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Abstract

In context of global challenges facing agriculture, our paper addresses the extent to which the synergistic nature of agroecological innovations may reconcile environmental and technical efficiency of farms. We develop an empirical model, namely conditional efficiency framework, which explicitly accounts for context-dependent drivers like synergy and complementarity of innovations. Using a sample of 567 banana farms in the French West Indies, our estimates confirm the complementarity effect since the joint adoption of agroecological innovations increases the technical efficiency scores much more than others drivers and each of the innovations taken in isolation. We also show that advice and extension services as well as human capital variables are key adoption levers for public policy since they reduce the variability of production and thus the risk associated with the joint adoption of the agroecological innovations.

Keywords: Conditional efficiency; complementarity; agroecological innovations; farm performance.
JEL Classification: C14; 033; Q16; Q55.

1 Introduction

Given the challenges of climate change, sustainable food and nutritional security, innovation in the agricultural and food system is a major concern and agro-ecological

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innovations and bio-based transitions are one of the avenues to be explored in order to meet these multiple challenges (OECD, 2021; WIPO et al., 2017; FAO, 2019). This is particularly true in the French West Indies where the intensive use of chemical inputs in banana monoculture, especially pesticides (chlordecone), has led to soil and ecosystem contamination and human health risks in large areas of the islands (Cabidoche et al., 2009). To mitigate these negative externalities and reduce pesticide use, agroecological innovations have been developed (Blazy et al., 2010). Since agroecological systems are the result of complex interactions at a local level between technologies and biological components of the agroecosystems (Duru et al., 2015), agroecological innovations are then based on a bundle of complementary technologies and practices leading to emergent and synergistic sustainable properties (Altieri, 2002). The main issue addressed by our paper is whether the adoption of complementary agroecological innovations that increase the environmental performance of the farm may also increase its economic performance (Edmeades et al., 2008; Lambrecht et al., 2014).

The meta-analysis conducted by Rosenbusch et al., (2011) shows that the innovation-performance relationship is context-dependent, and using recent advances in efficiency analysis we suggest the conditional efficiency framework (Daraio and Simar, 2007; Daraio et al., 2021) to measure performance (technical efficiency) while explicitly accounting for contextual drivers. The contextual drivers refer to factors which are neither inputs nor outputs, but that form the backdrop of farmer decision-making. Among the relevant contextual drivers, we mainly focus on complementarity between innovations and its impact on technical efficiency since the literature shows that the adoption of complementary innovations improves firm performance (Arora et al., 2010; Fares et al., 2018; Mohnen, 2019).

Our estimates on a database of 567 banana farms in the West Indies confirm this complementarity effect since the joint adoption of two synergistic agroecological innovations, i.e. Disease Free seedlings (DFS) and Fallow, increases the technical efficiency score much more than each of the innovations taken in isolation. We also show that advice and extension services and other human capital variables are key adoption lever since they reduce the variability of production and thus the risk associated with the joint adoption of the agroecological innovations.

The remaining sections are organized as follows. In section 2, we present the empirical model and the context of our farm survey database as well as the the variables of test. Econometric results are presented in section 3 adjoining to discussion and section 4 concludes.

2 Materials and Methods

2.1 Methods

Farmers' production decisions are modeled using the conditional efficiency framework (Daraio and Simar, 2007; Daraio et al., 2021; Belmonte-Martin et al., 2021), where inputs $X \in R^p_+$ are combined to produce outputs $Y \in R^q_+$ given contextual (conditioning) variables $Z \in R^r_+$. In this framework, a production process is defined by a production technology ψ^Z that describes the set of all technically feasible input-output combinations given the conditioning variables:

$$\psi^Z = \{(x, y)|z : x \text{ can produce } y\} \tag{1}$$

A farm is technically efficient (i.e., located on the boundary of ψ^Z) if it produces the maximum possible level of outputs for a given level of inputs[1].

The production process defined in [1] can be fully characterized by the joint-conditional probability: $\mathcal{S}_{(Y|X,Z)}(y|x, z)F_{(X|Z)}(x|z)$, where $\mathcal{S}_{(Y|X,Z)}(y|x, z)$ denotes the conditional survival function Y, with $\mathcal{S}_Y(y) = Prob(Y \geq y)$, and $F_{(X|Z)}(x|z)$ the marginal conditional distribution function of X, with $F_X(x) = Prob(X \leq x)$. An output-oriented conditional efficiency score is defined as follows by the upper-boundary ψ^Z of the support of $\mathcal{S}_{(Y|X,Z)}(y|x, z)$:

$$\theta(x, y|z) = sup\left\{\theta|\mathcal{S}_{(Y|X,Z)}(\theta y|x, z) > 0\right\} \tag{2}$$

To account for outlying observations, we define an order-m frontier that characterizes the expected maximum level of outputs achievable for a subset of m randomly drawn production units with $X \leq x$ as a yardstick (Daraio and Simar, 2007). That is, for any value y, there exists $\widehat{\theta}^Z_m(x, y) = sup\left\{\theta|(x, \theta y) \in \widehat{\psi}^Z_m(x)\right\}$ such that the conditional output-oriented order-m efficiency measure is defined as:

$$\begin{aligned} \theta_m(x, y\,|z) &= E_{(Y|X,Z)}\,(\widehat{\theta}^Z_m(x, y)\,|X \leq x, Z = z) \\ &= \int_0^\infty [1 - (1 - \mathcal{S}_{(Y|X,Z)}(uy|x, z))^m]du \end{aligned} \tag{3}$$

The survivor function $S_{(Y|X,Z)}(y|x, z)$ is estimated using the following kernel function:

$$\widehat{\mathcal{S}}_{(Y|X,Z,n)}(y|x, z) = \frac{\sum_{i=1}^n I(X_i \leq x, Y_i \geq y)K_{\hat{h}}(z, z_i)}{\sum_{i=1}^n I(X_i \leq x)K_{\hat{h}}(z, z_i)} \tag{4}$$

where $K_{\widehat{h}}(.) = h^{-1}K((z, z_i)h^{-1})$, with $\hat{h} = (\hat{h}_1, \ldots, \hat{h}_r)$ a vector of r-estimated bandwidth parameters and $I(.)$ is an indicator function which equals to unity if its argument is true and zero otherwise. Then, the conditional efficiency estimator $\hat{\theta}_m(x, y|z)$ is given by plugging $\hat{\mathcal{S}}_{(Y|X,Z,n)}(y|x, z)$ into equation [3] (see for more details Minviel and de Witte, 2017).

To investigate the influence of the contextual drivers on technical efficiency, we use a location-scale nonparametric regression model (Badin et al., 2012):

$$\theta_i(x_i, y_i|z_i) = g(z_i) + \sigma(z_i)\xi_i \tag{5}$$

where ξ_i is an error term, $g(.) = E[\theta_i(x_i, y_i|z_i)]$ and $\sigma^2(z_i) = V[\theta_i(x_i, y_i|z_i)]$. The nonparametric functions $g(.)$ and $\sigma^2(.)$ are estimated using kernel local linear regression methods. To introduce complementarity effect, we decompose the contextual drivers in two components by rewriting $z_i = \delta^0 s_{00} + \delta^{DFS}s_{10} + \delta^F s_{01} + \delta s_{11} + \zeta X_i$, where ζX_i represent the other drivers and $\delta^0 s_{00} + \delta^{DFS}s_{10} + \delta^F s_{01} + \delta s_{11}$ the four agroecological innovation strategies of the farmer when he can adopt DFS or Fallow innovations. The latter are said to be complements only if the marginal effect of joint adoption is positive ($\delta > 0$) (Fares, 2013).

[1]In the conventional approach, this set is not conditional to the contextual drivers (Z).

2.2 Materials

To control parasitism and therefore reduce pesticide use in French West Indies banana production, two agroecological innovations have been developed: *(i)* introducing a fallow period (FP) in rotation with banana; and *(ii)* using disease-free seedling (DFS) after the fallow period, where seedlings are produced in-vitro (Chabrier and Quenerve, 2003). Although both innovations can be used separately, they are complementary in managing pest pressure since DFS makes it possible to avoid exogenous parasitism after the fallow period. If this synergistic effect may ensure environmental efficiency since it reduces the social cost of having recourse to chemical pesticide, it does necessarily generates incentives to joint adoption by increasing the performance of the farm.

Table 1: Description of the variables

Variables	Description	Mean	Std	Min	Max
Output					
Banana production	Banana production in tons	464.19	975.53	1	10300
Inputs					
Land	Area in banana production (ha)	11.31	19.77	0.5	210
Labor	Labor used in annual working unit	7.46	13.36	0.14	151.42
Fertilizer	Fertilizers used in tons	23.25	45.24	0.31	453.6
pesticides	Pesticides used in kg	15.46	33.85	0.05	441
Contextual drivers					
DFS (Disease Free Seedlings)	1 if farmer has adopted DFS	0.35	0.48	0	1
Fallow	1 if the system includes fallow	0.39	0.49	0	1
DFS x Fallow	1 if joint adoption of DFS and Fallow	0.27	0.45	0	1
Intercropping	1 if the system includes intercropping	0.61	0.49	0	1
Share of mechanized land	mechanized banana land (%)	4.318	0.483	0	1
Share of irrigated land	Irrigated banana land (%)	0.31	0.41	0	1
Guadeloupe	1 for farms located in Guadeloupe	0.26	0.44	0	1
Farm size	Total Farm area (ha)	16.77	29.95	0.5	262
Technical Assistance	Number of links with researchers & technicians	31.47	23.41	0	194
Agricultural training	1 if farmer has training in Agriculture	0.51	0.50	0	1
Higher education	1 if farmer has made high study	0.07	0.263	0	1
Social group	1 if Household belongs to a social group	0.37	0.48	0	1
Older farmer	1 if Age >= 60	0.12	0.32	0	1
Price Expectation	1 if farmer expects increasing prices	0.20	0.43	0	1

To address this issue a survey questionnaire on innovation adoption was administered in Guadeloupe and Martinique between March and June 2008, through one-time face-to-face interviews, to a random sample of 607 banana planters with a sampling rate of about 80% in each island. After eliminating missing values and zero values for input-output vectors, the final dataset used contains 567 observations. To estimate our conditional efficiency model using this dataset, we selected one output, four inputs, and fourteen contextual drivers. The output is measured as the physical value of the banana production in tons. The four inputs include the agricultural area, the labor used, the quantity of chemical fertilizers used, and the quantity of chemical pesticides. Among the relevant contextual drivers, we mainly focus on complementarity between innovations and its impact on technical efficiency (see Table 1).

3 Results and discussion

The estimates for the mean effects obtained from the order-m conditional efficiency model are reported in table 2. The average conditional technical efficiency score amount to 0.67, while the unconditional score is only 0.6. This suggests first that farmers in our sample generate 33% less outputs than it is technically feasible. That is, farmers could increase their output by 33% without increasing their input use. Second, in average contextual drivers induces a 7% increase of the efficiency score.

Regarding the average marginal effects of these contextual drivers, our results show that the potential of increase mainly comes from our variable of interest, i.e., complementarity between DFS and Fallow agroecological innovations since marginal effect of joint adoption induces an increase in farmer efficiency of about 20%, while the adoption of DFS alone generates only 15% of increase and Fallow alone has no significant effect. These results highlight that by jointly adopting complementary innovations, farmer becomes more productive (Miravette and Pernias, 2006).

For the other contextual variables, we find that technical assistance and agricultural training significantly increases the conditional efficiency scores since both provide precise information and know-how on agroecological innovations use (Xayavong et al., 2016). Likewise, expectation of increasing selling prices may play as an insurance and incentive to improve farm productivity and this can explain its positive impact on the conditional efficiency score (Karian et al., 2014).

For the dispersion effects, the results indicate a positive effect of the DFS/Fallow joint adoption on the variance of the conditional efficiency scores. That is, while synergistic agroecological systems have the advantage of increasing marginal efficiency scores, they also have the disadvantage of increasing their variability, which seems to be a general rule of coupled innovations since intercropping systems (*intercropping*) also increase the variability. These innovative systems are indeed complex to manage and therefore require high human capital. Our results show that some key variables, such as the existence of *technical assistance* (Xayavong et al, 2016), *higher education* (El-Osta, 2011), more experienced farmer (*older farmer*; Ainembabazi and Mugisha, 2014; Karki et al., 2020) and some insurance against risks (*expectation prices*; Karian et al., 2014), reduce the risk associated with agroecological innovation by decreasing the output (and thus the efficiency scores) variability.

Table 2: Conditional Efficiency Estimates

	Marginal effects		**Dispersion effects**	
	Estimate	Bootstrap S.E	Estimate	Bootstrap S.E
DFS	0.1547**	0.0683	-0.0142	0.0099
Fallow	-0.0384	0.0564	-0.0129	0.0101
DFS x Fallow	0.1980**	0.0820	0.0295**	0.0148
Intercropping	-0.0416	0.0266	0.0122**	0.0059
Share of mechanized land	0.0051	0.0479	-0.0025	0.0120
Share of irrigated land	0.1248***	0.0532	-0.0019	0.0104
Guadeloupe	0.0422	0.0485	-0.0137	0.0087
Technical assistance	0.0013*	0.0008	-0.0007***	0.0001
Agricultural training	0.0530*	0.0282	0.0026	0.0066
Higher education	0.1152	0.0828	-0.0263***	0.0099
Social group	0.0232	0.0347	-0.0072	0.0064
Older farmer	0.0364	0.0344	-0.0249***	0.0056
Price expectations	0.0658**	0.0328	-0.0158**	0.0077
Mean conditional TE		0.67		
Mean unconditional TE		0.60		

4 Conclusion

This paper uses a context-dependent framework, the nonparametric conditional efficiency model, to examine the innovation-performance nexus in agriculture. Our estimates on a database of 567 banana farms in the West Indies confirm this complementarity effect since the joint adoption of two synergistic agroecological innovations, i.e. Disease Free seedlings (DFS) and Fallow, increases the technical efficiency score much more than each of the innovations taken in isolation. We also show that advice and extension services, as well as well as farmer human capital increase, are key adoption levers for public policy since they reduce the variability of production and thus the risk associated with the joint adoption of the agroecological innovations.

The main limitation of this work is that we analyze the complementarity effect using only two agroecological innovations. It would be interesting in a future research to study the impact and interactions between a large number of agroecological innovations to test the robustness of our complementary result.

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