Stringency of environmental standards, yield, product quality and revenue: Evidence from French wheat production

by Marie Lassalas, Sabine Duvaleix, and Laure Latruffe

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Marie Lassalas[1], Sabine Duvaleix[1], Laure Latruffe[2]

1. SMART-LERECO, INRAE, Institut Agro, 35011 Rennes, France
2. INRAE, GREThA, Université de Bordeaux, 33608 Pessac, France

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Abstract

Many environmental standards were developed over the past three decades and the agricultural sector is not an exception. Environmental standards differ by their stringency. This paper aims at understanding whether farmers have incentives to adopt an intermediate environmental standard to limit the negative impact of their agricultural practices without changing all their farming system. As intermediate standards have various levels of environmental restrictions, we investigate and compare two environmental standards that differ by their stringency levels. We assess their impacts on pesticides use on yield, product quality and sales revenue at the plot level. We focus on two quality attributes, specific weight and protein content, which are used in marketing contracts for milling activities and bakers. To control for the possible selection bias in the decision to adopt the most stringent environmental standard, we use an endogenous switching regression method. We show that there is a selection bias on the adoption of the most stringent environmental standard regarding quality attributes. Our results highlight that banning most toxic pesticides at the plot level to limit the negative impact of agricultural practices on biodiversity has mixed effects on technical results. It decreases yield by 1.4%, decreases specific weight by 0.3kg/hl, and increases protein content by 0.02 point of percentage. It increases sales revenue by 13€ per ha. Thus, farmers have low monetary incentives to adopt the most stringent environmental standard to preserve biodiversity.

1. Introduction

Environmental labels are growing worldwide. The Ecolabel Index (2021) identifies 455 environmental labels in 199 countries, and 25 industry sectors. Firms often use them to differentiate their products in the market. However label proliferation can lead to inefficient outcomes on welfare (Bonroy and Constantatos, 2015; Yokessa and Marette, 2019). The Farm to Fork Strategy (part of the European Green Deal) reports that the European Commission is looking for ways to create a sustainable label and to harmonize voluntary green claims. The agricultural sector counts numerous environmental labels developed both by public and private organizations (mainly non-governmental organizations and firms). French public policies recognized organic farming in 1981 and then harmonized it at the European level in 1992. Another example is the French *High Environmental Value* (Haute Valeur Environnementale) created in 2012. Private organization have also developed their own environmental labels (e.g. Agri Confiance (2002), Bee Friendly (2012)). Sometimes, firms' labels can be confounded with trademarks as they define their own environmental set of rules to be applied to farmers. When it comes to explore the diversity of the development of environmental labels, the literature pay attention to consumers' behavior and preferences. Consumers are not willing to increase price premium when the number of labels reported on a product increase (Tebbe and von Blanckenburg, 2018). Several theoretical articles investigated the impact of label competition in the market depending on the stringency of the sets of rules (Ben Youssef and Abderrazak, 2009; Fischer and Lyon, 2014; Li and van 't Veld, 2015; Poret, 2019). However, to our knowledge no attention has been carried out on farmers' choice when a variety of environmental labels was offered.

The literature investigating the effect of environmental standard adoption at the farm level mainly focused on the organic label. The agronomic literature wildly studied the impact of the adoption of the organic standard on yield (de Ponti *et al.*, 2012; Seufert *et al.*, 2012; Reganold and Wachter, 2016). These studies highlighted a negative impact of the adoption of organic practices on yield. There is no consensus in the economic literature on the link between the adoption of the organic standard and financial performances. Uematsu and Mishra (2012) founded that, despite income increase with the adoption of the organic standard, organic farms do no earn significantly higher income than conventional ones. Froehlich *et al.* (2018) showed that organic farms' profit are lower. The links between the adoption of environmental practices and yield as well as economic return was explored in numerous case studies in developing countries. Most of them showed a positive relationship. Di Falco *et al.* (2011) found that farmers who adopted new varieties, soil conservation strategies and tree planting to cope with climate change in Ethiopia got higher yields (Di Falco *et al.*, 2011). Abdulai and Huffman (2014) founded similar results in Ghana, they showed that the adoption of soil and water conservation technology increased rice yields and net returns. Kleemann and Abdulai (2013) showed a positive relationship between the intensity of agro-ecological practice use and return on investment for pineapple farmers in Ghana. In addition, other studies investigated the effects of input use on yield and economic results. Koussoubé and Nauges (2017) investigated the effect of nitrogen use on maize yield and its profitability. Kawasaki and Lichtenberg (2015) assessed the impact of pesticides use on yield and quality. Few papers took into account how inputs use influenced quality, although some studies showed that ignoring quality underestimated the economic value of pesticide use (Babcock *et al.*, 1992; Cobourn *et al.*, 2013; Kawasaki and Lichtenberg, 2015). Furthermore, most studies examined the adoption of new practices and input use strategies at the farm level. Only, Koussoubé and Nauges (2017) focused their analysis at the plot level .

In this paper, we explore the effects of environmental labels on farmers. Farmers must comply with several environmental standards, each of them defined by a different label with different levels of stringency. We apply our analysis to the French wheat production in which many environmental standards exist. We contribute to the existing literature by dealing with intermediate environmental requirements to investigate the effect of the adoption of environmental standards, that is to say the standards examined have environmental requirement lower than the organic standard and higher than conventional practices. Little attention is paid to these standards although, despite lower environmental requirement, they may lead to an improvement of agricultural practices and limit the negative impact of agriculture on the environment. To our knowledge, there is no study investigating the role of those intermediate standards on technical and economic results. We examine how different intermediate standards, with different levels of stringency, influence wheat yield, quality attributes and sales revenue though an empirical application on wheat production in France in 2014-2020. We pay attention to two quality attributes: specific weight and protein content. Specific weight is a quality attribute for milling activities and protein content is another quality attribute useful for bakers. Farmers get a marketing contract that provides quality premiums for these quality attributes. Our study is conducted at the plot level to take into account the possibility for farmers to adopt several environmental standards and to choose on which plot each set of rules is applied. We focus on two environmental standards whose goals are to reverse the decline in biodiversity. The standard with higher environmental requirements ban most toxic pesticides thus it modifies agricultural practices whereas the standard with lower requirements only requires the presence of habitat on plots to favor biodiversity.

The rest of the article is organized as follows. Firstly, we describe the data used and discuss summary statistics. Then, we explain our empirical strategy based on the endogenous switching regression method. In the fourth section, we analyze and discuss our results. Finally, we conclude.

2. Data

Our empirical study is applied to wheat production in France. Wheat is the main cereal produced in France; it represents 54% of total French cereal production. On average, from 2014 to 2018, 5 millions of hectares where cultivated with wheat, representing 17% of the French agricultural land. France is the first producer of wheat in Europe and the fifth at a world scale (FranceAgriMer, 2021).

We focus on environmental labels with intermediate environmental requirements, between organic standard and conventional farming system. The adoption of the organic standard is excluded from our analysis because it requires a three-year transition. Thus, the decision to adopt this standard may wildly differ from the environmental standards studied in our analysis that can be reached on a year basis. Secondly, the adoption of the organic standard changes the whole farming system and it does not only change practices at the plot level. Organic farming is one of the most stringent standard but the share of organic wheat produced in France is low. Organic certified wheat represents 2.7% of the annual wheat production for human food (Renault *et al.*, 2020). We consider two standards. The first standard, the one with lowest requirement, tend to favor biodiversity by enforcing the existence of biodiversity habitats. For example, the standard requires the existence of bird perches and that 3% of the arable land of the farm to be dedicated to honey plant fallow. The second standard go further. Beyond the presence of habitats to favor biodiversity, it requires to reduce the negative impact of agricultural practices on biodiversity by limiting most toxic pesticides use. Most toxic active ingredients are prohibited and farmers can only use a limited list of active ingredients. This standard also defines a list of non-recommended active ingredients, which are allowed but the quantity applicable is limited.

We carry out our study with data from arable plots obtained from an agricultural cooperative. The data were collected between 2014 and 2020. Farmers can decide for each plot either to adopt the low requirement standard (L standard) or the high requirement standard (H standard). Our database contains 8,139 plot observations, corresponding to 281 farms. Unlike the analysis of Bravo-Ureta *et al.* (2020) that is conducted at plot level on wine grape, we were not able to build a balanced panel data. Crop rotation prevents us from building a balanced panel data because each year, farmers change the crops produced on each plot. Moreover, we do not observe what is done on a plot when farmers choose a crop different from wheat. For example in Table 1, we observe that from 2014 to 2020, 64% of the plots only had one year with wheat production, 25% of the plots received wheat twice and 9% had wheat production three times in the seven-year period. The database includes information about plot characteristics, the input management, as well as the farms operating the plots. Tables 2 presents descriptive statistics and a comparison of mean characteristics between the plots with the H standard and plots with the L standard. For each plot, the database also gives us information on technical results (yield and quality attributes) and sales revenue. Sales revenue represents the revenue that farmers perceived from the cooperative when selling their wheat.

Table 1: Structure of the unbalanced panel data

Panel length[1]	Frequency	Percentage
1	3476	63.9 %
2	1372	25.2 %
3	484	8.9 %
4	108	2.0 %
5	7	0.0 %
6	0	0.0%
7	0	0.0%
8	0	0.0 %
Total	5440	100.00 %

[1]Panel length correspond to the number of observations in the sample for a same plot from 2014 to 2020

To quantify pesticides use on each plot, we rely on the treatment frequency index (TFI) which is an indicator widely used by French decision-makers for monitoring the use of pesticides in agriculture. TFI counts the number of reference rates used per hectare during a crop year. We only take into account pesticides applied on the crop. It is determined as follows.

$$\mathrm{TFI} = \frac{\text{applied rate}}{\text{reference rate}} * \frac{\text{area treated}}{\text{plot area}} \tag{1}$$

Almost two third of the observations (65%) adopted the H standard. Some plots, irrespective to pesticides use are not eligible to the H standard because of their intrinsic characteristics, such as being close to a highway. In our sample, 55% of the plots with the L standard are eligible to the H standard. Most plots (90%) are cultivated by farmers with a previous experience with H standard.

About one third of the plots are tilled, which is close to the French average for wheat plots (Agreste, 2020b). The mineral nitrogenous (N) fertilization applied is 180 kg N/ha on average, and is slightly higher than the French average, 164 kg N/ha (Agreste, 2020a). Herbicide TFI and insecticide TFI are close to the regional average, respectively 1.8 and 0.3. Fungicide TFI is slightly lower than the regional average (1.5). The average wheat yield per plot reaches approximatively 6 tons/ha. As far as the quality attributes are concerned, the specific weight is 79.25 kg/hl and the protein content in wheat reaches 12.10% on average.

We compare mean characteristics between plots with H and L standards (Table 2). We show that the two groups have different farm and plot characteristics. We note that the plots with H standard are more frequently observed in livestock farm. Plots with H standard are on average larger, and are more tilled than plots with L standard. We observe differences in pest management at 1% of significance whereas fertilization management differ only at 10% of significance. Herbicide TFI, insecticide TFI and fungicide TFI are higher for plots with H standard. Likewise, herbicide, insecticide and fungicide expenditures are higher for plots with H standard. We were not expecting plots with H standard to get higher quantity of pesticides. However, the set of rules implies binding requirements on the applied quantity of moderate toxically active ingredients but not on the total applied quantity. In addition, farmers cannot use as efficient active ingredients with low rate because of the ban of most toxic ingredients. In terms of technical results, we observe similar yields and specific weight between the two groups. However, protein content is slightly higher for plots with H standard. Wheat sales revenue per hectare, which is the revenue farmers get from the cooperative when they sale their wheat, is higher for plots with H standard by 42€/ha on average.

Table 2: Variables definition and descriptive statistics

Variable	Definition	Full sample		Comparison of mean characteristics		
		Mean	Std. dev.	Plots - L standard	Plots - H standard	Significance[1]
Outcome variables						
	TECHNICAL RESULTS					
Yield	Yield (tons/ha)	5.96	2.08	5.95	5.97	n.s
Specific weight	Specific weight (kg/hl)	79.25	2.94	79.21	79.27	n.s
Protein content	Protein rate (%)	12.10	0.96	12.06	12.13	***
	SALES REVENUE					
Wheat sales revenue	Wheat sales revenue per ha (€/ha)	1,017.85	374.93	990.28	1,032.50	***
Input management at plot level						
	FERTILIZATION					
Mineral N quantity	Mineral nitrogen unity applied (kg/ha)	180.46	36.87	181.13	180.08	*
Fertilizer expenditure	Fertilizer expenditure (€/ha)	229.21	67.77	233.80	226.79	***
	CROP PROTECTION					
Herbicide TFI	Treatment frequency index for herbicide	1.74	0.79	1.70	1.76	***
Insecticide TFI	Treatment frequency index for insecticide	0.33	0.56	0.27	0.37	***
Fungicide TFI	Treatment frequency index for fungicide	1.36	0.64	1.33	1.38	***
Herbicide expenditure	Herbicide expenditure (€/ha)	64.91	30.69	60.53	67.23	***
Insecticide expenditure	Insecticide expenditure (€/ha)	1.91	3.34	1.51	2.12	***
Fungicide expenditure	Fungicide expenditure (€/ha)	69.49	26.29	67.35	70.63	***
Control variables						
	PLOT CHARACTERISTICS					
Corn previous crop	1 if the previous crop was corn	0.34		0.55	0.23	***
Tillage	1 if the plot has been tilled	0.38		0.22	0.46	***
	FARM CHARACTERISTICS					
Livestock	1 if livestock on farm	0.24		0.17	0.27	***
Individual governance	1 if farm in under individual governance	0.39		0.41	0.38	***
H standard experience	1 if farmers have previous experience with the highest standard	0.90		0.86	0.92	***
Exclusion variables						
Plot size	Plot size (ha)	5.06	4.84	3.95	5.64	***
Highway	1 if the plot is located close to an highway	7.6		0.22	0.00	
Number of observations		8,139		2,819	5,320	

, **, * indicate significance at 10%, 5% and 1%, respectively.*

[1] A Wilcoxon rank-sum test is performed for continuous variables and a chi-square test of independence is performed for categorical variables.

3. Empirical strategy

We aim at estimating the effect of the adoption of the H standard on three technical outcomes at the plot level (yield, specific weight and protein content) and on an economic outcome (sales revenue) taking into account the level of input use. The decision to adopt the H standard on a plot is voluntary and may be the consequence of self-selection. Observable and unobservable characteristics might affect self-selection and then affect the estimation of yield, quality and sales revenue. We thus choose to implement an endogenous switching regression model (ESR) to deal with the potential endogeneity of the adoption of the H standard. We choose to implement this method rather than propensity score matching because this model take into account observed and unobserved factors when estimating the impact of adopting the H standard. Propensity-score matching methodology rely only on observed characteristics (Imbens and Wooldridge, 2009). Besides, the difference-in-difference methodology is wildly use in the literature to estimate the impact of a treatment such as adoption of new practices or consequences of public policies implementation (Bravo-Ureta *et al.*, 2020; Mennig and Sauer, 2020). We were not able to implement this method because we do not have enough observations before and after the adoption of the H standard. Therefore, the advantage of the ESR method is that it allows us considering two different technologies for the plots adopting the H standard and the plots adopting the L standard adopters.

To implement the ESR model we follow the Maddala (1983) specification. The first stage of the ESR aims at determining the factors which influence the adoption of the H standard on a plot, named the selection equation. We assume that the decision to adopt the H standard on plot *p* depends on the expected net utility of this decision. If the utility derived by the adoption of the H standard is greater than the decision not adopting it, the H standard will be adopted on the plot. We assume that we can model expected net utility on plot *p*, A_p^*, as a function of factors affecting the expected utility of the H standard. These factors are included in vector Z_p as follows:

$$A_p^* = Z_p\gamma + \mu_p \tag{1}$$

where γ is a vector of parameters to be estimated and μ_p is the error term

We do not observe the latent variable, A_p^*; only the decision whether or not the H standard was adopted on the plot in observed, A_p, which is related to A_p^* as follows:

$$A_p = \begin{cases} 1 & if\ A_p^* > 0 \\ 0 & otherwise \end{cases} \tag{2}$$

We consider input use, plot characteristics, as well as farm characteristics as factors affecting the expected utility of the H standard. Agricultural practices determine the probability of adopting the H standard. We take into account pesticides TFI and mineral N quantity, as there are input use requirements in the H standard. We also consider the type of crop previously grown on the plot and if the plot has been tilled. These two factors may influence the expected utility of the H standard as they affect pesticides use. Plots not tilled have more weed, farmers may need to rely on an efficient and toxic active ingredients to get rid of it, compromising plots possibility to adopt the H standard. Alike, wheat grow on plots where was previously grown corn are more sensitive to *Fusarium wilt*, thus these plots may get more fungicide or need to spray a more toxic active ingredient. We also control for soil quality. Our database does not gather information on soil quality at the plot level. However, we know the region where each farm is located. Those regions are divided into five sub-regions of the studied area. We consider sub-region localization as a proxy for soil quality. Then, farm characteristic can also play a role on the perception of the H standard utility. For example, we might expect that farmers who have a previous experience with the H standard are more willing to adopt the H standard on a plot, as they already know the practices to implement. We use exclusion variables that is to say variables that directly affect the selection variable but not the outcome variables. In our model, we use two exclusion variables: highway and plot area. A plot being close to a highway cannot be eligible to the H standard. The standard enforces binding restrictions on distances from the plots to highway Farmers may have incentives to adopt the H standard on larger plots as they can expect higher returns on their investment, in addition the latter may imply fixed costs that can be spread across a larger area.

In the second stage, we estimate the outcome variables, y_p, for the two regimes: the adopter of the L standard and the adopter of the H standard. The equations are defined as follows.

$$Regime\ 1\ (adoption\ of\ H\ \text{standard}):\ \ y_{1p} = X_{1p}\beta_1 + \varepsilon_{1p} \quad if\ A_p = 1 \qquad (3a)$$
$$Regime\ 0\ (adoption\ of\ L\ \text{standard}):\ \ y_{0p} = X_{0p}\beta_0 + \varepsilon_{0p} \quad if\ A_p = 0 \qquad (3b)$$

where X_{1p} and X_{0p} are vectors of inputs, agronomic plot characteristics, and soil quality. β_{1p} and β_{0p} are vectors of parameters to be estimated, ε_{1p} and ε_{0p} are error terms.

We assume that the error terms of equation (1), (3a) and (3b) have a trivariate normal distribution with mean vector zero and covariance matrix such as

$$\Omega = \begin{bmatrix} \sigma_\mu^2 & \sigma_{1\mu} & \sigma_{0\mu} \\ \sigma_{1\mu} & \sigma_1^2 & . \\ \sigma_{0\mu} & . & \sigma_0^2 \end{bmatrix} \qquad (4)$$

where σ_μ^2 is the variance of the error term in the selection equation (1), and σ_1^2 and σ_0^2 are variances of the error terms in the outcome variables estimation equations (3a et 3b). We can consider σ_μ^2 equal to 1 as γ is estimable only up to a scale factor. $\sigma_{1\mu}$ and $\sigma_{2\mu}$ are, respectively, covariances of μ_p and ε_{1p}, μ_p and ε_{0p}. The covariance between ε_{1p} and ε_{0p} is not defined since y_{1p} and y_{0p} are never observed simultaneously.

In the presence of selection bias, when μ_p is correlated to ε_{1p} and ε_{0p}, the expected values of ε_{1p} and ε_{0p} conditional on the sample selection are different from zero.

$$E(\varepsilon_{1p} \,|A_p = 1) = \sigma_{1\mu} \frac{\varphi(Z_p\gamma)}{\phi(Z_p\gamma)} = \sigma_{1\mu}\lambda_{1p} \qquad (5a)$$

$$E(\varepsilon_{0p} \,|A_p = 0) = -\sigma_{0\mu} \frac{\varphi(Z_p\gamma)}{1-\phi(Z_p\gamma)} = \sigma_{0\mu}\lambda_{0p} \qquad (5b)$$

where φ and ϕ are respectively the standard normal density function and the standard normal distribution. λ_{1p} and λ_{0p} are defined as follows:

$$\lambda_{1p} = \frac{\varphi(Z_p\gamma)}{\phi(Z_p\gamma)} \qquad (6a)$$

$$\lambda_{0p} = \frac{\varphi(Z_p\gamma)}{1-\phi(Z_p\gamma)} \qquad (6b)$$

Thus, using equations (3a) and (3b), the outcome estimation functions can be written as follows:

$$Regime\ 1\ (adoption\ of\ H\ standard):\ \ y_{1p} = X_{1p}\beta_1 + \sigma_{1\mu}\lambda_{1p} + \upsilon_{1p} \quad if\ A_p = 1 \qquad (7a)$$

$$Regime\ 0\ (adopter\ of\ L\ standard):\ \ y_{0p} = X_{0p}\beta_0 + \sigma_{0\mu}\lambda_{0p} + \upsilon_{0p} \quad if\ A_p = 0 \qquad (7b)$$

Maddala (1983) suggests to estimate equations (7a) and (7b) by weighted least squares rather than ordinary least squares to account for the error terms, ν_1 and ν_0, heteroscedasticity. However, a more efficient method is the full information maximum likelihood (FIML) method (Lokshin and Sajaia, 2004; Di Falco *et al.*, 2011; Läpple *et al.*, 2013; Abdulai and Huffman, 2014; Abdulai, 2016).
Given previous assumptions on the distribution of the error terms, the log likelihood function is written as follows:

$$\ln L_i = \sum_{i=p}^{N} A_i \left[\ln\ \varphi\left(\frac{\varepsilon_{1p}}{\sigma_1}\right) - \ln\sigma_1 + \ln\phi(\theta_{1p})\right] + (1-A_p)\left[\ln\varphi\left(\frac{\varepsilon_{0p}}{\sigma_0}\right) - \ln\sigma_0 + \ln\left(1-\phi(\theta_{2p})\right)\right] (8)$$

$$\theta_{jp} = \frac{Z_p\gamma + \frac{\rho_j\varepsilon_{jp}}{\sigma_j}}{\sqrt{1-\rho_j^2}} \quad with\ j = 0{,}1 \qquad (9)$$

$$\rho_1 = \frac{\sigma_{1\mu}^2}{\sigma_\mu \sigma_1} \qquad \rho_0 = \frac{\sigma_{0\mu}^2}{\sigma_\mu \sigma_0} \tag{10}$$

where ρ_1 and ρ_0 are, respectively, the correlation coefficients between the error term μ_p of the selection equation (1) and the error terms ε_{1p} and ε_{0p} of the equations (3a) and (3b).

The FIML is implement with clustered standard errors at the farm level and year dummies are added. We clustered standard errors at the farm level because we assume that plots belonging to the same farm are subject to a global farm management.

We follow the same methodology for the estimation of wheat sales revenue. However, we use input expenditures instead of input quantities in vectors X_{1p} and X_{0p} and add quality attributes (specific weight and protein content) to account for the impact of grain quality on farm revenue. Farmers get a marketing contract that provides quality premiums for the two quality attributes: specific weight and protein content. Specific weight is a quality attribute for milling activities and protein content is another quality attribute useful for bakers.

Treatment effect on the treated

The results of the ESR allow us to compute the expected outcome variables for plots with the H standard $E(y_{1p}|A_p = 1)$ and to determine the expected outcome variables in the counterfactual hypothetical case where the plots with the H standard adopt the L standard $E(y_{0p}|A_p = 1)$. The conditional expectations are specified as follows:

$$E\left(y_{1p} \,|A_p = 1\right) = X_{1p}\,\beta_1 + \sigma_{1\mu}\lambda_{1p} \tag{11a}$$
$$E\left(y_{0p} \,|A_p = 0\right) = X_{0p}\,\beta_0 + \sigma_{0\mu}\lambda_{0p} \tag{11b}$$

In line with Heckman and Vytlacil (2001), we compute the effect of the treatment, the H standard, on the treated (TT). TT represents the effect of the adoption of the H standard on the outcome variables for plots that actually adopt the H standard. TT can be obtained as follows:

$$\begin{aligned} TT &= E\left(y_{1p} \,|A_p = 1\right) - E\left(y_{0p} \,|A_p = 1\right) \\ &= X_{1p}\,(\beta_1 - \beta_0) + \left(\sigma_{1\mu} - \sigma_{0\mu}\right)\lambda_{1p} \end{aligned} \tag{12}$$

4. Results and discussion

Effect of the H standard adoption on technical results – yield and quality

We present the results of the ESR model for technical results on Tables 3 to 5. The first column shows the results for the selection equation. Columns 2 and 3 present the estimates of the ESR on outcomes for, respectively, the group of plots with the L standard and the group of plots with the H standard.

Table 3: Parameters estimates when yield is the outcome variable – ESR model

	(1)		(2)		(3)	
	Selection		L standard		H standard	
Yield	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Mineral N quantity	0.001	0.001	0.006***	0.001	0.004***	0.001
Herbicide TFI	-0.021	0.045	-0.008	0.057	-0.041	0.046
Insecticide TFI	0.213***	0.069	0.291***	0.100	0.229***	0.065
Fungicide TFI	-0.010	0.058	0.214**	0.085	0.183***	0.067
Corn previous crop	-1.552***	0.097	-0.157	0.112	0.326***	0.112
Tillage	1.442***	0.109	0.251**	0.115	-0.200*	0.103
H standard experience	0.570***	0.143	-0.209	0.157	0.049	0.139
Livestock	0.189	0.136	-0.243	0.147	-0.078	0.109
Individual governance	-0.051	0.084	-0.390***	0.125	-0.234**	0.109
Highway	-9.624***	0.242				
Plot size	0.051***	0.008				
Constant	-0.927***	0.285	5.008***	0.386	5.494	0.338
$ln\sigma_0$	0.629***	0.020				
ρ_0	0.032	0.040				
$ln\sigma_1$	0.578***	0.017				
ρ_1	-0.143	0.103				
Log likelihood	-19,294.981					
Wald test of independence: χ^2	2.31					
Number of observations	8,068		2,819		5,249	

, **, * indicate significance at 10%, 5% and 1%, respectively.*

Note: we include control dummy variables for soil quality and years. We implement the FIML method with clustered standard errors at the farm level

Table 4: Parameters estimates when specific weight is the outcome variable – ESR model

	(1)		(2)		(3)	
	Selection		L standard		H standard	
Specific weight	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Mineral N quantity	0.000	0.001	0.005***	0.001	0.003	0.002
Herbicide TFI	-0.013	0.041	-0.057	0.095	-0.046	0.072
Insecticide TFI	0.170***	0.062	0.067	0.147	0.001	0.124
Fungicide TFI	-0.024	0.057	0.185	0.123	0.257***	0.097
Corn previous crop	-1.490***	0.098	-0.164	0.195	1.213***	0.192
Tillage	1.401***	0.107	-0.049	0.165	-0.816***	0.172
H standard experience	0.526***	0.145	-0.087	0.215	-0.140	0.270
Livestock	0.161	0.125	-0.139	0.268	-0.412**	0.169
Individual governance	-0.045	0.079	-0.219	0.166	0.017	0.155
Highway	-9.516***	0.248				
Plot size	0.047***	0.008				
Constant	-0.754***	0.283	75.623***	0.477	77.255***	0.578
$ln\sigma_0$	0.757***	0.028				
ρ_0	0.138**	0.060				
$ln\sigma_1$	0.862***	0.032				
ρ_1	-0.779***	0.057				
Log likelihood	-20,519.300					
Wald test of independence: χ^2	58.81***					
Number of observations	8,068		2,819		5,249	

, **, * indicate significance at 10%, 5% and 1%, respectively.*

Note: we include control dummy variables for soil quality and years. We implement the FIML method with clustered standard errors at the farm level

Table 5: Parameters estimates when protein content is the outcome variable – ESR model

	(1)		(2)		(3)	
	Selection		L standard		H standard	
Protein content	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Mineral N quantity	0.000	0.001	0.001	0.001	0.001*	0.001
Herbicide TFI	-0.020	0.044	0.041	0.047	0.020	0.024
Insecticide TFI	0.204***	0.066	-0.133***	0.051	0.006	0.039
Fungicide TFI	-0.015	0.058	0.099**	0.048	0.084**	0.037
Corn previous crop	-1.538***	0.098	-0.152***	0.059	-0.297***	0.081
Tillage	1.428***	0.112	0.047	0.060	0.196**	0.094
H standard experience	0.572***	0.143	-0.019	0.109	0.164*	0.094
Livestock	0.174	0.135	0.330***	0.080	0.066	0.072
Individual governance	-0.036	0.084	0.011	0.070	0.091	0.056
Highway	-9.627***	0.251				
Plot size	0.052***	0.008				
Constant	-0.871***	0.320	11.620***	0.244	11.055***	0.254
$ln\sigma_0$	-0.233***	0.026				
ρ_0	-0.025	0.057				
$ln\sigma_1$	-0.217***	0.036				
ρ_1	0.415*	0.189				
Log likelihood	-12,546.985					
Wald test of independence: χ^2	3.92					
Number of observations	8,068		2,819		5,249	

, **, * indicate significance at 10%, 5% and 1%, respectively.*

Note: we include control dummy variables for soil quality and years. We implement the FIML method with clustered standard errors at the farm level

We show that exclusion variables explain the probability for a plot to adopt the H standard, validating our choice as exclusion variables. Being close to a highway has a negative effect. It is not surprising as plots close to a highway are not eligible to the H standard. On the other hand, plot size has a positive effect. It validates our hypothesis that farmers may have higher incentives to adopt the H standard on larger plots as they expect higher returns on their investment. Farms characteristics do not affect the probability for a plot to adopt the H standard. Only, the experience of farmers with the H standard increases plots probability to adopt the H standard. Plots probability to adopt the H standard also depends on agricultural practices. The probability to adopt the H standard increases if the plot is tilled and decreases if the previous crop grown is corn. Tilling is an alternative technique to the use of herbicide to destroy weeds. As most toxic (and thus most efficient) herbicide are prohibited, farmers tend to rely more on tillage to control weeds on plots with H standard. Plots where was previously grown corn are more sensible to *Fusarium wilt*, thus farmers may choose not to adopt the H standard on these plots as they are limited in fungicide use in terms of active ingredients and quantity. Besides, insecticide TFI affect positively plots probability to adopt the H standard.

We highlight that there exists a selection bias on the adoption of the H standard on a plot regarding quality attributes but not on yield. For the yield estimation (Table 3), both estimated coefficients of the correlation terms, ρ_1 and ρ_0, are not significantly different from zero. These two coefficients measure the correlation between the error term of the selection equation and the outcome equation for plots with the L standard (ρ_0) and plots with the H standard (ρ_1). For specific weight estimation (Table 4), the estimated coefficients of the correlation terms ρ_1 and ρ_0 are both significant, ρ_1 is negative whereas ρ_0 is positive. It indicates a positive selection bias for plots with the H standard and a negative selection bias for plots with L standard. It suggests that plots with higher than average specific weight are more likely to adopt the H standard whereas plots with lower than average specific weight are more likely to adopt the L standard. For protein content (Table 5), the ρ_1 is positive at 10% of significance. It highlights a negative selection bias, plots with lower than average protein content are more likely to adopt the H standard.

Despite the absence of self-selection on the adoption of the H standard regarding yield, our results show that there are differences in the coefficients estimation of the yield equations between plots with L standard and plots with H standard (Table 3, columns 2 and 3). Thus, it illustrates the presence of heterogeneity in the sample. For both groups, increasing the quantity on plots of mineral N, insecticide TFI and fungicide TFI positively affect wheat yield. However, the effect of tillage on yield is opposite between the two groups. Tilling has a positive effect on plots with L standard whereas it has a negative effect on plots with H standard. Previous crop being corn has a significant effect only for plots with H standard. Coefficient estimations also differ between groups for quality attributes. Specific weight is positively affected by an increase in mineral N quality for plots with the L standard. For plots adopting H standard, fungicide TFI and corn being the previous crop positively affect specific weight whereas tilling negatively affect this quality attribute. Mineral N quantity only increase significantly protein content for plots with H standard. It could be surprising to note that mineral N quantity does not affect protein content for plots with L standard. However, protein content is mainly affected by the last application of mineral N and not the all quantity applied. Fungicide TFI has a positive effect on protein content for both groups. Plots with L standard are negatively affect by insecticide TFI and plots with H standard are negatively affect by the previous crop being corn.

Table 6 presents the average outcome results for yield, specific weight and protein content, under actual (highlight in grey) and counterfactual conditions. The last column reports the treatment effects of the adoption of the H standard on the treated (TT) for plots with the H standard. Our results show that, for plots with the H standard, the adoption of the H standard decreases yield and has mixed effect on quality attributes. Adopting the H standard reduces yield by 80kg/ha, representing a 1.4% decrease in yield. It decreases specific weight by 0.3kg/hl whereas it increases protein content by 0.02 point of percentage. Farmers have incentives for quality through a marketing contract that provides quality premiums for specific weight and protein content. If specific weight is higher than the threshold 76.3kg/hl, a reduction of 0.3kg/hl have no financial consequence. However, if the specific weight is below this threshold, a reduction by 0.3kg/hl can lead to a penalty up to 10€/ton of wheat. An increase of protein content by 0.02 point of percentage do not have financial impact, an increase of 0.1 point of percentage is needed to get a prime of 0.5€/ton of wheat.

Our results highlight that the adoption of the H standard on a plot in comparison to the L standard has overall a negative effect on technical results. Thus, banning most toxic pesticides at the plot level to limit the negative impact of agricultural practices on biodiversity decreases yield by 1.4%, decreases specific weight by 0.3kg/hl, and increases protein content by 0.02 point of percentage. The following section aims at estimating the consequences of the adoption of the H standard on sales revenue by hectares. More specifically, we examine whether the prime premium of the H standard compensates its negative effect on technical results and whether farmers get monetary incentives to adopt the H standard.

Table 6: Treatment effect on the treated - Effect of the H standard on technical results

	Decision stage		
Sub-samples: Plot with H standard	To adopt H standard	To adopt L standard	Treatment effects
Yield	5.96 (0.01)	6.05 (0.01)	TT = -0.08***
Specific weight	79.26 (0.03)	79.58 (0.03)	TT = -0.32***
Protein content	12.13 (0.01)	12.11 (0.01)	TT = 0.02***

, **, * indicate significance at 10%, 5% and 1%, respectively.*

Effect of H standard adoption on sales revenue

Our results show that there is no selection bias on the adoption of H standard on a plot regarding sales revenue (Table 7). However, there are differences in the coefficients estimation of sales revenue equations between plots with H standard and L standard (Table 7, columns 1 and 2). Sales revenue of both groups are influenced positively by the increase of mineral N, insecticide, and fungicide expenditures. Plots characteristic influence L standard and H standard in an opposite way. Corn being the previous crop has a negative impact on sales revenue for plots with the L standard whereas it has a positive impact for plot with the H standard. Tilling plots increases sales revenue for plots with the L standard and decreases it for plots with the H standard. Regarding quality attributes, the increase in specific weight enhances sales revenue for both groups. Protein content is negative and significant only for the plots with H standard. This result could be surprising as there is a monetary incentive for protein content in the marketing contract. However, there is a negative relation between yield and protein content while sales revenue per ha highly depends on yield.

Table 7: Parameters estimates when sales revenue is the outcome variable – ESR model

	(1)		(2)		(3)	
	Selection		L standard		H standard	
Sales revenue	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Mineral N expenditure	0.001	0.001	0.443***	0.161	0.311***	0.102
Herbicide expenditure	0.002*	0.001	-0.066	0.282	-0.162	0.196
Insecticide expenditure	0.034***	0.012	11.225***	3.125	7.372***	2.486
Fungicide expenditure	0.003***	0.001	1.306***	0.313	1.187***	0.266
Corn previous crop	-1.521***	0.096	-30.233*	17.984	32.249**	16.546
Tillage	1.440***	0.108	53.760***	18.050	-26.172*	14.830
Specific weight	0.012	0.013	46.801***	3.725	33.316***	2.497
Protein content	0.030	0.042	-9.527	9.521	-28.520***	6.439
H standard experience	0.540***	0.142	-41.652*	25.189	2.115	21.285
Livestock	0.222*	0.123	-29.639	29.109	3.751	16.352
Individual governance	-0.046	0.082	-62.359***	19.833	-34.392**	16.882
Highway	-9.885***	0.216				
Plot size	0.049***	0.008				
Constant	-2.676**	1.247	-2482.812***	330.65	-1183.11***	237.078
$ln\sigma_0$	5.761***	0.026				
ρ_0	0.060	0.039				
$ln\sigma_1$	5.701***	0.016				
ρ_1	-0.089	0.088				
Log likelihood	-60,634.581					
Wald test of independence: χ^2	3.19					
Number of observations	8,068		2,819		5,249	

, **, * indicate significance at 10%, 5% and 1%, respectively.*

Note: we include control dummy variables for soil quality and years. We implement the FIML method with clustered standard errors at the farm level

Table 8 reports the report the TT of the H standard on sales revenue. Our results show that the adoption of the H standard for plots adopting the H standard increases sales revenue by 13.0€ per ha, representing a 1.3% increase of sales revenue per ha. On average, increasing sales revenue per ha by 13.0€ leads to an increase of 2€/ton. Thus, we conclude that the H standard price premium merely compensates the negative impact of H standard adoption on yield and quality. Monetary incentives for farmers to adopt the environmental standard with the highest requirements, limiting toxic pesticides for biodiversity, is low.

Table 8: Treatment effect on the treated - Effect of the H standard on sales revenue

	Decision stage		
Sub-samples: Plot with H standard	To adopt H standard	To adopt L standard	Treatment effect
Sales revenue	1031.91 (2.96)	1018.84 (3.10)	TT = 13.07***

, **, * indicate significance at 10%, 5% and 1%, respectively.*

Our analysis highlights that farmers receive very low monetary incentives to implement the standard with the highest requirements. Thus, we wonder what are their motivation to choose to change their practices on some plots by banning efficient pesticides but harmful for the biodiversity. Meta-analysis and literature review show that access to information, knowledge on sustainable practices, financial capacity, connection with local network, environmental awareness, risk tolerance, and social factors are part of the factors explaining the adoption of sustainable practices by farmers (Baumgart-Getz *et al.*, 2012; Dessart *et al.*, 2019). However, these factors cannot be taken into account when it comes to understand why they choose to adopt the standard with the highest environmental requirement on some plots and not on other plots. Ambec and Lanoie (2008) and Lanoie and Llerena (2015) highlight that the adoption of environmental practices in an opportunity to access some markets. Thus, by adopting two different standards on different plots of their farm, farmers can have access to two different markets.

5. Conclusion

We contribute to the existing literature by investigating the effect of the adoption of a stringent environmental standard enforcing restrictions on pesticides use on technical and economical results. This standard aims at favoring biodiversity by enforcing the presence of biodiversity habitats and at reducing the negative effects of agricultural practices by banning most toxic pesticides. The set of rules is an intermediate level between organic standard and conventional practices. We explore the role of intermediate environmental standards on wheat yield, quality and sales revenue. For technical results, we pay attention to yield and two quality attributes: specific weight and protein content. We choose to focus on to these attributes as farmers have monetary incentives for them through a marketing contract. Thus, a decrease in this two quality attributes would negatively affect economic results. For economic result, we estimated the impact of the adoption of the stringent environmental standard on sales revenue per ha. Our empirical analysis is conducted at the plot level on wheat production in France from 2014 to 2020.

We implement an endogenous switching regression method to take into account possible heterogeneity in the decision to adopt the most stringent environmental standard. We reveal there is selection bias on the adoption of the highest environmental standard regarding quality attributes. Furthermore, our results highlight that banning most toxic pesticides at the plot level to limit the negative impact of agricultural practices on biodiversity decreases yield by 1.4%, decreases specific weight by 0.3kg/hl, and increases protein content by 0.02 point of percentage. The adoption of the highest environmental standard increases sales revenue by 13.0€ per ha, representing on average an increase of 2€/ton. Thus, monetary incentives for farmers to adopt the environmental standard limiting toxic pesticides for biodiversity are low. Farmers may have other incentives to implement them on some of their plots such as access to market.

We analyze the impact of adopting a more stringent environmental standard at the plot level to examine accurately the effect of inputs use on technical results such as yield and product quality. Moreover, it allows us to take into account the existing differences in plot management within a farm. For future work, we would like to deepen our analysis and better understand the effects of the adoption of environmental standards on farms' economic performance. We would then be able to study farms' multi-output strategy. Bravo-Ureta *et al.* (2020) showed that plot level management differences do not have a significant effect on farm efficiency. They found that farm level management determined farm efficiency. We could thus explore the trade-off between economic and environmental performance at the farm level when farmers adopt an environmental standard with different levels of stringency.

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