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The technical and economic effects of biodiversity standards on wheat production

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Abstract

Our paper assesses the technical and economic effects of adopting environmental standards aimed at favouring biodiversity on wheat production. We consider two standards with different levels of environmental stringency. We use data on French wheat production at the plot level from the period 2014–2020. We implement an endogenous switching regression model taking into account two sources of endogeneity, environmental standards adoption and inputs quantity use. Our results indicate that adopting the more stringent standard slightly decreases wheat yield and quality. In contrast, it induces a low increase in wheat price. The price premium of the more stringent environmental standard merely compensates for the negative effect of the standard's adoption on quality.

Keywords: environmental standard, biodiversity, agricultural practices, endogenous switching regression, selection bias, input endogeneity

JEL classification: C34, Q57, L15

1. Introduction

Biodiversity preservation is essential for crop production; 75 per cent of the world's food crops need animal pollination. Furthermore, an additional ecosystem service provided by biodiversity is natural biological pest control (IPBES, 2019). However, the Intergovernmental science-policy Platform on Biodiversity and Ecosystem Services (IPBES) report highlights that approximately

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one million animal and plant species are threatened with extinction (IPBES, 2019), mainly because of agriculture and the overexploitation[1] of wild species (Maxwell *et al.*, 2016; Tilman *et al.*, 2017; IPBES, 2019). Intensive agricultural practices have a negative impact on biodiversity through various channels. One channel is the destruction of species habitats by converting them into agricultural land, another is habitat homogenisation through increased single-crop farming and the removal of hedgerows (Benton, Vickery and Wilson, 2003; IPBES, 2019; Sánchez-Bayo and Wyckhuys, 2019; Raven and Wagner, 2021). Moreover, conventional agricultural practices rely on the intensive use of chemical inputs (pesticides and fertilisers) and on tillage that are harmful to biodiversity (Hautier, Niklaus and Hector, 2009; Geiger *et al.*, 2010; Beketov *et al.*, 2013; Arslan, 2018; Sánchez-Bayo and Wyckhuys, 2019).

The increased awareness of the harmful effects of agriculture on biodiversity can be illustrated by the ambitious objectives set by the Farm to Fork Strategy (European Commission, 2020), part of the European Green Deal. The goal is to reduce by 2030 the use and risk of chemical pesticides at the European level by 50 per cent. Acknowledging that the current Sustainable Use of Pesticides Directive[2] is not sufficiently binding and is unevenly implemented, thus hindering the attainment of this objective, the European Commission proposes to convert the Directive into a Regulation[3] directly applicable in all Member States. Besides the European initiatives, several public and private instruments may be used to prevent biodiversity loss, among which are environmental standards and labels. Environmental labels provide information to consumers about the environmental practices implemented by farmers following standard requirements and that cannot be observed directly by consumers. Consumers are becoming increasingly interested in environmental labels. The European Commission conducted a survey in 2014 that revealed that 75 per cent of Europeans are 'willing to buy environmentally friendly products, even if it costs a little more to do so' (European Commission, 2014). Sessego and Hébel (2019) found that, in 2018, 70 per cent of French people had purchased at least one product with the certified organic label in the previous 6 months, whereas in 1998 only 44 per cent of them had done so. The use of environmental labels is increasing worldwide; for instance, the Ecolabel Index (2021) identified 455 environmental labels in 199 countries and 25 industry sectors. In the agricultural sector, public and private organisations have developed numerous environmental standards. As far as the public sector is concerned, the organic standard was recognised in 1981 by the French government and harmonised at the European level in 1992. Since 2012, the French Ministry of Agriculture has supported a second standard, the French *High Environmental*

1 Species are overexploited when harvesting rates cannot be compensated for by reproduction or regrowth.

2 Directive 2009/128/EC of the European Parliament and of the Council of 21 October 2009 establishing a framework for Community action to achieve the sustainable use of pesticides (OJ L 309, 24.11.2009, p. 71).

3 Proposal 2022/0196 (COD) of the European Commission of 22 June 2022 for a Regulation of the European Parliament and of the Council on the sustainable use of plant protection products and amending Regulation (EU) 2021/2115.

Value (‘Haute Valeur Environnementale’). This standard is less binding than the organic one, and aims to assess farm environmental performance using four criteria: biodiversity preservation, crop protection management, fertilisation management and irrigation management. In 2020, through the Farm to Fork Strategy, the European Commission aims to create a sustainable label and to harmonise voluntary green initiatives (European Commission, 2020). Private organisations (firms and Non-Governmental Organisations) have also developed their own environmental standards, such as the Marine Stewardship Council in 1996 and Bee Friendly in 2012, to respond to consumer demand for environmentally-friendly products (Saitone and Sexton, 2017). Such standards allow farmers to differentiate with labels their products in the market or to improve market access (Ambec and Lanoie, 2008). Introducing environmental standards in agricultural production affects the structure and the organisation of supply chains. Compliance and monitoring of standards require tighter vertical coordination along the supply chain (Beghin, Maertens and Swinnen, 2015). It is also a way to guarantee farmers a certain price in a food chain that is highly concentrated and where farmers request fair prices and better competition regulations (Swinnen, Olper and Vandevelde, 2021). The wild development of private and public agri-food standards impacts international trade between countries; however, the precise effects on trade remain ambiguous (Drogué and DeMaria, 2012; Beghin, Maertens and Swinnen, 2015; Curzi *et al.*, 2018; Fiankor, Martínez-Zarzoso and Brümmer, 2019; Santeramo and Lamonaca, 2019; Fiankor, Curzi and Olper, 2021).

In the literature studying farmers’ choices in adopting an environmental standard, a large body of work has focused on farmers’ preferences between adopting an organic standard or remaining under conventional practices (for a review, see Dessart, Barreiro-Hurlé and Van Bavel (2019)). In contrast, the literature is scarce on cases where a variety of environmental standards is offered. Our article contributes to this literature, specifically in the case of French wheat production, as we compare farmers’ choices between two standards aiming at favouring biodiversity: a more stringent and a less stringent standard. While both these environmental standards require the presence of species habitats on farm plots such as bird perches, hedges, field margins and fallow land dedicated to nectar source plants, the more stringent standard also bans the most toxic pesticides. Wheat produced according to either of the two environmental standards under consideration in this study is exclusively aimed at the French market and is not exported. Farmers engaged in these standards receive a yearly base price, with a penalty-bonus system linked to quality and a premium linked to the stringency of the environmental standard.

In this article, we assess the effects of adopting the most stringent environmental standards in terms of wheat yield and wheat quality (technical effects) and price received (economic effect). The link between the adoption of environmental practices on the one hand, and yield and economic return on the other, has been explored widely in developing countries. Most of the studies show a positive relationship. Di Falco, Veronesi and Yesuf (2011) found that farmers who adopted new varieties, soil conservation strategies and tree planting to cope with climate change in Ethiopia obtained higher yields. Abdulai and Huffman (2014) found similar results in Ghana, where 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 the use of agro-ecological practices and return on investment for pineapple farmers in Ghana. Another part of the literature aimed at understanding the effect of sustainable agricultural standards on socio-economic and environmental indicators in developing countries as well as their effect on the agri-food supply-chain. Literature reviews highlight mixed evidence and context-dependent results (Oya, Schaefer and Skalidou, 2018; Meemken *et al.*, 2021; Traldi, 2021). However, the adoption of environmental practices in developing countries is triggered by a diverse set of drivers, such as adaptation to climate change and food security, which differs from that in developed countries where economic incentives play a role. The effects of the adoption of sustainable standards are therefore likely to be different.

The agronomic literature has widely studied the effect on crop yield of the adoption of the organic standard (de Ponti, Rijk and van Ittersum, 2012; Seufert, Ramankutty and Foley, 2012; Ponisio *et al.*, 2015; Reganold and Wachter, 2016). Studies have generally identified a negative effect of the adoption of organic practices on yield. In contrast, no consensus has arisen in the economic literature on the relationship between the adoption of the organic standard and technical-economic performance. Most studies have shown that technical efficiency is higher in cases of organic farming as opposed to non-organic farming (Tzouvelekas, Pantzios and Fotopoulos, 2001, 2002; Oude Lansink, 2002; Tiedemann and Latacz-Lohmann, 2013; Grovermann *et al.*, 2021). However, some studies have identified a negative effect of organic certification on technical efficiency (Sipilainen and Oude Lansink, 2005; Kumbhakar, Tsionas and Sipilainen, 2009; Serra and Goodwin, 2009), while others did not indicate a significant effect (Mayen, Balagtas and Alexander, 2010; Sauer, 2010; Grovermann *et al.*, 2021). Another strand of literature observes that biodiversity could be considered as a productive ecosystem service (Di Falco, 2012; Bareille and Letort, 2018; Bareille, Boussard and Thenail, 2020). However, despite the clearly positive link between biodiversity and crop yield (Garibaldi *et al.*, 2016; Binder *et al.*, 2018; Dainese *et al.*, 2019), results from studies evaluating the effect of conservation measures suggested that biodiversity often fails to improve crop yield (Begg *et al.*, 2017).

Our analysis differs from previous studies for several reasons. While most studies examined the adoption of new practices and input use strategies at the farm level, we conduct our empirical analysis at the plot level. This enables the possibility for farmers to implement several environmental standards on their farms on different plots to be taken into account. In contrast to other studies, we do not compare plots under an environmental standard versus those without environmental standard. We consider two environmental standards, one less stringent and one more stringent. Contrary to the organic standard that modifies the whole farming system, the two environmental standards considered here only affect practices on plots and can be considered as intermediate environmental standards. From a public policy point of view, the latter may be considered useful instruments with potential benefits for the environment, since their adoption rate is higher than that of the (more binding) organic standard. In France, organic certified wheat represented just 2.7 per cent of annual wheat production for human consumption in 2019 (Renault *et al.*, 2020). In comparison, the most stringent standard studied here (later referred to as the *H standard*) accounted for 10 per cent of French annual wheat production for such purposes, while the less stringent standard (later denoted the *L standard*) has been adopted by 4 per cent of French farmers producing wheat. To our knowledge, no study has investigated the role of such intermediate standards on farm's technical and economic outcomes.

The second contribution is that our study complements the literature on the effects of input use on farm outcomes through quality assessment. Most studies have focused on the effects on yield and economic results in order to assess input economic value or productivity (Carpentier and Weaver, 1997; Sexton, 2007; Kawasaki and Lichtenberg, 2015; Koussoubé and Nauges, 2017). Only a limited number of papers have taken into account how input use influences product quality, showing that ignoring quality underestimates the economic value of pesticide use (Babcock, Lichtenberg and Zilberman, 1992; Cobourn, Goodhue and Williams, 2013; Kawasaki and Lichtenberg, 2015). Here, we assess the effect on wheat quality of input management changes (required by the adoption of the more stringent environmental standard). We specifically consider two quality attributes: test weight and protein content. Both quality attributes are important for wheat processing activities (Larue, 1991). Test weight is a quality attribute for milling activities and protein content is useful for bakers.

Finally, we implement an endogenous switching regression (ESR), allowing a counterfactual analysis. Several studies also used an ESR to account for the endogeneity of technology adoption when assessing the effect of technology adoption in developing countries (Di Falco, Veronesi and Yesuf, 2011; Di Falco and Veronesi, 2013; Kleemann and Abdulai, 2013; Abdulai and Huffman, 2014; Kassie *et al.*, 2015; Abdulai, 2016; Kassie *et al.*, 2018). However, a limited number of ESR analyses have been conducted in developed countries. Lapple, Hennessy and Newman (2013) assessed the effect of a public programme on farm profit. More recently, two studies assessed the effect of foreign labour and innovation towards climate variability on firm performance (Antonioli, Severini and Vigani, 2021; Auci *et al.*, 2021). With the exception of Auci *et al.* (2021), previous studies only took technology adoption endogeneity into account. By contrast, here, we account for two endogeneity issues: one related to the adoption of the most stringent standard; the second on the use of input quantities. When estimating wheat yield, quality and price, inputs may be correlated to the error term as we omit pest infestation measures because of lack of information (Frisvold, 2019). We follow the approach of Murtazashvili and Wooldridge (2016), based on an ESR. This enables the endogeneity of the explanatory variables in addition to the selection variable endogeneity to be accounted for.

The rest of the article is organised as follows. Firstly, we describe the data used and discuss summary statistics (section 2). Then we explain our empirical strategy based on the ESR method (section 3), and we present and discuss our results (section 4). In the final section, we offer our conclusions (section 5).

2. Data

Our empirical study is applied to wheat production in France, which is a major crop production in the country. Wheat represents 54 per cent of total French cereal production, and from 2014 to 2018, 5 million hectares on average were cultivated with wheat, representing 17 per cent of French agricultural land. France is the largest producer of wheat in Europe and the fifth largest on a world scale (FranceAgriMer, 2021).

We focus on two specific intermediate environmental standards for which farmers can change practices at the plot level and within a production year. We refer to an environmental standard as intermediate if its requirements are higher than conventional practices but lower than the organic requirements. We exclude from our analysis the organic standard that requires a radical change in farming system and a 3-year transition period. The two intermediate environmental standards considered here are: the *L standard* that has lower requirements on biodiversity and only requires the existence of biodiversity habitats (e.g. bird perches or hedges), and 3 per cent of arable land covered with nectar-source plant fallow; the *H standard,* that has higher requirements than the *L standard* because it constrains the use of pesticides. More precisely, most toxic active ingredients are prohibited under the *H standard*, and there is a list of non-recommended active ingredients, which are allowed but the quantity used should be limited. Although the *H standard* requirements do not impose a limit on the total amount of pesticide use, we note that its requirements are in line with the Farm to Fork Strategy's objective to reduce the risk of chemical pesticides by binding the most toxic pesticides.

Studies in ecology have shown that biodiversity increases in response to conservation measures, such as those requiring habitat diversification and low-input practices (Attwood *et al.*, 2008; Begg *et al.*, 2017; Graham *et al.*, 2018; Albrecht *et al.*, 2021). Thus, when adopting the *L* or *H* standards, farmers modify their agricultural practices in a way that favours biodiversity. However, as explained above, the private consequences for farmers of adopting one or the other standard are not clear. Our level of observation is plots. All of the plots in our database are cultivated with wheat under an environmental standard, either *L* or *H* standard. We will estimate the effect for three outcomes (yield, quality, price) of producing under the *H standard* rather than the *L standard*. The data were collected between 2014 and 2020 by an agricultural cooperative whose substantial share of wheat production is dedicated to agricultural products under different standards. The cooperative offers technical services to their members to encourage them to change their agricultural practices. The agricultural cooperative collects precise agronomic data on input use and wheat quality for plots. Farmers who choose to adopt standards on their plots receive technical visits from the cooperative's advisors at least four times a year. These visits aim to provide technical advice to farmers and to ensure that they comply with the requirements of the standards' specifications. Farmers who adopt one of the standards are obliged to inform the cooperative of all practices on plots where they adopted a standard (e.g. date of sowing; date, quantity and product used for each pesticide and fertiliser application; date and type of tillage, etc.). Farmers can either provide this information via a web application linked to the cooperative database or record the information on monitoring sheets provided by the cooperative. During their visits, the cooperative advisors ensure that the information provided corresponds to the practices implemented. Control is facilitated by the obligation of farmers to purchase crop protection and fertiliser inputs from the cooperative. In addition, the cooperative measures wheat quality systematically and precisely because the price paid to the farmer is calculated with a penalty-bonus system based on quality. However, the cooperative does not collect information on input use for plots under conventional agricultural practices. Farmers who are members of the cooperative can decide for each plot whether they would like to adopt the *L standard*, the *H standard* or neither of them.

Our database includes 8,015 observations at the plot level for the whole period 2014–2020. The database is composed of all the plots cultivated under the *H* or *L standard* within the cooperative. The plots are operated by 278 farms located in the French region Poitou-Charentes. Each year, farms in the sample have, on average, seven plots of wheat cultivated under one of the environmental standards. The 8,015 plot observations are not panel data. Table 1 highlights that most plots (64 per cent) are present only one year in the database and about 11 per cent of the plots appear more than twice. This is due to crop rotation, which prevents the production of wheat on the same plot in consecutive years. There are various types of crop rotations, varying in length; e.g. 3 year crop rotation (canola-common wheat-barley), 4 year crop rotation (corn-peas-durum wheat-common wheat) and 5 year crop rotation (corn-common wheat-sunflower-durum wheat-barley) (Chambres d'agriculture, 2020). Our database includes 7 years and is composed of plots cultivated with common wheat. Thus, for short rotations, we can expect to identify them two to three times in the database; however, for long rotations they will probably appear only once. Almost two-thirds of the plot observations (65 per cent) are produced under the *H standard*. Some plots, irrespective of the pesticides used on them, are not eligible for the *H standard* because of their intrinsic characteristics, such as being close to a highway. In our sample, 55 per cent of the plots with the *L standard* are eligible to apply the *H standard*. Most plots (90 per cent) are cultivated by farmers with previous experience of the *H standard*. In addition, the majority of the plots in our dataset (72 per cent) are cultivated by farmers who adopted both the *L* and the *H standard* but on different plots and in different proportions.

The database also includes information about the farms operating the plots, input management, plot characteristics and technical (i.e. yield and quality attributes) and economic (i.e. wheat price) outcomes. We consider two quality attributes of wheat: test weight and protein content. Wheat price is determined

Table 1. Observation of plots across years in the database

Number of years a specific plot is observed	Number of plots	Percentage of plots
1	3,431	64%
2	1,367	25%
3	464	9%
4	107	2%
5	6	0.1%
6	0	0%
7	0	0%

by a set of parameters depending on the quality level. The wheat price formula is based on a yearly base price and includes a bonus-penalty system for quality attributes, and price premiums for the adoption of the environmental standards. While the base price is only known at harvest time, farmers know the values of the bonus-penalty system and the price premiums prior to wheat sowing. As all plots in our sample are cultivated by farmers who are members of the same cooperative, in a given year, the latter face the same market environment.

In addition to the plot-level data provided by the agricultural cooperative, we used information on weather conditions from SICLIMA Extraction at a resolution of 8 km^2. SICLIMA Extraction is a web application developed by the INRAE Agroclim research unit from daily weather information provided by Météo-France (the French national centre for meteorological research). We used the R meteoRIT package (Desjeux, 2019) to transfer weather data at a resolution of 8 km^2 to municipality resolution. Thus, knowing the localisation of each plot in terms of the municipality where it is located, we were able to match plot-level data with municipality-level weather data. We used two weather variables: daily average temperature and cumulated precipitation over the wheat growing season (10 March to 10 July).

Table 2 presents descriptive statistics of the data and a comparison of mean characteristics between plots with the *H standard* and plots with the *L standard*. In our database, about one-third of the plots are tilled, which is in line with the French average for wheat plots (Agreste, 2020b). The mineral nitrogenous (N) fertilisation applied is 180 kg N/ha on average, slightly higher than the French average of 164 kg N/ha (Agreste, 2020a). The herbicide treatment frequency index (TFI)[4] and insecticide TFI are close to the regional average, 1.8 and 0.3, respectively. The 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 test weight is 79.25 kg/hl and the protein content in wheat reaches 12.10 per cent on average.

4 TFI is an indicator widely used by French decision makers for monitoring the use of pesticides in agriculture. It counts the number of reference rates used per hectare during a crop year:

$$TFI = \sum_{pesticides} \frac{\text{applied rate}}{\text{reference rate}} * \frac{\text{area treated}}{\text{plot area}}$$

Table 2. Variables definition and descriptive statistics for the plots

Variable	Definition	Full plot sample: Mean	Full plot sample: Std. dev.	Comparison of mean characteristics: Plots - *L standard*	Comparison of mean characteristics: Plots - *H standard*	Comparison of mean characteristics: Significance[1]
Outcome variables						
	Technical outcomes					
Yield	Yield (tons/ha)	5.96	2.08	5.96	5.96	n.s
Test weight	Test 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	***
	Economic outcome					
Wheat price	Price paid to farmers (€/ton)	170.62	13.26	166.94	172.59	***
Plot agricultural practices and characteristics						
	Fertilisation management					
Mineral N quantity	Mineral nitrogen unity applied (kg/ha)	180.43	36.90	181.19	180.02	*
	Crop protection management					
Herbicide TFI	Treatment frequency index for herbicide	1.74	0.79	1.70	1.77	***
Insecticide TFI	Treatment frequency index for insecticide	0.34	0.56	0.27	0.37	***
Fungicide TFI	Treatment frequency index for fungicide	1.36	0.64	1.33	1.38	***
	Plot management					
Corn as previous crop	1 if the previous crop was corn, 0 if not	0.34		0.55	0.22	***
Tillage	1 if the plot has been tilled, 0 if not	0.38		0.22	0.47	***
	Variety					
High quality varieties	1 if high quality variety, 0 if not	0.89		0.88	0.89	n.s
	Plot size					
Plot size	Plot size (ha)	5.06	4.85	3.45	5.64	***

(continued)

Table 2. (Continued)

		Full plot sample		Comparison of mean characteristics		
Variable	Definition	Mean	Std. dev.	Plots - *L standard*	Plots - *H standard*	Significance[1]
Farm characteristics						
Livestock	1 if livestock on farm, 0 if not	0.24		0.17	0.27	***
H standard previous experience	1 if farmers have previous experience with the *H standard*, 0 if not	0.90		0.86	0.92	***
Weather variables						
Temperature	Daily average temperature (°C)	14.42	0.79	14.33	14.48	***
Precipitation	Cumulated precipitations (mm)	224.94	51.87	223.85	225.55	***
Exclusion variable						
Highway	1 if the plot is located close to a highway, 0 if not	0.08		0.22	0.00	***
Number of observations		8,015		2,789	5,226	

*, **, *** *indicate significance at the 10 per cent, 5 per cent and 1 per cent levels, respectively.*

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

Quality attributes for our sample are, on average, above the French average wheat quality (78.27 kg/hl for test weight and 11.58 per cent for protein content).

Comparing mean characteristics between plots with *H standards* and plots with *L standards*, figures show that the two groups have significantly different agricultural practices and farm characteristics. We note that the plots with the *H standard* are more frequently observed in farms with livestock and are on average bigger. Farmers may have higher benefits from adopting the H standard on larger plots as they can expect higher returns from this adoption. In addition, adoption may imply fixed costs and the latter can be spread across a larger area. More plots with the *H standard* are tilled, and are less likely to have been planted with corn in the previous season compared to plots with the *L standard*. Since most toxic herbicides are prohibited in the *H standard*, on plots where this standard applies, farmers rely on agronomic strategies to limit pesticide use, such as tilling (which can destroy weeds) and not planting wheat after corn (thus limiting the use of fungicide to treat Fusarium wilt). We find no significant difference in terms of quality of the chosen variety. French wheat varieties are classified in two categories according to their baking qualities. The variable *high quality varieties* reports this classification. We observe differences in crop protection management at the 1 per cent level of significance, whereas fertilisation management differs only at the 10 per cent level of significance. Herbicide TFI, insecticide TFI and fungicide TFI are higher for plots with the *H standard* than for plots with the *L standard*. We did not expect that plots with the *H standard* would receive a higher quantity of pesticides. However, although the set of rules for the *H standard* implies binding requirements on the applied quantity of moderate toxically active ingredients, it does not limit the total applied quantity. In other words, farmers producing under the *H standard* use less effective active ingredients at a higher rate, because of the ban on the most toxic ingredients that are also the most effective active ingredients. In terms of technical outcomes, we observe similar yield and similar test weight in the two groups. In contrast, protein content is slightly higher for plots with the *H standard*. The price received by farmers by ton of wheat sold to the cooperative is higher for plots with the *H standard*, by EUR 5.65/ha on average.

3. Empirical strategy

Our objective is to estimate the effect of the adoption of more stringent environmental standard on three technical outcomes (yield, test weight and protein content) and on an economic outcome (wheat price) at the plot level. We consider only plots where farmers choose to adopt an environmental standard. Farmers can decide whether they only want to adopt the less stringent standard, the *L standard*, or whether they prefer to adopt the more stringent standard, the *H standard*. We then estimate the effect of adopting the *H standard* rather than the *L standard*.

Two endogeneity issues arise for the empirical analysis. Firstly, we may encounter the issue of farmers' self-selection of specific plots. Observable and unobservable farmer and plot characteristics might affect the choice of adopting the *H standard* and consequently it might affect the estimation of yield, quality and wheat price. Secondly, another source of endogeneity is linked to omitted variables. When estimating yield, quality and wheat price, we use input quantities (fertiliser and pesticides) as explanatory variables. Inputs may be correlated to the error term as we omit pest infestation measures because of lack of information (Frisvold, 2019).

To deal with the potential endogeneity of the adoption of the *H standard*, we implement an ESR model for three reasons. Firstly, this approach is more robust than a classic instrumental approach due to the forbidden regression problem (Angrist and Pischke, 2008). Secondly, the ESR approach, which allows observable and unobservable characteristics to be taken into account, is also more robust than matching methodologies which rely only on observed characteristics (Imbens and Wooldridge, 2009). Thirdly, while a more robust approach would be to compare observations before and after the adoption of the *H standard* as in the difference-in-difference methodology, we cannot use it since we do not have panel data due to crop rotation at the plot level.[5] The advantage of the ESR method is that it allows us to consider two different technologies, one on plots producing under the *H standard* and another on plots producing under the *L standard*.

To implement the ESR model, we follow the Murtazashvili and Wooldridge (2016) specification. The advantage of this methodology over others (such as Fuglie and Bosch (1995), Di Falco, Veronesi and Yesuf (2011), Drukker (2016)) is that it deals with the two sources of endogeneity mentioned above: the self-selection issue and that associated with omitted explanatory variables. The ESR approach is a two-stage procedure based on the control function approach. At the first stage of the ESR, we determine the factors that influence the adoption of the *H standard* on a plot and that refers to 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 from the adoption of the *H standard* is greater than that for the decision to adopt the *L standard*, then the *H standard* will be adopted on the plot. We define the latent variable A_p^* that represents the expected net utility on plot p from the adoption of the *H standard* instead of the adoption of the *L standard*. A_p^* is a function of factors that affect the expected net utility of producing under the *H standard*. However, we do not observe the latent variable, A_p^*. We only observe the decision whether the *H standard* is adopted on the plot or not, A_p, which is related to the latent variable A_p^* as follows:

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

5 The difference-in-difference methodology is widely used in the literature to estimate the impact of a treatment such as the adoption of new practices or the consequences of the implementation of public policies (Bravo-Ureta *et al.*, 2020; Mennig and Sauer, 2020).

Thus, the first stage of the ESR relies on a probit model given by:

$$A_p = 1\left[k + x_p^{exo}\pi_1 + z_p\pi_2 + q_p\pi_3 + u_p > 0\right],\ u_p \sim N[0,1] \tag{2}$$

where k represents the constant, x_p^{exo} is a vector including the exogenous variables of the outcome equation (see equation (3) below), z_p is a vector gathering the instruments of the endogenous explanatory variables and q_p is the vector of the instruments of the selection variables. $\square_1$, $\square_2$ *and* $\square_3$ are vectors of parameters to be estimated and u_p is the error term.

To instrument the selection variables, we rely on an exclusion variable q_p that directly affects the selection variable but not the outcome variables (yield, test weight, protein content and wheat price). As the exclusion variable we use a dummy defining whether or not plots are located close to a highway (*highway*), since a plot close to a highway cannot be eligible for the *H standard* to avoid possible contaminations of wheat grains by the pollutions emitted into the air by vehicles. This constraint shows that, beyond the objective of preserving biodiversity, the *H standard* seeks to reassure consumers on health aspects. Indeed, several studies show that health attributes are major motivating factors for consumers to buy products with environmental standards (see Asioli *et al.* (2017) for a review). The *highway* variable thus affects the probability that a plot is certified under the *H standard* but we can reasonably assume that distance to a highway does not affect the outcome variables (yield, test weight, protein content or price). Unlike in developing countries, in France, the proximity of a plot to a highway does not facilitate access to certain input or output markets. Highway exits are not frequent and therefore proximity to a highway does not indicate that a plot would be better connected to the road network. Furthermore, cooperatives are the main input providers and buyers for French farmers and they ensure equal treatment of their members. Farmers thus have the same market access to inputs and outputs regardless of the geographical location of their plots.

In the second stage of the ESR, we estimate separately the equations of the outcome variables, y_p. The second-stage equation is a linear combination of two technologies:

$$y_p = A_p y_p^1 + \left(1 - A_p\right) y_p^0 \tag{3}$$

where y_p^1 and y_p^0 represent the technologies used on the plots producing under the *H standard* and *L standard,* respectively.

The selection bias is tackled by adding the generalised residuals estimated in the first stage (g_p). For a detailed description of the model, see Vella and Verbeek (1999) and Murtazashvili and Wooldridge (2016). The second stage is estimated with two-stage least squares (2SLS) using the following equation:

$$cy_p = x_p^{exo}\beta_0^{exo} + A_p x_p^{exo}\beta_T^{exo} + x_p^{endo}\beta_0^{endo} + A_p x_p^{endo}\beta_T^{endo} + \rho_0\widehat{gr}_p + \rho_T A_p\widehat{gr}_p + a_p \tag{4}$$

$$with\ E\left(a_p | A_p\right) = 0$$

where the vectors x_p^{exo} and x_p^{endo} include the exogenous variables and the endogenous explanatory variables, respectively. $\square_0^{exo}$, $\square_0^{endo}$, $\square_T^{exo}$, $\square_T^{endo}$, $\square_0$ and $\square_T$ are vectors of parameters to be estimated. a_p is the error term.

Equation (4) estimates the outcome variable as a linear combination of the two technologies. $\square_T^{exo}$ is the difference between the two coefficients of x_p^{exo} or, in other words, the difference between the adopters of the *H standard* (technology 1) and the adopters of the *L standard* (technology 0), thus $\square_T^{exo} = \square_1^{exo} - \square_0^{exo}$. Likewise, $\square_T^{endo} = \square_1^{endo} - \square_0^{endo}$ and $\square_T = \square_1 - \square_0$.

In our specification, the endogenous explanatory variables are the input quantities (mineral N quantity, herbicide TFI, insecticide TFI and fungicide TFI) as we expect them to be correlated with the error term. Previous studies used various instrumental variables to instrument pesticide use, which is a major concern when estimating production function (Frisvold, 2019). In the same vein as Kawasaki and Lichtenberg (2015), we instrument input quantities by the average quantities used on neighbouring plots. We assume that neighbouring plots of a specific plot are those located in a municipality within a radius of 10 km from the specific plot's municipality. Similar to Kawasaki and Lichtenberg (2015), in our database, we do not account for all neighbouring plots since we cover only wheat plots under environmental *L* or *H standards*. Average input quantities used by neighbouring plots are expected to be correlated to input quantities used on the specific plot considered, since neighbouring plots face similar pest infestations. We can reasonably assume that our instruments do not directly affect outcome variables because wheat yield, quality and price depend highly on the plot characteristics, such as soil quality and plot management. Our exogenous variables are: *previous crop* (the crop produced the previous year on the same plot); *tillage; high quality varieties; plot size*; farm characteristics and weather conditions. We include *year* dummy variables to take into account annual variability and *small agricultural region* dummy variables as a proxy of soil quality. In our database, we count five small agricultural regions.

Past studies have found that various characteristics of farmers and farms, such as age, education, risk aversion, environmental concern, neighbouring farms' practices and knowledge, affect the adoption of environmental practices or environmental standards (see Knowler and Bradshaw (2007) and Dessart, Barreiro-Hurlé and Van Bavel (2019) for literature reviews). In our estimations, we take into account only a few of these farm and farmer characteristics (namely, a dummy for the presence of livestock on farm and a dummy for *H standard* previous experience) due to lack of information in our database. Because of the unbalanced nature of our dataset, we are not able to add farm fixed-effects to our model that uses the Mundlak device as recommended by Murtazashvili and Wooldridge (2016). Indeed, farmers and plots are not observed each year, and averaging variables across different years may not effectively capture the individual characteristics of farms due to varying weather conditions and fluctuating pest pressures. However, unlike other studies, farmers here choose to adopt the *H standard* instead of the *L standard* at the plot level and not at the farm level. A majority of the plots (72 per cent) are operated by farmers who choose to adopt both standards on their farm but on different plots. Thus, farmers' characteristics should not have a strong effect on the adoption of the standard on a specific plot, as compared to the effect of plot technical and agronomic characteristics.

A wide range of literature demonstrates the effect of weather on crop yields (Di Falco, Veronesi and Yesuf, 2011; Chavas *et al.*, 2019; Ramsey, 2020; Miller, Tack and Bergtold, 2021; Wing, De Cian and Mistry, 2021). Some studies also show that weather affects crop quality (Lyman *et al.*, 2013; Kawasaki and Uchida, 2016). Therefore, it is important to control for weather conditions when estimating wheat yield and quality. However, this is challenging as some weather effects are cumulative whereas others differ depending on timing and duration (Chavas *et al.*, 2019) and weather influences on yield depending on the crop stage of development (Ben-Ari *et al.*, 2018). In the economic literature, there are no standardised indicators to take into account weather effects. The most commonly used indicators are cumulative precipitation and temperature (mean, degree-days or thresholds). Some studies have used indicators across the year (Chavas *et al.*, 2019), across the growing season (Deschênes and Greenstone, 2007; Ramsey, 2020; Miller, Tack and Bergtold, 2021; Wing, De Cian and Mistry, 2021), at a seasonal level (Van Passel, Massetti and Mendelsohn, 2017; Bozzola *et al.*, 2018) and at a crop-stage level (Kawasaki and Uchida, 2016). We use the most common indicators in the literature, namely average temperature and cumulative precipitation across the growing season.

Separating equation (4) into the two technologies allows us to compute the expected outcome variables for plots with the *H standard* $E(y_p^1|A=1)$, and to determine the expected outcome variables in the counterfactual hypothetical case where the plots with the *H standard* adopt the *L standard*, $E(y_p^0|A=1)$. The conditional expectations are specified as follows:

$$E\left(y_p^1|A=1\right) = x_p^{exo}\beta_1^{exo} + x_p^{endo}\beta_1^{endo} + \rho_1\widehat{gr}_p \tag{5a}$$

$$E(y_p^0|A=1) = x_p^{exo}\beta_0^{exo} + x_p^{endo}\beta_0^{endo} + \rho_0\widehat{gr}_p \tag{5b}$$

In line with Heckman, Tobias and Vytlacil (2001), we compute the effect of the treatment, which is adopting the *H standard*, on the treated plots (TT) (plots under the *H standard*). In other words, 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 by combining equations (5a) and (5b) as follows:

$$\begin{aligned} TT &= E\left(y_p^1|A=1\right) - E(y_p^0|A=1) \\ &= x_p^{exo}\left(\beta_1^{exo} - \beta_0^{exo}\right) + x_p^{endo}\left(\beta_1^{endo} - \beta_0^{endo}\right) + \left(\rho_1 - \rho_0\right)\widehat{gr}_p \end{aligned} \tag{6}$$

4. Results

Estimation of the ESR model was implemented in Stata following the procedure described by Murtazashvili and Wooldridge (2016). The first step, namely the probit model, was run with the command *probit* with standard errors clustered at the farm level. The calculation of generalised residuals is performed with the command *predict var, score*. The second step was estimated by 2SLS with the command *ivregress*, with bootstrapped standard errors.

4.1. Explaining the adoption of the *H standard* on a plot

The results of the first stage of the ESR model are presented in Table 3. The probability of adopting the *H standard* on a plot depends on agricultural practices. More precisely, the probability of adopting the *H standard* is higher if the plot is tilled compared to not tilled, and lower if corn is the previous crop grown compared to other previous crops. Since most toxic (and thus most effective) herbicides are prohibited in the *H standard*, farmers tend to rely more on tillage to control weeds on the plots operated under the *H standard*. The plots where corn was the previously grown crop are more sensitive 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. *Plot size* has a positive effect on probability of adopting the *H standard*. This is in line with expectations that farmers may see higher benefits in adopting the *H standard* on larger plots as they expect higher returns on their investment. However, ecologists have shown that reducing plot size can favour biodiversity (Sirami *et al.*, 2019; Martin *et al.*, 2020). This result highlights a limit of the *H standard* as there are higher benefits for farmers to adopt this standard on larger plots. Moreover, farmers' past experience with the *H standard* increases the probability of adopting the *H standard* on a plot. This suggests that the adoption of new practices may imply entry costs for farmers; farmers who already know the agricultural practices used to obtain the *H standard* are more willing to further adopt it on their plots. Finally, we show that the exclusion variable explains the probability of a plot adopting the *H standard*. More precisely, being close to a highway has a negative effect, which conforms to intuition, as plots close to a highway are not eligible for the *H standard*.

To check the relevance of using *highway* as an exclusion variable, we implement falsification tests on each outcome variable, following the ESR literature (Di Falco, Veronesi and Yesuf, 2011; Di Falco and Veronesi, 2013; Antonioli, Severini and Vigani, 2021; Auci *et al.*, 2021). As previously discussed, the instrument variable *highway* is a significant driver of the probability of adopting the *H standard*. In addition, we perform a Wald test, presented in Table 3, confirming this result ($L^2(1)$= 183.87***). Falsification tests are presented in Appendix, Table A1. Wald tests implemented on the instrumental variable reveal that the latter does not affect technical outcomes (yield: $\chi^2(1)=2.55$; test weight: $\chi^2(1)=2.28$; protein content: $\chi^2(1)=1.95$). This result supports our choice of selection instruments. However, the Wald test performed on instrumental variables for the outcome variable price is significant ($\chi^2(1)=31.28$***), since being close to a highway is statistically significant in the estimation of wheat price for plots that did not adopt the *H standard*.

We assume that farmers are risk-neutral toward the adoption of the *H standard* on their plots compared to the *L standard*. There exists a large body

Table 3. First-stage coefficient estimation - selection equation

	H standard adoption	
Dependent variable	Coef.	Robust Std. Err.
Corn as previous crop dummy	−1.550***	0.101
Tillage dummy	1.431***	0.117
High quality varieties dummy	0.121	0.091
Plot size	0.053***	
H standard experience dummy	0.599***	0.146
Livestock dummy	0.143	0.141
Temperature	0.174	0.618
Precipitation	−0.003	0.035
Temperature * Precipitation	0.001	0.002
Mineral N quantity—neighbouring plots	−0.007*	0.004
Herbicide TFI - neighbouring plots	−0.021	0.267
Insecticide TFI - neighbouring plots	0.718**	0.295
Fungicide TFI - neighbouring plots	0.195	0.271
Highway dummy	−3.371***	0.249
Constant	−3.860	9.160
Pseudo R^2	0.412	
Wald test $\chi^2(24)$	604.56***	
Wald test on exclusion restriction $\chi^2(1)$	183.87***	
Number of observations	8,015	

*, **, *** *indicate significance at the 10 per cent, 5 per cent and 1 per cent levels, respectively.*
Note*: We include the year's dummy variables and small agricultural region dummy variables but do not show the results. Standard errors are clustered at the farm level.*

of literature exploring the role of risk aversion in individuals' decisions and risk management (Arrow, 1964; Akerlof, 1970; Pratt, 1978; Antle, 1983). Dessart, Barreiro-Hurlé and Van Bavel (2019) identified risk tolerance as a behavioural factor positively affecting the adoption of sustainable farming practices. Gardebroek (2006) and Serra, Zilberman and Gil (2008a) showed that organic farmers are less risk averse than conventional ones. Our risk-neutral assumption is justified for several reasons. Firstly, the adoption of the *H standard* affects pesticide use as it prohibits the most toxic pesticides, but there is no limitation on total quantity use. Thus, farmers have other alternatives for controlling pests on their plots. Secondly, there is no consensus in the literature as to whether pesticides are considered to be risk decreasing. Some studies found that pesticides are an input-reducing production risk (Di Falco and Chavas, 2006; Koundouri *et al.*, 2009; Antle, 2010; Gong *et al.*, 2016) whereas others found them to be risk-increasing for output (Gotsch and Regev, 1996; Serra, 2006; Serra, Zilberman and Gil, 2008b; Antle, 2010). Furthermore, studies that tended to quantify the impact of risk aversion on pesticide quantity mainly showed that the effect is small (Carpentier, 1995; Pannell, Malcolm and Kingwell, 2000; Bontemps, Bougherara and Nauges, 2021). Using an expected utility model, Bontemps, Bougherara and Nauges

(2021) estimated that risk aversion is accountable for less than 4 per cent of the optimal pesticide expenditures.

4.2. Effect of the *H standard* adoption on technical outcomes - yield and quality

We present the results of the second stage of the ESR model for technical outcome variables (yield and quality attributes, namely test weight and protein content) in Table 4. Columns (1), (2) and (3) show the results of the outcome equations for yield, test weight and protein content, respectively. As explained in the empirical strategy section, we present the estimates of the outcome variables as a linear combination of the two technologies. It should be stressed that, in this specification, the coefficients for the adopters of the *H standard* ($\square_1$) are the sum of the estimated coefficients for the adopters of the *L standard* ($\square_0$) and the estimated coefficients of the variables with *H standard* interaction terms ($\square_1 = \square_T + \square_0$). In other words, in Table 4, the effect of a specific variable, e.g. *mineral N quantity*, for plots under L standard is provided by the estimated coefficient of the variable *mineral N quantity* alone; while the effect of *mineral N quantity* for plots under *H standard* is provided by the estimated coefficient of the variable *mineral N quantity* plus the estimated coefficient of the interacting term *mineral N quantity* * *H standard*.

We show that a selection bias exists in the adoption of the *H standard* on a plot regarding test weight, but no selection bias is found for yield and protein content. For the yield and protein content estimation, both estimated coefficients of the generalised residuals 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 error term of the outcome equation for plots with the *L standard* (ρ_0) and plots with the *H standard* (ρ_1). For test weight, ρ1 is negative whereas ρ0 is positive at 10 per cent of significance (ρ1 = -0.487* and ρ0 = 0.260*). It indicates a positive selection bias for plots with the *H standard* and a negative selection bias for plots with the *L standard*. It suggests that plots that get higher than average test weight are more likely to adopt the *H standard* whereas plots with lower average test weight are more likely to adopt the *L standard*. Furthermore, the Anderson-Rubin test on our instrumental variables validates our choice to instrument input quantities by average input quantities used by neighbouring plots.

Table 4 shows that the constant of the model is not significant in all models. This may arise from the fact that farmer-specific effects cannot be included due to the non-panel data structure of our data. Results show that the coefficient of the *H standard* adoption variable (*H standard dummy*) is statistically significant for quality attributes and yield, meaning that the intercepts of the two technologies (technology under *H standard* and technology under *L standard*) differ. Results also show that agricultural practices have an influence on yield and quality attributes, but their effect differs between the two technologies; that is to say, depending on whether the plot is under *H standard* or *L standard*. For example, tillage has an opposite effect on yield between the *H standard*

Table 4. Second-stage coefficient estimation - outcome equations

Dependent variable	(1) Yield	(2) Test weight	(3) Protein content	(4) Wheat price
Mineral N quantity	0.013**	0.036***	−0.003	0.038**
	(0.005)	(0.009)	(0.003)	(0.018)
Herbicide TFI	0.306	1.534***	0.064	0.932
	(0.327)	(0.457)	(0.122)	(0.995)
Insecticide TFI	0.558	0.488	−0.059	4.061**
	(0.384)	(0.881)	(0.243)	(1.829)
Fungicide TFI	0.844***	−0.419	−0.068	0.472
	(0.284)	(0.425)	(0.170)	(1.075)
Corn as previous crop dummy	−0.083	0.109	−0.090	−3.061***
	(0.145)	(0.255)	(0.070)	(0.441)
Tillage dummy	0.252**	−0.097	0.117**	3.763***
	(0.088)	(0.156)	(0.047)	(0.358)
High quality varieties dummy	0.209	0.867***	0.043	2.061***
	(0.185)	(0.213)	(0.084)	(0.538)
Plot size	−0.009	0.006	0.004	−0.033
	(0.010)	(0.023)	(0.005)	(0.045)
H standard experience dummy	−0.240**	−0.196	0.003	0.143
	(0.106)	(0.135)	(0.053)	(0.417)
Livestock dummy	0.182	0.578**	0.102	3.342***
	(0.184)	(0.264)	(0.100)	(0.632)
Temperature	−0.087	2.724	−0.552	1.694
	(1.106)	(1.895)	(0.505)	(4.771)
Precipitation	0.042	0.113	−0.062*	−0.116
	(0.067)	(0.120)	(0.033)	(0.331)
Temperature * Precipitation	−0.003	−0.008	0.004*	0.009
	(0.005)	(0.008)	(0.002)	(0.023)
H standard dummy	31.600*	87.640***	−18.258**	124.00**
	(20.264)	(25.825)	(7.568)	(69.735)
Mineral N quantity * H standard	−0.006	−0.025***	0.008**	−0.039**
	(0.006)	(0.009)	(0.003)	(0.023)
Herbicide TFI * H standard	0.557	−1.689***	0.087	2.416
	(0.384)	(0.564)	(0.168)	(1.156)
Insecticide TFI * H standard	−1.153*	−0.404	−0.110	−4.969**
	(0.668)	(0.869)	(0.260)	(1.983)
Fungicide TFI * H standard	−1.252***	0.304	−0.068	−1.356
	(0.345)	(0.511)	(0.170)	(1.311)
Corn as previous crop * H standard	0.643**	0.281	0.017	3.146***
	(0.201)	(0.298)	(0.091)	(0.540)
Tillage * H standard	−0.557***	−0.172	−0.029	−3.782***
	(0.160)	(0.193)	(0.077)	(0.467)
High quality varieties * H standard	−0.581***	−0.553**	−0.105	−0.929
	(0.206)	(0.241)	(0.094)	(0.573)

(continued)

Table 4. (Continued)

Dependent variable	(1) Yield	(2) Test weight	(3) Protein content	(4) Wheat price
Plot size * H standard	0.009	0.013	−0.012**	−0.006
	(0.012)	(0.025)	(0.006)	(0.044)
H standard experience * H standard	0.266	0.463**	−0.035	0.613
	(0.180)	(0.195)	(0.076)	(0.573)
Livestock * H standard	−0.196	−0.831***	−0.048	−3.473***
	(0.205)	(0.290)	(0.102)	(0.634)
Temperature * H standard	−1.947	−5.525***	1.092**	−7.790*
	(1.384)	(1.783)	(0.530)	(4.733)
Precipitation * H standard	−0.107	−0.300**	0.102***	−0.294
	(0.076)	(0.119)	(0.034)	(0.328)
Temperature * Precipitation * H standard	0.007	0.021**	−0.007***	0.019
	(0.005)	(0.008)	(0.002)	(0.022)
Generalised residuals	0.068	0.260*	0.033	1.741***
	(0.073)	(0.140)	(0.038)	(0.318)
Generalised residuals * H standard	−0.414	−0.487*	−0.071	−1.735***
	(0.262)	(0.256)	(0.105)	(0.569)
Constant	3.786	29.578	21.591***	151.470***
	(16.105)	(27.467)	(7.269)	(69.957)
R^2	0.11	0.34	0.27	0.79
Wald test $\square^2$ *(49)*	2.4e + 07***	1.8e + 06***	7.6e + 05***	1.9e + 06***
Wald test on generalised residuals $\square^2$ *(2)*	3.28	7.27**	1.04	44.34***
Anderson-Rubin test	45.50***	86.27***	19.88***	47.79***
Wald test on instruments	32.22***	58.52***	15.79**	52.71***
Number of observations	8,015	8,015	8,015	8,015

, **, * indicate significance at the 10 per cent, 5 per cent and 1 per cent levels, respectively.*
Note: We include the year's dummy variables and small agricultural region dummy variables but do not show the results. Bootstrap standard errors are presented in parentheses.

and the *L standard*: in column (1), the coefficient for *tillage* is 0.252 implying that the effect for *L standard* plots is positive; while the sum of this coefficient and of the coefficient for the interacting variable *tillage * H standard* is negative (=0.252–0.557) implying that the effect of tillage for the H standard plot is negative. A similar reading of the coefficients in Table 4 show that, contrary to yield and test weight, input management barely affects protein content. The result indicating mineral N quantity only slightly affects protein content for plots with the *H standard* (and does not affect protein content for plots with the *L standard)*, may seem counterintuitive. However, protein content mainly depends on the last application of mineral N and not on the total quantity applied and it is mainly affected by weather conditions. The results show no evidence of an effect of weather conditions on yield. This result differs from previous studies showing that weather conditions do affect yield (Di Falco, Veronesi and Yesuf, 2011; Chavas *et al.*, 2019; Ramsey, 2020; Miller, Tack and Bergtold, 2021; Wing, De Cian and Mistry, 2021). However, in our analysis, we only consider a 7-year period and we control in part for localisation with the dummies for small agricultural regions. This implies that there is only a slight variation in weather conditions among the considered plots, which may explain why we do not detect a weather effect on yield.

Table 5 presents the average outcomes for yield, test weight and protein content, under actual 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 wheat yield and quality attributes. Adopting the *H standard* on a plot in comparison to the *L standard* reduces yield by 150 kg/ha, representing a 2.5 per cent decrease in yield. In addition, it decreases test weight by 0.54 kg/hl and protein content by 0.02 points. Our results thus indicate that banning the most toxic pesticides at the plot level to limit the negative impact of agricultural practices on biodiversity (as required by the *H standard*) has an overall negative effect on technical outcomes. This is in line with the study by Begg *et al.* (2017) who suggest that biodiversity improvements, thanks to the implementation of conservation practices, often fail to improve crop yield. Several reasons may explain why we do not find a positive relationship between yield and the adoption of practices aimed at favouring biodiversity. Firstly, the requirements of the *H standard* may not be stringent enough. Moreover, the implementation of practices on a small area such as a plot may not be sufficient to significantly improve biodiversity. Coordination among farmers may be needed to ensure a spatial coordination in the adoption of environmental practices (Franks, 2011; Westerink *et al.*, 2017). Finally, despite a plot being under the *H standard*, the practices on neighbouring plots may be harmful and limit the effect of *H standard* practices on biodiversity.

4.3. Effect of *H standard* adoption on economic outcome - wheat price

Farmers receive monetary incentives to produce high-quality wheat through a specific price premium. The price formula is based on a bonus-penalty system depending on the different quality attributes. As seen above, the adoption of the *H standard* over the *L standard* negatively affects quality for our sample. It would also indirectly have a negative effect on economic outcome through a penalty on the base price. However, farmers also receive monetary incentives

Table 5. Treatment effects on the treated (TT) - effect of the *H standard* on outcome variables

Sub-samples: Plot with *H standard*	Decision stage: To adopt *H standard*	Decision stage: To adopt *L standard*	Treatment effects
Yield	5.96 (0.02)	6.11 (0.02)	TT = -0.15***
Test weight	79.27 (0.03)	79.81 (0.04)	TT = -0.54***
Protein content	12.13 (0.01)	12.15 (0.01)	TT = -0.02**
Wheat price	172.59 (0.16)	171.40 (0.16)	TT = 1.19**

*, **, *** *indicate significance at the 10per cent, 5per cent and 1per cent levels, respectively.*

for adopting more stringent environmental standards: the higher the requirements, the higher the price premium. Therefore, we now assess whether the price premium of the *H standard* compensates for its negative effect on quality; that is to say, what is the effect of adopting the *H standard* on wheat price (the latter includes both the quality bonus-penalty value and the standard's premium).

We present the results of the second-stage of the ESR model for wheat price in column (4) of Table 4. The estimated coefficient of the generalised residuals term ρ_0 is significant and positive ($\rho_0 = 1.741$***). This indicates a negative selection bias for plots producing under the *L standard*. It suggests that the plots with lower than average wheat price are more likely to adopt the *L standard*. The *H standard* variable is statistically significant, revealing a strong positive effect of adoption of this standard on wheat price. Results also show that wheat price significantly depends on agricultural practices and farm characteristics. In addition, some interaction terms of explanatory variables with the *H standard* variable are significant, suggesting differences in technologies and the presence of heterogeneity in our sample.

Table 4 reports the TT of the *H standard* on wheat price. It shows that the adoption of the *H standard* for plots adopting the *H standard* increases wheat price by EUR 1.19/ton. This is a low increase, as wheat price fluctuation is much higher than this across years. We conclude that the *H standard* price premium merely compensates for the negative effect of the *H standard* adoption on quality. The monetary benefits for farmers when they adopt the environmental standard with the higher requirements, the *H standard* (limiting toxic pesticides for biodiversity), are low.

Our analysis highlights that the adoption of the *H standard* over the *L standard* negatively affects yield and quality outcomes, and that farmers receive low monetary benefits from implementing the standard with the higher requirements (*H standard*). Other reasons may thus explain why farmers choose to change their practices and adopt the *H standard* although they receive low economic incentives. The literature reports various non-monetary motivations toward the adoption of environmental practices and standards

(Ambec and Lanoie, 2008; Baumgart-Getz, Prokopy and Floress, 2012; Lanoie and Llerena, 2015; Dessart, Barreiro-Hurlé and Van Bavel, 2019; Thompson *et al.*, 2023). Firstly, the adoption of the *H standard* may enable farmers to access to a different market and diversify their selling outlets. Secondly, the adoption of the *H standard* could also be motivated by access to information and knowledge on environmental practices. Indeed, adopting the standard on some plots implies that farmers receive technical visits from the cooperative's advisors at least four times a year. Furthermore, the effect of social factors should not be underestimated. The cooperative studied is deeply involved in the development of environmental labels, and thus, the adoption of the *H standard* may facilitate connections with the cooperative members and local networks. Finally, environmental concern and awareness of farmers can also be drivers of the adoption of the *H standard*.

5. Conclusion

We contribute to the existing literature by investigating the effects of the adoption of a more stringent environmental standard on technical and economic outcomes for wheat production at the plot level in France from 2014 to 2020. We compare two standards which aim to preserve biodiversity but with different levels of stringency. Measuring the level of uptake of environmental practices is not straightforward, and it may be difficult to distinguish clearly between low and high uptake (Barnes *et al.*, 2021). For this reason, using labels with clear sets of requirements is a robust approach. The less stringent standard (*L standard*) requires the presence of biodiversity habitats. The more stringent one (*H standard*) bans the most toxic pesticides and encourages the preservation of biodiverse habitats in order to reduce the negative effects of agricultural practices on biodiversity. The sets of rules for these two standards are an intermediate level between the organic standard and conventional practices. We analyse the effect of adopting the more stringent environmental standard at the plot level on wheat price, yield and quality, the latter consisting of two attributes: test weight and protein content. We choose to focus on these attributes since farmers receive monetary incentives to improve them through a marketing contract. Thus, a decrease in these two quality attributes would negatively affect the farm's economic outcome. Wheat price is the economic outcome by which we estimate the effect of the adoption of the more stringent environmental standard.

Our results show that banning the most toxic pesticides at the plot level (through adoption of the more stringent standard) has a negative effect on technical outcomes: it decreases yield by 2.5 per cent, test weight by 0.54 kg/hl and protein content by 0.02 points, on average. Our results also highlight the importance of considering quality effect along with yield effect when estimating the effect of the adoption of environmental practices. The adoption of a higher environmental standard induces an average increase in wheat price of EUR 1.19/ton, which is lower than wheat price fluctuation across years. The price premium of the higher environmental standard merely compensates for the negative effect of the standard's adoption on quality. Thus, monetary benefits for farmers adopting the higher environmental standard, limiting toxic pesticides for biodiversity, are low.

From a public policy point of view, intermediate environmental standards such as those investigated here may be interesting instruments to favour biodiversity, since their adoption rate is higher than that for the organic standard. The *H standard* appears to be an instrument that could be worth implementing in pursuit of the Farm to Fork goal of reducing by 2030 the risk of chemical pesticides by 50 per cent, as most toxic pesticides are prohibited under its conditions. However, results show that the economic incentives that compensate for the negative effect on technical outcomes are low. Although the literature highlights non-monetary motivations behind the adoption of environmental practices and standards (access to different markets, access to information, knowledge on sustainable practices, connection with a local network, environmental awareness, risk tolerance and social factors (Ambec and Lanoie, 2008; Baumgart-Getz, Prokopy and Floress, 2012; Lanoie and Llerena, 2015; Dessart, Barreiro-Hurlé and Van Bavel, 2019)), it is not clear whether such non-monetary motivations are sufficient for the adoption of this standard on a larger scale. It should be highlighted that our study focuses on plots cultivated by farmers who are members of a cooperative aiming at the development of environmental standards. This is therefore a specific sample of farmers, whose behaviour may not be generalisable to others. It is possible that the behaviour of our sample's farmers is influenced by shared non-monetary motivations as well as shared monetary motivations that extend beyond monetary benefits. These motivations may include having access to diverse markets and expanding the range of selling outlets. To up scale the adoption of the H standard, economic incentives should be carefully designed. Accompanying public policies could be designed to achieve higher participation and spatial coordination in order to obtain a better environmental impact. Moreover, to ensure the development of a standard on a larger scale, it is not enough simply to focus on the supply side; it is also necessary to increase demand on a larger scale.

We could suggest a number of possible further research avenues. Firstly, it would be useful to assess the margin effect at the plot level of the adoption of the more stringent environmental standard. When adopting this standard, production costs might be reduced, since farmers use pesticides which are less toxic, and taxes on pesticides are toxicity-dependent in France. Unfortunately, our database does not contain information on production costs. We were only able to collect price information to take into account potential revenue. Furthermore, farm-level information would give us more information with which to assess the effects of the adoption of environmental standards on farms' performance. Bravo-Ureta *et al.* (2020) showed that, while plot-level management does not have a significant effect on farm efficiency, farm-level management does. Analysing farm performance would enable the farm's multi-output strategy to be studied. Trade-offs could be measured, relating to economic and environmental performances at the farm level, when farmers adopt environmental standards with different levels of stringency on different plots. In addition,[6] to confirm the environmental benefits of the H standard adoption, it would be worthwhile to explore indicators on pesticides that take into account the associated risk, such as the Harmonised Risk Indicator 1 and the Load Index (European Commission, 2019; Möhring *et al.*, 2020). Finally,[7] further investigation of weather aspects could be undertaken when estimating wheat yield. Climate change may have adverse effects on crop yields and agricultural production risk (Ray *et al.*, 2012; Nelson *et al.*, 2014; Gammans, Mérel and Ortiz-Bobea, 2017; Arora *et al.*, 2020; Anderson *et al.*, 2023). It means that a risk analysis of agricultural production must be conducted ex-ante, treating weather shocks as uncertain (Chavas *et al.*, 2019, 2022). However, integrating weather variables observed in the same year of wheat production and environmental standard, as we did in this article, could be problematic as it implies that weather is known. Thus, weather aspects in previous years should be included, so that weather shocks can be serially correlated.

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Appendix

Table A1. Falsification test - test on the validity of the instrument

Dependent variable	Yield	Test weight	Protein content	Price
Mineral N quantity	0.013**	0.037***	−0.003	0.046**
	(0.006)	(0.008)	(0.003)	(0.019)
Herbicide TFI	0.348	1.560***	0.074	1.203
	(0.249)	(0.383)	(0.134)	(1.106)
Insecticide TFI	0.547	0.363	−0.097	2.912
	(0.496)	(0.774)	(0.241)	(1.947)
Fungicide TFI	0.841***	−0.454	−0.071	0.264
	(0.286)	(0.402)	(0.143)	(1.022)
Corn as previous crop dummy	−0.030	0.290*	−0.065	−1.821***
	(0.127)	(0.170)	(0.054)	(0.489)
Tillage dummy	0.174*	−0.285**	0.084*	2.366***
	(0.102)	(0.144)	(0.049)	(0.391)
High quality varieties dummy	0.174	0.835***	0.030	1.719**
	(0.206)	(0.294)	(0.084)	(0.692)
Plot size	−0.012	0.002	0.003	−0.068
	(0.011)	(0.016)	(0.006)	(0.042)
H standard experience dummy	−0.265***	−0.261	−0.008	−0.334
	(0.100)	(0.166)	(0.054)	(0.365)
Livestock dummy	0.195	0.592**	0.106	3.474***
	(0.236)	(0.272)	(0.088)	(0.702)

(continued)

Table A1. (Continued)

Dependent variable	Yield	Test weight	Protein content	Price
Temperature	−0.140	2.590	−0.575	0.710
	(1.209)	(1.668)	(0.406)	(4.176)
Precipitation	0.039	0.104	−0.063**	−0.177
	(0.074)	(0.107)	(0.028)	(0.265)
Temperature * Precipitation	−0.003	−0.008	0.004**	0.012
	(0.005)	(0.008)	(0.002)	(0.018)
Highway dummy	0.168	0.228	0.066	2.050***
	(0.105)	(0.151)	(0.047)	(0.382)
Constant	4.632	31.583	21.952***	166.443***
	(17.391)	(24.461)	(6.051)	(60.299)
R^2	0.15	0.11	0.29	0.75
Wald test $\chi^2(25)$	973.87***	2668.20***	2421.97***	14,883.18***
Wald test on instrumental variables $\chi^2(1)$	2.55	2.28	1.95	31.28***
Number of observations	2,789	2,789	2,789	2,789

*, **, *** *indicate significance at the 10 per cent, 5 per cent and 1 per cent levels, respectively.*
Note: We include year's dummy variables and small agricultural region dummy variables but do not show the results. Bootstrap standard errors are presented in parentheses.