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Agricultural Training, Peer-Learning and Sustainable Intensification in Southern Ghana:

A Control Function Joint Modelling Approach with Panel Data

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ABSTRACT

Agro-ecological practices that build up soil fertility and mulching which conserves soil-moisture are innovations for sustainable intensification in Sub-Saharan Africa, which is a major development goal. Their use is currently low. We utilize unique panel data for pineapple farmers in southern Ghana and jointly estimate what determines the individual adoption probability of mulching and agro-ecological practices together with their district diffusion and the probability that a farmer receives the specific training. We control for omitted variables with control functions. Training is only significant for the more knowledge intensive and less diffused agro-ecological practices. For mulching the main constraint to adoption is financial, even though we identify subgroups that also benefit from training in mulching.

We also find that the benefit of adoption varies with external factors, such as rainfall, soil organic matter and labor costs.

As we find that complex innovations such as AEPs require more information and expensive innovations such as mulching require better financing, we suggest to

(a) Increase trainings and set up demonstration farms for AEPs and similar innovations and (b) to support the diffusion of capital-intensive innovations, such as mulching, with targeted financial services that meet the farmers' needs for capital and insurance.

Section 1: Introduction

The sustainable intensification of agricultural production is a major development goal in Sub-Saharan-Africa (McIntyre, Herren, Wakhungu, & Watson, 2009; Pretty, Toulmin, & Williams, 2011; World Bank, 2008). We define sustainable intensification as "increasing yields per hectare, increasing cropping intensity (i.e. two or more crops) per unit of land or other inputs (i.e. water), and changing land use from low value crops or commodities to those that receive higher market prices", while also taking into account the environmental impacts and positive contributions to natural capital (Pretty et al., 2011). Diao and Sarpong (2007) find that in Ghana, there is a direct link between soil degradation due to unsustainable land use and poverty. Kleemann and Abdulai (2013) analyze a representative sample of Ghanaian pineapple farmers and find the adoption of sustainable farming practices to be profitable, especially when used more intensively. The government of Ghana and several development initiatives are hence highly interested in widely diffusing sustainable intensification innovations amongst Ghana's smallholder farmers but the question is how to best achieve this (German Society for International Cooperation, 2005; Government of Ghana, 2010; Millenium Development Authority, 2011; USAID, 2009, 2013).

Knowing that sustainable intensification is profitable for the farmers, the question is why these innovations are not diffusing quicker. There is a large literature on this well-known phenomenon (Feder, Just, & Zilberman, 1985; Foster & Rosenzweig, 2010) and a small selection of constraints that very often contribute (individually or in combination) to the slow diffusion of seemingly profitable innovations in agriculture:

1. Heterogeneity in profits: Suri (2011) looks at the adoption of modern seeds and fertilizers in Kenya and finds that for most farmers who do not adopt, this is the right choice, because location specific constraints increase adoption costs until they out-weight benefits.

2. Risk and credit constraints: Karlan, Osei, Osei-Akoto, and Udry (2012) analyze the role of risk and credit-constraints in northern Ghana and find that especially uninsured risk is a major adoption constraint even when returns to capital are extremely high as Udry and Anagol (2006) find.

3. Tenure rights: Abdulai, Owusu, and Goetz (2011) analyze the effect of insecure tenure rights on investment decisions in Ghana and find that this can be a major barrier, whereas Fenske (2011) shows that this effect is heterogeneous for different technologies.

4. Information: The adoption of new technologies requires learning about their profitability and proper use, so slow adoption rates can stem from information disequilibria (Bandiera & Rasul, 2006; Conley & Udry, 2010; Krishnan & Patnam, 2014).

In this study, we attempt to understand whether information is a binding constraint to the diffusion of sustainable intensification innovations (mulching, composting, green manure, rotations and intercropping with legumes) and how the other potential constraints fit into the picture. As there has been extensive research on the role of peer-learning (see Foster and Rosenzweig (2010) for a recent overview) we focus especially on the role that agricultural trainings can play in this regard.

This topic has received some attention lately (Genius, Koundouri, Nauges, and Tzouvelekas (2014) in Greece, Krishnan and Patnam (2014) in Ethiopia, Thuo et al. (2013) in Kenya and Uganda) with interesting findings: Using detailed panel-data, Krishnan and Patnam (2014) find that the effect of extension services in Ethiopia was high in the beginning but wore off in time, while learning from neighbors stayed always important. Thuo et al. (2013), using cross-sectional data, conclude, in line with Hounkonnou et al. (2012) and Hartwich and Scheidegger (2010), that advisory services often fail because they are not enough interlinked with complementary services that go beyond the mere information provision.

For this study, we revisit the pineapple farmers in southern Ghana, who have been surveyed by Kleemann and Abdulai (2013) in 2010. Using this panel-data from 173 farmers, we estimate a joint model about the adoption, district diffusion and training of two innovations:

1. Mulching, which means that soils are covered with plastic or organic materials like grass, to conserve soil moisture and mitigate weeds. (Erenstein, 2003) and

2. Agro-ecological techniques, which mitigate the loss of soil fertility (Florentin, Penalva, Calegari, & Deprsch, 2011; Snapp & Pound, 2011).

Our methodological contribution is the development of a joint modelling framework, in which the adoption of an innovation, its district diffusion and the probability to receive training are simultaneously estimated, which allows to understand better, how these processes interrelate. An example is training in agro-ecological practices, which significantly drives individual adoption but district diffusion is more affected by soil quality, rainfall and topography. Furthermore, some district and farmer characteristics might affect both how likely it is to receive training and the probability to use an innovation. While we use control functions to control for unobserved endogeneity, the joint modelling framework allows to explicitly model observable endogeneity. We find that the combination of both controls works best.

Our main results suggest that whether training has a significant effect on the adoption of an innovation depends on the novelty and complexity of the innovation but also on the importance of all other constraints. Furthermore, we find that learning from trainings and learning from other farmers can both be understood as complements and as substitutes. So while the greatest effect is observed for farmers who received training and who's neighbors demonstrate the innovation's use and benefit (complementarity), trainings loose in importance the more the innovation is diffused (substitutability).

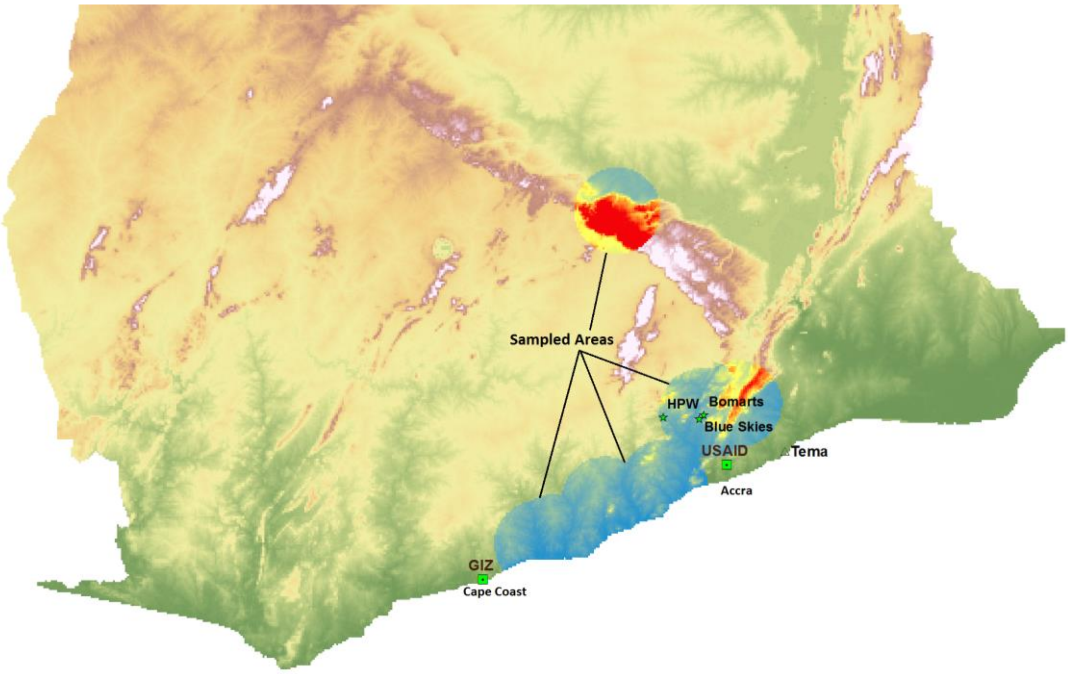
As specific examples from our study, mulching is relatively easy to understand, usually expensive and wider diffused than any other sustainable intensification innovation (about 40%). Hence, current constraints are mostly of financial nature and trainings do not play a major role for most farmers at this point. In contrast, agro-ecological practices are more difficult to implement, much less diffused (about 15%) but relatively cheap. For these innovations, training is a major adoption-driver.

The remainder of this paper is structured as follows: In the next section we describe our data (2). Then, we summarize the study-context (3) and develop our model (4). Then, section 5 explains our variables and section 6 presents our results, which are checked for their robustness in section 7. We conclude the study in section 8.

Section 2: Data

We use unique panel data, which has been collected in two periods. First, data from 386 pineapple farmers was collected in 75 villages in Southern Ghana between January and March 2010. 173 of these were interviewed again in 2013. The sampling in 2010 was representative, using stratified random sampling in three stages. First, pineapple growing areas were identified, second, only farmers certified by Globalgap or organic standards under option 2 (group certification) were chosen and thirdly, the certified farmers were proportionally sampled from each group. The focus lies on certified farmers because being a quasi-precondition for export, pineapple-export is a major incentive to produce more. The certification process is also a source of information about farming practices. By restricting our sample to these farmers, we increase the homogeneity of our sample and reduce the risk of including farmers for whom innovation-adoption is not profitable.

Map 1: The sampled areas in southern Ghana



The map shows the topography of Ghana. The circles between Accra and Cape Coast show the sampled areas in the Central Region, while the circles north of Accra show the sampled areas in Greater Accra and the Eastern Region. Dark green represent the coastal lowland and brown represents higher elevation.

It can be seen that all pineapple processors (Blueskies, Bomarts and HPW) are located in the south of the Eastern Region, which has better suited soils for the cultivation of pineapple and is also close to the main port (Tema).

In 2013, we were able to survey 173 farmers from the first period again. These farmers are not systematically different from the full sample of the first period and we can hence treat the sample as representative. The three major regions sampled are the Central Region, the Eastern Region and Greater Accra. In these regions, trained enumerators collected detailed information on the variables described in section 5. Generally, farmers were asked a range of questions about their households, their fields, their farming systems as well as their production and marketing choices. They were also asked a range of attitudinal and perception questions and participated in two small experiments to reveal their risk and time preferences. To estimate each farmer's level of risk aversion, he or she were asked to choose between six hypothetical pineapple varieties, which give different payoffs depending on a 50% chance of a good or a bad harvest. The least risky variety always gives the same profit but the most risky variety gives either four times the profit or none at all. (see Appendix A)

To estimate a farmer's time preference, he or she were asked to choose their preferred scenario from a list of seven. The first gives the highest profit in the first season but the lowest thereafter while the sixth scenario gives the lowest "known" profit this season but a rather high profit thereafter and the seventh scenario gives an "unknown" profit this season but the highest profit thereafter. (see Appendix B)

For our dependent variables, we asked farmers to indicate which practices from a list they currently use, whether they have used one but stopped (and why) and when they adopted the practices they currently use. For our "information"-variables, we asked farmers whether they received trainings, with which content, when and by whom. We also asked them how many farmers they knew, who already adopted the practice when they themselves decided to adopt; how many of the adopters they knew were happy with their decision when they themselves decided to adopt; and from how many adopters they could directly observe the results of adoption and how many of those looked positive. We then used Arcgis software to map these positive adopters as reportedly observed by other farmers and calculated their number and share for each farmer ("positive observations absolute" and "positive observations share").We also asked the farmers with how many people they communicate, who these people are, where they live and other details to be able to clearly delimit the farmers' communication networks. In our survey, about 40% of the farmers report that their network lies within their district, 27% report their network to be mostly in their village, 28% say their network is fully within their village and 2% state not to be part of any information network. Therefore, we define the district as the network boundary (variable "district diffusion)[1].

We also used the approximate location of the surveyed farmers to locate them on a geographical map and produce additional information in Arcgis software, such as distances to important locations (pineapple companies or the main port), infrastructure, soil organic matter and the topography of the areas.

Other explanatory variables concern details about the household's age, education and whether they received credit or insurance in the past or why not, which pineapple varieties are grown, location and quality of the fields, details about prices, the weather and marketing choices, such as whether or not they farm under contract.

In our sample of small producers, about half of the pineapples are sold to processors, while the rest is sold on local markets. The mean household consists of 6 people, with a 46 year old male head and an income of about 80 US$. A major problem is the unavailability of credit. 60% of the farmers never received a credit, mostly because there was none available. Usually credits are given to farming groups but because pineapples take longer than a year to mature, with significant production and marketing risks, pineapple farmers are not particularly attractive to most banks.

The role of risk can be understood by the fact that about 30% of the farmers already experienced a major income shock, which is not easy to compensate for most farmers in West Africa, as analyzed by Kazianga and Udry (2006) in Burkina Faso.

We also tested more network definitions and show in section 7 that our results are robust across different network boundaries.

As can be seen in the upper part of table 1, all pineapple farmers strongly avoid land under traditional tenure rights such as Abunu and Abusa., with the exception of family land, which is counted as own land. Renting land is perceived as safe because all relevant rights are more clearly defined.

In general, adopters of sustainable intensification innovations are better educated, have higher incomes, lager households and hence usually more available labor, more rented land and more likely to have received a loan.

We also asked the farmers about their information sources (see the lower part of table 1). Reportedly, the most important source for new information is extension agents and advisors, followed by other farmers, whereas the most important source for learning about profitability and usage of innovations is other farmers. When it comes to information sources, differences between adopters and non-adopters are much more pronounced then in the previously discussed table on other farmer characteristics. Non-adopters are much less likely to have heard about an innovation from other farmers or a company employee. Similarly, even though the difference is small again, for non-adopters the role of training for learning is more important than for adopters.

Altogether, the descriptive statistics suggest that non-adopters are more capital constraint than adopters, and the most important capital forms seem to be financial (i.e. loans) and information (i.e. knowledge in the peer-group).

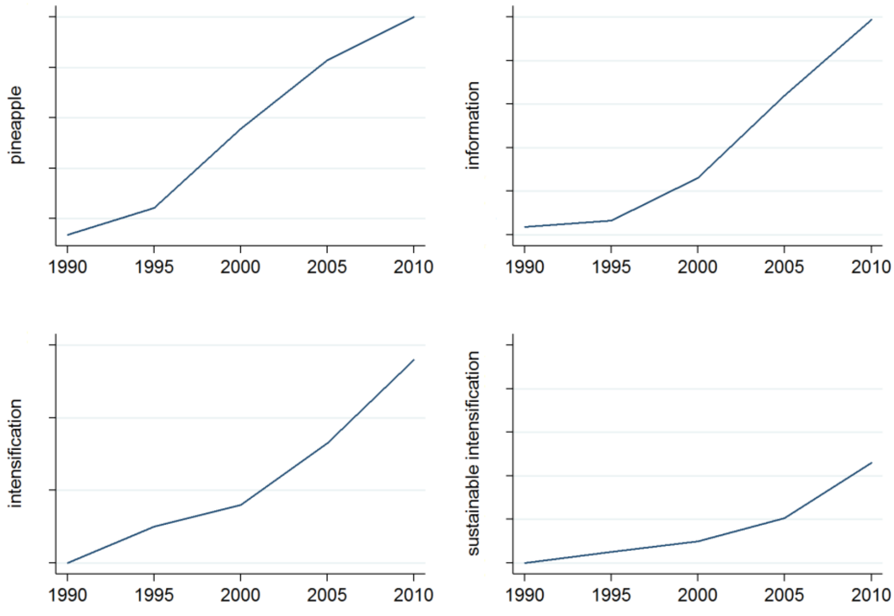
Table 1: Descriptive Statistics

Characteristics	Adopters Agro-Ecological Practices Mean	(Std. Dev.)	Adopters Mulching Mean	(Std. Dev.)	Non-Adopters Mean	(Std. Dev.)
Export share (%)	.52	(.38)	.49	(.40)	.44	(.47)
Certified (%)	.82	(.37)	.88	(.32)	.84	(.36)
Income level (1-5)	3.19	(1.19)	3.02	(1.29)	2.80	(1.10)
Household (people)	6.57	(2.67)	6.45	(2.84)	6.07	(2.73)
Family labor (people)	2.36	(1.64)	2.27	(1.70)	2.11	(1.43)
Age (years)	47.14	(13.12)	46.90	(11.01)	45.02	(10.08)
Education level (1-6)	2.95	(1.21)	2.99	(1.17)	2.74	(1.08)
Alphabetism (%)	72	(45)	77	(41)	61	(48)
Stool land (%)	06	(24)	01	(08)	02	(14)
Share land (%)	0	(0)	0	(0)	03	(17)
Rented land (%)	68	(47)	70	(45)	62	(48)
Family land (%)	17	(37)	20	(40)	20	(40)
Purchased land (%)	08	(28)	07	(26)	09	(29)
Pineapple fields (ha)	.94	(.25)	.98	(.12)	.94	(.24)
Loan (%)	40	(49)	46	(50)	34	(47)
No credit avail. (%)	36	(48)	29	(45)	41	(49)
Income shock (%)	36	(48)	26	(44)	33	(47)
Credit constr. (rank)	1		1		1	
Labor constr. (rank)	2		2		2	
Weather constr. (rank)	3		3		3	
MD2 variety (%)	14	(35)	27	(44)	22	(42)
SC variety (%)	29	(46)	28	(45)	42	(49)
SL variety (%)	40	(49)	40	(49)	25	(43)
Information-sources						
Info advisor (%)	89	(31)	86	(34)	89	(30)
Info farmers (%)	78	(41)	70	(45)	59	(49)
Info company (%)	42	(49)	35	(48)	25	(43)
Learn farmers (%)	93	(24)	96	(18)	94	(23)
Learn training (%)	46	(50)	44	(49)	54	(49)
Learn labor (%)	06	(24)	14	(35)	10	(30)

Section 3: Context

Our study area in Southern Ghana is optimal to learn about the diffusion of innovations for several reasons. First, agricultural development is dynamic and hence panel data over a relatively short period is likely to reveal interesting patterns. Pineapple is Ghana's most developed horticultural sector and until 2003, the production was vital and pineapple exports generated jobs and foreign exchange (estimated at US$50 million). However, currently Ghana does not seem to be competitive on the world market so that exports fell from 71,000 tons in 2004 to 35,000 tons in 2013 (Gatune, Chapman-Kodam, Korboe, Mulangu, & Raktoarisoa, 2013). One reason is a change in demand in the European Union, towards a new variety (MD2), which requires more intensive production. Knowledge about how to produce this new variety successfully diffused slowly and consequently many farmers failed and dropped out of business. Today, there is strong demand for the "old" and "new" variety in particular from pineapple processors, which are troubled by low pineapple supply. The proposed reason why Ghana's farmers cannot supply more pineapples is their low productivity together with high costs. According to Gatune et al. (2013), Costa Rica has 6 times more revenue per hectare than Ghana, producing double the amount of pineapples per hectare (120 tons vs. 60 tons) while getting better qualities as attested by an export yield of 85% versus 65% for Ghana (including small-scale producers and the more efficient large-scale producers in terms of export rate).

Graph 1: The Diffusion of Innovations in Southern Ghana (cumulative share of farmers)



Graph 1 depicts selected historical developments, as reported by the sampled farmers. It shows the cumulative number of farmers who grew pineapple, had information about intensification and who intensified – generally and sustainably – at each five year interval. These development are graphed until 2010 as the current interval is not yet finished. However, the results of this study allow to forecast how political, social, environmental and economic changes might affect the current interval.

Before any commercialization, the farmers mostly intercropped maize and cassava. They ensured minimum soil fertility through slash and burn, followed by fallow periods. With the introduction of pineapples (upper left graph), which are exported mostly to the European Union, the farmers adapted their farming systems and started to learn about techniques to actively improve soil fertility through organic and inorganic fertilizers (upper right graph). More and more farmers started to intensify their production systems (lower left graph) and until 2013, 40% of the farmers used mulching and 15% agro-ecological practices (their combined development until 2010 is displayed in the lower right graph).

Section 4: The Model

The basis for our model is the standard situation in which a farmer decides whether to adopt and innovation or not, depending on the expected utility of the innovation and a given a number of constraints. If information is a binding constraint, we would expect training and peer-learning to be important, as long as other constraints are not also binding.

To model the effect of trainings, we first define the effect of the provided information as "knowledge", like Feder, Murgai, and Quizon (2004) understood as "the possession of analytical skills, critical thinking, ability to make better decisions, familiarity with specific agricultural practices and understanding of interactions within the agro-ecological system".

We specify a farmer's knowledge about the profitability and proper usage of an innovation according to Feder et al. (2004) as:

$$K_t = (1 + e^{-\alpha t - \beta_1{}' S(t) - \beta_2{}' X(t) - \beta_3{}' c(t)})^{-1} \quad , \tag{1}$$

where K_t denotes his knowledge, α is the parameter governing the rate of learning over time, β_1 is a vector of parameters relating to the impact of farmer attributes **S**(t), β_2 is a vector of parameters relating to the impact of the innovation attributes **x**(t) and β_3 is a vector of parameters relating to the context **c**(t).

In the absence of any training, the farmer learns through own trials and those of his peers:

$$\ln\{k(t_1)\} - \ln\{k(t_0)\} = \alpha(t_1 - t_0) + \beta_1' \Delta S + \beta_2' \Delta X + \beta_3' \Delta c \quad . \tag{2}$$

As developed by Besley and Case (1997), this learning process can be modelled as Bayesian updating:

$$K_{t+1} = K_t - (\frac{\mu_t}{\mu_{t+}\phi_t} (\bar{\pi}_t - E\{\bar{\pi}_t | K_t\})), \tag{3}$$

where a farmer's current knowledge about an innovation (i.e. what profit to expect) is denoted by K_t, his profit expectation is denoted by $E\{\bar{\pi}_t | K_t\}$ and average observed profits on all fields (his own and on those of his neighbors) are $\bar{\pi}_t$. Furthermore, $\frac{\mu_t}{\mu_{t+}\phi_t}$ consists of $\mu_t\ (N(t)) \equiv (\frac{\sigma_K^2 + \sigma_\epsilon^2}{N(t)} + \sigma_u^2)^{-1}$ and $\phi_t =$

$\frac{1}{\sigma_b^2}$ and describes how the number of trials (N) and the uncertainty of the payoffs (σ is the standard deviation of K, ϵ und u) affect the rate of learning.

Now consider that the farmer receives a training in period t^*, so there is a number of seasons before $(t^* - t_0)$ and a number of seasons after $(t_1 - t^*)$ and the learning process from equation (2) can be written like this:

$$\ln\{k(t_1)\} - \ln\{k(t_0)\} = \alpha(t^* - t_0) + \gamma(t_1 - t^*) + \beta_1' \Delta S + \beta_2' \Delta X + \beta_3' \Delta c \quad , \tag{4}$$

where γ denotes the growth of knowledge after training and the impact of the provided information on the farmer's knowledge can be measured by $(\gamma - \alpha)$.

Assuming that $(\gamma - \alpha)$ is positive, that is assuming that farmers who receive training learn something from it, an important question remains: Is the knowledge increase sufficient to induce adoption of the innovation in question? If $(\gamma - \alpha)$ is not positive, this would indicate that either the provided information is already available through other channels or there is a communication barrier, such as insufficient demonstration or a lack of trust. Either way, it is also possible that farmers learn from the training but lack the motivation or the means to act on their new knowledge or that they do not learn from the training but feel motivated by it to change behavior now.

To empirically identify whether the provision of training increases the probability that pineapple farming in Ghana gets sustainably intensified, we use a random utility framework as point of departure for a model similar to Brock and Durlauf (2001, 2006) and Ben-Akiva et al. (2012), where social interactions are incorporated into a discrete choice model. Social interactions are at the core of our model, as social interactions through weak ties (trainings) and strong ties (neighbors)(Granovetter, 2005), can be complements and substitutes for each other, and are possibly major determinants for the adoption of an innovation (Ruef, 2002). Hence, we are interested in the following equation:

$$E_{nt}(U_{int}) = V_{int}(x_{int}; s_{nt}; c_{nt}; \beta_{nt}) + F + \gamma_1 L_{int}^p + \gamma_2 tr_{int} + \varepsilon_{int} \ , \tag{5}$$

where $E_{nt}(U_{int})$ is the expected utility of the innovation *i* for farmer *n* at time *t*, V is the observed part of utility (consisting of farmer characteristics s, attributes of the innovation x, the context c and demand-elasticities β), F are fixed effects for time and space, L^p is a field effect variable, capturing the information-externality provided by other farmers and tr_{int} is the effect of trainings.

Furthermore, γ_1 and γ_1 are parameters to be estimated together with the other elasticities β and ε is the unexplained part of utility.

We assume that farmers only adopt an innovation if they expect it to be better than their status quo technology:

$$E_{nt}(U_{int}) > U_{jnt} \ \forall j \neq i \qquad , \tag{6}$$

Denoting the (expected) utility difference between adoption and non-adoption by y^*_{int}, we observe:

$$y_{int} = \begin{cases} 1 & if \ y^*_{int} > 0 \\ 0 & otherwise \end{cases} \qquad , \tag{7}$$

Equation (7) acknowledges that we cannot observe a farmer's utility but observing his choices, we know which technology he prefers. Hence, we are able to estimate the following model, in which we substituted the farmer's (expected) utility from equation (5) with the observed ordinal utility difference:

$$y^*_{int} = b_{int} + F + V_{int}(x_{int}; s_{nt}; c_{nt}; \beta_{nt}) + \gamma_1 L^p_{int} + \gamma_2 tr_{int} + \varepsilon_{int} \, . \tag{8}$$

The problem in estimating this equation is, however, the endogeneity of the peer-leaning and training variables. As Manski (1993, 2000) discusses, the field effect variable capturing the effect of learning from peers is very likely to also capture contextual interactions and correlated effects. For example, a group of farmers might independently from any learning effects decide to adopt an innovation at the same time if it solves a common problem. Furthermore, similar farmers might tend to behave similar – with and without learning and participation in training might be affected by prior interest.

To account for endogeneity in a discrete choice model, the two main techniques are the BLP approach and control functions (Petrin & Train, 2010; Train, 2009):

If adoption shares can be precisely measured and endogeneity occurs at an aggregate level (i.e. village or district), then endogeneity can be corrected for using the Berry, Levinsohn and Pakes (BLP) correction, which introduces group specific constants that control for the omitted variables that cause the endogeneity bias (Walker, Ehlers, Banerjee, & Dugundji, 2011). In our context, where adoption shares cannot precisely be measured, the preferred alternative is the construction of control functions.

To construct control functions, two steps are necessary:

First, the endogenous variable is regressed on a number of explanatory variables and at least one instrument, which is a variable that correlates with the endogenous variable but not with the error-term. In a spatial context, feasible instruments are often times the values of the endogenous variables in spatially adjacent zones (Walker et al., 2011). In our context, it is apparent that i.e. the adoption behavior of spatially adjacent zones correlate with each other, as they share similar environmental and market characteristics. For the exclusion restriction to be fulfilled, we need relatively precise boundaries of our peer-networks. The reason is that if we have defined the networks correctly, then farmers within the networks do not learn from farmers outside the network and also do not hear from them about offered trainings.

To ensure this, we asked farmers questions to identify these boundaries for us and used additionally different boundaries of the peer-networks, identified in Arcgis software based on distances, farm-groups, districts and villages and compared the estimates as robustness checks. We also include the values of the endogenous variables in broader areas (i.e. explaining the reception of training with the amount of training offered in the district, thereby mitigating the problem of endogenous training due to prior interest of the participants) and stated numbers of other adopters, farms where the innovation could be observed and farmers who were known to be happy with their adoption at the time of the surveyed farmers' adoption choice.

The second step of the control function procedure is to save the error terms of the first stage estimation and include them as additional explanatory variables in the main model (equation 9), to "condition out" the endogenous part of utility (Petrin & Train, 2010):

$$P_{int} = \alpha_{int} + \beta_1 x_{int} + \beta_2 s_{nt} + \beta_3 c_{nt} + F + \gamma_1 L_{int}^{p} + \gamma_2 tr_{int} + \lambda_{nt}^{p} \mu_{int}^{p} + \lambda_{nt}^{tr} \mu_{int}^{tr} + \varepsilon_{int}, \quad (9)$$

where P_{int} is the estimated probability of adoption, α_{int} is a constant and $\lambda_{nt}^{p}\mu_{int}^{p}$ and $\lambda_{nt}^{tr}\mu_{int}^{tr}$ are the included control functions for peer-learning and trainings, together with their coefficients.

Our data also helps to include additional measures against endogeneity, as the panel-nature allows to identify who adopts when and various location based fixed effects, i.e. for districts and peer-networks, allow to control for unobserved, common influences in a given location.

The main contribution of our study, however, is that we develop an empirical model that does not only control for endogeneity but makes the process as observable as possible. That is, additionally to our various controls, we explicitly model the probability that a farmer adopts a sustainable farming together with which network characteristics affect the diffusion of an innovation and which farmer are most likely to be trained. Hence, we make visible, which observable factors lead to our two main explanatory variables and we do so in a system of simultaneous equations (Roodman, 2009, 2013; Wilde, 2000) that is jointly maximized using the Geweke, Jajivassiliou and Keane (GHK) algorithm:

$$P_{int} = \alpha_{int}^{1} + F + V_{int}(x_{int}; s_{nt}; c_{nt}; \beta_{nt}) + \gamma_1 L_{int}^{p} + \gamma_2 tr_{int} + \lambda_{nt}^{p}\mu_{int}^{p} + \lambda_{nt}^{tr}\mu_{int}^{tr} + \varepsilon_{int}^{1} \qquad (10a)$$

$$L_{int}^{p} = \alpha_{imt}^{2} + F + \beta_1 + \beta_2 x_{imt} + \beta_3 s_{mt} + \beta_4 c_{mt} + \gamma_2 L_{imt}^{tp} + \varepsilon_{imt}^{2} \qquad (10b)$$

$$P_{tr_{int}} = \alpha_{int}^{3} + F + \beta_1 + \beta_2 s_{nt} + \beta_3 c_{nt} + \varepsilon_{int}^{3} \qquad (10c)$$

where (10a) is a probit modelling the individual adoption probability, (10b) models the diffusion of the innovation (OLS) and (10c) is another probit, modelling the probability that the farmer receives training. All variables are still defined as explained below equation (5). All estimations are performed in STATA, using the cmp routine of Roodman (2009, 2013).

An interesting feature of our framework is that the district diffusion of an innovation does not necessarily have to be the sum of the individual behaviors, as emergent properties are possible (Geroski, 2000). This means that the factors that lead to faster individual adoption and those that lead to broader diffusion must not be the same. As we will see, the district diffusion of our innovations is broadly driven by external factors that affect the innovations' relative benefit. On the individual level, details matter.

5. Variables

The following list describes our explanatory variables:

training in mulching	whether the farmer received training in mulching
training in AEP	whether the farmer received training in agro-eco.pr.
positive observations abs.	number of neighbors who demonstrated benefit of X
positive observations perc.	Share of neighbors who demonstrated benefit of X
district diffusion	Share of adopters of X in the district
export price	price paid by exporting companies per KG of fruit
local market price	price paid by local market women per KG of fruit
price volatility	Squared change in pineapple price between years
contract farming	Whether the farmer is in a contract with a company
labor costs	Reported problem of high labor costs from 1 to 5
family labor available	How many family members are helping with farming
no credit available	Whether the farmer wants a credit but cannot get one
non-farm income	Share of non-farm income on overall income
income shock experienced	Whether a major income shock has been experienced
dry fields	Whether the farmer considers his fields too dry
risk aversion	How much the farmer dislikes risk, 1-6
time preference	How strongly the farmer discounts the future, 1-7
age	Age of the farmer in years
education	Level of formal schooling of the farmer, 1-7
farmland	Size of the whole farm in hectares
pineapple hectares	Size of all pineapple fields in hectares
smooth cayenne variety	Whether the farmer grows Smooth Cayenne
sugar loaf variety	Whether the farmer grows Sugar Loaf
md2 variety	Whether the farmer grows MD2
district training X	Share of farmers who received training in X
district loan availability	Share of farmers who can get a credit
average district price	The average price for pineapples in a district
distr. rainfall variability	The squared change in rainfall between the years
blue skies contract	Whether the farmer is in a contract with Blueskies
hpw contract	Whether the farmer is in a contract with HPW

training giz (moap)	Whether the farmer has been trained by the GIZ
training usaid (tipcee)	Whether the farmer has been trained by USAID
regional number training	How many trainings were offered in the wider region
influence in network	Self-reported network-centrality of the farmer
perceived soil fertility	Reported soil fertility of fields, 1-5
fertility understanding	Whether the farmer knows basics of soil fertility
income level	Reported income level, 1-5
foodland	Hectares of fields used for own consumption
cashland	Hectares of fields used for cash-crops
inexperienced	If the farmer reported to be less exp. than peers
rented fields	Whether the farmer rents his pineapple fields
price diff. exp. and loc.	Gap between export and local price
port distance	Distance from the farm to the port
topography	Standard deviation of elevation
training blueskies	Whether the farmer has been trained by Blueskies
training giz (moap)	Whether the farmer has been trained by GIZ
training NGOs	Whether the farmer has been trained by NGOs
peers certified_organic	Whether the peers of the farmer are certified org.
regional farm size	The average farm size of the region

Interactions with training:

training X complementary practices	already adopted row planting or similar
training X no credit access	does not have credit access
training X peer learning	Adoption-rate amongst his peers
training X contract farming	whether he is in a farming contract
training X inexperience	whether he reports himself to be inexp.

Section 6: Results

Table 2 shows the results for mulching and table 3 shows the results for agro-ecological practices. Table 4 and 5 show interaction effects between the trainings and other adoption-determinants. All variables are normalized.

We find that training in mulching is not (anymore) a significant adoption- nor diffusion-driver. Information does play a prominent role but it is provided by other farmers, who directly demonstrate usage and profitability. In contrast, for agro-ecological practices (AEP) all information sources are significant and important (training, positive observations absolute and in percentage, district diffusion). The results also suggest why training is currently more effective for AEPs than for mulching. As the farmers told us, mulching is relatively expensive while AEPs are not always easy to implement.

Accordingly, table 2 shows that credit-access, non-farm income and a lower time-preference increase the adoption probability while higher labor costs, having experienced an income shock in the past and price-volatility decrease it. This suggests that financial capital constraints the adoption of mulching, while information might be less limiting for most farmers because mulching is relatively easy to learn and already somewhat diffused (about 40% in the sample). Most farmers hence have at least some information about it but many seem to lack the financial capital to implement it.

Because mulching conserves soil moisture, farmers who have drier fields are likely to adopt it.

Testing the interpretation above with interaction terms, we find that a lack of credits reduces the benefit of trainings while the use of complementary farming techniques (like row planting) and contract farming (which increases access to credit and lowers marketing risks) increase the benefit of trainings.

Table 2: Results for the Adoption and Diffusion of Mulching (M)

(a) Individual Adoption M	Coef.	Std. Err.
training in mulching	.165	(.212)
positive observations abs.	1.504***	(.685)
positive observations perc.	.016	(.149)
district diffusion	.098	(.157)
export price	.176	(.171)
local market price	-.006	(.162)
price volatility	-.130**	(0.726)
contract farming	.327***	(.091)
labor costs	-.089*	(.053)
family labor available	.148*	(.104)
no credit available	-.274***	(.099)
non-farm income	.261***	(.091)
income shock experienced	-.274***	(.098)
dry fields	.227***	(.112)
risk aversion	-.071	(.106)
time preference	-.176***	(.092)
age	-.071	(.079)
education	.051	(.089)
farmland	.194*	(.121)
pineapple hectares	-.277***	(.114)
smooth cayenne variety	.014	(.111)
sugar loaf variety	-.244*	(.171)
md2 variety	.062	(.104)
fixed effects period	yes (2)	
fixed effects networks	yes (9)	
fixed effects districts	yes (6)	
control functions	yes (2)	
constant	Yes (1)	

Significance levels: ***=0.95;**=0.9;*0.8. S.E. robust and clustered

(b) District Diffusion Mulching	Coef.	Std. Err.
district training mulching	.004	(.014)
district loan availability	.037***	(.036)
average district price	.012***	(.004)
district rainfall variability	.086***	(.020)
fixed effects districts	yes	(6)
Constant	.423	(.032) .

Significance levels: ***=0.95;**=0.9;*0.8. S.E. robust and clustered

(c) Training Mulching	Coef.	Std. Err. .
blue skies contract	.261***	(.757)
hpw contract	.264***	(.093)
training giz (moap)	.338***	(.101)
training usaid (tipcee)	.558***	(.175)
regional number training	1.01***	(.355)
influence in network	.174*	(.110)
fixed effects districts	yes	(6)
Constant	-1.614	(.424) .

Significance levels: ***=0.95;**=0.9;*0.8. S.E. robust and clustered

Table 3: Interaction-Effects between training and other adoption determinants for Mulching

Interactions Adopt. Mulching	Coef.	Std. Err.
training X complementary practices	.677***	(.217)
training X no credit access	-.210**	(.122)
training X peer learning	1.156***	(.589)
training X contract farming	.359***	(.133)

Table 4: Results for the Adoption and Diffusion of Agro-Ecological Practices (AEP)

(a) Individual Adoption AEP	Coef.	Std. Err.
training in AEP	.341***	(.002)
positive observations abs.	3.674***	(.019)
positive observations perc.	1.669***	(.034)
district diffusion	1.767***	(.000)
perceived soil fertility	-3.494***	(1.299)
age	-.081*	(.062)
education	.013	(.050)
fertility understanding	.103**	(.058)
income level	.132**	(.070)
foodland	.074*	(.053)
cashland	-.079*	(.059)
land	.092***	(.041)
inexperienced	-.111**	(.063)
no credit available	-.132**	(.069)
time preference	.068*	(.048)
risk aversion	.134**	(.075)
income shock	.014	(.047)
rented fields	.215***	(.085)
dry fields	.064	(.052)
SL variety	-.041	(.073)
SC variety	.090*	(.059)
MD2 variety	-.067	(.063)
price volatility	.105	(.234)
price diff. exp. and loc.	.440	(.455)
port distance	-.662***	(.327)
topography	-.266	(.568)
fixed effects period	yes (2)	
fixed effects regions	yes (2)	
control functions	yes (2)	
constant	Yes (1)	.

Significance levels: ***=0.95;**=0.9;*0.8. S.E. robust and clustered

(b) District Diffusion AEP	Coef.	Std. Err.
district training AEP	-.010	(.436)
district weather	-.055***	(.000)
district topography	-.044***	(.000)
district soil organic matter	-.419***	(.001)
fixed effects districts	yes (4)	
constant	Yes (1)	.

Significance levels: ***=0.95;**=0.9;*0.8. S.E. robust and clustered

(c) Training AEP	Coef.	Std. Err.
training blueskies	1.304***	(.176)
training giz (moap)	.469***	(.218)
training NGOs	.289***	(.123)
peers certified_organic	.278**	(.152)
regional farm size	-.256*	(.172)
fixed effects districts	yes (4)	
constant	Yes (1)	.

Significance levels: ***=0.95;**=0.9;*0.8. S.E. robust and clustered

Table 5: Interaction-Effects between training and other adoption determinants for AEP

Interactions Adopt. AEP	Coef.	Std. Err.
training X contract farming	.338***	(.134)
training X compl. practices	.528***	(.199)
training X inexperience	.514***	(.147)
training X peer learning	.818***	(.188)

Table 4 shows how information is the most important determinant for the adoption of AEPs. Most farmers belief their soils to be quite fertile (at least this is what they report), even if fallow periods are short and often, no fertilizer is applied. However, perceived lack of soil fertility is the strongest determinant for the adoption of AEPs, suggesting that if farmers understand the need to replenish nutrients they are more likely to choose AEPs. Similarly, those who could answer basic questions about their soils are more likely to adopt, while those who reported to be less experienced than their peers are less likely to adopt. Fortunately, table 6 shows that inexperienced farmers benefit above-average from trainings, so a lack of information is a problem we know how to solve. Other sub-groups that benefit above-average from training in AEPs are contract-farmers, those whose peers have already adopted and those who already adopted complementary practices (i.e. row planting).

Our data also says something about the way the Ghanaian pineapple farmers learn. In contrast to mere imitation (Banerjee, 1992) the main learning channel is found to be observation of positive results (Conley & Udry, 2010). We also tested knowledge about other adopters and how many of them are happy about their decision but these variables have no explanatory power in any of our tested models.

On the district level, the diffusion is mostly driven by external factors that increase or decrease an innovation's profitability and a farmer's ease of implementation (for mulching this is average price, loan availability and rainfall while for agro-ecological practices it is low levels of soil organic matter, rainfall and topography).

Interestingly, if we omit our measure for soil organic matter at the district level, training becomes significant. As training is not estimated to be a significant district-diffusion driver if soil organic matter is included, this indicates that trainings in AEPs are especially offered in areas with low soil fertility.

The trainings we analyze are offered by a variety of stakeholders, often involving large development organizations like USAID and the German GIZ. Because there is much cooperation and mutual support, many trainings are offered jointly and hence we cannot analyze easily the comparative effect of either training provider. However, in our joint modelling framework, we can analyze the contribution of the most important actors to the probability that a farmers is trained in mulching or agro-ecological practices.

For mulching, these are USAID with their "Trade and Investment Program for a Competitive Export Economy" and GIZ with their "Market Oriented Agriculture Program". The trainings in AEPs are mostly offered by a private company called Blue Skies, the GIZ and NGOs.

For mulching we find that contract farming and a farmer's (self-reported) influence in his network increase his chances to receive training, as does the amount of regionally offered trainings. For AEPs, being certified, being in contact with the Blueskies company and being located in a region with smaller farms increase the probability to be trained.

Section 7: Robustness Checks

It is of great importance for our identification strategy to correctly delimit the boundaries of the farmers' information networks. We therefore check the robustness of this endeavor in the following. Alternatively to our main network definitions, it would also be plausible to define networks on the basis of villages and farm-groups.

Table 7: The effect of differently defined networks

(a) Adoption AEP	Model 1		Model 2	
training	.324***	(.107)	.324***	(.095)
positive observations abs.	3.865***	(1.497)	3.805***	(1.394)
positive observations perc.	1.636***	(.751)	1.517***	(.646)
district diffusion	1.769***	(.147)	1.642***	(.118)
Network Diffusion			.177***	(.065)

(b) Adoption Mulching	Model 1		Model 2	
training	.165	(.212)	.146	(.232)
positive observations abs.	1.504***	(.685)	1.472***	(.693)
district diffusion	.098	(.157)	.005	(.166)
Village and Group Network			.215*	(.133)

Table 7 shows the results and it can be seen that our main results are not significantly different, with the new network boundary being significant in both models.

We also tested different control functions, and chose the ones that had the greatest effect on the endogenous variables. The effect of the finally chosen CFs can be seen in table 8 below.

Table 8: The Comparative Effect of Joint Modelling (JM) and Control Functions (CF)

	all controls		only CFs		only JM		no controls	
	Coef.	(Std.Err.)	Coef.	(Std.Err.)	Coef.	(Std.Err.)	Coef.	(Std.Err.)
Mulching								
training	.178	(0.470)	.291**	(0.065)	.178	(0.457)	.338***	(0.000)
pos. observ.	1.511***	(0.027)	1.486785	(0.035)	1.518	(0.019)	1.374***	(0.039)
distr. diff.	.022	(0.892)	.272**	(0.051)	-.051817	(0.605)	.052	(0.574)
AEP								
training	.333***	(0.002)	.750***	(0.000)	.390***	(0.016)	.821 ***	(0.000)
pos. observ.	3.625***	(0.012)	7.382***	(0.013)	6.280***	(0.000)	6.274***	(0.001)
distr. diff.	1.764***	(0.000)	1.124***	(0.000)	1.830***	(0.000)	1.144***	(0.000)

Table 8 shows that for mulching, it is especially the joint modelling framework that controls for endogeneity but in combination, CFs and JM achieve the best correction. For AEPs, the information variables are always significant, with and without endogneity control. However, it can be seen that their magnitude would greatly be overestimated under endogeneity and even more than in the case of mulching, the combination of the approaches achieves the best result.

Testing various random effects on different levels did not further improve the results nor did scaling down the model to the field level (instead of farmer level).

Section 8: Conclusion

We find evidence that benefits of adopting sustainable intensification practices are heterogeneous across farmers. As mulching especially conserves soil moisture but is also labor intensive, farmers with drier fields and more affordable labor are more likely to adopt mulching; and as agro-ecological practices (AEPs) improve soil fertility but can be difficult to implement, farmers with less fertile fields but more knowledge are more likely to adopt AEPs.

Uninsured risk clearly plays a role in decision making too. For mulching, the most important risk is price volatility while for AEPs it is the weather. Considering that a third of our surveyed farmers reports to have experienced a major income shock in the past, risk must be taken seriously in this context. Furthermore, a lack of credit availability constrains adoption and is named the number one constraint by the farmers, especially for mulching. In contrast, tenure rights, are important for the adoption of AEPs but not significantly for mulching. The latter might be the case because the benefits from mulching accrue quicker than from AEPs but the role of tenure rights is limited either way, because most pineapple farming is done on rather secure, rented fields, while less secure fields, under traditional rights, are used for less profitable crops, such as maize and cassava.

Our main finding is that information is important for all farmers but its importance can be differentiated by innovations. For mulching, we are at a point in time where information is still crucial, but it is only positive observations (currently from other farmers) that appear to significantly increase the knowledge of potential adopters. In contrast for AEPs, all information sources are highly significant, be it training or other farmers.

Because trainings are most helpful to start the diffusion process of an innovation (see also Krishnan and Patnam (2014)), it is important to consider whether trainings in already moderately diffused practices should either focus on new areas or less diffused innovations to have the strongest effect.

Generally, our results suggest that for complex and little diffused innovations such as AEPs, setting up demonstration farms to create situations in which the innovations are observable could be of great help to many farmers. Adjognon and Liverpool-Tasie (2014) describe how in Nigeria, a development agency and a private fertilizer company effectively diffuse an innovative fertilizer through village promoters, who are farmers based in each village, who have sufficient social capital to be able to teach other farmers new practices while simultaneously serving as the local input supplier. In addition, there are demonstration plots that are set up next to traditionally farmed fields, so differences can clearly be observed. In the light of our findings, this strategy seems promising for all rather complex farming practices – such as AEPs – in Ghana too. Contrarily, to foster the adoption of capital intensive, less complex and more diffused innovations such as mulching, it seems likely that the development or enhancement of financial services has a larger effect than better communication. In our specific case, we recommend specialized financial products for pineapple-farming-groups that need not be paid back before pineapples have been sold and perhaps coupled with insurance (against weather and price fluctuations).

Because there is an apparently large, positive effect of contract farming on the adoption of innovations, additional research into the diffusion of contract farming seems worthwhile (see also Wuepper (2014)).

As our concluding remark: We find that complex, less known innovations such as AEPs require more information and expensive, better known innovations such as mulching require better financing, so we suggest to (a) Increase trainings and set up demonstration farms for AEPs and similar innovations and (b) to support the diffusion of capital-intensive innovations such as mulching with targeted financial services that meet the farmers' needs for capital and insurance.

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References

Abdulai, A., Owusu, V., & Goetz, R. (2011). Land tenure differences and investment in land improvement measures: Theoretical and empirical analyses. *Journal of Development Economics, 96*(1), 66-78.

Adjognon, S., & Liverpool-Tasie, L. S. O. (2014). Spatial Dependence in the Adoption of the Urea Deep Placement for Rice Production in Niger State, Nigeria: A Bayesian Spatial Autoregressive Probit Estimation Approach.

Bandiera, O., & Rasul, I. (2006). Social networks and technology adoption in northern mozambique*. *The Economic Journal, 116*(514), 869-902.

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics, 107*(3), 797-817.

Ben-Akiva, M., de Palma, A., McFadden, D., Abou-Zeid, M., Chiappori, P.-A., de Lapparent, M., . . . Hess, S. (2012). Process and context in choice models. *Marketing Letters, 23*(2), 439-456.

Besley, T., & Case, A. (1997). *Diffusion as a learning process: Evidence from HYV cotton*. Working paper 174. Princeton University.

Brock, W. A., & Durlauf, S. N. (2001). Discrete choice with social interactions. *The Review of Economic Studies, 68*(2), 235-260.

Brock, W. A., & Durlauf, S. N. (2006). Multinomial Choice with Social Interactions. In L. Blume & D. S. (Eds.), *The Economy as an Evolving Complex System III*. New York: Oxford University Press.

Conley, T. G., & Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *The American Economic Review*, 35-69.

Diao, X., & Sarpong, D. B. (2007). *Cost implications of agricultural land degradation in Ghana: an economywide, multimarket model assessment*: International Food Policy Research Institute, Ghana Strategy Support Program.

Erenstein, O. (2003). Smallholder conservation farming in the tropics and sub-tropics: a guide to the development and dissemination of mulching with crop residues and cover crops. *Agriculture, Ecosystems & Environment, 100*(1), 17-37.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change*, 255-298.

Feder, G., Murgai, R., & Quizon, J. B. (2004). The acquisition and diffusion of knowledge: The case of pest management training in farmer field schools, Indonesia. *Journal of agricultural economics, 55*(2), 221-243.

Fenske, J. (2011). Land tenure and investment incentives: Evidence from West Africa. *Journal of Development Economics, 95*(2), 137-156.

Florentin, M. A., Penalva, M., Calegari, A., & Deprsch, R. (2011). Green Manure / Cover Crops and Crop Rotation in Conservatio Agriculture on Small Farms *Plant Production and Protection division Food and agriculture organization of the United Nations*. Rome.

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics, 2*.

Gatune, J., Chapman-Kodam, M., Korboe, K., Mulangu, F., & Raktoarisoa, M. (2013). Analysis of Trade Impacts on the Fresh Pineapple Sector in Ghana *FAO Commodity and Trade Policy Research Working Paper No.41*. Rome: Food and Agricultural Organization of the United Nations.

Genius, M., Koundouri, P., Nauges, C., & Tzouvelekas, V. (2014). Information Transmission in Irrigation Technology Adoption and Diffusion: Social Learning, Extension Services, and Spatial Effects. *American Journal of Agricultural Economics, 96*(1), 328-344.

German Society for International Cooperation. (2005). Market Oriented Agriclture Programme (MOAP).

Geroski, P. A. (2000). Models of technology diffusion. *Research policy, 29*(4), 603-625.

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

Granovetter, M. (2005). The impact of social structure on economic outcomes. *Journal of economic perspectives*, 33-50.

Hartwich, F., & Scheidegger, U. (2010). Fostering Innovation Networks: the missing piece in rural development. *Rural Development News, 1*(2010), 70-75.
Hounkonnou, D., Kossou, D., Kuyper, T. W., Leeuwis, C., Nederlof, E. S., Röling, N., . . . van Huis, A. (2012). An innovation systems approach to institutional change: smallholder development in West Africa. *Agricultural systems, 108*, 74-83.
Karlan, D., Osei, R. D., Osei-Akoto, I., & Udry, C. (2012). Agricultural decisions after relaxing credit and risk constraints: National Bureau of Economic Research.
Kazianga, H., & Udry, C. (2006). Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso. *Journal of Development Economics, 79*(2), 413-446.
Kleemann, L., & Abdulai, A. (2013). Organic certification, agro-ecological practices and return on investment: Evidence from pineapple producers in Ghana. *Ecological Economics, 93*, 330-341.
Krishnan, P., & Patnam, M. (2014). Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption? *American Journal of Agricultural Economics, 96*(1), 308-327.
Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies, 60*(3), 531-542.
Manski, C. F. (2000). Economic analysis of social interactions: National bureau of economic research.
McIntyre, B., Herren, H., Wakhungu, J., & Watson, R. (2009). Agriculture at a Crossroads: Sub-Saharan Africa. *Science And Technology, 5*.
Millenium Development Authority. (2011). *Millenium Challenge Account Ghana Program Agriculture Project*.
Petrin, A., & Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research, 47*(1), 3-13.
Pretty, J., Toulmin, C., & Williams, S. (2011). Sustainable intensification in African agriculture. *International journal of agricultural sustainability, 9*(1), 5-24.
Roodman, D. (2009). Estimating fully observed recursive mixed-process models with cmp. *Center for Global Development Working Paper, 168*, 1-57.
Roodman, D. (2013). CMP: Stata module to implement conditional (recursive) mixed process estimator. *Statistical software components*.
Ruef, M. (2002). Strong ties, weak ties and islands: structural and cultural predictors of organizational innovation. *Industrial and Corporate Change, 11*(3), 427-449.
Snapp, S., & Pound, B. (2011). *Agricultural Systems: Agroecology and Rural Innovation for Development: Agroecology and Rural Innovation for Development*: Academic Press.
Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica, 79*(1), 159-209.
Thuo, M., Bell, A. A., Bravo-Ureta, B. E., Lachaud, M. A., Okello, D. K., Okoko, E. N., . . . Puppala, N. (2013). Effects of social network factors on information acquisition and adoption of improved groundnut varieties: the case of Uganda and Kenya. *Agriculture and Human Values*, 1-15.
Train, K. (2009). *Discrete choice methods with simulation*: Cambridge university press.
Udry, C., & Anagol, S. (2006). The return to capital in Ghana. *The American Economic Review*, 388-393.
USAID. (2009). *Trade and Investment Program for a Competitive Export Economy - Final Report*.
USAID. (2013). Agricultural Development and Value Chain Enhancement (ADVANCE) - Project profile.
Walker, J. L., Ehlers, E., Banerjee, I., & Dugundji, E. R. (2011). Correcting for endogeneity in behavioral choice models with social influence variables. *Transportation Research Part A: Policy and Practice, 45*(4), 362-374.
Wilde, J. (2000). Identification of multiple equation probit models with endogenous dummy regressors. *Economics letters, 69*(3), 309-312.
World Bank. (2008). *World Development Report 2008: Agriculture for Development*: World Bank.
Wuepper, D. (2014). Opportunities and constraints to integrate Ghana's smallholder farmers into global values chainsAfrican Economic Outlook 2014: African Development Bank, Development Centre of the Organisation for Economic Cooperation and Development (OECD), United Nations Development Programme (UNDP). Retrieved from http://www.africaneconomicoutlook.org/en/.

Appendix A

Please imagine that you can chose between pineapple varieties that are differently risky and the more risky ones produce on average more profit. Which one would you choose?

Option	Profit when harvest is bad	Profit when harvest is good	Please indicate your choice (once)
1	1000	1000	
2	900	1800	
3	800	2400	
4	600	3000	
5	200	3800	
6	0	4000	

Appendix B

Please imagine that you can shift your profits between this season and the following ones. How would you prefer the distribution of profits?

Option	Profit this season	Profit from next season on	Please indicate your choice (once)
1	3400	1800	
2	2800	1900	
3	2000	2000	
4	1900	2800	
5	1800	3400	
6	1600	4000	
7	unknown	8000	