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RESEARCH ARTICLE

Are less polluting and synergistic farming technologies complementary?

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Abstract
The objective of our paper is to provide an explanation for the lack of joint adoption by farmers of cleaner technologies in banana production, specifically fallow period (FP) and disease-free seedlings (DFS). Our hypothesis is that while these technologies are synergistic from an agronomic and environmental perspective, and thus efficient from a social interest perspective, they are substitutable rather than complementary from a farmer's private interest perspective. In other words, farmers receive lower returns from adopting both technologies together than from adopting them in isolation. To test this hypothesis, we present a unified empirical framework for assessing complementarity. We estimate a structural model of complementarity that overcomes the unobservable heterogeneity bias found in previous models using a database of 607 banana farmers in the French West Indies. Our results support our hypothesis, showing a substitution effect between FP and DFS rather than a complementarity effect. Moreover, we observe a contrasting profile of adopting farmers: smallholders who are reluctant to change adopt FP, while more specialized farmers who anticipate a pesticide ban adopt DFS. A public policy that promotes joint adoption should compensate smallholders for the cost of the DFS technology, while compensating more productive farmers for leaving their land fallow.

Keywords: Agroecology; clean technologies; complementarity; joint adoption

Introduction
Intensive banana farming practices and monoculture in the French West Indies have resulted in parasitic pressure, reduced soil fertility, and increased soil and water pollution due to pesticides. These issues pose risks to human health (Bocquene and Franco 2005; Cabidoche et al. 2009). The social and political crisis that followed the pollution caused by chlordecone, a banana pesticide, and its consequences on human health, including a dramatic increase in the number of cancer cases in the French West Indies population,

have prompted the public policy and local agricultural research community to develop less polluting crop sanitation technologies.

In the late 1990s, disease-free seedling technology (DFS) for bananas was developed. The seedlings are produced in vitro, making them free of pests, mainly nematodes. This new technology is efficient if the plantation is preceded by a fallow period (FP) of 12 months as it reduces the population of pests for several years without using pesticides (Chabrier and Quénehervé 2003). To maintain the duration of the FP cleaning effect, it is recommended to use DFS technology in conjunction with it. This is because DFS technology prevents rapid re-infestation of the soil.

Although the technologies can be used separately, from an agroecological perspective, they are synergistic and should be jointly adopted by farmers (Bonin and Cattan 2006). However, even though joint adoption can increase social welfare by reducing nematicide spraying by 50% and increasing yields, its adoption by farmers remains low (Blazy et al. 2009; Chopin and Blazy 2013).

Sustainable agroecological systems are the result of complex interactions at the local level between technologies and biological components of agroecosystems (Duru et al. 2015; Meynard et al. 2018). These systems are based on a bundle of technologies and practices that lead to emergent and synergistic sustainable properties (Altieri 2002). In this case, joint adoption ensures soil sanitation through nematode destruction by first implementing FP and then DFS to avoid exogenous re-infestation after FP. The joint adoption of synergistic technologies provides better control of pest pressure, resulting in a significant reduction in pesticide use and lower production costs.

The joint adoption of synergistic technologies can result in an additional gain, known as a (economic) complementary effect, compared to the adoption of each technology in isolation (Edmeades et al. 2008; Lambrecht et al. 2014). If such a complementary effect exists, then even a "selfish" farmer who maximizes her/his own utility may have sufficient incentives to jointly adopt socially efficient technologies that drastically reduce pesticide use. Without this additional gain, or in the case of a substitution effect, the joint adoption rate may be low even though the two agroecological technologies can have synergistic effects from an agronomic and environmental perspective by reducing the use of pesticides, thereby inducing a large benefit to society.

To confirm this hypothesis, it is necessary to test the existence of such a complementary effect between agroecological technologies in banana production.

To test for complementarity, we use a framework developed by Athey and Schmutzler (1995) and Athey and Stern (1998). We implement a production approach by testing for complementarity using ordinary least squares regression to estimate a banana production function. This production approach tests the contribution of different combinations of technologies, along with observable characteristics, directly on the performance measure (farm income). However, OLS regression may produce biased estimates (endogeneity bias) due to the co-movement phenomenon in the adoption decision, which may be caused by unobserved heterogeneity.

To account for the correlation between decisions, we have recourse to a second approach, known as the adoption approach, which uses a bivariate probit. The correlation coefficient between the errors indicates the presence or absence of a complementary effect in joint adoption decisions. However, the bivariate probit model may also be inconsistent when unobserved heterogeneity is present (Miravete and Pernias 2010). To address this issue, we estimate a structural model using an original multinomial probit model that separate the complementary effect and unobserved heterogeneity.

Our paper is related to the emerging literature on the joint adoption of agricultural technologies. The standard approach to innovation adoption in agriculture used to focus on a single technology (Qaim and de Janvry 2003; Foltz and Chang 2002; Adesina and Zinnah 1993; Feder and Umali 1993; Nowak 1992; Marra et al. 2003; Feleke and Zegeye 2006; Duflo et al. 2008; Brown et al. 2016; Takahashi et al. 2020; Beaman et al. 2021; Gedikoglu et al. 2023).

However, some papers have also considered the case where the farmer can choose a set or bundle of technologies (Caswell and Zilberman 1985; Rauniyar and Goode 1992; Dorfman 1996; Fares 2014; DeLay et al. 2022). Several estimation models have been proposed to analyze the complementarity between decisions to adopt different technologies, such as multinomial logit and probit (Caswell and Zilberman 1985; Dorfman 1996) and bivariate/multivariate probit (Kassie et al. 2013; DeLay et al. 2022).

We also highlight the estimation bias that arises when using the other approach to complementarity, the production approach, which is more widely used in innovation economics. For example, Mohnen and Röller (2005) and Kamutando and Tregenna (2024) directly estimate the objective function and investigate whether R&D make-buy decisions are complementary. Lockshin et al. (2008) investigate the complementarity of product, process, and organizational innovations and their impact on labor productivity. Ichniowski et al. (1997) examine the complementarity of various human resource management practices.

The remaining sections are organized as follows. Section 2 presents the context of agroecological crop sanitation technologies in banana production in the French West Indies (Guadeloupe and Martinique). Section 3 discusses the theory of complementarity and the empirical models of the two approaches to testing for complementarity (production and adoption approaches). In Section 4, we provide some details on our survey and the variables used in the empirical tests. Section 5 presents the econometric results, followed by a discussion. The paper concludes with section 6.

Background

Banana production is a significant economic activity in Guadeloupe and Martinique, accounting for approximately 20% of their export earnings and providing a major source of local employment. However, the liberalization of banana markets since the 1990s has had a negative impact on banana exports from these two small Caribbean islands, as their competitiveness is generally lower compared to Central American production. The lack of competitiveness in the French West Indies banana industry can be attributed to higher labor costs, limited farm size, and frequent natural disasters such as hurricanes. Additionally, the control of black weevils and nematodes, which are the main pests of bananas, presents a major challenge for banana growers.

To manage these pests, farmers have increasingly relied on nematicides and insecticides since the 1980s. To maintain their incomes, farmers have intensified their systems with chemical inputs, mainly to manage pests like nematodes (Blazy et al. 2009). However, pesticides are only efficient in the short term and are responsible for dramatic soil and water pollution in both islands (Cabidoche et al. 2009). The social and political crisis surrounding the pollution caused by chlordecone, a banana pesticide, and its impact on human health, including a dramatic increase in the number of cancer cases in the population of French West Indies, highlights the urgent need for public policy and local academic research to find less polluting solutions to manage pest pressure.

To address these challenges, the local agricultural research community has developed various agroecological crop sanitation technologies. One such innovation is the banana disease-free seedling, which was introduced in the late 1990s. These seedlings are produced in vitro and are therefore free of pests.

However, it is important to note that this technology is only efficient from an environmental or social point of view (reduction of pesticide use) if the DFS plantation is preceded by a fallow period. Otherwise, the alternative to the fallow period is to treat the soil with nematicides before planting DFS. This DFS-only strategy, i.e. without a previous fallow, can be efficient for farmers who only consider their "private interest." This can be the case for farmers highly specialized in banana production, for whom the opportunity cost of a 12-month fallow may be too high.

It is possible to reduce nematode populations for several years without using pesticides by implementing a fallow period of 12 months (Chabrier and Quénehervé 2003). To maintain the duration of the fallow period cleaning effect, it is highly recommended to use DFS technology. This technology helps to avoid rapid re-infestation of the soil by producing nematode-free seedling in vitro. Therefore, from an agroecological perspective, it is recommended that farmers adopt both technologies in conjunction. However, despite the potential benefits of reducing nematicide spraying by 50% and increasing yields, joint adoption rates among farmers remain low (Blazy et al. 2009).

Testing for complementarity: theory and empirical models

The complementarity approach used in our paper traces back to a mathematical theory of lattices and supermodularity functions (2.1). This theoretical framework allows us to make predictions about the complementarity of technology adoption strategies selected by farmers (2.2). We test these predictions using two empirical approaches to complementarity: the production approach and the adoption approach.

Supermodularity and complementarity

The complementarity approach is based on the theory of supermodularity (Topkis 1978, 1998). To define the notion of supermodularity, suppose that the banana production technology depends on two agroecological crop sanitation technologies (s^1 for FP and s^2 for DFS) and a vector of exogenous production factors (X). If s^j are discrete choices, i.e. $s^j \in \{0, 1\}$ with $j = 1, 2$, the farmer can combine both technologies differently, leading to four exclusive, and therefore not collinear, combinations of strategies: $\left(s^j = 0\right)$ if neither technology is used; $\left(s^1 = 1,\ s^2 = 0\right)$ if FP is used but DFS technology is not (FP-only); $\left(s^1 = 0,\ s^2 = 1\right)$ if, symmetrically, DFS is used but FP is not (DFS-only); and $\left(s^j = 1\right)$ if both technologies are jointly used (FP&DFS).

When the banana farmer chooses the optimal strategy to maximize the objective function $\left(s^1, s^2; X\right)$, the latter is supermodular if the following inequality holds

$$F(1,1;X) - F(0,1;X) \geq F(1,0;X) - F(0,0;X). \tag{1}$$

This means that there will always be increasing differences from not adopting any technology to adopting both technologies. That is, the presence of one technology $\left(s^1 = 1\right)$ increases the marginal return of the other technology $\left(s^2 = 1\right)$, when exogenous variables are fixed. In other words, when the objective function is supermodular in technologies this implies that the latter are complementary and are jointly adopted[1].

[1]Symmetrically, a function f is said to be submodular and innovations are substitutes if -f is supermodular, i.e. if the inequality $\geq$ in equation (1) is replaced by $\leq$.

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Empirical models of complementarity

To test for complementarity, we use the two approaches suggested by Athey and Schmutzler (1995) and Athey and Stern (1998).

The production approach

The production approach tests for complementarity consists of regressing a performance measure on dummy variables representing the adoption of different combinations of agroecological crop sanitation technologies, along with observable farm and farmer characteristics. Supporting evidence for complementarity (or substitutability) is obtained when the coefficient on the joint adoption dummy variable is significant and positive (or negative).

The production approach is implemented by assuming as before that an individual farmer i has agroecological strategies, denoted s_i^j. The impact on production efficiency of agroecological crop sanitation technologies (FP and DFS) carried out in farms is captured by the log Cobb-Douglas production function

$$f = log[F(K, L, T, S, X)] = \alpha k_i + \beta l_i + \gamma t_i + \theta s_i^j + \zeta X_i + \varepsilon_i, \tag{2}$$

where K, L, T are capital, labor and land inputs respectively and $S = \left(s^1, s^2\right)$. X is the vector of exogenous variables and ε_i the error terms (unobserved characteristics) are i.i.d. with zero mean and $\mathrm{Var}(\varepsilon_i) = \sigma^2$. θ is the vector of coefficients capturing the marginal effect of the choice of strategy s_i^j.

To test for complementarity, we estimate the production function with OLS on mutually exclusive, and therefore not collinear, combinations of agroecological technologies

$$\begin{aligned} f(k, l, t, S; X) =& \alpha k_i + \beta l_i + \gamma t_i + \left(1 - s_i^1\right)\left(1 - s_i^2\right)\theta_{00} + s_i^1\left(1 - s_i^2\right)\theta_{10} \\ &+ \left(1 - s_i^1\right)s_i^2\theta_{01} + s_i^1 s_i^2\theta_{11} + \zeta X_i + \varepsilon_i \end{aligned} \tag{3}$$

where alternative combinations are included as explanatory variables through dummies: θ_{11} is the productivity coefficient for joint adoption FP and DFS, θ_{01} the coefficient for FP-only, θ_{10} for DFS-only and θ_{00} for adopting neither technology. The production function is supermodular and s^1 and s^2 are complements only if $\theta_{11} + \theta_{00} > \theta_{10} + \theta_{01}$.

We can simplify somewhat equation (3)

$$f(.) = \alpha k_i + \beta l_i + \gamma t_i + \theta_0 + s_i^1\theta^F + s_i^2\theta^{DFS} + s_i^{12}\theta + \zeta X_i + \varepsilon_i, \tag{4}$$

where $\theta_0 = \theta_{00}$ $\theta^F = \theta_{01} - \theta_{00}$; $\theta^{DFS} = \theta_{10} - \theta_{00}$; $\theta = [\theta_{11} + \theta_{00}] - [\theta_{01} + \theta_{10}]$. That is, θ_0 is the intercept (neither adoption), θ^F captures the non-exclusive and therefore not collinear partial returns of FP-only (FP adopted in isolation), θ^{DFS} captures the partial returns of DFS-only (DFS adopted in isolation) and θ captures the returns of joint adoption of both agroecological technologies (FP and DFS). The latter is exactly the complementarity parameter we want to test. Thus, the condition for the above production function to be supermodular and then generate a complementary effect can be simplified as

$$\theta = [\theta_{11} + \theta_{00}] - [\theta_{01} + \theta_{10}] \geq 0. \tag{5}$$

However, the estimates of the linear model (4) may be biased if the classical method of ordinary least squares (OLS) is applied. Indeed, Athey and Stern (1998) explained that the existence of unobserved heterogeneity (among farmers) may have an impact on the joint

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adoption of innovations. If the adoption of FP and DFS technologies is correlated with unobserved elements in the error term (ε_i), then the OLS regression may also show complementary effect while in reality there is no complementarity or *vice versa*. To overcome this problem, they suggest the development of an adoption approach to take into account correlations in joint adoption decisions.

The adoption approach

The adoption approach suggests that the co-movement phenomenon of two technologies is the first indication of a complementary effect. This means that if the adoption of one technology is likely to increase the marginal return of another innovation, then the joint adoption of technologies can be efficient.

Co-movement can be measured by the positive correlation between pairwise technologies using a Pearson correlation coefficient. One shortcoming of using a Pearson correlation is that it can only provide preliminary results. This is because in the Pearson correlation there is no control for heterogeneity in farm and farmer characteristics, which is a source of noise in the adoption process.

Arora and Gambardella (1990) and Arora (1996) were the first to show that complementarity can be tested based on a positive correlation between error terms using a bivariate probit model. The bivariate probit model predicts the adoption of non-exclusive, and therefore not collinear, agroecological technologies (FP and DFS) as a function of exogenous control variables (X_i) but explicitly account for the correlation between them[2].

Formally, suppose that farmer i chooses an innovation s_i^j that maximizes her/his (latent) utility $U_i^{j*} = \beta^j X_i + \varepsilon_i^j$, where the vector of parameters β^j are unknown and are the object of inference. Some of these characteristics are observed by the researcher and some are not. The (latent) utility of adopting the non-exclusive technologies Fallow $\left(s_i^1\right)$ and DFS $\left(s_i^2\right)$ can then be written as

$$U_i^{1^*} = \beta^1 X_i + \varepsilon_i^1, \qquad s_i^1 \begin{cases} = 1 & if \ \ U_i^{1^*} > 0, \\ = 0 & \text{otherwise}, \end{cases}$$

$$U_i^{2^*} = \beta^2 X_i + \varepsilon_i^2, \qquad s_i^2 \begin{cases} = 1 & if \ \ U_i^{2^*} > 0, \\ = 0 & \text{otherwise}, \end{cases}$$

where the error terms ε_i^1 and ε_i^2 are independent of X_i but not necessarily independent of each other. That is, $E\left(\varepsilon_i^1\right) = E\left(\varepsilon_i^2\right) = 0$, $\mathrm{Var}\left(\varepsilon_i^1\right) = \mathrm{Var}\left(\varepsilon_i^2\right) = 1$, $\mathrm{Corr}\left(\varepsilon_i^1, \varepsilon_i^2\right) = \rho$. If the estimation with the bivariate probit shows a positive (negative) correlation coefficient, we can conclude in favor of evidence of complementarity (substitutability).

However, it is important to note that a positive correlation does not necessarily indicate complementarity. In fact, according to the adoption approach, a supermodular function only implies a positive correlation between strategies if the strategic choices are continuous (Arora 1996). For discrete choices, this approach leads to an inconsistent model[3].

[2]Athey & Stern (1998) show that this reduced form or CORR approach can be easily derived from supermodularity. Suppose that $f\left(s^1, s^2, X\right)$ is supermodular in s^1, s^2 and X. Then $S^*(X) = \left(s^{1^*}(X), s^{2^*}(X)\right)$, the optimal choice of activities is monotonic and non-decreasing in X. This implies that for cross sectional data, $s^1(X)$ and $s^2(X)$ will be positively correlated.

[3]To show this, let us define the subsets $S_i(1,0)$, $S_i(0,1)$ $S_i(1,1)$, and $S_i(0,0)$ of the error combination $\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right)$ leading to the adoption of FP only, DFS only, both, and no innovations respectively. Drawing the associated four regions depicts overlapping for the subsets of $S_i(1,1)$ and $S_i(0,0)$. This overlapping

The bivariate model fails to provide consistent results because it relies only on the correlation between the error terms to index complementarity. As previously mentioned, this may result in unobserved factors in the error term that are correlated with the adoption of non-exclusive, and therefore not collinear, strategies.

This can lead to either the acceptance of the complementarity hypothesis when there is no actual complementarity, or the rejection of the complementarity hypothesis when the technologies are, in fact, complementary (Athey and Stern 1998). A consistent model involves estimating two parameters to separate the complementarity effect from unobserved heterogeneity. This requires estimating a structural model.

The structural model: a Multinomial Probit approach

To solve the inconsistency problem, we first need to depart from the reduced form approach of the bivariate probit model, which considers only two strategies (FP and DFS). We then consider four possible exclusive strategies for the farmer: adopt neither technology, adopt FP only, adopt DFS-only, and adopt jointly both technologies. The utility of the farmer i choosing among the j alternatives $\left(j = 1, 2, 3, 4\right)$ is

$$U_i^j = \beta^j X_i + \varepsilon_i^j. \tag{6}$$

The vector of random terms $\varepsilon_i^j = \left(\varepsilon_i^0, \varepsilon_i^1, \varepsilon_i^2, \varepsilon_i^3\right)'$ represents the unobserved returns of the decisions. It is assumed to be multivariate normal, distributed as identically and independently across the n farmers, with zero mean and a covariance matrix $\sum = \sigma_i^j > 0, \ \ \forall j$ (positive definite) and $\sigma_{11} = 1$.

The utility function U_i^j in (6) is specified differently for the joint adoption alternative

$$U_i^{3^*} = U_i^{1^*} + U_i^{2^*} + \delta, \tag{7}$$

where δ captures the effect of complementarity between agroecological technologies. Using (6), this becomes

$$U_i^{3^*} = \left(\beta^{1^*} + \beta^{2^*}\right)X_i + \left(\varepsilon_i^{1^*} + \varepsilon_i^{2^*}\right) + \delta \tag{8}$$

with the assumption that the utility of joint adoption is greater than that obtained with all other strategies, i.e. $U_i^{3^*} > U_i^{0^*}$, $U_i^{3^*} > U_i^{1^*}$ and $U_i^{3^*} > U_i^{2^*}$. Let us define $\zeta^{j^*} = \beta^{j^*} X_i$, where $\zeta^{j^*} = \left(\zeta^{1^*}, \zeta^{2^*}\right)'$ represents the observable characteristics along with $\left(\varepsilon_{\mathrm{i}}^1, \varepsilon_i^2\right)$ as unobserved returns. Identification of the error terms would result in variances σ_1^{2*} and σ_2^{2*}, and a correlation parameter ρ.

Since we also estimate a parameter δ that captures the complementary effect, a positive value of ρ will only capture unobserved heterogeneity among farmers in the joint adoption of technologies[4]. A positive (negative) correlation may imply unobserved gains from adopting technologies jointly (in isolation).

This separation generates a consistent empirical model. To show this, let us rewrite the conditions $U_i^{3^*} > U_i^{0^*}$, $U_i^{3^*} > U_i^{1^*}$ and $U_i^{3^*} > U_i^{2^*}$ so that we obtain the following constraints on the error terms

intermingles the choices of adopting both and none of the technologies, which explains the inconsistency problem of the bivariate probit model (Miravette & Pernias, 2010).

[4]In contrast, in a bivariate model where only a correlation parameter is estimated, a positive value of ρ would indicate that farmer who gets a higher utility from adopting FP will also receive higher utility from adopting DFS, even if there is no complementarity between the two technologies.

$$\begin{aligned} \varepsilon_i^{1^*} &> -\zeta^{1^*} - \delta, \\ \varepsilon_i^{2^*} &> -\zeta^{2^*} - \delta, \\ \varepsilon_i^{1^*} + \varepsilon_i^{2^*} &> -\zeta^{1^*} - \zeta^{2^*} - \delta. \end{aligned} \tag{9}$$

Using the system of constraints (9), we define the subset S_3 of the combination of errors $\left(\varepsilon_i^1, \varepsilon_i^2\right)$, leading to the joint adoption strategy $\left(j = 3\right)$

$$S_3 = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} > -\zeta^{1^*} - \delta, \varepsilon_i^{2^*} > -\zeta^{2^*} - \delta, \varepsilon_i^{1^*} + \varepsilon_i^{2^*} > -\zeta^{1^*} - \zeta^{2^*} - \delta\right\}.$$

Similarly, we define the subsets S_1, S_2, S_0 of error combinations that lead to the adoption of the FP-only profile $\left(j = 1\right)$, the DFS-only profile $\left(j = 2\right)$, or no-innovation profile $\left(j = 0\right)$, respectively. This produces a consistent model since we can easily show graphically that there is no overlap between these different sets in either supermodularity ($\delta > 0$) or submodularity ($\delta < 0$) configurations (see Fares 2014).

Survey and test variables

The data was collected from a survey conducted on a large network of 439 farms in Martinique, representing 64% of the total population of banana producers in 2018, and 168 farms in Guadeloupe, representing 80% of the population. The survey was carried out by a team of seven surveyors hired specifically for the needs of the study. Collective training sessions were organized to ensure homogeneous farmer interviews.

For each face-to-face interview, the researchers spent an average of one hour and ten minutes collecting data on three main points of the questionnaire: (i) the socio-demographic characteristics and preferences of the farmers, (ii) the farm structure, and (iii) the banana crop management system and production output. The sample of farms provides a comprehensive representation of the agronomic and economic situation of the farms in both islands, as well as the farmers' choice of technology and the types of crops produced. The sample was also designed to account for variability in farm size and spatial location.

Depending on our empirical model, we use one of two types of dependent variables. To test the production approach with a regression model using OLS, we use farmer income (*Income*) as the dependent variable. To test the adoption approach with discrete choice models (bivariate probit, multinomial probit and logit), we use the different adoption strategies as dependent variables: FP only strategy (*Adopt_Fallow*), disease-free seedling only strategy (*Adopt_DFS*), joint adoption strategy (*Adopt_both*). The no-adoption strategy (*Adopt_none*) is considered as the reference variable.

The adoption of synergistic agroecological innovations is not common among farmers in our database, with only 25.1% reporting its use. In comparison, 37.1% of farmers reported using fallow alone, and 32.6% reported using DFS alone. Each adoption strategy has a different impact on farmers' income (Blazy et al. 2010).

Information on agronomic practices and crop sanitation technologies was provided directly by the farmers, while other performance parameters, such as the level of production and the inputs used, were calculated from the information collected in the crop management system survey and approved by the farmer. This makes it possible to calculate the total income of the farm, i.e. the total annual sales in euros generated by the farm.

Farm-specific characteristics are usually used in the literature as explanatory variables of the performance and adoption process (Feder and Umali 1993; Edwards-Jones 2006). In the present study, we consider the level of specialization in banana production and the percentage of mechanizable land (*BLand*, *MLand*, *MBLand*) as factors that may promote technology adoption.

Other important farm characteristics may also facilitate the technology adoption process, such as flexibility in labor management (*Fullfarm*, *IncomDecrease*, *Labor*, *HouseSize*) (Ayaz and Mughal 2024), access to credit (*CAccess*) (Batz et al. 1999; Dorfman 1996; Caffey and Kazmierczak 1994; Gomez and Vargas 2009), especially in Guadeloupe and Martinique (Blazy et al. 2009; Bonin and Cattan 2006).

In addition to farm characteristics, human capital variables such as the farmer's high school education (*High_S*) (Bartel and Lichtenberg 1987; Foster and Rosenzweig 1995) and her/his access to information and learning about new technologies (*Crotation_tested*; *Crotation_info*; *Info_intern*; *Info_research*; *Info_others* and *Implication*) may also have an impact on the adoption process (Conley and Udry 2010, Duflo et al. 2008; Lichtenberg & Lleras-Muney 2006; Brown et al. 2016; Takahashi et al. 2020; Beaman et al. 2021; Gedikoglu et al. 2023).

Farmers' preferences about innovation and the future of the banana industry can change their perceptions of technology benefits (Diederen et al. 2003). However, after experiencing adverse economic and climatic conditions over the past decade, farmers' perceptions of change are ambiguous. Some farmers may be reluctant to change their production system and adopt innovative technologies during hard times or just after a crisis, while others may seize the opportunity to drastically change their previous system, especially after hurricane episodes.

Since risk aversion alone cannot explain farmers' attitudes toward risk (Hellerstein et al. 2013), we try to capture the perception of the risk of change with a simple dummy variable indicating whether the farmer is willing to adopt an innovation, regardless of the type of innovation (*Aversion_chg*).

Farmers' expectations about the future may also drive the adoption process (Nerlove and Bessler 2000). We include dummies to capture different expectations about the future of public policy on banana subsidies (*Future_subsidies*), market price (*Future_price*), and pesticide bans (*Future_Pest*).

Finally, because environmental concerns and the presence of extension services may be important factors in explaining adoption (Orr and Ritchie 2004; Bandiera and Rasul 2006), we include a regional dummy variable indicating whether production takes place in Guadeloupe (*Gwada*), where environmental concerns are higher than in Martinique but extension services are less developed than on the island of Martinique.

The test variables and their descriptive statistics are presented in Table 1.

Results and discussion

Our methodology to test for complementarity between FP and DFS strategies consists of estimating the production approach and adoption approach models. The results of our empirical models estimation are presented in Table 2.

First, in the production approach, the estimates of the OLS model suggest a complementary effect, as the coefficient of the joint adoption of agroecological crop sanitation technologies increases farm income (*Adopt_both*=1.046*). In contrast, adopting only fallow (*Adopt_Fallow*) or only DFS (*Adopt_DFS*) has no significant effect on total farm income. When we perform the complementarity test, where the null hypothesis is the binding inequality (5), we find evidence of a complementarity effect since the null hypothesis is not rejected at the 1% level (LR Test =59.13***).

In addition to the technology adoption decision, other factors have an impact on total farm income. First, the different land variables have a positive impact on total income. Specialization in banana production seems to have a positive effect, as a higher percentage of land devoted to banana (*Bland*) significantly increases income, as does a higher

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Table 1. Summary statistics

Variable	Definition	Mean	Std. Dev.	Min	Max
Income	Farm total income (log)	2.115	.154	0.583	2.317
Adopt_Fallow	=1 if fallow is adopted alone	0.371	0.489	0	1
Adopt_DFS	=1 if DFS is adopted alone	0.326	0.473	0	1
Adopt_both	=1 if agroecological technologies are jointly adopted	0.251	0.442	0	1
Adopt_none	=1 if no agroecological technology is adopted (reference)	0.052	0.499	0	1
Gwada	=1 if production is located in Guadeloupe island	0.277	0.448	0	1
Labor	Log number of full-time workers in the farm/ha	0.061	0.216	0	1.386
Fullfarm	=1 if full-time farming	0.898	0.303	0	1
MLand	% of mechanizable agricultural land (log)	4.116	0.695	0	100
BLand	% of land dedicated to Banana production (log)	4.307	0.372	0	100
MBLand	% of mechanizable land dedicated to Banana production (log)	4.318	0.483	0	100
HouseSize	Number of family members depending on the farming activity	4.348	7.619	0	160
High_S	=1 if the farmer has at least a high school formation	0.208	0.406	0	1
Info_research	=1 if the farmer information comes from research institutions	0.165	0.371	0	1
Info_intern	=1 if the farmer information comes from internet	0.163	0.37	0	1
Info_others	=1 if farmer information comes from other farmers	0.551	0.498	0	1
CrAccess	=1 if the farmer has access to credit	0.484	0.5	0	1
Crotation_tested	= 1 if crop rotation has been adopted	0.092	0.29	0	1
Crotation_info	=1 if the farmer has information on crop rotation	0.703	0.457	0	1
Obj_Ext	=1 if the main farmer's objective is farm growth	0.222	0.416	0	1
IncomDecrease	= 1 if the farmer can accept a temporary decrease of income	0.292	0.455	0	1
Future_Sub	= 1 if the farmer expects that subsidies will be eco-conditioned	0.194	0.396	0	1
Future_Pest	= 1 if the farmer expects pesticide ban	0.496	0.500	0	1
Future_Price	=1 if the farmer expects a banana price increase	0.201	.401	0	1

(*Continued*)

Table 1. (*Continued*)

Variable	Definition	Mean	Std. Dev.	Min	Max
Implication	=1 if the farmer is member of an agricultural professional group	0.366	0.482	0	1
Aversion_chg	=1 if the farmer has aversion to change the technology in place	0.239	0.427	0	1
Commercial contacts	=1 if the farmer has at least one commercial contacts	0.239	0.427	0	1
Number of observations			567		

percentage of mechanizable land. The number of full-time workers per hectare (*Labor*) has a negative effect on income, as expected (Ayaz and Mughal 2024).

Other variables, such as the household size (*Housesize*) or having completed high school (*high_S*), have no significant effect. The organizational and institutional environment of the farmer also does not seem to have a significant effect, since having access to credit (*CrAccess*) does not significantly increase or decrease income (Batz et al. 2009). On the other hand, the farmer behavior variable that captures the perception of aversion to change (*Aversion_chg*) has a negative effect on total farm income (−0.669** (−1.95)) (Hellerstein et al. 2003). Finally, the model shows that producing on the island of Guadeloupe (*Gwada*) has a negative effect on farm income (−1.259*** (−3.31)), which may be partly due to the difficulty in accessing extension services.

Second, knowing that the main shortcoming of the production approach estimates is the unobserved heterogeneity bias, we use the adoption approach to circumvent this problem. The important finding in the bivariate probit estimates is the significant positive correlation between adoption decisions, as indicated by the positive and significant correlation coefficient ($\rho = 0.635^{***}$). This suggests that FP and DFS are likely to occur in combination, which is a first indication of complementarity.

However, the analysis of the drivers of adoption suggests a substitution effect, since the "profile" of farmers adopting FP or DFS strategy is different. DFS adopters seem to be more specialized farmers, i.e. those with a higher percentage of mechanizable banana land (*MBLand*, *MLand*). They also do not seem to be averse to change (*Aversion_chg*), although access to credit improves DFS adoption (0.814*(2.19)) (Gomez and Vargas 2009).

In contrast, FP smallholders with a lower percentage of mechanizable banana land (*MBLand*, *MLand*) seem to be more averse to change. Access to credit (0.395*(1.56)) and the expectation of higher future price (0.169*(1.10)) improve FP adoption. Even for common drivers of adoption, such as access to agronomic information and extension services, the source of information and advice is not the same for the two types of adopters.

For FP adopters, information comes mainly from "peers" in the farmer organization (*Implication*) or from research institutes (*Info-research* and *Crotation-info*). In contrast, DFS adopters seem to have access to a larger information network, as they receive information and advice from research institutes (0.673***(3.28) (Gedikoglu et al. 2023), but also from other stakeholders (*Info_others*) (0.596***(2.97))) (Duflo et al. 2008; Conley and Udry 2010) and from the Internet (*Info_Intern*) (0.361*(1.82)).

This implies that the bivariate probit estimates give inconsistent results. Indeed, the correlation coefficient suggests a positive co-movement between FP and DFS decisions and

Table 2. OLS, bivariate probit, and multinomial probit estimates

		Bivariate Probit		Multinomial Probit		
Variables	OLS	Adopt_Fallow	Adopt_DFS	Adopt_Both	Adopt_Fallow	Adopt_DFS
	Coef. (t -stat)	Coef. (Z-stat)	Coef. (Z-stat)	Coef. (Z-stat)	Coef. (Z-stat)	Coef. (Z-stat)
Gwada	−1.259*** (−3.31)	1.001*** (7.09)	1.338*** (8.26)		0.305* (1.84)	0.495** (2.36)
Labor	−0.706*** (−2.49)	0.148 (1.26)	0.052 (0.38)		0.112 (0.87)	−0.263 (−1.48)
MLand	0.025*** (3.42)	0.002 (0.71)	0.004 (1.18)		0.016 (0.43)	0.036 (0.91)
Bland	0.018*** (2.67)	0.008** (2.36)	0.051*** (7.56)		−0.027*** (−2.76)	0.012*** (3.11)
MBLand	0.019*** (2.56)	0.005 (1.59)	0.069** (1.97)		0.04 (0.12)	0.001 (0.653)
HouseSize	−0.001 (−0.01)	0.17 (1.34)	0.272 (1.26)		0.204 (0.85)	0.019 (0.38)
High_S	−0.187 (−0.46)	0.202 (1.53)	0.112 (0.77)		0.0133 (0.073)	0.003 (0.07)
CrAccess	0.103 (0.32)	0.395* (1.56)	0.814** (2.19)		0.450 (0.643)	−0.060 (0.214)
Implication	−0.162 (−0.71)	0.056* (1.82)	0.195 (1.33)		−0.109 (−0.71)	0.135 (0.72)
Info_intern	−0.478 (−1.04)	0.316 (1.81)	0.361* (1.82)		0.053 (0.26)	0.149 (0.61)
Info_Research	0.02 (0.05)	0.533*** (2.85)	0.673*** (3.28)		−0.131 (−0.58)	0.195 (0.76)
Info_others	−0.36 (−1.22)	0.146 (1.18)	0.596*** (2.97)		0.048 (0.35)	0.05 (0.30)
Crotation_tested	0.252 (0.48)	0.247 (1.20)	0.245 (1.04)		0.189 (0.74)	0.011 (0.40)
Crotation_info	−0.668** (−1.94)	0.281* (1.93)	0.146 (0.86)		0.115** (0.71)	0.107 (0.48)
Aversion_chg	−0.669** (−1.95)	−0.392* (−2.58)	0.04 (1.16)		−0.173* (−1.96)	−0.006 (−0.31)
Obj_Ext	0.367 (1.02)	−0.117 (−0.77)	−0.125 (−0.75)		−0.03 (−0.54)	−0.105 (0.212)
IncomDecrease	0.296 (0.93)	0.154 (1.17)	0.07 (0.614)		0.153 (1.01)	0.097 (0.51)

(Continued)

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Table 2. (*Continued*)

		Bivariate Probit		Multinomial Probit		
Variables	OLS	Adopt_Fallow	Adopt_DFS	Adopt_Both	Adopt_Fallow	Adopt_DFS
Future_Price	−0.006 (0.02)	0.169** (1.10)	0.118 (0.69)		0.096 (0.59)	0.078 (0.04)
Future_Sub	−0.289 (−0.76)	0.108 (0.73)	2.658 (1.47)		−0.029 (−0.18)	−0.076 (−0.32)
Future_Pest	−0.402 (−1.39)	0.128 (1.08)	0.322 (2.32)		0.059 (0.43)	0.303* (1.73)
Adopt_both	1.046* (1.67)					
Adopt_Fallow	−0.654 (−1.42)					
Adopt_DFS	0.442 (0.75)					
Intercept	6.181*** (8.70)	−2.02*** (−4.39)	−3.13*** (−5.74)	(θ) : −0.576* (−1.486)	−1.492*** (−2.77)	−2.870*** (4.12)
R^2	0.089	$\rho_{(FP,DFS)}$	0.635***	$\rho_{(both,FP)}$	−0.015 (−0.17)	
F (22, 584)	3.12***			$\rho_{(both,DFP)}$	−0.409*** (−3.97)	
LR Test	59.13***			$\rho_{(FP,DFS)}$	0.184** (1.97)	

*$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$ (OLS: Heteroscedasticity-robust standard errors).

thus a complementary effect, while the drivers of adoption suggest substitution effect between agroecological technologies since the "profile" of farmers adopting both technologies is not the same. This inconsistent result in our estimates is not really surprising because, as noted in our discussion of the empirical models, the bivariate probit can be an inconsistent model in the presence of unobserved heterogeneity.

Estimating a structural model of complementarity using a multinomial probit can overcome the bias of unobserved heterogeneity (OLS) and the inconsistent estimates that it can generate (bivariate probit). While OLS and bivariate probit models can only estimate one parameter, a well-designed multinomial probit can actually separate complementarity from unobserved heterogeneity by estimating two different parameters: (i) as in the case of the bivariate probit case, a parameter ρ (the correlation coefficient) can capture the unobserved heterogeneity among farmers; and (ii) as in the case of the OLS regression, a constant θ associated with the decision to jointly adopt FP and DFS can capture the complementary effect.

First, the separation ensures that the correlation coefficient between the two decisions (parameter ρ) captures only unobserved heterogeneity. Indeed since the parameter $\left(\rho_{FP,DFS} = 0.184^{**}\right)$ is significant and positive in the multinomial probit estimation, we can infer that the co-movement phenomenon of the two technologies, observed in the bivariate probit correlation coefficient estimation ($\rho = 0.635^{***}$), is caused by unobserved heterogeneity and not by complementary effect. Second, the complementary parameter in the multinomial probit estimation is significant and negative ($\theta = -0.576^{*}$), suggesting a substitution effect rather than a complementary effect between agroecological crop sanitation technologies.

This substitution effect is consistent with the contrasting profiles of farmers adopting DFS-only and FP only. A specialized banana farmer will be willing to adopt only DFS, especially if he expects a regulatory change (pesticide ban: *Future_Pest*), while a less specialized smallholder farmer with an aversion to change will adopt FP only.

It is worth noting that the expectation of a stronger regulation of pesticide use (*Future_Pest*) does not lead the specialized farmers to choose the more socially efficient strategy (Diederen et al. 2003), i.e. the joint adoption of FP and DFS, which reduces pesticide use the most. This suggests that the threat of a pesticide ban is not credible enough to align the "private interest" of the more specialized farmers with the "social interest." This can be partly explained by the fact that the implementation of a FP period of 12 months on different plots of the farm, in addition to the adoption of DFS, may generate too high opportunity costs for farmers specialized in banana production. The fact that farmers that adopt only DFS or only FP explains why there is no more joint adoption of crop sanitation technologies.

The contrast between the two profiles is even more pronounced in the multinomial results than in the bivariate results. For example, where previously the percentage of land devoted to banana production increased the probability of FP adoption, its impact is now negative, while it still increases the probability of DFS adoption. This reinforces the evidence that FP adopters are smallholders with diversified farming systems (Blazy 2011).

In addition, the common factors that increased the probability of joint adoption of agroecological technologies in the bivariate probit estimates (*Credit-access*, *info-research*) are no longer significant in the multinomial estimates (Brown et al. 2016; takahashi et al. 2020; Beaman et al. 2021). Therefore, our robust substitution effect result can explain why the farmers adopt agroecological crop sanitation technologies in isolation rather than together even though they are synergistic from an agronomic and environmental point of view.

This result clearly suggests that without the additional gain generated by a complementary effect, the farmer's "private interest" cannot be aligned with the "social interest," and therefore the bundle of technologies that reduces pesticide use the most cannot be adopted by farmers.

Conclusion

Agroecological sanitation systems are based on a coherent set of innovative technologies that generate environmental and agronomic synergies (Altieri 2002). To see whether these synergies also generate an (economic) complementary effect, whereby the joint adoption of agroecological technologies generates a higher return than their adoption in isolation, we need to test for complementarity.

Following the empirical framework developed by Athey and Schmutzler (1995) and Athey and Stern (1998), we test for complementarity in two ways. First, we use the production approach to estimate the contribution of different combinations of innovations to farm income using linear regression with OLS method. Second, we use the adoption approach to correct for unobserved heterogeneity bias with a structural model of complementarity..

Using a database of 607 banana producers in the French West Indies, our econometric estimates of the adoption of two agroecological technologies (fallow period and disease-free seedlings) provide robust results. Although the two agroecological technologies appear to be complementary in the production approach, after separating complementarity from unobserved heterogeneity, we find evidence of a substitution effect between the two agroecological technologies. That is, the complementarity parameter shows a negative and significant effect, while the positive co-movement phenomenon (correlation) of both agroecological technologies seems to be caused by unobserved heterogeneity.

The analysis of the adoption drivers of both technologies confirms this result, as the profile of farmers is contrasted. Farmers adopting only FP are smallholders with an aversion to change, while more specialized farmers in banana production are willing to adopt only DFS technology, especially if they expect a regulatory change (pesticide ban). In addition, the two technologies do not share significant common adoption drivers.

Therefore, this robust substitution effect may explain why the joint adoption rate of FP and DFS is so low in the French West Indies, despite the agronomic and environmental benefits of using both technologies together. This result clearly suggests that without the additional gain generated by a complementary effect, the farmer's "private interest" cannot be aligned with the "social interest."

Because of their agronomic and environmental synergies, which help to drastically reduce the use of pesticides, a socially efficient public policy can aim to promote the joint adoption of FP and DFS agroecological technologies. This policy can be implemented by designing a menu of agri-environmental contracts so that: (i) small farmers adopting only FP can be compensated for the cost of adopting DFS technology; (ii) more productive farmers adopting only DFS technology can be subsidized to leave part of their mechanizable land fallow for banana production.

In our research agenda, the next step is to empirically analyze the incentives provided by such a menu of contracts using a choice experiment approach (DCE), which would allow for a complementary effect between less polluting farming technologies; and therefore, for a much greater benefit to society.

A possible limitation of our study is the lack of comparison of the FP&DFS bundle with another bundle of agroecological technologies that may have a higher rate of joint adoption. Comparing the complementary/substitutable effect that may exist in these two bundles may be another area of research for our study.

Data availability statement. The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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References

Adesina AA and Zinnah MM (1993) Technology characteristics, farmer perceptions and adoption decisions: A tobit model application in Sierra Leone. *Agricultural Economics* **9**, 297–311.

Altieri MA (2002) Agroecology: The science of natural resource management for poor farmers in marginal environments. *Agriculture, Ecosystems & Environment* **93**, 1–24.

Arora A (1996) Testing for complementarities in reduced-form regressions: A note. *Economics Letters* **50**, 51–55.

Arora A and Gambardella A (1990) Complementarity and external linkages: The strategies of the large firms in biotechnology. *Journal of Industrial Economics* **38**, 361–379.

Athey S and Schmutzler A (1995) Product and process flexibility in an innovative environment. *The RAND Journal of Economics* **26**(4), 557–574.

Athey S and Stern S (1998) An Empirical Framework for Testing Theories about Complementarity in Organizational Design. NBER working paper #6600. Available at https://scholar.harvard.edu/files/athey/files/testcomp0498.pdf. Accessed February 2025.

Ayaz M and Mughal M (2024) Farm size and productivity - the role of family labor. *Economic Development and Cultural Change* **72**(2), 959–995.

Bandiera O and Rasul I (2006) Social networks and technology adoption in Northern Mozambique. *The Economic Journal* **116**, 869–902.

Bartel A and Lichtenberg F (1987) The comparative advantage of educated workers in implementing new technology. *The Review of Economics and Statistics* **69**(1), 1–11.

Batz FJ, Peters KJ and Janssen W (1999) The influence of technology characteristics on the rate and speed of adoption. *Agricultural Economics* **21**, 121–130.

Beaman L, BenYishay A, Magruder J and Mobarak AM (2021) Can network theory-based targeting increase technology adoption? American Economic Review **111**, 1918–1943.

Blazy J-M (2011) Innovation and adoption of new practices in the banana sector. *Innovations Agronomiques* **16**, 25–37.

Blazy J-M, Ozier-Lafontaine H, Dore T, Thomas A and Wery J (2009) A methodological framework that accounts for farm diversity in the prototyping of crop management systems. Application to banana-based systems in Guadeloupe. *Agricultural Systems* **101**, 30–41.

Blazy J-M, Tixier P, Thomas A, Ozier-Lafontaine H, Salmon F and Wery J (2010) BANAD: A farm model for ex ante assessment of agro-ecological innovations and its application to banana farms in Guadeloupe. *Agricultural Systems* **103**, 221–232.

Bocquene G and Franco A (2005) Pesticide contamination of the coastline of Martinique. *Marine Pollution Bulletin* **51**, 612–619.

Bonin M and Cattan P (2006) Convergences and differences between the objectives of the financial support facilities and those of the farmers: The case of fallow periods in banana production of Guadeloupe. *Fruits* **61**, 9–23.

Brown P, Hart G, Small B and Montes de Oca O (2016) Agents for diffusion of agricultural innovations for environmental outcomes. *Land Use Policy* **55**, 318–326.

Cabidoche Y-M, Achard R, Cattan P, Clermont-Dauphin C, Massat F and Sansoulet J (2009) Long-term pollution by chlordecone of tropical volcanic soils in the French West Indies: A simple leaching model accounts for current residue. *Environmental Pollution* **157**, 1697–1705.

Caffey RH and Kazmierczak RF Jr (1994) Factors influencing technology adoption in a Louisiana aquaculture system. *Journal of Agriculture and Applied Economics* **26**, 264–274.

Caswell M and Zilberman D (1985) The choices of irrigation technologies in California. *American Journal of Agricultural Economics* **67**, 224–234.

Chabrier C and Quénehervé P (2003) Control of the burrowing nematode (Radopholus similis Cobb) on banana: Impact of the banana field destruction method on the efficiency of the following fallow. *Crop Protection* **22**, 121–127.

Chopin P and Blazy JM (2013) Assessment of regional variability in crop yields with spatial autocorrelation: Banana farms and policy implications in Martinique. *Agriculture, Ecosystems and Environment* **181**, 12–21.

Conley T and Udry C (2010) Learning about a New Technology: Pineapple in Ghana. *American Economic Review* **100**(1), 35–69.

DeLay ND, Thompson NM and Mintert JR (2022) Precision agriculture technology adoption and technical efficiency. *Journal of Agricultural Economics* **73**, 195–219.

Diederen P, Meijl H, Wolters A and Bijak K (2003) Innovation adoption in agriculture: innovators, early adopters and laggards. *Cahiers d'nomie et sociologie rurales* **67**, 29–50.

Dorfman J (1996) Modeling multiple adoption decisions in a joint-framework. *American Journal of Agricultural Economics* **78**, 547–557.

Duflo E, Kremer M and Robinson J (2008) How high are rates of return to fertilizer? Evidence from field experiments in Kenya. *American Economic Review Papers and Proceedings* **98**(2), 482–488.

Duru M, Fares M and Therond O (2015) Designing agroecological transitions: a review. *Agronomy for Sustainable Development* **35**, 1237–1257.

Edmeades S, Phaneuf DJ, Smale M and Renkow M (2008) Modelling the crop variety demand of semi-subsistence households: Bananas in Uganda. *Journal of Agricultural Economics* **59**, 329–349.

Edwards-Jones G (2006) Modeling farmer decision-making: Concepts progress and challenges. *Animal Science* **82**, 783–790.

Fares M (2014) Using a multinomial probit to test for complementarity. *Applied Economics Letters* **21**(3), 180–184.

Feder G and Umali D (1993) The adoption of agricultural innovations, a review. *Technological Forecasting and Social Change* **43**, 215–239.

Feleke S and Zegeye T (2006) Adoption of improved maize varieties in Southern Ethiopia: Factors and strategy options. *Food Policy* **31**(5), 442–457.

Foltz J and Chang H-H (2002) The adoption and profitability of rbST on Connecticut dairy farms. *American Journal of Agricultural Economics* **84**(4), 1021–1032.

Foster AD and Rosenzweig MR (1995) Learning by doing and learning from others: human capital and technical change in agriculture. *Journal of Political Economy* **103**, 176–1209.

Gedikoglu H, Tandogan S and Parcell J (2023) Neighbor effects on adoption of conservation practices: Cases of grass filter systems and injecting manure. *The Annals of Regional Science* **70**, 723–756.

Gomez J and Vargas P (2009) The effect of financial constraints, absorptive capacity and complementarities on the adoption of multiple process technologies. *Research Policy* **38**, 106–119.

Hellerstein D, Higgins N and Horowitz J (2013) The predictive power of risk preference measures for farming decisions. *European Review of Agricultural Economics* **40**(5), 807–833.

Ichniowski C, Shaw K and Prennushi G (1997) The effects of human resource management practices on productivity: a study of steel Finishing Lines. *American Economic Review* **87**, 291–213.

Kamutando G and Tregenna F (2024) Complementarity between product and process innovation in small and micro-enterprises in Johannesburg, South Africa. *Economics of Innovation and New Technology* **33**, 792–818.

Kassie M, Jaleta M, Shiferaw B, Mmbando F and Mekuria M (2013) Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological Forecasting and Social Change* **80**(3), 525–540.

Lambrecht I, Vanlauwe B and Maertens M (2014) Integrated soil fertility management: From concept to practice in eastern DR Congo. Bioeconomics Working Paper Series. Available at http://ageconsearch.umn.edu/bitstream/180062/2/BioeconWP_2014_5b.pdf. Accessed February 2025.

Lichtenberg F and Lleras-Muney A (2006) The effect of education on medical technology adoption: Are the more educated more likely to use new drugs? Annales d'Economie et Statistique **79/80**, 671–696.

Lockshin B, Belderbose R and Carree M (2008) The productivity effects of internal and external R&D: Evidence from a dynamic panel data model. *Oxford Bulletin of Economics and Statistics* **70**(3), 399–413.

Marra M, Pannell DJ and Abadi Ghadim A (2003) The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: Where are we on the learning curve? *Agricultural Systems* **75**(2/3), 215–234.

Meynard J-M, Charrier F, Fares M, Le Bail M, Magrini M-B, Charlier A and Messéan A (2018) Socio-technical lock-in hinders crop diversification in France. *Agronomy for Sustainable Development* **38**, 54.

Miravete EJ and Pernias JC (2010) Testing for complementarity when strategies are dichotomous. *Economics Letters* **106**, 28–31.

Mohnen P and Röller LH (2005) Complementarities in innovation policy. *European Economic Review* **49**, 1431–1450.

Nerlove M and Bessler D (2000) Expectations, information and dynamics. In Gardiner B and Rausser G (eds), *Handbook of Agricultural Economics*. Amsterdam: Elsevier Science, 155–206.

Nowak P (1992) Why farmers adopt production technology: Overcoming impediments to adoption of crop residue management techniques will be crucial to implementation of conservation compliance plans. *Journal of Soil and Water Conservation* **47**, 14–16.

Orr A and Ritchie JM (2004) Learning from failure: Smallholder farming systems and IPM in Malawi. *Agricultural Systems* **79**, 31–54.

Qaim M and de Janvry A (2003) Genetically modified crops, corporate pricing strategies, and farmers adoption: The case of Bt cotton in Argentina. *American Journal of Agricultural Economics* **85**(4), 814–828.

Rauniyar G and Goode F (1992) Technology adoption in small firms. *World Development* **20**, 275–282.

Takahashi K, Muraoka R and Otsuka K (2020) Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics* **51**, 31–45.

Topkis DM (1978) Minimizing a submodular function on a lattice. *Operations Research* **26**(2), 305–321.

Topkis DM (1998) *Supermodularity and Complementarity*. Princeton, New Jersey: Princeton University Press.

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