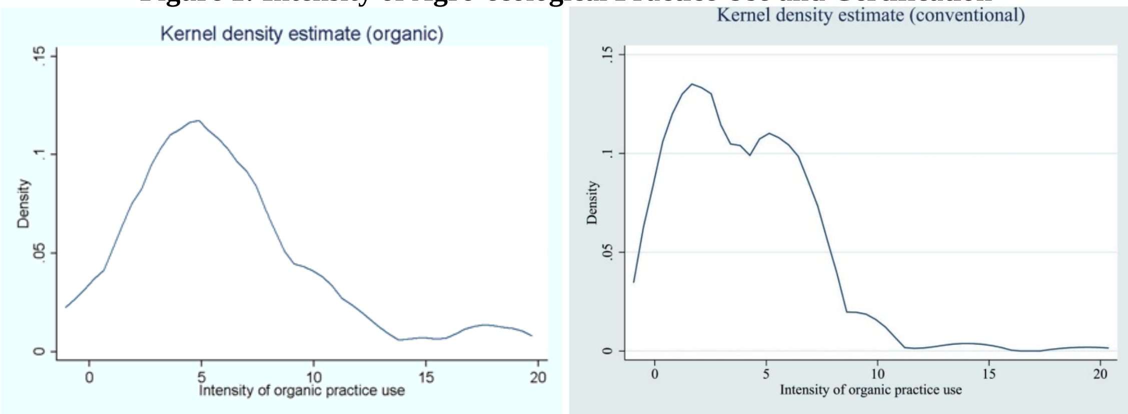
Valkila, J. (2009). Fair Trade organic coffee production in Nicaragua - Sustainable development or a poverty trap? *Ecological Economics*, 68, pp. 3018-3025.

Wollni, M., D.R. Lee, and J.E. Thies (2010). Conservation agriculture, organic marketing, and collective action in the Honduran hillsides. *Agricultural Economics*, 41 (3-4), pp. 373–384.

World Development Indicators (WDI) (2011). The World Bank.

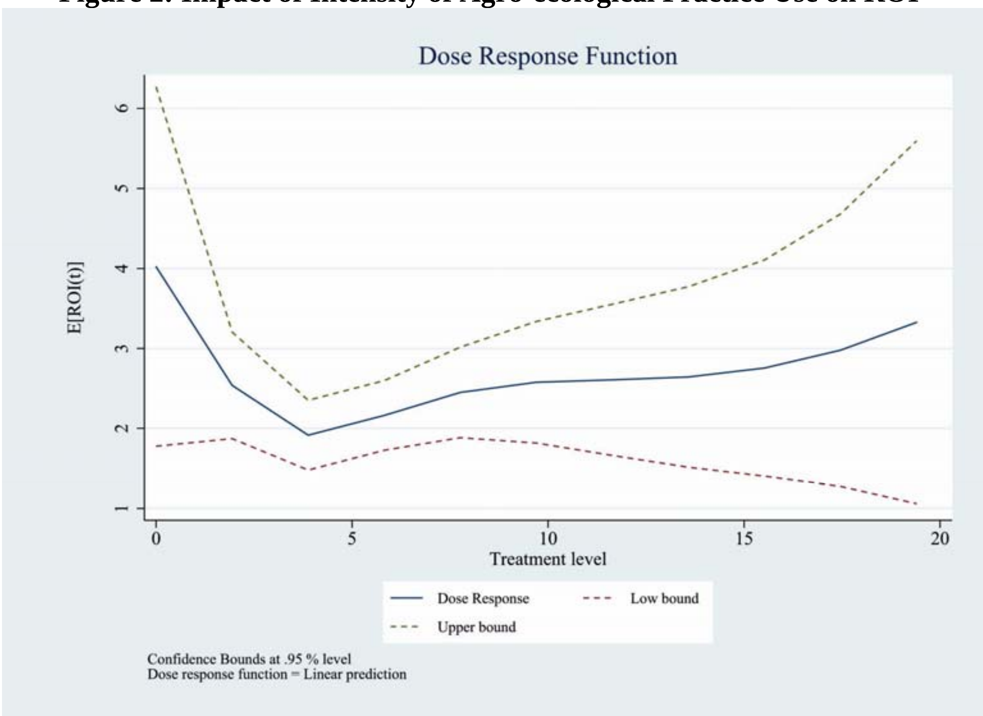
Figures and Tables

Figure 1: Intensity of Agro-ecological Practice Use and Certification



Source: own estimation.

Figure 2: Impact of Intensity of Agro-ecological Practice Use on ROI



Source: own estimation.

Table 1: Descriptive Statistics of Variables Included in the Estimations

Definition	Variable	Organic Farmers (N=185)	Convent. Farmers (N=201)	t-Stat.
Gender of household head (HHH) =female, 1=male	GENDER	0.891	0. 982	-3.51***
Age of HHH	AGE	46.313	42.970	2.82***
Household size (persons living in household)	HHSIZE	5.23	5.917	-2.35**
Fraction of adults in household (older than 15) (%)	ADULT	0.684	0.665	0.75
Being native in community 0=no, 1=yes	NATIVE	0.738	0.738	-0.01
Maximal educational level in household 1=none, 2=primary school, 3=junior secondary, 4=senior secondary, 5=technical/vocational training, 6=tertiary/university	EDUC	9.470	10.195	-3.19***
Farm size (acre)	FSIZE	10.35	18.720	-5.02***
Share of land owned	OWNLAND	0.549	0.204	7.628***
Pineapple land (acre)	PINLAND	4.014	3.066	2.07**
Access to credit during the last 5 years 0=no, 1=yes	CREDIT	0.317	0.232	1.78*
Bank account with more than 200 GHS 0=no, 1=yes	BANK	0.339	0.512	-3.21***
Number of durable goods owned	WEALTH	4.765	8.481	-10.875***
Relation to the local government 1=none, 2=HHH knows someone in the local government, 3=HHH has friends in the local government, 4=strong relation/politically active	GOVERN	2.257	1.774	4.27***
Self-stated openness to innovation and risk (factor analysis: the stronger the agreement, the higher the factor)	RISK	0.152	-0.166	3.01***
Years of experience in pineapple farming	EXPER	11.557	11.595	-0.05
How pineapple farming was learned				
from family members and friends 0=no, 1=yes	LEARN 1	0.863	0.501	7.97***
as a laborer on a farm or from 0=no, 1=yes	LEARN 2	0.071	0.286	-5.51***
Importance of preserving the environment 1= very important, ..., 4= not important	ENV	1.775	1.281	6.91***
Number of years being certified	CERTIFYEARS	3.165	2.032	3.875***
Distance to the closest local market (hours)	DIST	0.698	0.804	-1.59
Soil characteristics 1=red or black sandy, 2=white sandy, 3=white rocky, 4=rocky red or black, 5=sandy or rocky clay, 6=clay, 7=other	SOIL	2.781	2.304	2.13**
Smooth Cayenne	SC	0.098	0.351	-5.99***
Sugar Loaf	SL	0.634	0.036	15.06***
Share of production cost for (of total labor costs) hired workers	HIRED	0.484	0.607	-3.13***
Assistance or training for farming received during last 5 years 0=no, 1=yes	ASSIST	0.732	0.708	0.50
Number of farm inspection during the last 5 years	INSPECT	1.913	2.619	-0.94
Written contract with exporter 0=no, 1=yes	CONTR	0.410	0.417	-0.13
Organizer of the certification process 0=else than farmer organization, 1=farmer organization	ORGA	0.508	0.143	7.84***

Significance levels: *: 10% **: 5% ***: 1%.

We use a conversion factor of 1 GHS = 0.46 Euros (calculated on the basis of the exchange rate on January 12, 2012).

Table 2: Descriptive Statistics of Economic Variables

Variable	Organic Farmers	Conventional Farmers	t-Stat.
Agricultural equipment	0.002	0.009	-2.77 ***
Agricultural inputs	0.011	0.077	-5.97 ***
Renewal of certification	0.000	0.006	-4.27 ***
Land used for pineapple	0.004	0.004	-0.004
Hired workers	0.037	0.019	3.77 ***
Household labor	0.034	0.009	5.68 ***
Yield (pineapple per acre)	15780	18259	-4.11 ***
Quantity sold (in Kg)	23486	36235	-2.81 ***
Average local price (GHS per Kg)	0.210	0.131	8.50 ***
Average export price (GHS per Kg)	0.251	0.196	5.40 ***
Share sold on local market	0.495	0.354	3.00 ***
Revenue (GHS per Kg)	0.219	0.170	5.80 ***
Production costs (GHS per Kg)	0.105	0.118	-0.94
Profits (GHS per Kg)	0.114	0.052	4.01 ***
ROI	2.760	1.800	3.11 ***

We use a conversion factor of 1 Ghana Cedi (GHS)=0.46 Euros. The t-statistic belongs to the mean difference test between column (2) and (3). Significance levels: *:10% **:5% ***:1%

Table: 3 Descriptive Statistics of Agro-Ecological Practices

Variable	**Organic Farmers** (N=176)	**Conventional Farmers** (N=168)	**t-Statistics**
Organic fertilizer	2.164	0.030	8.288***
Organic fertilizer	2.164	0.030	8.288***
Organic pesticides	0.083	0.082	-0.032
Mulch	1.590	1.328	5.294***
Manure	1.998	0.912	3.543***
Weeding	2.410	2.327	0.566
Cover crops	0.175	0.161	0.353
Crop rotation	0.980	0.132	6.343***
Trash lines	2.932	1.043	9.451***
Infiltration ditches	1.066	0.721	1.979**
Leguminous residues	0.066	0.018	2.217**

Significance levels for the t-statistics of the mean difference test: *: 10% **: 5% ***: 1%

Table 4: Estimation results of ESR for Impact of Organic Certification on Agro-ecological Practice Use

Variable	Selection Eq.		Organic farmers		Convent. farmers	
	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
	(1)	(2)	(3)	(4)	(5)	(6)
GENDER	-0.122	0.513	0.173	0.101	1.769	0.597
AGE	0.004	0.018	-0.006	0.023	-0.056**	0.024
NATIVE	-0.151	0.275	0.443	0.513	0.401	0.399
RISK	0.306***	0.095	-0.133	0.207	0.135	0.196
HHSIZE	-0.058	0.052	-0.146	0.099	-0.068	0.071
EDUC	-0.094*	0.059	0.323**	0.096	0.135	0.286
WEALTH	-0.296***	0.090	0.397***	0.142	0.138	0.089
FSIZE	-0.012	0.010	-0.006	0.012	0.0001	0.011
OWNLAND	0.586**	0.236	1.051**	0.558	0.927	0.827
EXPER	0.034	0.032	0.020	0.036	0.024	0.033
LEARN1	0.829**	0.597	1.053	1.146	-0.774	0.440
LEARN2	-0.537**	0.217	0.357	1.387	-0.223	0.530
DIST	-0.341**	0.164	-0.130	0.405	-0.947**	0.373
SOIL	0.008	0.058	-0.316***	0.1281	-0.268***	0.085
ORGA	1.403***	0.218	-1.232*	0.665	0.828	0.747
ENV	1.431***	0.325	-1.423***	0.412	0.038	0.388
GOVERN	0.445***	0.164				
BANK			-0.468	0.558	0.403	0.497
CREDIT			-0.526	0.466	-0.239	0.487
VARIETYMD2			2.550***	0.989	-0.128	0.396
HIRED			-0.569	0.821	0.452	0.578
INSPECT			-0.113	0.026	0.074**	0.029
CONTR			1.154**	0.543	-0.083	0.380
CERTIFYEARSNO			0.299**	0.141	-0.203	0.457
INTERCEPT	1.038	0.985	1.027	1.347	3.455**	1.754
ρ_{1D}			-0.320	0.466		
$ln\sigma_1$			0.916***	0.070		
ρ_{0D}					0.260	1.048
$ln\sigma_0$					0.744***	0.104
Log-Likelihood: -993.143						
Wald test of indep. eqns.: $\chi^2(2)$ = 3.69***						

Significance levels for the t-statistics of the mean difference test: *: 10% **: 5% ***: 1%

Table 5: Results of Impact of Organic Certification on Agro-ecological Practice Use

Method	Predicted Use of certified	Predicted Use of non-certified	ATT	t-Statistic
ESR				
Organic certified farmers	5.921	2.518	3.403	13.314***
Conventional farmers	8.135	3.788		
Alternative Specifications				
ESR using different weights				
Organic certified farmers	6.102	3.046	3.056	11.465***
Conventional farmers	7.979	3.594		
ESR using no weights				
Organic certified farmers	5.986	2.136	3.851	12.258***
Conventional farmers	8.115	3.266		
ESR (weeding excluded)				
Organic certified farmers	5.728	2.667	3.061	10.894***
Conventional farmers	7.934	3.363		
PSM				
Kernel (bandwidth=0.4)	6.751	2.680	4.071	7.98***
Radius (caliper=0.05)	6.751	2.523	4.228	7.34***
Nearest-neighbor	6.751	2.351	4.400	6.98***

Significance levels for the t-statistics of the mean difference test: *: 10% **: 5% ***: 1%

For PSM, standard errors are calculated with bootstrapping using 1000 replications. Bootstrapping of standards errors is necessary because the estimated variance does not include the variance that may appear due to the estimation of the propensity score and the imputation of the common support assumption (Caliendo and Kopeinig (2008)). Even though Abadie and Imbens (2008) criticism the use of bootstrapping for the nearest-neighbor algorithm, its application is still common practice.

Appendix

Table A.1: Estimation Results of Generalized Propensity Score

Variable	Coefficient	Std. Err.
Equation 1		
ORGANIC	0.165***	0.026
GENDER	0.050	0.052
AGE	-0.005**	0.002
RISK	0.019	0.048
HHSIZE	-0.041***	0.018
EDUC	0.101**	0.079
FSIZE	0.003**	0.001
OWNLAND	0.283***	0.096
EXPER	0.042*	0.021
LEARN1	-0.101*	0.060
LEARN2	0.108*	0.074
DIST	-0.152	0.135
ORGA	-0.126	0.114
SOIL	-0.112***	0.022
WEALTH	0.165***	0.071
ENV	0.266**	0.170
INTERCEPT	0.935***	0.149
Equation 2		
INTERCEPT	0.31***	0.014

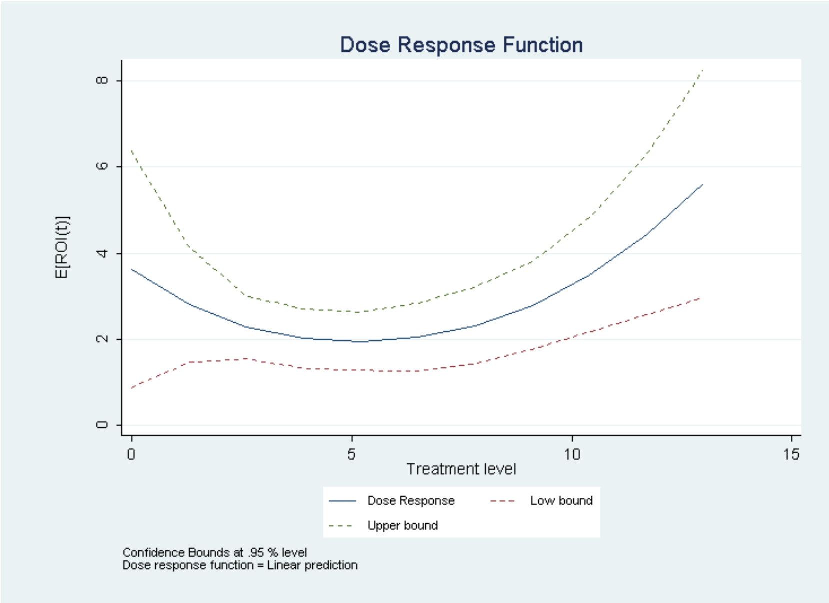
Significance levels for the t-statistics of the mean difference test:*: 10% **: 5% ***: 1%

Table A.2: Estimation Results of the Coefficients of the Dose Response Function

Variable	Coefficient	Std. Err.
T	-0.305**	0.121
T^2	0.019***	0.004
GP S	-3.252**	1.401
T * GP S	0.385	0.259
INTERCEPT	4.638***	1.251

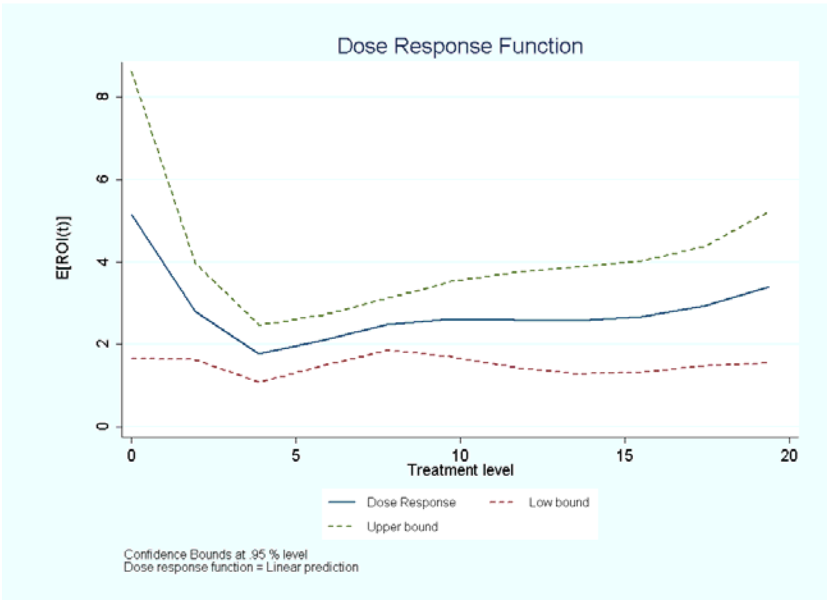
Significance levels for the t-statistics of the mean difference test:*: 10% **: 5% ***: 1%

Figure A.1: Impact of Intensity of Agro-ecological Practice Use on ROI (restricted to values lower than 13)



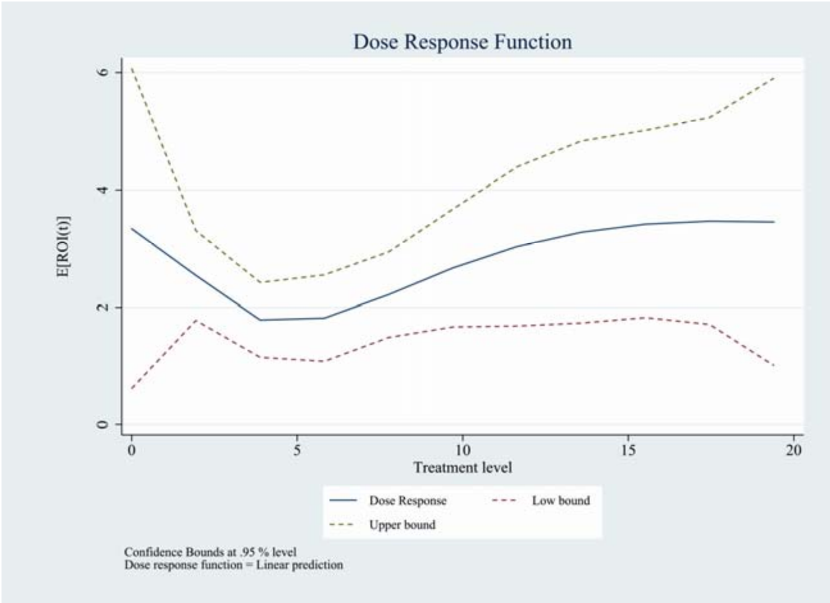
Source: own estimation.

Figure A.2: Impact of Intensity of Agro-ecological Practice Use on ROI (different weights for agro-ecological practices)



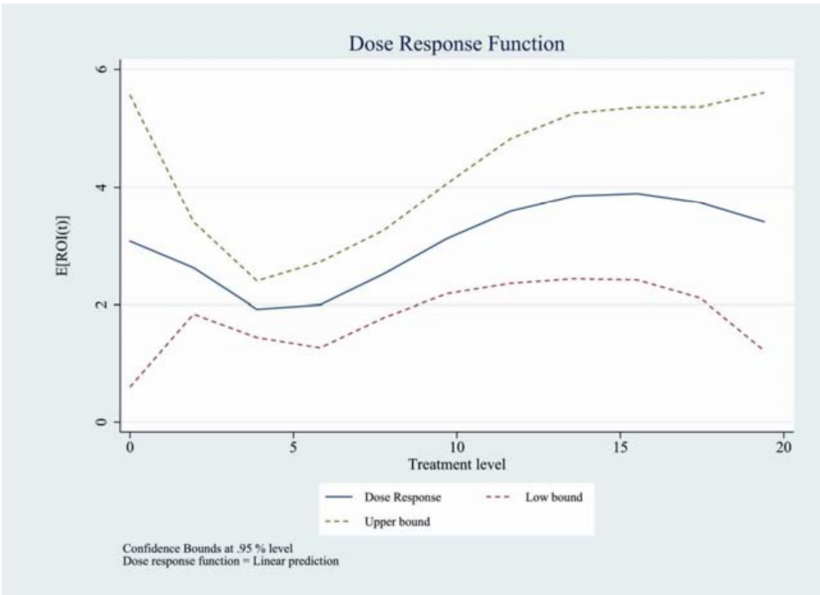
Source: own estimation.

Figure A.3: Impact of Intensity of Agro-ecological Practice Use on ROI (no weights)



Source: own estimation.

Figure A.4: Impact of Intensity of Agro-ecological Practice Use on ROI (weeding excluded)



Source: own estimation.

Notes

[1] Source: http://www.organic-world.net/statistics-data-tables-dynamic.html.

[2] Ajumako Enyan Esiam, Akuapem South, Ewutu-Efutu-Senya, Ga, Kwahu South and Mfantseman.

[3] We are aware that measurement errors are frequent in measuring agricultural inputs and outputs in developing countries. However, when farmers in both groups are sufficiently similar in their sociodemographic characteristics we can assume that measurement errors do not significantly differ between farmers.

[4] In these cases either it was logical to pose the question with a yes/no option only, as in the case of cover crops or the quality of the data retrieved from the survey did not allow the division into frequency of use, as in the case of organic pesticides and leguminous residues.

[5] The unbiased treatment effect is hard to measure because, when treatment is non-random as in our case, untreated individuals may differ systematically because of self-selection into treatment. A popular approach to avoid biased results is to randomize treatment. In our case randomization over which farmers use which agro-ecological methods is impossible to realize because all the methods in question are already common or widely known by the farmers. The underlying treatment is not a development intervention, but the outcome of various interventions in a longer time horizon.

[6] For testing the balancing property of the GPS, the treatment variable was divided into 4 intervals with cut-off points at 25%, 50%, etc. Without adjusting for the GPS, t-tests of mean difference between the intervals revealed that 14 t-tests were significant at the 5% level, after dividing into 4 intervals and conducting block-wise t-tests this number was reduced to 2. We repeated the analysis with more intervals, namely 7, which did not affect our conclusions, but the number of observations in each interval becomes quite small, so the results are weaker.

[7] The estimated quadratic dose response function regression is shown in Table A.2 in the appendix. All GPSM regressions were also repeated with net farm income as impact variable. Due to the low investment level of the farmers, the results did not change significantly. Therefore the results are omitted here, but are available upon request from the authors.

[8] When the farm is strongly specialized in pineapple, mulching material and manure cannot be produced on the farm (see also e.g. Branca et al., 2011). The required material is often available at no or low cost, but needs to be transported to the farm. Since this material is relatively bulky, transport costs can impede their use in case of lack of cash, or if their perceived benefits are lower than the effort of organizing and paying for their transport.