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Sustainable Intensification of Pineapple Farming in Ghana: Training and Complexity

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Abstract

Sustainable intensification of Ghana's smallholder farming is critical to mitigate rural poverty. Innovations for sustainable intensification include agro-ecological practices, which build up soil fertility, and mulching, which conserves soil moisture. To stimulate the adoption of these innovations, development organizations and business stakeholders provide training for farmers, to demonstrate proper usage and convince the farmers of their profitability. Using unique panel data, we analyze whether the provided training increases adoption-rates.

We find effect of training is significant for the adoption of agro-ecological practices but not for mulching. The explanation is that agro-ecological practices are complex but inexpensive, so that information is the main constraint. Mulching in contrast is already a little more diffused, easier to understand but more expensive. Therefore, mulching is less constrained by lacking information and mostly by finance, which includes restricted credit access and uninsured risk.

Keywords: Agricultural Training; Sustainable Intensification; Development Organizations; Social Learning; Agro Ecological Practices; Mulching; Ghana

JEL codes: C3, C5, O2, O3, D8, Q1

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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 export certified pineapple farmers in Ghana and find the adoption of sustainable farming practices to be profitable, especially when used more intensively. The government of Ghana, development initiatives and business stakeholders are hence interested in widely diffusing sustainable intensification innovations amongst Ghana's smallholder farmers but the question is how to best achieve a significant level (German Society for International Cooperation, 2005; Government of Ghana, 2010; Millenium Development Authority, 2011; USAID, 2009, 2013).

Knowing that sustainable intensification is profitable for Ghana's pineapple farmers, the question remains why these innovations are not diffused more widely by now – as reflected by our sample, which covers a panel of Ghana's pineapple farmers between 2010 and 1013: Agro-ecological practices are used by 15% of the farmers and mulching by 40%. Overall, 55% of the farmers use neither.

There is a large literature on this well-known phenomenon of a rather slow diffusion of seemingly profitable innovations in agriculture as well as factors often contributing to this (Feder, Just, & Zilberman, 1985; Foster & Rosenzweig, 2010):

1. Heterogeneity in profits: Suri (2011) looks at the adoption of modern seeds and fertilizers in Kenya and finds that the decision to not adopt appears to be the right choice for most farmers as location specific constraints increase adoption costs until they out-weight benefits.
2. Financial 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, even though Fenske (2011) shows that this effect varies over different investments.
4. Information: The adoption of new technologies requires learning about their profitability and proper use which implies that 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) in southern Ghana and whether training is an effective tool to overcome it. The advantage of training might be that experts bring in completely new information, however, the disadvantage might be communication barriers between smallholder farmers and experts (Rogers, 2003; Ruef, 2002).

We focus especially on training provided by development organizations as so far, studies have mostly focused on extension services (Anderson & Feder, 2004; Birkhaeuser, Evenson, & Feder, 1991).

Recently, the impact of training has received increased attention (Genius, Koundouri, Nauges, and Tzouvelekas (2014) in Greece, Krishnan and Patnam (2014) in Ethiopia, Thuo et al. (2013) in Kenya and Uganda and Pamuk, Bulte, Adekunle, and Diagne (2014) in Central Africa) with interesting findings: Also using 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 (see also Anderson and Feder (2004)). Pamuk, Bulte, Adekunle, et al. (2014) use experimental data, comparing the conventional top-down extension approach with a more participatory, bottom-up approach. They find that both approaches support poverty reduction but the latter is more effective.

Pamuk, Bulte, and Adekunle (2014) however, find that there is considerable heterogeneity in the effect on innovation adoption and diffusion, depending on the type of innovation and village characteristics, especially the level of social capital.

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, we estimate a joint model with respect to adoption, diffusion at district level and training (top down, delivered by experts) for two sustainable intensification innovations:

1. Mulching, which means that soils are covered with plastic or organic materials (like grass or crop residues), to conserve soil moisture and mitigate weeds. (Erenstein, 2003) and
2. Agro-ecological techniques (AEPs; such as using compost, green manure or sustainable crop rotations), which mitigate the loss of soil fertility (Florentin, Penalva, Calegari, & Deprsch, 2011; Snapp & Pound, 2011). Most AEPs also improve the soils capacity to hold water but this effect takes some time and is perhaps less salient to the farmers.

Methodologically we contribute by demonstrating the advantages of modelling the innovation adoption in a joint estimation framework. In our model the adoption of an innovation, its district diffusion and the probability to receive training on it are simultaneously estimated, which allows to gain empirical insight in the linkages of these processes. First, the drivers for the diffusion at the district level can be identified as well as determinants for the adoption at the individual farm level (interestingly, these drivers do not necessarily coincide). Second, besides controlling for observable factors that drive district diffusion and training we also control for unobservables. Finally we are also interested to see what makes it more likely to receive the training in the first place. We find that this is mostly externally determined to the farmer and strongly linked to his location.

Since the joint modelling framework only controls for observable variables, we complement it with control functions (also known as Hausman-correction), aiming to control for local influences that affect the probability to participate in training and induce farmers to behave spatially homogenously independent of network-effects such as peer-learning (Manski, 1993, 2000).

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 as well as on the importance of all other constraints. That is, training improves a farmer's knowledge most when the provided information is not available elsewhere in the farmer's network. Whether he can directly use this new knowledge depends on the severity of other constraints such as uninsured risk, lack of credit or lack of profitable labor.

Furthermore, we find that learning from trainings and learning from other farmers can both be understood as complements and as substitutes. While the greatest effect is observed for farmers who received training and whose neighbors demonstrate the innovation's use and benefit (complementarity), trainings are less important if the innovation is diffused (substitutability). As specific examples from our study, mulching is relatively easy to understand, relatively expensive and wider diffused than other sustainable intensification innovations (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, as provided information new in the farmers' networks and often sufficient to act on it.

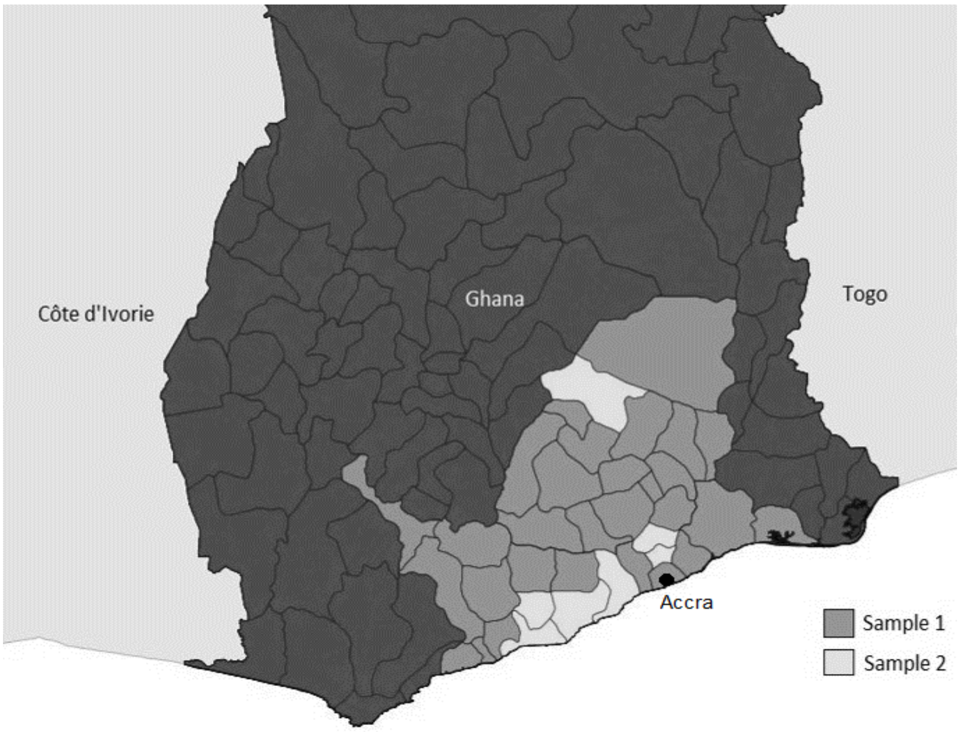
The remainder of this paper is structured as follows: In the next section we describe the data (2), followed by a summary of the study-context (3). In section 4 we develop our model and in section 5 we present the empirical results. The robustness of our specifications and estimates are comprehensively reviewed in section 6. We conclude the study with section 7.

Section 2: Data

We use panel data that we collected in 2010 and 2013. In the first round, data from 386 pineapple farmers was collected in 75 villages in Southern Ghana between January and March 2010. In the second round, we collected complete data from 173 out of the 386 farmers that we tried to interview again. The dropouts appear non-systematic except for a higher rate in the central region compared to the eastern region, which is however not related to farmer characteristics but caused by a larger and more mobile team of enumerators in the eastern region. Since we are using a discrete choice framework, we judge the representativeness of our sample as sufficient.

Map 1 shows the regions of Ghana where pineapple is grown (Sample 1) and where we sampled farmers (Sample 2). The Sample 2 areas west of Accra are located in the Central Region of Ghana, whereas the Sample 2 areas north of Accra are located in Greater Accra and the Eastern Region.

Map 1: The sampled areas in southern Ghana



The three major regions for the pineapple production 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 was asked questions about self-perception and 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). The results were broadly in line with farmers' reported self-perceptions.

To estimate a farmer's time preference, he or she were directly asked questions about self-perception and to indicate their preferred choice 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). Again, our experimental results are consistent with the farmers' self-categorization.

For our dependent variables, we asked farmers to indicate which practices they currently use, whether they have used one but stopped (and why) and when they heard about and 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 the farmer reports and create variables containing information about how many farmers were reported to be successful with an innovation in the neighborhood of a sampled farmer or what share of farmers achieved good results in a certain region.

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 an important network boundary (variable “district diffusion). To incorporate the fact that other, smaller networks might be influential over and above the wider network, we also included various other networks as well.

We also used the 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 (“Sold to company”) while the rest is sold on local markets. The mean household consists of 6 people (“Household”), with a 46 year (age) old male head and an income of about 80 US$ (“Income Level”). A major problem is the unavailability of credit (“No 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 (“Income shock”), 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 found i.e. by Kazianga and Udry (2006) in Burkina Faso.

As can be seen in table 1, all pineapple farmers strongly avoid land under traditional tenure rights (“stool land” and “share land”), with the exception of family land (“Family land”). Renting land is perceived as safe because all relevant rights are more clearly defined (“Rented land”).

In general, adopters of sustainable intensification innovations are better educated (“Education level” and “Alphabetism”), have higher incomes, lager households and hence usually more available labor (“Family labor”), more rented land and more likely to have received a loan (“loan”). Interestingly, adopters are not generally more likely to have adopted a modern pineapple variety ("MD2 variety" or "SC variety") but the traditional and robust variety Sugar Loaf, which is preferred for organic farming ("SL variety"). All farmers agree that besides knowledge, credit is the most serious constraint ("Credit constr."), followed by labor ("Labor constr.") and the weather ("weather constr.").

Table 1: General Descriptive Statistics

	Adopters Agro-Ecological Practices		Adopters Mulching		Non - Adopters	
Characteristics	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)
Sold to company (%)	.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 (%)	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)

We also asked the farmers about their main information sources (see table 2). Their most important source for new information, they said, are extension agents and advisors (“Info advisor”), followed by other farmers (“Info farmer”) whereas the most important source for learning about profitability and usage of innovations are other farmers (Learn farmers”). When it comes to information sources, differences between adopters and non-adopters are much more pronounced then in the previously discussed table 1 on general 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 smaller, for non-adopters the role of training for learning is more important than for adopters, possibly indicating a relative lack of general information access.

Table 2: Descriptive Statistics on Information Sources

	Adopters Agro-Ecological Practices		Adopters Mulching		Non - Adopters	
Info-Sources	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)
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)

List 1 briefly explains the variables we use in our empirical models.

List 1: Explanatory Variables used in the Empirical Models

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	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	Whether a major income shock has been experienced
dry fields	Whether the farmer considers his fields too dry
risk aversion	How much the farmer avoids 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
SC variety	Whether the farmer grows Smooth Cayenne
SL 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
district training X	How many trainings were offered in the district
own influence	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	Whether the farmer has been trained by GIZ (MOAP)
training usaid	Whether he has been trained by USAID (TIPCEE)
training NGOs	Whether the farmer has been trained by NGOs
peers certified organic	Whether the peers of the farmer are certified organic
regional farm size	The average farm size of the region

List 2: Interaction-Terms with Training:

X complementary practices	trained and already adopted row planting or similar
X district diffusion	trained and adoption-rate in farmer's district
X contract farming	trained and whether he is in a farming contract
X inexperience	trained and whether he reports himself to be inexperienced
X no loan	trained and whether the farmer is credit constraint

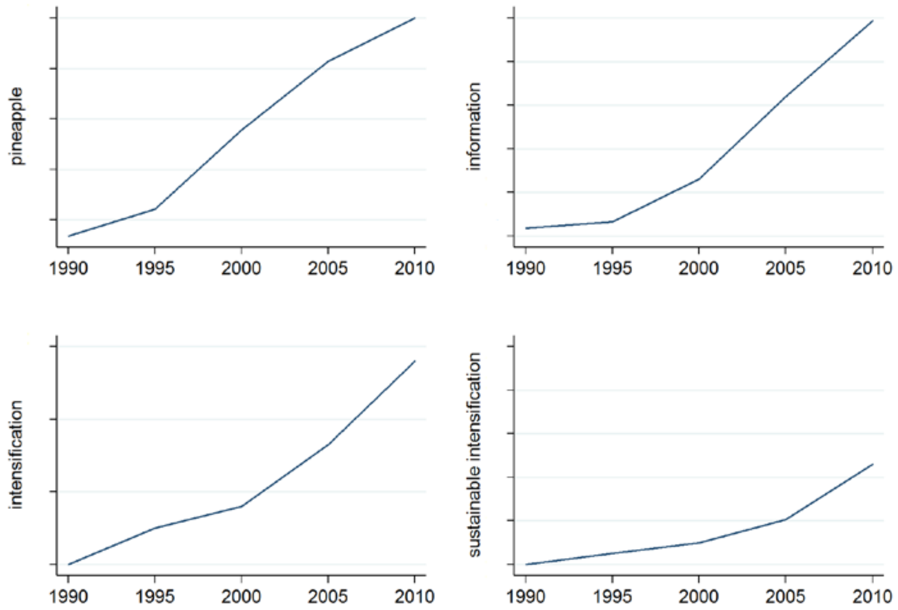
Section 3: Context

Our study area in Southern Ghana is optimal to learn about the diffusion of innovations for several reasons. First, agricultural development is dynamic (positively and negatively) and hence panel data over a relatively short period is more likely to reveal interesting patterns. Pineapple is Ghana's most developed horticultural sector. 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 sufficiently 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 successfully produce this new variety diffused slowly and both planting material and required inputs are expensive. Consequently many farmers failed with the new variety and dropped out of this 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 depicts selected historical developments, as reported by the sampled farmers. It shows the cumulative number of farmers who grew pineapple in each period (until 100% in the last period), had information about intensification (100% in the last period) and who intensified – generally (using any external inputs; finally 82%) and sustainably (using any sustainable intensification practices; finally 46%) – 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 might allow to forecast their future evolution.)

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 corner), 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 corner). More and more farmers started to intensify their production systems (lower left corner) and until 2013, 40% of the farmers used mulching and 10% agro-ecological practices (their combined development until 2010 is displayed in the lower right corner).

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



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:

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

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:

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

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

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

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:

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

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:

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

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:

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

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

$$y_{int} = \begin{cases} 1 & if \; y_{int}^{*} > 0 \\ 0 & otherwise \end{cases} \quad , \quad (7)$$

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:

$$y_{int}^{*} = b_{int} + F + V_{int}(x_{int}; s_{nt}; c_{nt}; \beta_{nt}) + \gamma_1 L_{int}^{p} + \gamma_2 tr_{int} + \varepsilon_{int} . \quad (8)$$

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. We hence need to control for local variables that could induce people to behave similar or to join a training. As an example, a drought might induce many farmers in a region to adopt a soil moisture conserving innovation and look out for a training how best to use it – which would lead to the overestimation of peer-learning and training effect.

To account for this kind of endogeneity in a discrete choice model, two well-tested 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, our 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, because then, the values from spatially adjacent zones are free of the local variables that could give rise to the endogeneity. Whatever local effects might be captured by the values of spatially adjacent zones, they are not the local effects that affect the zone of the farmer in question.

To ensure that we delimit our networks correctly, we directly 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). Hence, for farmers who reported their network to be within their village, the instruments are the values in adjacent villages, whereas for farmers who reported their network to be their district, the instruments are spatially adjacent districts, etcetera.

We also include the values of the endogenous variables in broader defined 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 logic of this second set of variables is similar to the first, with the difference that local effects are now excluded by a higher aggregation level.

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):

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

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:

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

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

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

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). As the dependent variables are of different kinds, the model is a “mixed process” regression. The equations have in common that they are linear in parameters with normal distributed error terms, which are correlated.

The estimations are performed in STATA, using the CMP routine of David 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 will be seen, the district diffusion of our innovations is broadly driven by external factors that affect the innovations’ relative benefit. On the individual level, details matter, generally capturing individual incentives, abilities and constraints.

Section 5: Results

Table 3 shows the results for mulching and table 5 shows the results for agro-ecological practices. Table 4 and 6 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). It seems that now, it is rather demonstrated profitability by other farmers that encourages taking the risk of investing into it. The main difficulty is then credit availability and uninsured risk (such as price volatility i.e.).

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

Testing the interpretation above with interaction terms, we find a complementarity between provided training and peer-learning (level of district diffusion). We also find that it is relevant to consider other farming practices of the farmers, as some practices are complementary (like row planting). Furthermore, there is a positive effect of contract farming on the impact of training in mulching.

Table 3: Results for Training, Adoption and Diffusion of Mulching (M)

(3a) Individual Adoption M	Coef. Std. Err.
training in mulching	.174 (.246)
positive observtions abs.	1.513***(.685)
positive observtions perc.	.026 (.150)
district diffusion	.022 (.166)
dry fields	.226** (.111)
contract farming	.358***(.091)
risk aversion	-.059 (.108)
time preference	-.178** (.090)
age	-.097 (.082)
education	.044 (.089)
family labor	.159 (.107)
labor costs	-.079 (.053)
farmland	.193 (.121)
no credit available	-.274***(.098)
income shock	-.200** (.097)
nonfarm income	.259***(.091)
price volatility	-.133* (.070)
export price	.152 (.166)
local market price	.013 (.160)
pineapple hectares	-.276** (.113)
SC variety	.012 (.110)
SL variety	-.244 (.171)
MD2 variety	.061 (.103)
fixed effects period	yes (2)
fixed effects networks	yes (9)
fixed effects districts	yes (6)
control functions	yes (2)
constant	Yes (1)

(3b) District Diff. Mulching	Coef. Std. Err.
district loan availability	.039***(.006)
average district price	.012***(.003)
district rainfall variab.	.083***(.017)
fixed effects districts	yes (6)
constant	Yes (1)

(3c) Training Mulching	Coef. Std. Err.
own influence	.174 (.109)
blue skies contract	.260***(.081)
hpw contract	.263***(.092)
training giz	.338** (.100)
training usaid	.556***(.175)
district training mulching	1.01*** (.354)
fixed effects districts	yes (6)
constant	Yes (1)

Significance levels: ***=0.95;**=0.9;*=0.8.

S.E. robust and clustered

Table 4: Interaction Effects 1

Training Mulching	Coef. Std. Err.
X complementary practices	.411** (.178)
X district diffusion	2.870* (1.605)
X contract farming	.227* (.128)
X no loan	-.184 (.121)

Table 5: Results for the Adoption and Diffusion of Agro-Ecological Practices (AEP)

(5a) Individual Adoption AEP	Coef. Std. Err.
training in AEP	.272***(.077)
positive observations abs.	3.188***(1.088)
positive observations perc.	1.318** (.545)
district diffusion	1.705***(.146)
age	-.058 (.043)
education	.005 (.038)
perceived soil quality	-2.931***(.959)
fertility understanding	.078* (.043)
inexperienced	-.085* (.049)
topography	.742***(.178)
distance port	-.590***(.240)
rented fields	.149***(.061)
dry fields	.041 (.038)
price volatility	.059 (.174)
price diff. exp. and loc.	.337 (.342)
income level	.100* (.052)
income shock	.011 (.035)
foodland	.062 (.038)
cashland	-.067 (.045)
farmland	.064** (.028)
no credit	-.107** (.053)
time preference	.066* (.037)
risk preference	.024 (.045)
SL variety	-.039 (.056)
SC variety	.058 (.046)
MD2 variety	-.038 (.044)
fixed effects period	yes (2)
fixed effects regions	yes (2)
control functions	yes (2)
constant	Yes (1)

(5b) District Diffusion AEP	Coef. Std. Err.
soil fertility	-.132***(.031)
district rainfall	-.057***(.012)
topography	-.046***(.011)
fixed effects districts	yes (4)
constant	Yes (1)

(5c) Training AEP	Coef. Std. Err.
training blueskies	1.295***(.169)
training giz	.473** (.217)
training NGOs	.300** (.122)
peers certified organic	.292** (.150)
mean district farm size	-.234 (.170)
fixed effects districts	yes (4)
constant	Yes (1)

Significance levels: ***=0.95;**=0.9;*=0.8.

S.E. robust and clustered

Table 6: Interaction Effects 2

Training AEPs	Coef. Std. Err.
X complementary practices	.116* (.061)
X district diffusion	.153* (.087)
X contract farming	.146* (.087)
X inexperience	.755* (.434)

Table 5 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. Perceived soil fertility is quite predictive for non-adoption (even though we must be careful treating this variable as exogenous as farmers who do not feel capable of improving their soils decide to ignore the problem altogether. However, measured regional soil fertility correlated with the stated perception, so there is likely an empirical foundation). We also find that understanding the concept of soil fertility is important, suggesting that if farmers understand the need to replenish nutrients they are more likely to choose AEPs. Similarly, those who reported to be less experienced than their peers are less likely to adopt but 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. Another sub-groups that benefit above-average from training in AEPs are contract-farmers.

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), as it is mainly reported observations that explain peoples' behavior. 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).

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 (see section c in tables 3 and 5).

For mulching, these are USAID with their "Trade and Investment Program for a Competitive Export Economy (TIPCEE)" and GIZ with their "Market Oriented Agriculture Program (MOAP)". 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 6: Model Evaluation and Robustness Checks

It is of great importance for our identification strategy to correctly delimit the boundaries of the farmers' information networks. We therefore have to carefully check the robustness of our results when networks are differently defined.

Table 7: The effect of differently defined networks

(7a) 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)
(7b) 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)

Most farmers are part of multiple networks (neighbors, farm-group, extension) that have differently strong impacts on their decisions. Alternatively to our main network definitions, it would hence also be plausible to define networks on the basis of villages and farm-groups, which we include in the estimation shown in table 7. It can be seen that our main results are not significantly different from before, even though the newly added network is 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)

(8a) Mulching	all controls		only CFs		only JM		no controls	
	Coef.	(Std.Err.)	Coef.	(Std.Err.)	Coef.	(Std.Err.)	Coef.	(Std.Err.)
training	.178	(0.470)	.291**	(0.065)	.178	(0.457)	.338***	(0.000)
pos. observ.	1.511***	(0.027)	1.486	(0.035)	1.518	(0.019)	1.374***	(0.039)
distr. diff.	.022	(0.892)	.272**	(0.051)	-.051	(0.605)	.052	(0.574)
(8b) 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 endogeneity control. However, it can be seen that their magnitude would be overestimated under endogeneity and, even more than in the case of mulching, the combination of control functions and joint modelling 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).

To evaluate our two models, table 9 shows selected criteria. Most importantly, we test our results by seeing how many observed adoptions between 2009 and 2013 we would have predicted. As can displayed, we would have correctly predicted about 80% of the adoption decisions, which seems quite good, given that the adoption of innovations in Sub-Saharan Africa is considered quite difficult to predict (Feder et al., 1985; Foster & Rosenzweig, 2010; Suri, 2011).

Table 9: Model Evaluation Criteria

	adoption AEPs	adoption Mulching
log-pseudolikelihood	-278.56	-209.13
prob > chi^2	0.000	0.000
AIC	461.13	300.27
BIC	276.50	73.33
correctly predicted obs.	78%	79%

Section 7: 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 and expensive, farmers with drier fields, credit access, more predictable prices 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 experience and 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 report 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 as 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 much faster than those from AEPs. However, it must be noted that most pineapple farming is generally done on rather secure, rented fields, while less secure fields, under traditional rights, are used for less profitable crops, such as maize and cassava.

We furthermore find that information is important for all farmers but its importance significantly varies by innovation type. For mulching, information is still crucial, but it is only observational learning from other farmers (who likely demonstrate profitability) that appears to significantly increase the knowledge of potential adopters, while training is not decisive anymore. For AEPs in contrast, all information sources are highly significant, including training, which is quite important for new information, such as how to integrate this complex innovation into the existing practices.

Because training is most helpful to start the diffusion process (see also Krishnan and Patnam (2014), it is important to consider whether training for already moderately diffused practices should either focus on less connected areas or other, 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 with sufficient social capital to be able to teach other farmers new practices while simultaneously serving as local input supplier. In addition, there are demonstration plots 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 as well.

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 probably also coupled with insurance (against weather and price fluctuations).

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

Another research question for the future is whether decentralized, participatory “innovation platforms” (Pamuk, Bulte, & Adekunle, 2014) would be more efficient than the here analyzed top-down trainings. We found that (1) adoption-benefits are heterogeneous, (2) farmers are aware of this, (3) farmers learn best through local demonstrations and (4) there are complementarities between innovations. A policy mix worth testing hence includes participatory “innovation platforms” and demonstration farms, that are complemented by farmer demands, which will often involve financial services.

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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 (in GHC)	Profit when harvest is good (in GHC)	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 (in GHC)	Profit from next season on (in GHC)	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	