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Is Organic Farming Worth its Investment?
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Abstract

Global food markets demand the adoption of food standards by small-scale farmers in developing countries when they enter international markets. While a conventional certification with GlobalGAP can be a market entry condition for conventional food, especially for horticultural products, organic certification is required for the growing organic food market that is usually associated with higher prices. This study analyzes the adoption and profitability of organic certified farming, using recently collected farm-level data of 386 Ghanaian pineapple farmers. We employ an endogenous switching regression model to examine the adoption and impact of organic certification on the return on investment (ROI). The empirical results indicate that both organic certification and GlobalGAP certification result in a positive ROI. However, organic certified farming yields a significantly higher ROI than GlobalGAP certified farmers, mainly due to the price premium on the organic market. Thus, certified organic farming is found to be the more profitable venture.

Keywords: return on investment, impact assessment, organic agriculture, GlobalGAP certification, contract farming

JEL codes: O13, Q13, Q17, Q56

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1 Introduction

A number of interesting trends have emerged in the global food markets over the last two decades. First, the restructuring of global food value chains and the increasing importance of private voluntary standards (PVS) driven by the trend towards stricter food safety and traceability standards in the major importing countries (Henson et al., 2011; Suzuki et al., 2011) have led to the marginalization of small-scale developing country producers and favored large scale plantations (e.g. Jaffee et al., 2011). Several PVS have responded by introducing group certification options for small farmers, to help enhance their integration into the global food market (Subervie and Vagneron, 2013). Second, during the same period of time, a horticulture industry has emerged in Sub-Saharan Africa (SSA), facilitated by diversification policies and the demand for tropical vegetables and fruit all year round by consumers in higher-income countries. Within the agricultural sector, horticulture may provide an opportunity for small-scale farmers, because of its labor intensity and high production value per unit.

Third, the demand for organic food has been increasing over this period. According to a report of the United Nations Conference on Trade and Development, worldwide organic food markets expanded by 10-15% in the last ten years, whereas conventional markets only grew by 2-4% (UNCTAD, 2008). In Europe, the market has grown from 10.8 billion to 18.4 billion Euros between 2004 and 2009 (FiBL, 2009). This is particularly significant because export crops are traditionally treated with pesticides to assure the required quality. Hence, the increasing significance of organic food exports will help mitigate the adverse impacts of high pesticide use and may also contribute to sustainable production by reducing land degradation, soil pollution, and soil erosion. To the extent that organic certified food benefits from higher prices, relative to conventional food and also provides access to new fast growing high-end markets, it attracts new classes of investors (UNEP, 2007). Thus, organic certification could contribute to poverty reduction by helping to improve the incomes of smallholders engaged in this sector, as well as environmental sustainability through environmentally friendly production methods.

A well-known example in the fresh produce trade is the certification by GlobalGAP, which was created by a consortium of European retailers in 1997. Although it is based on a framework of Good Agricultural Practices (GAP) that aims at ensuring compliance with public food safety requirements, it also covers other issues including employment practices, worker safety and traceability (Subervie and Vagneron, 2013). Retailers normally require that their suppliers are GlobalGAP certified, which virtually makes it a precondition for export of horticultural produce to many European and North American countries (Henson et al., 2011). By contrast, organic certification meets the rising demand for organic products and also acts as substitute for GlobalGAP certification. Requirements of organic certification concentrate on guaranteeing consumers that the products they buy fulfill organic production standards. In the EU the regulations (EC) 834/2007 and (EC) 889/2008 control the production, processing and trade of organic products. Organic certified pineapples from Africa receive a positive price premium on the European market (Kleemann, 2011).

Several studies have analyzed the impact of these certifications on small-scale farmers in developing countries. Many of the studies tend to focus on organic, GlobalGAP and Fairtrade certifications, with a large number of them dealing with coffee, and often Fairtrade and organic overlap.[1] Most researchers find modest positive impacts of different certifications on household welfare, using different measures (see e.g. literature reviews by Blackman and Rivera, 2010; ITC, 2011; and papers by Asfaw et al., 2009; Valkila, 2009; Bolwig et al., 2009; Fort and Ruben, 2009; Henson et al., 2011; Maertens and Swinnen, 2009, Subervie and Vagneron, 2013). Some other studies remain skeptical about the ability of organic and Fairtrade to help poor farmers because of access barriers, ambiguous effects on yields, or price premiums that may be too small to compensate for investment costs (Valkila, 2009; Beuchelt and Zeller, 2011; Lynbæk et al., 2001). Although the yield potential is estimated to be high on non-ideal tropical soils (Kassie et al., 2008; and others), in fact yields are often lower on organic farms in these countries (Beuchelt and Zeller, 2011; Lynbæk et al., 2001; Valikila, 2009), and the reduced dependence on potentially expensive external inputs is replaced by a reliance on the export market for price premia (Lynbæk et al., 2001).

Most of the past studies examined the impact of certification on yields, prices receives, farming practices, or welfare measures such as household income, without accounting for the investment in the certification and its requirements (e.g., Bolwig et al., 2009; Kassie et al., 2008; Subervie and Vagneron, 2013). In this study, we examine the impact of organic certification on the return on investment (ROI), accounting for production costs and include direct and indirect certification costs. The ROI is an indicator that takes into account the fact that farmers operating as entrepreneurs do not concentrate on improving farm income, but also consider the profitability of their investment (Udry and Anagol, 2006; Asfaw et al., 2009; Barham and Weber, 2012). We utilize recently collected farm-level data of 386 Ghanaian pineapple farmers from the Central, Eastern and Greater Accra regions of Ghana in the empirical analysis.

The study employs two different export-market oriented certification channels, which are organic certification and GlobalGAP certification. As pointed out by Bolwig (2009), it is essential to distinguish between the effects of contract farming, export market participation and certifications. This is because certification usually goes hand in hand with contract farming and export market participation. Most non-contracted farmers produce only for the local market, with the quality of their products differing from those produced for exports (Asfaw et al., 2009; Blackman and Rivera, 2010). Our analysis focuses on export markets and considers the effects of organic certification compared to GlobalGAP certification. From a development perspective, this analysis will attempt to investigate the extent to which organic certified farming offers new possibilities to farmers in contrast to export oriented conventional certified farming.

Our study also differs from previous studies in terms of the empirical strategy. We employ an endogenous switching regression approach to account for selectivity bias based on both observable and unobservable factors, and to capture the differential impact of organic certification on both adopters of organic certification and GlobalGap certification. The approach thus allows us to examine the determinants of adoption of the organic certification, as well as the impact of the adoption decision on return on investment from organic certification and GlobalGAP certification. We also employ propensity score matching method, which accounts only for observables, to examine the robustness of the results.

The rest of the paper is structured as follows: Section 2 gives an overview of the development of the pineapple sector in Ghana. This is followed by a description of the data used in the analysis. Section 3 presents the conceptual and empirical framework. The empirical strategy employed to estimate the effect of organic certification is then explained in section 4, while section 5 discusses the estimated results. Conclusions and implications are discussed in the final section.

2 The pineapple sector in Ghana

Exports of horticultural products have experienced substantial growth over the past three decades, with fresh fruits and vegetables now contributing significantly to the growth of the agricultural sector in the country. Pineapples were the first non-traditional export crop that Ghana produced in the 1980s. As shown in Figure 1, pineapple exports increased rapidly from the mid-1980s until 2004, after which a decline in exports set in. The decline resulted from a shift in the pineapple variety demanded on global markets from Smooth Cayenne to the MD2 variety (FAO, 2009). The market share of Ghanaian pineapple on the European market fell from 10.5% in 2003 to 5.2% in 2006. Many farms stopped producing pineapple, or went bankrupt, while others switched to the MD2 variety. Subsequently, alternative pineapple industry strategies such as processing of Smooth Cayenne and Sugar Loaf evolved in importance. The latter variety is usually produced for the local market.[2] It is estimated that about 40.000 tons of pineapple were exported from Ghana in 2010 (Figure 1).

Pineapple farming in Ghana is mainly located in 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 sector is dualistic in structure, with few large/medium-sized producers, and many small-scale farmers, who sell their fruits on the local market or as out-growers to an exporter, processor or large farm for export. The focus of the present study is on producers for the export sector. Pineapple export in Ghana is predominantly organized by export companies or processor, of which many also have own farm production. About 40% of all exported pineapples come from smallholders (UNCTAD, 2008; personal information given in interviews with the Ghana Export Promotion Council and the Sea Freight Pineapple Exporters of Ghana (SPEG)). The relationship between exporter and smallholder is usually oral, or based on written contract (Suzuki et al., 2011). Some exporters provide farm inputs like pesticides and herbicides, extension services or credit.

3 Data

The data employed in the present study come from a farm household survey that was conducted from January to March 2010 in six different districts (Ajumako Enyan Esiam, Akuapem South, Ewutu-Efutu-Senya, Ga, Kwahu South and Mfantseman) 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 commercial smallholder pineapple production were selected, using information from SPEG. Next, lists of all pineapple farmer groups in the selected districts that were GlobalGAP or organic certified were obtained. Finally, a percentage of farmers in each group was selected randomly from the lists. Identified household heads answered a detailed questionnaire on the household's management of the pineapple farm, inputs into the pineapple production, harvesting and marketing of the pineapples, the certification process, and relations with exporters. Respondents were also made to provide information on household characteristics, social capital and land disposition, as well as non-income wealth indicators and perceptions of different statements about environmental values, organic farming techniques and the use of fertilizers and pesticides[3].

The dataset includes 386 households from 75 villages with either GlobalGAP or organic certification for their pineapple farms. In total, 185 organic farmers and 201 conventional (GlobalGAP) certified farmers were interviewed. Organic farmers sold part of their produce as organic certified to exporters or processors and part of it on the local market, without any reference to the certification. Conventional farmers sold their produce as certified to exporters or processors and on the local market, without reference to GlobalGAP certification. In principle, 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, our sample differs in the sense that it is not possible for conventional farmers to sell on the export organic market. Organic certification refers to the European standards according to EU regulation (EC) 834/2007 and (EC) 889/2008. In view of the fact that all conventional farmers are GlobalGAP certified in our sample, we simply refer to them as conventional farmers in the study.

All sociodemographic variables that are included in the estimations are presented in Table 1. The average pineapple farmer in our sample has a similar income compared to the average in Ghana (country average is 88.83 GHS per month, survey average: highest density in income groups 51-150 GHS per month). Organic farming household heads are on average older and less educated than conventional farm households. They also have smaller farms, but these are more specialized in pineapple farming. About 39% of the farm land of organic farmers including the homestead and 16% of the conventional farms are used for pineapple cultivation. With higher labor costs in production, organic farmers more often recruit their workers from the family, which is reflected in the lower proportion of the production cost they spend on hired labor.

Compared to conventional farmers, organic farmers own a larger share of their land and grow pineapple on different soil types[4]. It was also observed that organic farmers tend to prefer Sugar Loaf, whereas conventional farmers favor Smooth Cayenne or MD2.

Their social relations are also different. For instance, they are more likely to have learned pineapple farming from friends or family members compared to in training courses, or as laborers on other farms. The person from who a farmer learned pineapple farming may influence attitudes towards certain technologies or farming practices greatly and over long time. On average, they also have a stronger link to the local government and visit the capital more frequently for private purposes. Moreover, their certification was more often organized by the farmer organization, instead of buyers or aid agencies as with conventional GlobalGAP certification. Note that this variable indicates who the farmers perceived as the ones responsible for organizing this process, which is not necessarily the same that financially supported it.

Total costs of production do not differ significantly between organic and conventional farming, but the structure of the production costs is quite different[5]. Columns (1) and (3) of Table 2 show the average costs of pineapple production per Kg pineapples. The different cost composition of organic and conventional production costs is obvious from columns (2) and (4) of Table 2, which summarize the percentages attributed to each cost category.

On average, both initial and yearly certification costs are higher for conventional farmers (Table 2). These are however not actual costs, but the part the farmers themselves cover. Moreover, the fact that all the farmers that were interviewed are part of a group certification process, the costs involved tend to be much lower than r individual certification costs.. The initial certification costs include investments in equipment and training that are required. Time spent in training is taken into account with 4 GHS/day, as done with household labor. The percentage of initial costs for training is much higher for organic farmers, namely 59%, while it is about 25% for conventional farmers. A detailed composition of initial certification costs is shown in Table A.2. The mean amortization shown in Table 2 reveals that it is about 3.5 times higher for conventional farmers, amounting to one third of the first production cycle's profits, than for organic farmers, where it is less than one tenth[6].

Table 2 also summarizes the mean values of variables that determine the ROI of one production cycle. Note that the production cycle on organic farms is on average longer than the one on conventional farms, namely 18.72 month instead of 15.46 month. The different lengths of the production cycles do not impair the informative value of the ROI, but obviously affect other key figures such as yearly income from pineapple farming. It should be noted that the data are calculated on the basis of per kilogram (Kg) instead of pieces to control for the fact that organic fruits are on average 0.18 Kg lighter than conventional fruits. The quantity of pineapples considered for the ROI is the amount of sold pineapples excluding those that were wasted on the field (on average 4.85% for conventional and 3.19% for organic farmers respectively) and those that were self-consumed, self-processed or given away as a gift, on average 2.78% and 3.86% for organic and conventional farmers respectively.

Table 2 shows that conventional farmers sold 1.5 times as many pineapples as organic farmers, a result of larger areas planted and higher yields. As expected, export prices were in general higher than local prices for both groups. However, organic pineapple achieved a price premium on both local and export markets, even though they were not marketed as organic certified locally, pointing towards different marketing strategies by organic farmers. The Sugar Loaf variety yielded the highest prices on the local and export markets and was produced more frequently by organic than by conventional farmers. Conventional pineapple farmers sold mostly Smooth Cayenne and MD2. For an overview of the prices for each variety see Table A.1.

Organic farmers benefited from producing Sugar Loaf on both local and export markets. Conventional farmers produced mainly pineapple varieties that are more specialized on the mass export market, and also sold a greater fraction of their harvest to exporters. Given that organic pineapples benefit from a price premium, and the production costs between organic and conventional pineapples do not differ significantly, average profits per Kg tend to be higher for organic pineapples, resulting in relatively higher return on investment.

4 Conceptual Basis and Empirical Specification

Organic certification is assumed to be a binary choice in which the producer weighs up the expected net utility from organic certification against the one of conventional certification. This choice between organic and conventional (GlobalGAP) certification is conditional on the decision to target the export market, i.e. it refers to the question among the group of exporters which type of export market to target, conventional or niche market. The adoption decision can then be viewed as a standard binary choice problem that is based on the maximization of an underlying utility function.

If we let D_{1i}^* represent the expected utility derived from organic certification (adoption), and D_{0i}^* the expected utility derived from getting GlobalGAP certification (non-adoption) of an individual $\mathrm{i}(\mathrm{i} = 1, \ldots, \mathrm{N})$ of an observed population of size *N*, then the difference between the expected utilities of the two certifications $D_i^* = D_{1i}^* - D_{0i}^*$ reveals the choice made by the individual. The actual level of utility of each farmer cannot be observed, but can be represented by the observed choice D_i where $D_i(D_i \in \{0, 1\})$ is a dummy variable, with $D_i = 1$ being attributed to the treatment, i.e. adoption and $D_i = 0$ to non-adoption:

$$\begin{aligned} &D_i^* = Z_i'\alpha + \epsilon_{D_i} \\ &D_i = 1 \quad \text{if} \quad D_i^* > 0 \\ &D_i = 0 \quad \text{if} \quad D_i^* \leq 0 \end{aligned} \tag{1}$$

where D_i^* depends on a vector of observable variables Z and an error term ϵ_D, with mean zero variance σ_D^2 .

The probability of adoption can then be expressed by:

$$Pr(D_i = 1|Z_i) = Pr(D_{1i}^* > D_{0i}^*) = Pr(D_i^* > 0) = F(Z_i'\alpha) \quad (2)$$

where F is the cumulative distribution function of ϵ_D.

As indicated earlier, we are only interested in the adoption decision, but also the impact of adoption on the return on investment (ROI). The ROI, a widely used relative profitability performance measure, is for a single investment:

$$\text{ROI}= \frac{\text{Profit}}{\text{Investment}}$$

where investment in our case is the investment in the specific farming type including the certification. The advantage of the ROI compared to other measures such as net income is that it relates the profit to the farmer's investment decision and consequently indicates how well the available assets have been used. The ROI presents the results of one period, in our case one crop cycle[7].

The relationship between adoption and the outcome variable *Y* can be expressed as:

$$Y_i = f(X_i;\, D_i) \quad (3)$$

where X is a vector of exogenous variables, and D is the dummy for certification.. If Y_{D_i} is the outcome variable of individual *i* as a function of the adoption status D, Y can take two forms, Y_{1i} and Y_{0i}. An issue of significance in impact assessment is that of selection bias. Thus, when treatment is non-random, untreated individuals may differ systematically because of self-selection into treatment and at best the average treatment effect on the treated (ATT) can be estimated.

The ATT is defined by the following equation (Caliendo and Kopeinig, 2008):

$$\tau_{ATT} = E[Y_1|D = 1] - E[Y_0|D = 1] \quad (4)$$

where τ denotes the treatment effect, in this case the ATT and E[.] represents an expected value operator.

Given that randomization is not possible in our case, we employ quasi-experimental techniques to correct for selection bias in estimating treatment effects. Selection bias caused by observables such as farm size can normally be controlled for with regression techniques. However, when selection is based on unobservable factors that simultaneously influence the adoption decision as well as the outcome variable (e.g. ability, risk aversion, trust), or discrimination by firms or NGOs as indicated in Bellemare (2012) and Barrett et al. (2012) this will result in an omitted variables problem. We can account for these points when the data is sufficiently rich. For instance, firms are likely to discriminate on the basis of observables that are potentially also available to the researcher and we conducted interviews with most of the exporting firms and farmer organizations to verify that selection is based on available data such as farm size and did not differ between organic and conventional firms. Since both our control and treatment groups are exporting farmers from the same region, they are a more homogeneous population that in previous studies. Many of the unobservable factors mentioned in the literature are assumed to apply in the same, or a very similar way to both groups, such as entrepreneurship, risk preferences, and trustworthiness (Barrett et al., 2012; Blackman and Rivera, 2010)[8].

We employ the endogenous switching regression model (ESR henceforth) to account for selection bias from both observable and unobservable factors. The ESR (Lee, 1978 and Maddala, 1983) is a parametric approach that uses two different estimation equations for organic and conventional farmers while controlling for the selection process by adding the inverse Mills ratio that is calculated via a selection equation in a first step, i.e. sample selectivity is treated as a missing value problem. The outcome equations are disposed differently for each regime conditional on the adoption decision, which is estimated by a probit model. Previous impact evaluations as for example Fuglie and Bosch (1995) and Abdulai and Binder (2006) have used an endogenous switching regression model to estimate the effect of different technology adoptions in agriculture.

Given the adoption and outcome equations in (1) and (3), respectively, the two regimes for adoption and non-adoption can be specified as

$$Y_{0i} = X_i'\beta_0 + \epsilon_{0i} \qquad \text{if} \quad D_i = 0 \tag{5}$$

$$Y_{1i} = X_i'\beta_1 + \epsilon_{1i} \qquad \text{if} \quad D_i = 1 \tag{6}$$

where Y_0, Y_1 define the outcomes of interest separately for the two regimes of adopting and of not adopting the technology, and $\epsilon_{0i}, \epsilon_{1i}$ are the error terms Self-selection based on observables is thereby taken into account but unobservable factors could create a correlation between ϵ_D and ϵ_0, ϵ_1. To solve this problem, the Mills ratios λ_0 and λ_1 are derived and the equations are transformed into the following specification:

$$Y_{1i} = X_i'\beta_1 + \sigma_{1D}\lambda_{1i} + u_{1i} \qquad \text{if } D_i = 1 \tag{7}$$

$$Y_{0i} = X_i'\beta_0 + \sigma_{0D}\lambda_{0i} + u_{0i} \qquad \text{if } D_i = 0. \tag{8}$$

where $\sigma_{0D} = cov(\epsilon_0, \epsilon_D)$ and $\sigma_{1D} = cov(\epsilon_1, \epsilon_D)$. In these equations the error terms u_{0i} and u_{1i} have conditional zero means. Following Lokshin and Sajaia (2004) we use the full information maximum likelihood method (FIML) to estimate this model. In this framework, the selection (probit) equation and the outcome equations are estimated simultaneously.

When the correlation coefficients of ϵ_0, and ϵ_D of ϵ_1 and ϵ_D ,ρ_{0D} and ρ_{1D} are significant, the model has an endogenous switch. The signs of ρ_{0D} and ρ_{1D} can also be interpreted economically. Alternate signs signal that the individuals have adopted the technology according to their comparative advantages. When ρ_{0D} and ρ_{1D} have the same sign this implies “hierarchical sorting”, i.e. adopters have an above-average return compared to the non-adopters independent of the adoption decision (Fuglie and Bosch, 1995; Maddala, 1983).

The ATT τ_{ATT}^{ESR} in this case is:

$$\tau_{ATT}^{ESR} = E(Y_1|D = 1) - E(Y_0|D = 1) = X'(\beta_1 - \beta_0) + (\sigma_{1D} - \sigma_{0D})\lambda_1. \tag{9}$$

The literature on technology adoption offers some guidance on the potential influence exogenous variables that may be included can have on farmers’ adoption decisions. Previous studies have shown that exporting farmers and certified farmers alike are younger, more innovative, better educated, better connected, wealthier and have larger farms (Bolwig et al., 2009; Kerstin and Wollni, 2012). Given that this study compares two certifications, we try to differentiate according to farming type within the group of exporting farmers. The farmers’ decision to enter the export market is the precondition for each of the two certifications and we are thus left with characteristics that differ in their influence on the decision to apply for organic or conventional GlobalGAP certification respectively.

The variable ENV captures the stated level of importance that farmers attribute towards preserving the natural environment and thus an implicit preference for or against environmental friendly certifications more directly. Since organic cannot only be regarded as a technology, but also as an ideological question, the attitudes of farmers towards environmental protection and chemical use may play a significant role in the choice.

A larger household may generally be more beneficial for organic farming with its higher labor requirements, when manual labor is not readily available in the region under scrutiny. Furthermore, according to Fort and Ruben (2009) low education measured here as the maximal number of years of formal education present in the household, may be a hindrance to standard adoption when record keeping requirements are high. Since they are less sophisticated for the organic standard compared to the GlobalGAP standard, the former may attract farmers with lower levels of education.

Since GlobalGAP requires a larger investment than organic certification (see Table 2), and a larger part of it is in equipment, which potentially leads to economies of scale, larger farms (FSIZE) are expected to be more likely to invest in GlobalGAP certification beyond the decision to export (Kersting and Wollni, 2012; Kassie et al., 2008). Along the same lines wealthier farmers could be more likely to invest in GlobalGAP certification (WEALTH). Security of tenure rights is expected to be more important for organic farmers, which we measure directly through the share of the total farmland owned and indirectly through the connection to the local government and local authorities (Goldstein and Udry, 2008)[9]. Another proxy that covers a different aspect of tenure security is the length of the stay in the same village, which we approximate by a dummy on whether or not someone is native to the community. Distance to major markets is usually a relevant factor for certification (e.g. Fort and Ruben, 2009; Kassie et al., 2008). Since in our case all farmers export through Accra airport or Tema harbor, distance to alternative local markets, is considered to be more relevant.

Since ENV captures the implicit preference for or against environmental friendly production standards, this makes it a suitable candidate for the exclusion restriction, because it is correlated with the certification decision but has certainly no influence on the ROI. The selection equation of the endogenous switching regression model needs an exclusion restriction to avoid collinearity, because the covariates included in the selection equation enter the second stage estimation twice, non-linear through the inverse Mills ratio and linear as a coefficient for the ROI. ACCRA, the frequency of visits to the capital, is a second potential exclusion restriction. This variable measures private (as opposed to farm-related) visits to the capital and therefore forms part of the social environment of the farmer, which in turn shapes his beliefs. These beliefs in turn influence the adoption decision, but should not influence the ROI. We captured farming related information exchange in the variables covering training, inspection, and contacts to other farmers. Some of the variables used in the selection equation are potentially relevant for our outcome variable as well. For instance, following Bellemare (2012) higher education is expected to lead to higher returns through higher farm productivity. Age may have a nonlinear effect on productivity (Abdulai and Binder, 2006), while the distance to the next market may have an effect through lower transport costs or better access to inputs and information. Moreover, the use of the modern world-market variety could also be relevant, since it is more expensive to grow, but tends to yield relatively higher export prices.

5 Results

The results of the endogenous switching regression model are presented in Table 3. Columns (1) and (2) present the estimated coefficients and standard errors of the selection equation, while the outcome equations are presented in columns (3) to (5).

From the selection equation we can confirm that younger, higher educated, wealthier but more risk averse farmers with larger farms, but a lower share of own land to show preferences for GlobalGAP certification. Whereas experience does not play a significant role, how it was acquired appears to be important. This is probably because the decision to produce organically is partly a question of belief and farming values that are also transmitted during the learning process. In particular, learning from the family mostly involves learning more traditional ways of farming.

When the farmer organization organized the certification process organic certification is more likely. GlobalGAP certification is more often NGO induced, organic certification is more often farmer group supported. Organization by the farmer group may allow less educated farmers to participate in the standard adoption, reducing the influence of education[10]. Surprisingly, farmers producing non-organic pineapples appear to have a greater concern for preserving the environment. This is probably due to the fact that the term environment is normally not mentioned in organic certification training material, whereas it is specifically mentioned in non-organic certification training material. As expected, OWNLAND is positive and highly significant, indicating that farmers that own their land are more likely to invest in long-term measures, i.e. organic certification. Finally, GENDER, DIST, HHSIZE and GOVERN are insignificant, which shows that variables that have repeatedly been shown as highly important determinants of adoption of any standard may not be so relevant for the choice between different standards.

As indicated previously, the estimates in columns 3 to 5 show the impacts of the farm-level and household characteristics on the return on investment. The results show that some of the variables such as age, household size, access to credit, years of certification have the same signs in both outcome equations, while others such as native and experience have alternating signs. Thus, the variables with similar signs tend to exert the same impacts on both organic and conventional farmers, while those with alternating signs exert different impacts on the two categories. Specifically, wealth and savings exert a positive influence on conventional, but a negative influence on organic farmers. The positive sign on conventional farmers is expected, since production according to GlobalGAP standards requires higher capital investments. The negative and significant coefficient of the farm size variable for organic farmers suggest that for this group of farmers, larger farms obtained significantly lower returns of their investments compared to smaller farms. For conventional farmers, farm size did not significantly influence returns on investment. This finding supports the notion that smaller farms are more suitable for organic production.

The use of the MD2 variety results in significantly lower returns on investment for organic farmers, but does not appear to influence the ROI of conventional farmers. Both organic and conventional farmers benefit from a larger number of farm inspections. The results also reveal that organic farms are better off spending a larger part of their production cost on labor, whereas conventional farms should rather buy labor saving inputs, which clearly reveal the proclaimed comparative advantages of the two production techniques.[11]

Education loses its significance in the outcome equations, suggesting that education does that affect the returns to investment for both groups of farmers. It is further found that the larger the distance from the farm to the local market, the greater the ROI of conventional farmers. One possible explanation is that distance to the exporter-buyer, not the local market is relevant. Farmers that are far away from local markets, but along the main road, may benefit from better accessibility and lower land costs. The correlation coefficients ρ_{0D} and ρ_{1D} of the endogenous switching regression model are not significantly different from zero (last row of Table 3), and the Wald test of independent equations indicates that there is no significant correlation between the error terms of the selection and the regression equations. Therefore, the impacts of adoption can be calculated correctly, given their observed characteristics, i.e. there is no endogenous switch and unobservable factors do not significantly influence the certification decision.

The results from the ERS can be used to predict the ATT for adopters and non-adopters. The results are presented in Table 4. The ESR results in a significant positive impact of organic certification on the ROI of the small-scale pineapple farmers. Their ROI is on average 0.6 larger than it would be if they were GlobalGAP certified instead. The results illustrate that, while both organic and GlobalGAP certified pineapples farmers achieve a positive ROI, it is higher for organic farming. However, the production cycle on organic farms is on average longer than the production cycle on conventional farms. When boiled down to the same period, e.g. one year, the income from farming is about the same for organic and conventional farms, so that the starting point of being less wealthy than conventional farmers is not reversed.

Robustness Checks

First, the robustness of the ESR is checked by using different exclusion restrictions. The first one is using ACCRA instead of ENV, reported in detail in Table A.3. Further the following variations are made: using all possible combinations of ENV, WEALTH and ACCRA. The estimated ATTs then vary between 0.651 (when using ACCRA and ENV) and 0.986 (when using only WEALTH), i.e. the results are quite robust to changes in the exclusion restriction.

Second, because we find no significant influence of unobservable factors, we also test the robustness of the results, using a non-parametric technique that accounts for observables only, i.e. propensity score matching (PSM henceforth). Since there is no endogenous switch, the results should not change. PSM assumes selection on observables only, which is manifested in the conditional independence assumption (CIA), i.e. that potential outcomes are independent of the technology choice conditional on covariates Z.

The results are quite similar to the ones of the ESR explained above and will not be discussed in detail. The matching algorithms used are kernel matching with a bandwidth of 0.4, radius matching with a caliper of 0.05 and nearest-neighbor matching with different amounts of neighbors (the tables only display the results for four neighbors and kernel). The balancing property is satisfied with the underlying probit model used to generate the propensity scores (Table A.4). We use several methods to test the matching quality.

Rosenbaum and Rubin (1985) suggest that the differences in the means of the covariates between the two groups should vanish after matching. Table A.5 shows that t-tests result are insignificant after matching for all covariates except FSIZE. Next, the standardized bias before and after matching is shown in Table A.6. It is reduced by 70% from 27.67 to 8.19 when using the kernel algorithm. Since the balancing tests hold for the specified probit model, the ATT can be generated.

The results of the ATT for the PSM are shown in Table 4. They are slightly higher than the ATT generated by the ESR; they differ between 0.914 and 0.958 depending on the matching algorithm that was used[12]. We also perform several robustness checks for the PSM. Rosenbaum bounds were calculated to test the sensitivity of the results with respect to unobservable factors. The critical values of $\Gamma(\Gamma^{*})$ =1.3 (kernel) and 1.4 (nearest neighbor) indicate that the ATT would still be significant even if matched pairs differ in their odds of certification by the factor 1.3 or 1.4 respectively. As suggested by Dehejia (2005), higher ordered variables were also included in the base probit model to test for robustness of the results, but they results did not change much.

Then, we also used a weighted least squares regression (WLS), using the inverse of the propensity score as weighting scheme as proposed by Hirano and Imbens (2001), which again results in similar values for the ATT and similar values of the coefficients shown in Table A.8. The Table summarizes the estimated ATTs of PSM, ESR, WLS and OLS. The results reveal that the ATT estimates from WLS and OLS are a bit higher than the other approaches, which indicates that these methods tend to overestimate the ATT slightly. The most conservative estimate comes from our main model and still results in a significant positive impact.

6 Conclusions and Discussion

The role of certification in promoting farm incomes of smallholders and environmental sustainability in developing countries remains a contentious issue in the ongoing debate on the effects of globalization. This paper contributes to the empirical literature on the issue by examining the determinants of adoption and profitability of organic certified farming, using recently collected farm-level data of 386 Ghanaian pineapple farmers. We examined the returns to the investment in organic and GlobalGAP certification in our analysis. Both are worth their investment because they achieve on average a positive ROI, however organic certification is the more profitable option, i.e. the one with a higher ROI. The reason lies in the higher prices for organic fruit, which compensates for lower yields on organic farms. Employment effects are also likely to be higher for organic production, because this method is more labor intensive. This result is valid when we control for selection bias and single out the effect of certification vis-à-vis contract farming and exporting.

The results from the determinants of adoption of organic certification also reveal that relatively poorer, less educated households are more likely to produce organically. We show in this paper that they benefit from doing so. Hence, organic certification has the potential to reduce poverty and improve household welfare. This is a twofold positive result, because at the same time the demand for organic products is increasing faster than the demand for conventional food.

For development program designers this analysis shows that support for organic certification helps relatively poor farmers to profitably access export farmers, thus providing a development strategy for parts of the rural population. At the same time, given the longer production cycles and lower yield on organic farms, support for productivity improving organic management techniques could improve the results for organic farmers further.

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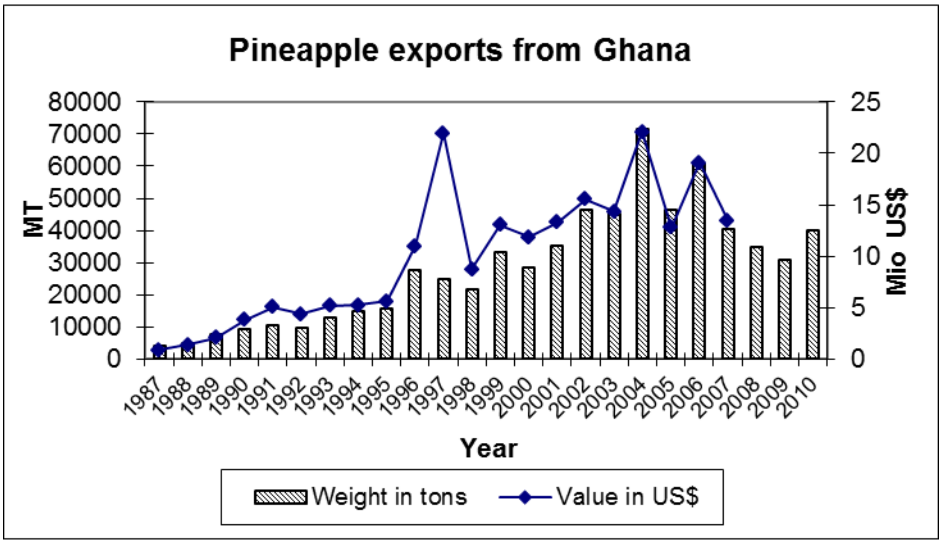
Tables and Figures

Figure 1: Volume and Value of Pineapple Exports from Ghana



Source: SPEG

Table 1: Descriptive Statistics of Variables Included in the Estimations

Variable	Definition	Organic Farmers (N=185)	Convent. Farmers (N=201)	t-Stat.
GENDER	Gender of household head (HHH) 1 if HHH is male, 0 otherwise	0.891	0. 982	-3.51***
AGE	Age of HHH	46.31	42.97	2.82***
HHSIZE	Household size (persons living in household)	5.230	5.917	-2.35**
ADULT	Fraction of adults (older than 15) in household	0.684	0.665	0.75
NATIVE	Being native in community (1 if yes, 0 otherwise)	0.738	0.738	-0.01
EDUC	Maximal educational level in household (years)	9.470	10.19	-3.19***
FSIZE	Farm size (acre)	10.35	18.72	-5.02***
OWNLAND	Share of land owned	0.549	0.204	7.63***
PINLAND	Pineapple land (acre)	4.014	3.066	2.07**
CREDIT	Access to credit during the last 5 years 1 if yes, 0 otherwise	0.317	0.232	1.78*
BANK	Bank account with more than 200 GHS 1 if yes, 0 otherwise	0.339	0.512	-3.21***
WEALTH	Number of durable goods owned	4.765	8.481	-*** 10.88
GOVERN	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	2.257	1.774	4.27***
RISK	Self-stated openness to innovation and risk (factor analysis: the stronger the agreement, the larger)	0.152	-0.166	3.01***
EXPER	Years of experience in pineapple farming	11.56	11.59	-0.05
	How pineapple farming was learned			
LEARN 1	from family members and friends (1 if yes, 0 otherwise)	0.863	0.501	7.97***
LEARN 2	as a laborer on a farm or from (1 if yes, 0 otherwise)	0.071	0.286	-5.51***
ACCRA	Frequency of being in Accra 1=never, 2=once, 3=at least once a year, …, 6=at least once a week	3.661	1.976	11.07***
ENV	Importance of preserving the environment 1= very important, ..., 4= not important	1.775	1.281	6.91***
CERTIF YEARS	Number of years being certified	3.165	2.032	3.88***
DIST	Distance to the closest local market (hours)	0.698	0.804	-1.59
SOIL	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	2.781	2.304	2.13**
MD2	Variety MD2 (1 if yes, 0 otherwise)	0.051	0.216	-7.12***
SC	Variety Smooth Cayenne (1 if yes, 0 otherwise)	0.098	0.351	-5.99***
HIRED	Share of labor cost for hired workers	0.484	0.607	-3.13***
ASSIST	Assistance or training for farming received during last 5 years (1 if yes, 0 otherwise)	0.732	0.708	0.50
INSPECT	Number of farm inspection during the last 5 years	1.913	2.619	-0.94
CONTR	Written contract with exporter (1 if yes, 0 otherwise)	0.410	0.417	-0.13
ORGA	Organizer of the certification process 1 if farmer organization, 0 otherwise	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, 2010).

Table 2: Descriptive Statistics of Production Costs and Revenues

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 ***
Initial certification costs (GHS)	70.497	444.116	-12.18***
Renewal of certification (GHS)	0.732	93.089	-6.16***
Amortization (years)	0.083	0.283	-3.28***

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: Estimation Results of ESR for Adoption and Impact of Adoption on ROI

	Selection Eq.		Return on Investment			
			Organic farmers		Convent. farmers	
Variable	**Coefficient** (1)	**Std. Err.** (2)	**Coefficient** (3)	**Std. Err.** (4)	**Coefficient** (5)	**Std. Err.** (6)
GENDER	-0.410	0.487	0.921**	0.452	-0.147	0.695
AGE	0.039**	0.014	0.004	0.015	0.057	0.023
NATIVE	-0.009	0.298	-0.424***	0.047	0.253	0.401
RISK	0.310**	0.111	0.130	0.207	-0.423*	0.242
HHSIZE	-0.044	0.045	-0.004	0.079	-0.025	0.065
EDUC	-0.414***	0.143	-0.218	0.164	-0.177	0.152
FSIZE	-0.018**	0.010	-0.048***	0.010	0.007	0.013
OWNLAND	0.764***	0.266	-0.061	0.387	0.712	0.639
GOVERN	0.177	0.128	0.198	0.185	-0.234	0.180
EXPER	-0.006	0.017	0.004	0.021	-0.048	0.031
LEARN1	0.297	0.415	-0.536	0.471	-0.088	0.514
LEARN2	-0.979***	0.488	-1.147	0.838	-1.025**	0.496
DIST	-0.266	0.221	0.069	0.195	0.859**	0.394
SOIL	0.168***	0.044	-0.052	0.075	0.099	0.112
ORGA	1.243***	0.341	-0.231	0.487	-0.856	0.697
WEALTH	-0.411***	0.087	-0.245*	0.113	0.097	0.056
ENV	0.502**	0.213				
BANK			-0.770**	0.354	0.807**	0.401
CREDIT			-0.193	0.354	-0.420	0.424
MD2			-2.143***	0.775	0.208	0.528
HIRED			0.512	0.524	-2.234***	0.464
INSPECT			0.054***	0.014	0.050**	0.024
CONTR			0.405**	0.219	-1.150***	0.436
CERTIFYEARSNO			-0.010	0.057	-0.287	0.248
INTERCEPT	2.899***	1.065	2.659**	1.327	2.712*	1.523
ρ_{1D}			-0.405	0.972		
$ln\sigma_1$			0.584***	0.081		
ρ_{0D}					0.438	0.419
$ln\sigma_0$					0.517***	0.112
Log-Likelihood:			-595.538			
Wald test of indep. eqns.:			$\chi^2(2)$ = 16.21***			

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

Table 4: Summary of Results ATT

Method	Predicted ROI of adopt.	Predicted ROI of non-adopt.	ATT	t-Statistic
ESR				
Organic farmers	2.412	1.732	0.6809	3.37***
Conventional farmers	-0.140	1.996		
ESR using ACCRA				
Organic farmers	3.111	1.212	0.899	4.97***
Conventional farmers	0.181	1.796		
Weighted Least Squares				
Organic farmers	3.967	2.677	1.113	5.69***
Conventional farmers	1.799	1.565		
OLS				
Organic farmers	2.662	1.282	1.180	5.92***
Conventional farmers	1.983	1.777		
	ROI of treated	**ROI of control group**	**ATT**	**t-Statistic**
PSM				
Kernel (bandwidth=0.4)	2.819	1.900	0.919	2.91**
Radius (caliper=0.05)	2.818	2.091	0.914	2.22**
Nearest-neighbor	2.818	1.861	0.958	2.04**

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

There are 125 adopters whose propensity scores lie within the common support region.

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) criticize the use of bootstrapping for the nearest-neighbor algorithm, its application is still common practice.

Appendix

Table A.1: Average Pineapple Prices (GHS per Kg)

Variety	Organic Farmers		Conventional Farmers	
	Local	Export	Local	Export
Smooth Cayenne	0.14	0.16	0.12	0.19
Sugar Loaf	0.22	0.28	0.24	0.21
MD2	0.10	-	0.14	0.20

Table A.2: Composition of Initial Certification Costs (in GHS)

Variable	Organic Farmers (N=142)		Conventional Farmers (N=111)		t-Statistic	
	(1)	(2)	(3)	(4)	(5)	
Certification	36.866	19.127 %	303.815	54.970%	8.44	***
Training	27.661	56.516%	51.171	25.834%	6.2	***
Equipment	9.394	22.622%	69.153	19.165%	12.70	***
Other	1.211	1.733%	0.108	0.031%	-0.86	

Significance levels: *: 10% **: 5% ***: 1%
Column (2) and (4) present the part of each cost category on the total initial certification costs of organic and conventional farmers. The t-statistic belongs to the test of difference in means of column (1) and (3).

Table A.3. Estimation Results of ESR using ACCRA

Variable	Selection Eq. Coefficient (1)	Std. Err. (2)	Organic farmers Coefficient (3)	Std. Err. (4)	Convent. farmers Coefficient (5)	Std. Err. (6)
GENDER	-0.457	0.487	0.872*	0.472	-0.029	0.751
AGE	0.042**	0.014	0.004	0.014	0.068	0.025
NATIVE	-0.289	0.308	-0.478***	0.038	0.302	0.384
RISK	0.208	0.134	0.117	0.170	-0.419*	0.246
HHSIZE	-0.085*	0.051	0.006	0.065	-0.069	0.083
EDUC	-0.378**	0.161	-0.225	0.177	-0.242	0.246
FSIZE	-0.018**	0.009	-0.040***	0.010	0.006	0.014
OWNLAND	0.769***	0.218	-0.054	0.412	0.669	0.688
GOVERN	0.200*	0.124	0.173	0.220	-0.331	0.281
EXPER	-0.023	0.018	0.005	0.022	-0.049*	0.027
LEARN1	0.471	0.302	0.367	0.481	-0.872	0.505
LEARN2	-0.881**	0.421	-0.866	0.838	-0.926*	0.504
DIST	-0.287	0.185	0.179	0.216	0.995**	0.402
SOIL	0.136**	0.077	0.022	0.075	0.093	0.114
ORGA	1.711***	0.645	-0.533	0.515	-0.790	0.668
WEALTH	-0.403***	0.067	-0.167	0.118	0.007	0.053
ACCRA	0.413***	0.116				
BANK			-0.741**	0.367	0.924**	0.402
CREDIT			-0.122	0.358	-0.270	0.398
MD2			-2.021*	1.084	0.126	0.506
HIRED			0.491	0.536	-1.921***	0.480
INSPECT			0.051***	0.015	0.061**	0.026
CONTR			0.474**	0.276	-1.280***	0.447
CERTIFYEARSNO			-0.024	0.058	-0.271	0.233
INTERCEPT	3.090***	1.097	2.141*	1.273	2.780*	1.532
ρ_{1D}			-0.336	1.159		
$ln\sigma_1$			0.534***	0.088		
ρ_{0D}					0.303	0.252
$ln\sigma_0$					0.493***	0.108
Log-Likelihood:		-552.494				
Wald test of indep. eqns.:		$\chi^2(2)$ = 18.50***				

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

Table A.4. Estimation Results of Probit Model

Variable	Coefficient	Std. Err.
GENDER	-0.691*	0.367
AGE	0.033***	0.040
NATIVE	0.004	0.190
RISK	0.176**	0.083
HHSIZE	-0.030	0.033
EDUC	-0.116***	0.398
WEALTH	-0.418***	0.074
FSIZE	-0.026***	0.005
OWNLAND	0.679***	0.237
GOVERN	0.287***	0.075
EXPER	0.008	0.129
LEARN1	0.191	0.341
LEARN2	-1.230***	0.406
DIST	-0.245*	0.127
SOIL	0.038	0.036
ORGA	1.101***	0.193
INTERCEPT	0.366	0.647

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

Table A.5: Results of T-tests before and after Kernel Matching

Variable	Sample	Mean Treated	Mean Control	%bias	%reduc. bias	t	p> |t|
GENDER	Unmatched	0.88028	0.97297	-37.6		-2.74	0.007
	Matched	0.90244	0.93456	-12.1	65.6	-0.27	0.778
AGE	Unmatched	48.489	42.541	54.0		4.18	0
	Matched	47.043	46.317	11.2	79.3	0.81	0.424
NATIVE	Unmatched	0.73239	0.74775	-3.5		-0.27	0.784
	Matched	0.73729	0.77324	-8.2	134.2	-0.64	0.523
RISK	Unmatched	0.14748	-0.18867	34.5		2.69	0.008
	Matched	0.13624	0.14944	-1.3	90.3	-0.12	0.904
HHSIZE	Unmatched	5.4577	6.2342	-27.1		-2.16	0.031
	Matched	5.5366	5.6321	-3.5	85.2	-0.33	0.740
EDUC	Unmatched	9.470	10.195	-32.7		-3.19	0.002
	Matched	9.6524	9.5154	6.2	81.1	0.51	0.614
WEALTH	Unmatched	4.765	8.481	-109.5		10.875	0
	Matched	5.521	5.958	-12.9	88.2	-1.09	0.317
FSIZE	Unmatched	10.151	18.797	-59.1		-4.76	0
	Matched	10.347	14.424	-27.9	52.9	-2.57	0.011
OWNLAND	Unmatched	0.549	0.204	53.35		-7.628	0
	Matched	0.437	0.402	7.6	65.8	-0.91	0.361
GOVERN	Unmatched	2.1972	1.8919	27.6		2.17	0.031
	Matched	2.178	2.2313	-4.8	82.5	-0.34	0.732
EXPER	Unmatched	11.986	13.288	-18.4		-1.43	0.153
	Matched	11.738	11.774	-0.5	97.3	-0.04	0.964
LEARN1	Unmatched	0.83099	0.57658	59.8		4.64	0
	Matched	0.80508	0.78239	12.9	78.3	0.34	0.733
LEARN2	Unmatched	0.7042	0.31532	-65.0		-5.31	0
	Matched	0.8475	0.14237	-15.3	76.5	-1.39	0.164
DIST	Unmatched	0.72889	0.82065	-19.9		-1.11	0.27
	Matched	0.70296	0.76285	-9.9	50.2	-0.89	0.377
SOIL	Unmatched	2.9507	2.4054	25		1.98	0.049
	Matched	2.7881	2.8872	-4.5	81.8	-0.34	0.737
ORGA	Unmatched	0.34507	0.07207	71.1		5.43	0
	Matched	0.315	0.233	21.4	69.8	1.49	0.138

Table A.6: Mean bias, Pseudo R^2 and Likelihood Ratio Before and After Matching

Algorithm	Sample	Mean bias	Pseudo R^2	LR χ^2	p>χ^2
Kernel	Unmatched	27.671	0.309	161.41	0.000
	Matched	8.189	0.046	18.43	0.299
Radius (0.05)	Unmatched	27.671	0.309	161.41	0.000
	Matched	11.278	0.041	14.84	0.462
Nearest-neighbor	Unmatched	27.671	0.309	161.41	0.000
	Matched	9.398	0.030	13.45	0.492

Table A.7: Results - ATT (reduced equipment costs)

Method	Predicted ROI of adopt. (mean)	Predicted ROI of non-adopt. (mean)	ATT	t-Statistic
ESR				
Organic farmers	2.825	2.205	0.803	5.361***
Conventional farmers	2.784	1.722		
	ROI of treated (mean)	**ROI of control group (mean)**	**ATT**	**t-Statistic**
PSM				
Kernel	2.892	2.283	0.609	1.86*
Radius (0.05)	2.892	2.250	0.642	1.44
Nearest-neighbor	2.892	2.016	0.782	1.76*

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

Table A.8: Estimation Results of WLS Regression

Variable	Organic farmers Coefficient	Std. Err.	Convent. farmers Coefficient	Std. Err.
GENDER	0.723	0.506	-0.154	0.464
AGE	-0.014	0.015	0.021	0.019
NATIVE	-0.618**	0.243	0.657*	0.407
RISK	-0.188	0.167	-0.165	0.221
HHSIZE	-0.06	0.065	0.010	0.061
EDUC	-0.055	0.067	-0.161	0.102
FSIZE	-0.035***	0.011	0.005	0.011
OWNLAND	0.178	0.365	0.259	0.497
GOVERN	0.208	0.163	-0.194	0.179
EXPER	0.018	0.024	-0.027	0.024
LEARN1	-0.410	0.468	-0.261	0.488
LEARN2	-0.501	0.890	-0.717**	0.405
DISTANCE	0.124	0.290	0.623**	0.307
SOIL	-0.093	0.076	0.043	0.104
ORGA	-0.193	0.424	-1.099*	0.568
WEALTH	-0.142	0.096	0.107**	0.045
BANK	-0.826**	0.347	0.827**	0.351
CREDIT	0.120	0.382	-0.418	0.477
MD2	-2.108***	0.520	0.321	0.410
HIRED	0.389	0.581	-1.779***	0.495
INSPECT	0.061***	0.014	0.040	0.031
CONTR	0.420	0.362	-0.720**	0.364
CERTIFYEARSNO	-0.031	0.059	-0.219	0.256
INTERCEPT	2.502	2.265	2.555*	1.438
N	176		173	
R^2	0.412		0.249	

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

Notes

[1] In addition, since certification usually comes with a contract with an exporter, the literature on impacts of contract farming is similar in terms of empirical strategy and in some cases overlaps. The link between contract farming and certification is that a contractual relationship can facilitate value addition through certification. The literature on contract farming that is not specifically related to certification under a private voluntary standard is skipped here.

[2] This switch was difficult for many farmers, in particular small-scale farmers, due to the necessary investment in expensive planting material and initial lack of information on production particularities and timing of inputs for MD2. Initially mainly large companies shifted to MD2 production (FAO, 2009). There were efforts made by the Ghanaian government and other donors to support the small-scale pineapple producers with the new variety, for instance through the distribution of MD2 suckers. During the same time Costa Rica, where the MD2 originated, increased its pineapple market share in Europe from 43.1% to 65% (UNCTAD, 2008). It is nowadays at over 70%.

[3] Out of the 386 farmers, one farmer had to be deleted because of answers that did not seem to be realistic and the ROI and other variables resulted in extreme outliers.

[4] Since our focus is not on the soil, we did not ask more detailed questions about the different soil types and their advantages and disadvantages for pineapple production.

[5] Household labor is taken into account with 4 GHS per day and person to include its opportunity costs. 4 GHS/day approximately corresponds to the Ghanaian minimum wage at the time of the survey and was approximately actually paid for manual farm labor. The exact minimum wage in February 2010 was 3.11 GHS/day and was recently increased to 3.73 GHS/day.

[6] Amortization is only generated for positive profits, which is the case for 271 farmers (organic: 154, conventional: 117). This falsifies the result but is the only reasonable calculation.

[7] As mentioned by Hottel and Gardner (1983) and others it is difficult to measure the adequate wage rate in agriculture and the exact amount of labor used for production which are needed to calculate the ROI. 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 socio-demographic characteristics we can assume that measurement errors do not significantly differ between the two groups. We will explain further below how we dealt with this problem. In addition, if organic production does not only affect the farmer's profit, but also his welfare in other ways (e.g. health) our measure will be incomplete. There are two reasons why this does not bother us. First, since the farmers under study are poor there should be at least a small monetary gain associated with the adoption of a new agricultural technology when a partial aim is to lift farmers out of poverty. Second, non-financial welfare gains are hard to measure, let alone to monetize. Therefore incorporating them into the return on investment might not improve our measure compared to reporting them separately.

[8] The variable RISK is one factor from a factor analysis of several subjective statements on risk, chemical use and input availability. This factor loaded high on the following statements: "I always want to try new farming techniques.", I need to take risks to achieve success", and "Using new agricultural techniques significantly increases agricultural income."

[9] Goldstein and Udry (2008) concluded from a study in Akwapim, Ghana, that individuals who have a more powerful position in the local hierarchy have more secure tenure rights and are thus more willing to invest in soil fertility.

[10] Literacy has been mentioned as an important entry barrier for certifications that require the keeping of farm records. When the certification process is organized by the farming group, and the latter takes care of the record keeping as well, education of a single farmer may not as important.

[11] To assure that farming equipment bought by the farmers during the evaluation period are not influencing the result of the ATT robustness checks were made. Therefore, the same estimations were done excluding the equipment costs of knifes, motor-driven vehicles, safety equipment for farm and storage facilities. The results can be found in Table 7.

[12] Calipers were actually varied, but only one result is presented here. The 1-nearest-neighbor matching generates the same ATT like caliper matching with a caliper being greater than 0.032 and is therefore assumed to be sufficiently precise. Radius matching with varying calipers of 0.05 and 0.1 also generates likewise results that do not differ significantly from the other results. Furthermore, as Abadie et al. (2004) suggest, we also apply the STATA command nnmatch to estimate the ATT with analytical estimators of the asymptotic variance for the nearest-neighbor algorithm to avoid bootstrapping of standard errors. The value of the ATT stays very similar.