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► To cite this version:

Benoît Chèze, Maia David, Vincent Martinet. Understanding farmers' reluctance to reduce pesticide use: A choice experiment. *Ecological Economics*, 2020, 167, pp.106349. 10.1016/j.ecolecon.2019.06.004 . hal-02317175

HAL Id: hal-02317175

<https://hal.science/hal-02317175v1>

Submitted on 16 Dec 2019

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Understanding farmers' reluctance to reduce pesticide use: A choice experiment

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June 19, 2019

Abstract

Despite reducing the use of pesticides being a major challenge in developed countries, dedicated agri-environmental policies have not yet proven successful in doing so. We analyze conventional farmers' willingness to reduce their use of synthetic pesticides. To do so, we conduct a discrete choice experiment that includes the risk of large production losses due to pests. Our results indicate that this risk strongly limits farmers' willingness to change their practices, regardless of the consequences on average profit. Furthermore, the administrative burden has a significant effect on farmers' decisions. Reducing the negative health and environmental impacts of pesticides is a significant motivator only when respondents believe that pesticides affect the environment. Farmers who earn revenue from outside their farms and/or believe that yields can be maintained while reducing the use of pesticides are significantly more willing to adopt low-pesticide practices. Policy recommendations are derived from our results.

Keywords: Pesticides; Agricultural practices; Production risk; Discrete choice experiment

JEL Classification: Q12, Q18, Q51, Q57, C35

1 Introduction

1 Reducing the use of synthetic pesticides in agriculture has become a major chal-
2 lenge in developed countries. As shown by the recent extremely rapid growth in
3 organic farming (+20% of sales in France in 2016; AgenceBio, 2017), consumers
4 are becoming increasingly aware of this issue (refer to Bernard and Bernard, 2010,
5 on the link between organic sales and public concern about pesticides).

6 Public policies over the last 10 years have attempted to provide adequate in-
7 centives to change behavior and boost research related to this topic. European
8 Union member states are required to implement National Action Plans that set
9 quantitative objectives, timetables, and indicators related to reducing the impact
10 of pesticide use (Directive 2009/128/CE). Several member states have also de-
11 veloped voluntary schemes that offer financial support to farmers to reduce their
12 use of pesticides and/or convert to organic farming (e.g., Denmark, France, Ger-
13 many, Spain, the Netherlands, the United Kingdom). The United States, Canada,
14 Australia, the European Union, Iceland, and Norway have developed programs
15 to monitor pesticide residues in food, as well as awareness campaigns. However,
16 thus far, the results of these policies have been disappointing. The use of chemical
17 inputs by farmers has increased, for example, in Europe during the last decade
18 (+12% in France between the three-year mean for the period 2009–2011 and that
19 for the period 2012–2014; Ecophyto, 2015), along with a lack of participation in
20 agri-environmental schemes on pesticides (Thoyer et al., 2015).

21 Several agricultural practices have now proven efficient in maintaining satis-
22 factory yields, while reducing the use of chemicals (Lechenet et al., 2017). Re-
23 ducing pesticides may reduce farmers’ costs, improve their health and environ-
24 ment, and prevent pest resistance (Wilson and Tisdell, 2001; Bourguet and Guille-
25 maud, 2016). What are the main obstacles preventing farmers from adopting
26 low-pesticide practices, which could be win-win strategies in some cases? Re-
27 searchers in ecology and agronomy, as well as public decision-makers (Solomon,
28 2015; Rousset et al., 2012), are looking to economists for a better understanding
29 of the socioeconomic factors that explain farmers’ behavior.

30 Our study contributes to the literature by measuring the relative weights of
31 various factors that influence the choice of conventional farmers to reduce – or
32 not – their use of synthetic pesticides. Several socioeconomic analyses have ex-
33 amined the motivations and obstacles to the adoption of environmentally friendly
34 practices by farmers. The methodologies employed by such studies include focus
35 groups, qualitative surveys, role-playing games, and agent-based models.¹ In con-
36 trast to these useful and complementary methodologies, we adopt a quantitative

¹Dumont et al. (2016); Malawska and Topping (2016); Greiner et al. (2009); Wilson and Tisdell (2001); Knowler and Bradshaw (2007).

37 approach to estimate the weight of each decision factor, as well as farmers' willing-
38 ness to pay (WTP) for/willingness to accept (WTA) changes in these factors. Our
39 methodology is based on a nonmarket valuation, using a discrete choice experiment
40 (DCE).

41 The DCE method has gained popularity among environmental economists dur-
42 ing the last 10 years. This stated preference method elicits preferences through
43 repeated fictional choices among different options, each defined by their attributes,
44 *i.e.*, fundamental characteristics of the respondent's situation in that option (Hoyos,
45 2010; Louviere et al., 2000). While other nonmarket valuation methods (e.g., con-
46 tingent valuation) can account for several characteristics in the description of the
47 scenarios to be valued, DCEs are specifically designed to assess the WTP/WTA
48 for each attribute that describes the choice options. As a result, the DCE approach
49 is useful for valuations of agri-environmental policies, for two main reasons. First,
50 it defines the relative importance of each consequence of reducing pesticide use on
51 farmers' decisions. As such, the DCE approach can help in setting priorities for
52 public action by identifying the most important factors for farmers, as well as the
53 trade-offs at stake. This is key to identifying why a public program is unsuccessful
54 or successful. Second, it enables a monetary valuation of the main consequences of
55 pesticide reduction, which helps to set policies at the right level (e.g., set adequate
56 subsidies).

57 The DCE approach has been used previously to examine farmers' choices
58 in adopting environmentally friendly practices. Depending on the studies, the
59 adoption of the alternative practice can occur within² or independently of ³ agri-
60 environmental contracts with public authorities. To the best of our knowledge,
61 only a few DCEs have studied the specific issue of pesticide reduction. Blazy et al.
62 (2011) examine the willingness to adopt agro-ecological innovations, in particular,
63 to reduce pesticide use, while maintaining a sufficient yield. Christensen et al.
64 (2011) analyze the motivations of Danish farmers in signing subsidy schemes for
65 pesticide-free buffer zones. They show that contract flexibility is a major decision
66 criterion. Kuhfuss et al. (2014) examine the decision of French wine growers to
67 sign an Agri-Environmental Scheme, in which the payment is partly individual and
68 partly based on a collective result (*i.e.*, there is a bonus payment if the number of
69 participants is above a given threshold). They show that farmers place significant
70 value on the collective component of the contract. Jaeck and Lifran (2014) study
71 the choice of rice-growers in Camargue (France) to reduce their use of chemical
72 inputs, showing that targeted contracts are necessary, owing to the heterogeneity
73 of farmers. Interestingly, they introduce production risk as an attribute of their

²Kuhfuss et al. (2014, 2016); Christensen et al. (2011); Broch and Vedel (2012); Espinosa-Goded et al. (2010); Ruto and Garrod (2009); Hudson and Lusk (2004); Peterson et al. (2015).

³Beharry-Borg et al. (2013); Jaeck and Lifran (2014); Birol et al. (2006); Vidogbena et al. (2015).

74 choice experiment.

75 Price and production risks can drastically affect a farmer’s revenue, including
76 its variability. Risk (or uncertainty⁴) is an important driver of farmers’ choices
77 (Menapace et al., 2013). Baerenklau (2005) show that risk preferences play an
78 important role in the adoption of pollution-reducing practices. Moreover as ex-
79 plained by Lechenet et al. (2017), “the transition towards low-pesticide farming
80 strategies might be hampered by the uncertainty behind any deep change (...).
81 Risk aversion may be a hindering factor.”

82 Roberts et al. (2008) show that uncertainty affects stated preferences, and that
83 surveys should explicitly incorporate uncertainty in the experimental design to
84 manipulate it across choice questions. Risk and uncertainty have been included in
85 many choice experiments (see Rolfe and Windle, 2015), but few that have examined
86 agricultural decisions.⁵ Hudson and Lusk (2004) examine the role of price risk in
87 contracting decisions. However, for pesticides, there is more at stake in terms of
88 production risk, because a change in the use of pesticides can have a major impact
89 on the stability of yields. We thus focus on production risk which is the most
90 relevant dimension of risk to vary when adopting low-pesticides practices. This
91 is consistent with the fact that pesticides are used to limit the risk of production
92 losses. Moreover, pesticide use may have an ambiguous effect on profit risk when
93 sources of risk other than pest damage are considered (refer to the discussion
94 initiated by Horowitz and Lichtenberg, 1994). Thus, we ignore market risks.

95 It has been recognized that maximizing profit is not the only driver of farmers’
96 behavior (refer to Malawska et al., 2014, and their literature review). Skevas and
97 Lansink (2014) show farms overuse pesticides compared with the profit-maximizing
98 levels. Pedersen et al. (2012) show that an important proportion of farms in their
99 sample apply pesticides to maximize yield, rather than profit. Therefore, our
100 analysis includes, among other attributes, the risk of large production losses due to
101 pests. We show that practices that increase this risk, notwithstanding their effect
102 on profit, negatively influence farmers’ decisions to reduce their use of pesticides.

103 We first describe our methodology in Section 2, including the experimental
104 design and data collection. In Section 3, we describe the selected econometric
105 model (a random parameter logit), which outperforms the conditional logit and
106 latent class models (see Appendix A.3). The results are discussed in Section 4.

⁴The literature distinguishes between risk (events with known probabilities) and uncertainty (events with unknown probabilities). In our literature review, we retain the term employed by individual studies, even when the authors acknowledge that they have used it loosely. In the remainder of this paper, we use the term risk, because we rely on the frequency of bad events to describe the variability of outcomes.

⁵Other methodological approaches have been used to investigate how risk affects farmers’ choices, particularly those related to applying risk-reducing inputs (see, e.g., Roosen and Hennessy, 2003; Just and Pope, 2003; Liu and Huang, 2013, and the references therein).

107 Subsections 4.1 and 4.2 present the results for the RPL model. We present the
108 WTP/WTA estimates in Subsection 4.3. Lastly, Section 5 contains the conclu-
109 sions, discussion, and policy implications of our results.

110 2 The choice experiment

111 The discrete choice experiment (DCE) approach relies on the economic theory of
112 consumer choice and nonmarket valuation. In a DCE survey, respondents must
113 choose from several options, defined by their attributes (*i.e.*, fundamental charac-
114 teristics of a respondent's situation). Often, three options are presented: nothing
115 changes (*i.e.*, the status quo), and two alternative options. The use of an opt-
116 out option (status quo) is known to improve realism in choices (Adamowicz and
117 Boxall, 2001; Kontoleon and Yabe, 2003). Respondents then choose their favorite
118 option. Each option has different levels of the attributes. One of these attributes
119 usually represents the monetary contribution of the respondents. Other attributes
120 can include environmental or social implications of the issue under consideration.
121 See Louviere et al. (2000) for a detailed description of the method.

122 By varying the level of the different attributes of options, the DCE framework
123 delivers more information on the trade-offs between the drivers of choice than
124 other stated preference methods do. In particular, it makes it possible to esti-
125 mate the marginal rates of substitution between different attributes. When one
126 attribute is expressed in monetary terms, these marginal rates of substitution can
127 be interpreted as the WTA or WTP for changes in the attributes' values.

128 In our case, the respondents are farmers who choose between conserving their
129 current agricultural practices (status quo) and adopting alternative practices that
130 reduce their use of pesticides. The attributes of the alternatives represent the
131 consequences of changes in agricultural practices. These changes are unspecified,
132 and could refer to any modification reducing the use of pesticides. We chose not
133 to be explicit on the description of the exact nature of these changes in order to
134 avoid being inappropriate to certain farmers' specific situations. However, we used
135 precise and diversified examples to make the options concrete for different types
136 of respondents (see Appendix A.1 for examples).

137 2.1 Choice of attributes and their levels

138 The first step in our study was to choose the attributes and their associated levels.
139 The reduction of pesticide use by farmers can have many drivers and consequences,
140 depending on context, e.g., if this reduction is associated with the adoption of
141 agroecological practices, the conversion to organic farming, or the participation in
142 an agri-environmental scheme. Such a change can result in monetary gains due

143 to a reduction of input costs, an increased sales price, or subsidies. It can pro-
144 duce non-monetary outcomes, such as the improvement of farmers' public image,
145 participation in a network, the improvement of farmers' quality of life and health,
146 and improved quality of the environment. It can also have negative outcomes, such
147 as reduced yields, increased risk, the necessity to train to learn new agricultural
148 techniques.

149 As Hanley et al. (2002) explains, the number of attributes considered in a DCE
150 must be limited in order to avoid the cognitive burden of making choices that are
151 too complicated. The selection of the attributes was based on (i) the literature,
152 (ii) discussions with experts in agronomy, epidemiology, ecology, and agricultural
153 economics, (iii) focus groups of farmers,⁶, and (iv) pretests on the choice sets.⁷
154 The focus groups and pretests revealed that pesticides are a sensitive topic among
155 the French farming community; thus, we were careful with the employed terms
156 and their potential interpretations. We were also careful to choose attributes that
157 are adapted to different types of farming systems, while remaining concrete for
158 farmers.

159 As shown in Table 1, the chosen attributes are as follows:

- 160 1. The farmer's yearly **profit** (or gross margin) per hectare, expressed in com-
161 parison with the status quo. This average profit per hectare per year, in
162 euro, is the monetary (or cost) attribute. The profit varies with changes
163 in agricultural practice, owing to unspecified factors such as the impact on
164 yields, pesticide expenses, public aid (e.g., subsidies), sales price, and so on.
165 Therefore, the farmer's profit can increase or decrease with a reduction of
166 pesticides. Following our discussions with experts and the focus groups, this
167 attribute was given the following possible values: -50 €, +0€, +50€, +100€.
- 168 2. The **production risk**, formalized as the frequency of years (number of years
169 out of 10) in which production is drastically and exceptionally reduced owing
170 to pests (*i.e.*, more than 30% of production is lost or damaged owing to dis-
171 eases, insects, weeds, and so on). This attribute characterizes the main effect
172 of the reduction of pesticides on the variability of production, independently
173 of the level of production or profit (the mean yearly profit is given by the
174 previous attribute). The production risk attribute is expressed in additional

⁶The focus groups included farmers who were supervising AgroParisTech students for intern-
ships on farms. Eight farmers, including field crop farmers, mixed crop/livestock farmers, and
vegetable farmers, answered open questions on our topic.

⁷The pretests consisted of five face-to-face interviews with farmers on a preliminary version
of the questionnaire. Additional pretests were done on five individuals of the general population
(nonfarmers) to test the readability and consistency of various versions of the questionnaire.
These pretests led to several modifications, in particular, the wording of attributes, as explained
below.

175 years out of 10 (+0, +1 year, or +2 years), compared with the status quo.
176 These levels were set after discussions with experts (farmers, agronomists,
177 and epidemiologists).

178 3. The administrative framework of the change in practice describes whether
179 the change accompanies an **administrative commitment**. A change of
180 agricultural practices inducing a reduction in pesticide use may be included
181 as part of an administrative framework. Such a framework can be perceived
182 positively, because it may imply better-valued products, or integration in a
183 network; however, it may also include an administrative burden and, thus, be
184 perceived negatively. This attribute is qualitative, and is expressed as addi-
185 tional commitment over and above the status quo, as follows: “No additional
186 administrative commitment,” “charter” (inducing no contractual specification
187 and flexible commitment), “agri-environmental contract with public authori-
188 ties” (with specification, and possibly a subsidy), and a “certification process”
189 (with a specification, controls, and a green label, possibly inducing higher
190 sales prices). The potential subsidy or higher sales prices are included in the
191 level of profit given in the first attribute. Only non-monetary aspects of the
192 administrative commitment are included in the administrative commitment
193 attribute.

194 4. The **health and environmental impacts** indicate the reduction in expo-
195 sure to harmful substances as a result of the change in practice. This includes
196 the local and global environmental quality (biodiversity, water quality) and
197 the health of farmers, neighbors, and general population. This attribute
198 takes the following values: -0% (status quo only), -20%, -50% -80%, com-
199 pared with the status quo.

200 Adding an attribute to encompass production risk helps to increase the cred-
201 ibility of valuation scenarios and reduces hypothetical bias (Rolfe and Windle,
202 2015). However, the concept of risk is difficult to express as an attribute in a way
203 that is convenient and understandable to respondents. Whereas a mean value ex-
204 pressed as an average is easy to understand by respondents, other scientific terms
205 used to describe a probability distribution, such as variance or standard deviation
206 (or worse, skewness and kurtosis), are poorly understood by the public. Jaeck
207 and Lifran (2014) expressed their risk attribute as the frequency of below-average
208 yields (zero, one, or three years over five years). This formulation is clear, but
209 it does not allow us to convey the idea of a risk of large production loss due to
210 pests.⁸ We wanted to capture the idea that pesticide reduction may induce a

⁸Having “zero years” of below-average yield implies no risk at all (i.e., the average yield is a sure outcome). Having “one year” of below-average yield conveys no information on the

Attribute	Description	Levels
Profit	Variation in the average yearly profit per hectare	-50 €; + 0 € (SQ); +50€; +100€
Production risk	Variation in the number of years, out of 10 years, with exceptionally large production losses	+0 year (SQ); +1 year; +2 years
Administrative commitment	Administrative framework of the change of practice, if any	None (SQ); Charter; Contract; Certification
Health and environmental impacts	Reduction in exposure to harmful substances	-0% (only SQ); -20%; -50%; -80%

SQ: level in the status quo (also possible in the other options)
only SQ: level only possible in the status quo option

Table 1: Attributes and levels

211 larger variability of production, along with an increase in the occurrence of pest
212 attacks resulting in exceptionally large production losses. Discussion within the
213 focus groups confirmed that this was a realistic outcome in the event of low or
214 no pesticide use. We thus opted for the frequency of years with large damages
215 and production losses, for a given mean profit (given by the first attribute). Our
216 production risk attribute is related to the variability of the losses due to pests, but
217 not to the mean yield or mean profit. Consequently, the profit attribute and the
218 risk attribute are independent. Various tests show that the proposed formulation
219 offers an easy way to express production variability due to an increase of extreme
220 losses.

221 For the “health and environmental impacts” attribute, we first considered hav-
222 ing two separate attributes for health and for the environment. We finally chose to
223 group them, because both are highly correlated (Juraske et al., 2007) and we were
224 limited in the number of attributes. In addition, we initially wanted to express this
225 attribute as a reduction of the treatment frequency index (TFI), a crop- and region-
226 normalized indicator of pesticide use, widely used and understood by European
227 farmers. However, pretests revealed that this formulation induced misinterpre-
228 tations and acceptability problems from farmers who perceived it as a technical
229 objective to be achieved. Whenever farmers believe that achieving the proposed
230 reduction is not possible for their farms, they opt for the status quo. Because
231 we wanted to value here the environmental and health impacts of the agricultural

magnitude of the risk. Having “three years” of below-average yield implies an asymmetry of the yield distribution, with smaller deviations from the average for the more frequent losses than for the less frequent gains (possibly a positive skew). It is the opposite effect we want to convey (increase in the probability of very large losses).

232 practice, rather than the constraints it implies (captured by other attributes), we
 233 opted for this formulation.

234 Figure 1 shows an example of a choice set, where the first column gives the
 235 attribute's title and short definition, the three following columns represent three
 236 options from which the respondent must choose (the last one being the status quo).

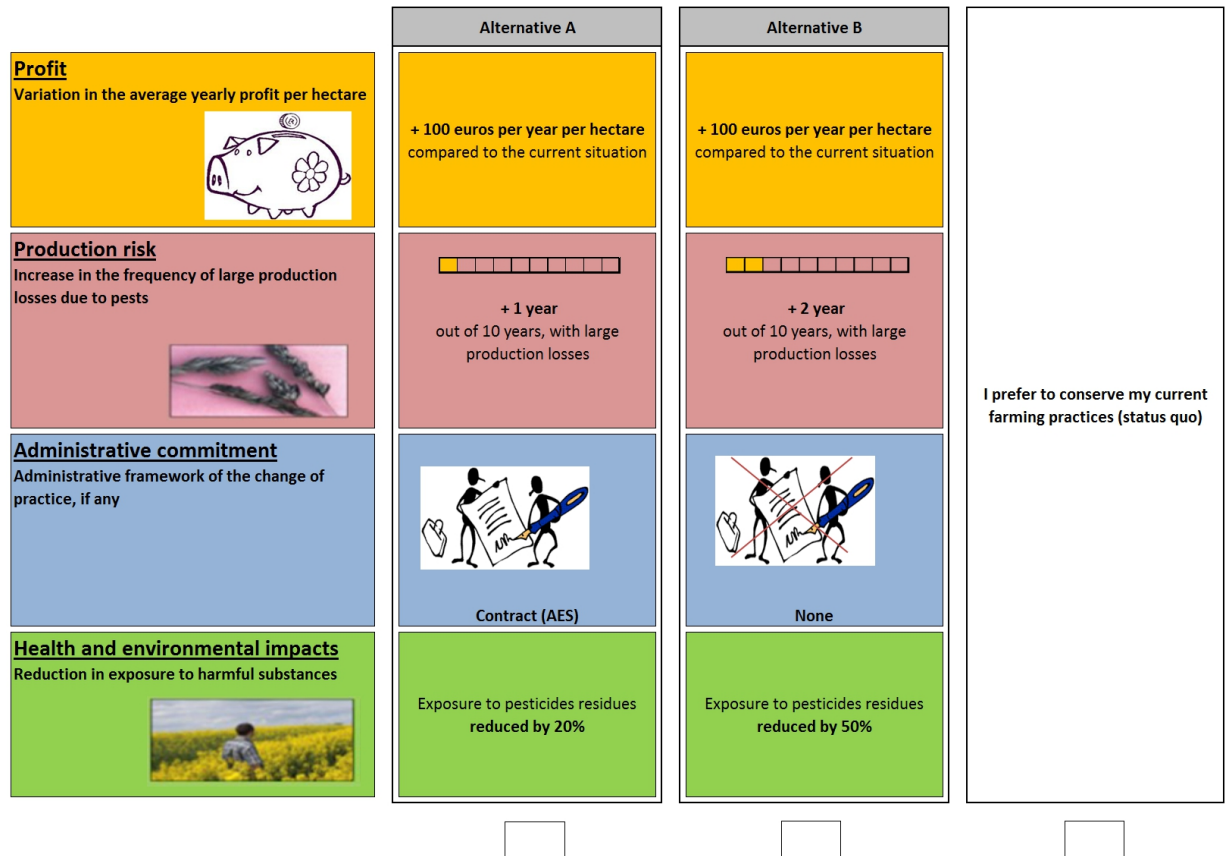


Figure 1: Example of a choice set (translated from French)

237 2.2 Experimental design

238 The aim of the experimental design is to construct the choice sets (i.e., combina-
 239 tions of attribute levels) that are presented to respondents. With four attributes
 240 and three to four levels each, the questionnaire would be far too heavy if all pos-
 241 sible combinations of attribute levels were submitted to respondents. To choose
 242 the most relevant choice sets, which are those yielding maximum information on
 243 respondents' preferences, we used experimental design techniques (see Louviere
 244 et al., 2000; Street et al., 2005) and a dedicated software package (*Ngene*), which

245 is a reference in this field. Using a Bayesian D-optimal design, in our case, a frac-
246 tional factorial efficient design set up for an econometric treatment with a random
247 parameter logit and using 100 Halton draws for the random parameters,⁹ we ob-
248 tained a statistically optimal subset of the possible combinations. According to
249 the literature, efficient designs have been shown to lead to lower standard errors
250 than orthogonal designs, particularly when the sample size is small (Bliemer and
251 Rose, 2010, 2011; Greiner et al., 2014; Rose and Bliemer, 2013).

252 This experimental design led to 16 different choice sets. These were divided
253 into two groups, and respondents were assigned randomly to the groups, as usual.
254 Consequently, the final questionnaire presented eight choice sets to each respon-
255 dent, which is an acceptable cognitive load, as per the literature (Bech et al.,
256 2011). The choice of two blocks thus seems appropriate in our case, both for the
257 cognitive load and given our sample size (see the description of the sample below).
258 This induces a reasonable number of respondents per block compared with other
259 published DCEs, such as Greiner (2016) (four blocks for 104 farmers), Schulz et al.
260 (2014) (three blocks for 128 farmers), and Hudson and Lusk (2004) (five blocks
261 for 49 farmers).

262 **2.3 Presentation of the questionnaire, data collection, and** 263 **descriptive statistics**

264 The DCE was conducted among a set of French farmers (field crops, vegetable
265 farming, wine growing, and mixed crop/livestock; see Table 7 in the Appendix),
266 excluding organic farmers, who were considered unable to significantly reduce their
267 use of synthetic pesticides. The survey was held from June 2016 to May 2017,
268 taking two forms: face-to-face interviews on the farms (20 respondents), and a
269 web survey (70 respondents). Face-to-face respondents were recruited by phone,
270 using the public directory and a farmer database supplied by a private directory
271 of firms (Kompass). The web survey sample was provided by Vivaxis, a French
272 survey institute. We were careful to give very similar information in both types of
273 interviews by ensuring that the face-to-face interviewer read precise text with exact
274 wording, and by introducing optional informational points equivalent to answers
275 to potential questions in the web mode.¹⁰

⁹Details of the efficient design used, and the associated program are available upon request.

¹⁰Using mixed-mode surveys is an efficient and satisfactory method to increase the sample size and representativeness (Dillman et al., 2009; de Leeuw and Hox, 2011), despite the risk of obtaining different answers to the same question according to the mode (de Leeuw and Hox, 2011; Dillman and Christian, 2005). Several articles show that the answers obtained in face-to-face surveys are very similar to answers in web surveys, including the number of protest answers, number of zeros, and the obtained WTPs (Nielsen, 2011; Covey et al., 2010; Van der Heide et al., 2008; Windle and Rolfe, 2011).

276 We obtained 90 completed questionnaires. This small sample size is a rather
277 common limitation of DCE studies targeting farmers, because this population is
278 more difficult to reach than those of regular citizens or consumers.¹¹ Moreover,
279 pesticide use is a sensitive issue among farmers, and many refuse to be involved
280 in a survey on this topic. This was particularly true for our study, which was
281 conducted during a period of controversy over pesticides in France, just after a
282 polemic documentary diffused to a large television audience, provoking protests
283 by many farmers. The sample size and representativeness are further discussed
284 below.

285 The questionnaire lasted less than 20 minutes. Respondents' were told that
286 the study was designed by the French Institute for Agricultural Research (INRA)
287 to implement better-tailored public policies.¹² Then, slides were used to briefly
288 explain the issue addressed by our study.

289 The first part of the questionnaire was dedicated to general questions on the
290 farmer's activities, size of the farm, and use of pesticides, as well as questions that
291 assess the status quo level of each attribute. The details of the four attributes
292 and their implications were presented thoroughly, delivering information in the
293 most objective and neutral way (see Appendix A.1 for examples of the attribute
294 presentation). We provided real-world examples in the survey description to make
295 the choice sets more realistic, and thus, limit the hypothetical bias. A set of qual-
296 itative questions was used to assess the respondent's awareness of the interactions
297 between agricultural practices, public policies, and pesticide issues (see Appendix,
298 Table 8).

299 The eight choice sets were then presented. The order of the choice sets was
300 randomized to avoid having potential declining concentration always affecting the
301 same choice sets (last choices). Respondents had access to the definition of each
302 attribute whenever needed during the choice sequence (accessible using informa-
303 tional icons in the web survey). In order to detect protest answers, those farmers
304 who chose the status quo in all choice sets were asked for additional information
305 about their choices.

306 After the choice sets, respondents were presented with questions on their so-
307 cioeconomic situation (income level, gender, age, level of education) and on their
308 understanding of the choice sets.

¹¹Many published DCEs target farmers with relatively small sample sizes, for example, 128 German farmers in Schulz et al. (2014), 104 Australian farmers in Greiner (2016), 97 English farmers in Beharry-Borg et al. (2013), 49 U.S. farmers in Hudson and Lusk (2004), and 104 French farmers in Jaeck and Lifran (2014).

¹²The information delivered in this introductory part favors consequentiality, that is, the fact that respondents believe there is a nonzero probability that their answers influence actual decisions, and that they may have to pay something as a result. Consequentiality is a necessary (but not sufficient) condition for incentive-compatibility (see Johnston et al., 2017).

309 Some respondents were removed from the sample, for various reasons: i) 10
 310 were removed because their response times were too short (those responding to
 311 the web survey in less than eight minutes were considered unreliable) (see Börger,
 312 2016, for an analysis of the link between response time and quality of the answer);
 313 and ii) five were removed owing to a lack of understanding or an unwillingness to
 314 answer truthfully.¹³

315 Tables 2 and 3 present the descriptive statistics for the final sample of 75
 316 farmers, 31% of whom are women. The respondents' ages range from 23 to 68
 317 years, with an average of 46 years. The mean size of their farms is about 117
 318 hectares.

	Obs	Mean	S.D	Min	Max
Age	75	45.67	10.60	23	68
Size of the farm (ha)	75	116.68	103.18	0.1	500
Yearly turnover (€)	65	168113	151770	1	650000
Yearly average profit/ha (€)	30	753.33	1398.91	10	8000

Table 2: Descriptive Statistics

319 In Table 4, we compare the main sociodemographic characteristics of our sam-
 320 ple with the population of French farmers.¹⁴ Our sample is representative of the
 321 population in terms of age, the sex ratio, and the proportion of respondents with
 322 high school diplomas. However, there is an over-representation of farmers with
 323 higher education diplomas (which is typical for web surveys), and the mean size
 324 of farms is significantly larger in our sample than it is for the country as a whole.

325 Additional descriptive statistics on farm location and type are presented in the
 326 Appendix (Table 7). Our sample is not fully representative of the various French
 327 administrative regions, with an over-representation of central areas and field crop
 328 farmers. This may explain why the mean farm size is larger than the mean value
 329 for France. The Appendix also presents statistics on respondents' awareness (Table
 330 8).

¹³These were identified by the follow-up question, "Were the explanations and the choice cards clear to you?: Yes/No. If you answered no, please provide further information" (open-ended question).

¹⁴A comparison with nonorganic French farmers only would have been more appropriate, but data were not available for this subpopulation.

	Nb	%
Number of farmers having some revenues from outside	39	52,0%
Number of farmers having suscribed to a harvest insurance	33	44,0%
Gender		
Women	23	30,7%
Men	52	69,3%
Education		
No formal qualifications	1	1,3%
Youth Training/BTEC 1st Diploma	13	17,3%
High School Diploma	25	33,3%
Bachelor	19	25,3%
Master's Degree	13	17,3%
PhD	1	1,3%
Other	3	4,0%

Table 3: Descriptive Statistics

	Our Sample	French farmers
Mean age	45.7	50.6
Farm size (hectares)	117	56
Men / women ratio	69% of men	68% of men
Proportion having a high school diploma	33%	21%
Proportion having a higher education diploma	43.9%	17%

Table 4: Comparison of socio-demographic characteristics

3 Theoretical foundations of the choice experiment approach and model specifications

The choice experiment modeling framework relies on the characteristics theory of value (Lancaster, 1966) and the random utility theory (McFadden, 1974). Lancaster (1966) assumes that a good may be defined by a set of characteristics. Therefore, the value of a good is the sum of the values of all its characteristics. Applying this theory in a choice experiment approach means that an alternative can be characterized by a set of characteristics (called attributes in the DCE literature), and that each attribute is associated with a utility level. The (indirect) utility $V_{n,i}$ of an alternative $i \in \{1, \dots, I\}$ for respondent $n \in \{1, \dots, N\}$, where I and N are given, possibly large, finite integers, is derived from the K observable attributes of the alternative, denoted by $X_i = (x_{i1}, \dots, x_{ik}, \dots, x_{iK})$. In addition, it depends on a set of A social, economic, and attitudinal characteristics (socioeconomic variables) that characterize the respondent, denoted by $Z_n = (z_{n1}, \dots, z_{na}, \dots, z_{nA})$:

$$(1) \quad V_{n,i} = V(X_i, Z_n) \quad \text{for } n = 1, \dots, N \text{ and } i = 1, \dots, I .$$

McFadden (1974) proposes that individuals make choices according to a deterministic part, with some degree of randomness. Combining the two theories, we assume that the random utility of alternative i for individual n , $U_{n,i}$, is composed of the deterministic component $V_{n,i} = V(X_i, Z_n)$, and a stochastic element, $\epsilon_{n,i}$:

$$(2) \quad U_{n,i} = V(X_i, Z_n) + \epsilon_{n,i} ,$$

where the error term $\epsilon_{n,i}$ is a random variable that captures the unsystematic and unobserved random element of the choice of respondent n (Hanley et al., 2005; Holmes and Adamowicz, 2003; Louviere et al., 2000).

Assuming the rationality of individuals, respondents are supposed to associate each alternative i with a random utility level $U_{n,i}$, and choose the option that provides them with the greatest utility within a given choice set. Therefore, agent n will choose alternative i from a finite set of alternatives S if this random utility is greater than the random utility $U_{n,j}$ of any other alternative j in S :

$$(3) \quad U_{n,i} > U_{n,j} \Rightarrow V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \quad \forall j \neq i; i, j \in S .$$

Before estimating an econometric model, we need to specify the deterministic part of the utility function. The linear specification is often chosen in the literature, because it is the simplest to work with. We thus introduce the column vector of coefficients $\beta_n = (\beta_{n1}, \dots, \beta_{nK})'$, which are the coefficients quantifying the (linear)

362 influence of the $K = 4$ attributes on utility and may be specific to each respondent
 363 n .

364 We also introduce an alternative-specific constant, which corresponds to the
 365 status quo. For this, we define the dummy variable SQ , which takes the value
 366 one in the status quo alternative, and zero otherwise. Thus, the SQ term defines
 367 a situation with no variation in the farmer’s profit, no additional years of large
 368 production losses, no additional administrative commitments, and no reduction
 369 in the impact on health and environment. Hence, a positive and statistically
 370 significant coefficient η for the SQ dummy variable (see equation 4 below) indicates
 371 a preference for not moving from the current situation.

372 The interactions with the socioeconomic characteristics can be modeled in dif-
 373 ferent ways, for example, by interacting with the status quo or with the attributes.
 374 Hence, the model is specified so that the probability of selecting alternative i is a
 375 function of the attributes X_i of that alternative, of the alternative specific constant
 376 for the status quo, and the socioeconomic characteristics Z_n of the respondent n .
 377 Because the utility $V_{n,i}$ is assumed to be an additive function, equation (2) becomes

$$(4) \quad U_{n,i} = (\eta + Z_n \alpha^{SQ}) SQ + X_i(\beta_n + \alpha Z'_n) + \epsilon_{n,i}.$$

378 The column vector of coefficients $\alpha^{SQ} = (\alpha_1^{SQ}, \dots, \alpha_A^{SQ})'$ captures the effect
 379 of the socioeconomic characteristics on the status quo utility. The vector $X_i =$
 380 $(x_{i1}, x_{i2}, x_{i3}, x_{i4})$ corresponds to the different levels taken by the attributes “*Profit*,”
 381 “*Production risk*,” “*Administrative commitment*,” and “*Health and environmental*
 382 *impacts*,” respectively. The matrix α of size (K, A) is composed of coefficients $\alpha_{i,a}$,
 383 capturing the cross-effect of socioeconomic characteristic a on attribute i . Thus
 384 specified, the coefficients $\beta_n = (\beta_{n1}, \beta_{n2}, \beta_{n3}, \beta_{n4})'$ quantify the influence of the
 385 various levels of the four attributes on the utility of respondent n , relative to the
 386 utility of the status quo option that appeared on every choice card.

387 Different econometric models, which rely on different assumptions in the distri-
 388 bution of error terms $\epsilon_{n,i}$, can be used to analyze the discrete choice data. Similarly,
 389 the attributes $X_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4})$ can be treated as discrete or continuous vari-
 390 ables, and it is possible to combine qualitative and quantitative attributes in the
 391 same model specification.

392 4 A Random Parameter Logit model to account 393 for farmers’ heterogeneous preferences

394 We used a random parameter logit (RPL) model, also called the mixed logit model,
 395 to analyze our data. Appendix A.3 presents the advantages of this model with
 396 respect to other econometric models we tested: the conditional logit (CL) model,

397 and the latent class (LC) model. The RPL model is shown to outperform the CL
398 and LC models, based on the CAIC and BIC criteria.

399 Table 5 presents the results of the estimation of the RPL model when both the
400 cost attribute (“*Profit*”) and the “*Health and environmental impacts*” attribute,
401 which have quantitative levels, are specified as continuous variables, and the two
402 other attributes (“*Production risk*” and “*Administrative commitment*”) are modeled
403 as dummy-coded variables.¹⁵ As commonly assumed in the literature (Hensher
404 and Green, 2003), the coefficient associated with the cost attribute is considered
405 to be constant, whereas the other RPL parameters are assumed to be normally
406 distributed.¹⁶

407 As explained by Burton (2018), econometric models that include categorical
408 variables (as here) are not invariant to the choice of the “base” category when
409 random parameters are estimated, unless they are allowed to be correlated. When
410 not taken into account, the invariance can lead to significant increases in Type-
411 I errors. To avoid this bias, all results for the RPL models presented here are
412 estimated using a full covariance matrix structure in which the random coefficients
413 are assumed to be correlated.

414 We considered two versions of the model. The first does not account for so-
415 cioeconomic variables: the vector Z_n is not introduced in equation 4 (left-hand
416 side model in Table 5). The second extends the model by considering interactions
417 with socioeconomic variables (right-hand side model in Table 5). We first present
418 the results of the model without interactions, and then discuss the effect of the
419 socioeconomic variables.

420 4.1 Model without interactions with socioeconomic variables

421

422 In the results of the RPL estimations without interactions with socioeconomic
423 variables, presented in the first two columns of Table 5, the standard deviations of
424 most coefficients are strongly significant, confirming that the RPL model provides
425 a significantly better representation of the choices than the CL model does.

¹⁵These attributes are encoded using *i*) two dummy-coded variables (“+ 1 year” and “+ 2 years”) for the “*Production risk*” attribute and *ii*) three dummy-coded variables (“*Charter*”, “*Contract*” and “*Certification*”) for the “*Administrative commitment*” attribute. Thus defined, the base categories for the attributes, which are tied to the *SQ*, are “no additional years of large production losses” and “no additional administrative commitment,” respectively.

¹⁶The normal distribution is symmetric and unbounded. It has the advantage of not making assumptions of farmers’ preferences; both positive and negative parameter values may be taken to capture heterogeneity in the population. On the contrary, not allowing the cost attribute to be a random parameter ensures that all respondents have a positive valuation of profits in their utility, according to intuition.

	RPL Model		RPL Model with interactions	
	Coefficient (S.E)	Coeff. Std. (S.E)	Coefficient (S.E)	Coeff. Std. (S.E)
. Attributes				
<i>.ASC-SQ</i>	-0.888** (0.388)	2.095*** (0.663)	0.280 (0.566)	2.963*** (0.604)
<i>.Profit</i>	0.010*** (0.004)	- -	0.010*** (0.004)	- -
<i>.Production Risk :</i>				
<i>+ 1 year</i>	-0.919*** (0.273)	0.555* (0.337)	-0.928*** (0.278)	0.801** (0.338)
<i>+ 2 years</i>	-1.503*** (0.409)	1.027*** (0.370)	-1.358*** (0.378)	1.141*** (0.326)
<i>.Administrative commitment :</i>				
<i>Charter</i>	-0.547* (0.331)	1.096*** (0.360)	-0.549* (0.305)	1.794*** (0.406)
<i>Contract</i>	-0.889*** (0.326)	1.553* (0.798)	-1.008*** (0.310)	1.120*** (0.331)
<i>Certification</i>	-1.221*** (0.393)	1.696*** (0.379)	-1.401*** (0.383)	1.980*** (0.369)
<i>.Health & Environmental Impacts (HEI)</i>	-0.004 (0.007)	0.030** (0.012)	-0.013* (0.008)	0.042*** (0.007)
. Socio-economic variables				
<i>Crossed with the HEI attribute</i>				
<i>.Awareness of environmental impacts of pesticides</i>	-	-	0.039*** (0.010)	-
<i>Crossed with the ASC-SQ</i>				
<i>. Outside revenues</i>	-	-	-1.692*** (0.511)	-
<i>. Awareness of possibility to maintain yields while reducing pesticides</i>	-	-	-1.708*** (0.564)	-
<i>. Cropland type :</i>				
<i>Vegetable farmers</i>	-	-	-3.843** (1.545)	-
<i>Wine-growers</i>	-	-	-1.537** (0.780)	-
<i>Mixed crop and livestock</i>	-	-	4.963*** (1.329)	-
N (ind.)	75		69	
N (obs.)	1800		1656	
Log Likelihood	-531.704		-476.539	

ASC-SQ: Alternative Specific Constant corresponding to the status quo alternative.

*** indicates significance at 1%, ** at 5% and * at 10%.

Table 5: Results of RPL models with and without socioeconomic interactions (estimated with a full covariance matrix structure in which the random coefficients are assumed to be correlated)

426 Owing to the rather small size of our sample, we retain the conservative value
427 of 5%, rather than 10%, as the chosen level of significance (*i.e.*, the probability of
428 committing a *Type-I error*) to reject (or not) the null hypothesis of the Student
429 tests. All attributes and levels, except for the “*Health and environmental impacts*”
430 attribute and the “*Charter*” level of the “*Administrative commitment*” attribute,
431 are statistically significant at this level. The fact that the “*Charter*” level is ig-
432 nored by respondents is not surprising, given that a charter is, in general, weakly
433 constraining compared with other administrative commitments (certification or
434 contracting). The fact that the environmental and health impacts of pesticides
435 do not affect respondents’ utility significantly may be intriguing, and is explored
436 further in the next subsection.

437 With regard to the statistically significant coefficients, the alternative specific
438 constant corresponding to the status quo *ASC-SQ* is negative: on average, farm-
439 ers place a negative value on maintaining the status quo. However, its standard
440 deviation is large (2.095), highly significant, and covers positive signs (*i.e.*, some
441 farmers value the status quo positively). The cost attribute coefficient (“*Profit*”)
442 is also strongly significant and, unsurprisingly, its positive sign indicates that a
443 higher profit has a positive effect on respondents’ utility.

444 As expected, the risk of large production losses has a negative effect on utility,
445 and the coefficients of both dummy variables “*+1 year*” and “*+2 years*” for “*Pro-*
446 *duction risk*” are strongly statistically significant. However, these negative effects
447 are very heterogeneous in the sample, as indicated by the large and significant
448 standard deviations for these attributes. If the farmers in our sample are reluctant
449 to face additional risk on production, their aversion to that risk varies from low
450 to high. In addition, the effect of “*+2 years*” is more negative, on average, than
451 that of “*+1 year*”, which denotes an overall perception of increased risk. However,
452 when computing the 95% Confidence Interval (CI) of these mean estimated coef-
453 ficients, we find that the 95% CI of the “*+2 years*” category overlaps with that of
454 the “*+1 year*” category.¹⁷ Thus, there seems to be no scope effect related to our
455 production risk, which may be considered almost qualitatively. We emphasize the
456 implication of this heterogeneity when discussing the WTA associated with the
457 additional production risk in subsection 4.3. Moreover, the interaction between
458 the profit attribute and the production risk attribute is not significant, as it would
459 be if that risk were treated jointly with the outcome, according to expected utility
460 theory. This result suggests a direct distaste of large production losses, rather than

¹⁷This CI is computed as follows:

$$(5) \quad \hat{\beta}_i \pm t_\alpha \hat{\sigma}_{\hat{\beta}_i} \Leftrightarrow \left[\hat{\beta}_i - t_\alpha \hat{\sigma}_{\hat{\beta}_i}; \hat{\beta}_i + t_\alpha \hat{\sigma}_{\hat{\beta}_i} \right],$$

where $\hat{\beta}_i$ is the (mean) estimated value of the i th attribute’s coefficient, $\hat{\sigma}_{\hat{\beta}_i}$ is its standard error, and t_α corresponds to the critical value for a significant threshold α (1.96, in our case).

461 standard risk aversion (refer to Glenk and Colombo, 2013).

462 The dummy variables associated with the “*Administrative commitment*” at-
463 tribute, except for “*Charter*”, have significant and negative coefficients. Thus, in
464 general, increased administrative commitments reduce respondents’ utility signifi-
465 cantly. Interestingly, the administrative frameworks “*Contract*” and “*Certification*”
466 represent a burden, rather than a support, for respondents.

467 4.2 Role of interactions with socioeconomic variables

468 In the extended model (Table 5, two last columns), we test the effect of the so-
469 cioeconomic variables on the coefficients associated with each attribute and the
470 *ASC-SQ* variable. Examining such interactions helps us to better understand
471 farmers’ preferences toward each attribute. We assume that the effects of the so-
472 cioeconomic variables are homogeneous over the sample, with constant coefficients,
473 as is common in the literature.

474 Interactions were tested using the following socioeconomic and attitudinal vari-
475 ables: age, income, level of education, farm size, sources of revenue from outside
476 the farm, farm type, whether the respondent is aware of the environmental and
477 health impacts of pesticide use, whether the respondent trusts in the possibility of
478 maintaining yields while reducing pesticide use, whether the respondent initially
479 knows her/his level of pesticide use, and whether the respondent has subscribed to
480 an insurance contract. We tested the significance of the interaction between these
481 variables and each attribute in an extended model, and identified significant inter-
482 actions using the backward elimination procedure. All but one of the interactions
483 that remain statistically significant after this procedure are interactions with the
484 status quo (*i.e.*, the *ASC-SQ* variable). These results are useful, because they pro-
485 vide information on which types of respondents (characterized by socioeconomic
486 variables) are more willing to move away from the status quo (*i.e.*, to reduce their
487 use of pesticides). Furthermore, there is one significant interaction between a so-
488 cioeconomic variable and an attribute: the awareness of the environmental impact
489 of pesticides plays a significant and positive role on the “*Health and environmental*
490 *impacts*” attribute (see below).¹⁸

491 All attribute coefficients in the extended model (top half of the two last columns)
492 are close to those in the model without interaction, showing that the estimations
493 are robust. The “*Health and environmental impacts*” and “*Charter*” attributes
494 remain nonsignificant at the 5% level. However, as already pointed out, the co-
495 efficient of the interaction term between the “*Health and environmental impacts*”

¹⁸“*Awareness of environmental impacts of pesticides*” is a dummy variable derived from the qualitative question “Do you think pesticides affect the environment?” The response takes the value one if respondents think the impact is “important” or “very important,” and zero otherwise (see Appendix A.2).

496 attribute and the dummy variable “*Awareness of environmental impacts of pes-*
497 *ticides*” is statistically significant at the 1% level, and positive. In other words,
498 our results show that respondents who think pesticides affect the environment are
499 significantly and positively motivated by the environmental and health outcome
500 of pesticide reduction, as is consistent with intuition but controversial in the lit-
501 erature (Isin and Yildirim, 2007). This represents about 65.4% of our sample (see
502 Appendix A.2).

503 With regard to the influence of other socioeconomic variables (crossed with the
504 *ASC-SQ* variable), the coefficient of “*Outside revenues*” is negative and statistically
505 significant at the 1% level: farmers who obtain some revenue from outside the
506 farm are significantly more willing to change their practices (because they have a
507 stronger disutility from staying in the status quo). We interpret this result jointly
508 with the effect of the production risk: Farmers with an outside, stable income may
509 be less reluctant to adopt pesticide-reducing practices, in spite of the increased risk
510 of large production losses. Farmers who are aware that they can maintain yields
511 while reducing their use of pesticides (“*Awareness of possibility maintaining yields,*
512 *while reducing pesticides*”) are also significantly more willing to leave the status
513 quo. This confirms the feedback provided by the focus groups and other discussions
514 with farmers that the yield, beyond total profits, is a major decision factor; this
515 pattern is mentioned frequently in the literature (Burton et al., 2008; Pedersen
516 et al., 2012). The cropland types are coded as dummies; their coefficients must be
517 interpreted as differences with respect to field crops farms (i.e., the reference level).
518 The results indicate that vegetable farmers and wine growers are more willing to
519 leave the status quo than are farmers of field crops. Mixed crop/livestock farmers
520 are significantly less willing to change their farming practices than field crops
521 farmers are.

522 Finally, the *ASC-SQ* coefficient is nonsignificant in the model with interactions.
523 Thus, in this setting, respondents are indifferent between staying or leaving the
524 status quo, on average. Therefore, the willingness to leave the status quo identi-
525 fied in the model without interactions can be explained fully by the socioeconomic
526 characteristics of respondents. Note that, because respondents are indifferent be-
527 tween changing and maintaining the status quo, our sample does not seem to be
528 biased toward farmers who particularly wish to change their farming practices.
529 This is reassuring, because farmers who agree to answer this survey may be people
530 who are naturally sensitive to the pesticide topic and are more willing to change
531 their practices than is the average farmer. There could be a selection bias due to
532 self-selection (Heckman, 1979), which does not seem to occur in our case.

4.3 WTA estimates

Welfare measures can be determined in the form of marginal WTP/WTA by estimating the marginal rate of substitution (MRS) between the considered attribute and income (Louviere et al., 2000). The marginal utility of income is represented by the cost attribute’s coefficient, β_{cost} . Because we study the motivation of farmers to reduce their use of pesticides, it is easier to interpret this MRS as a WTA. This is consistent with the fact that most nonmonetary attributes of our choices are valued negatively by respondents.

Because utilities are modeled as linear functions of the attributes, the MRS between two attributes is the ratio between the corresponding coefficients. For attributes modeled as dummy-coded variables, the WTA_k^l associated with attribute k and category l is $WTA_k^l = -\frac{\beta_k^l}{\beta_{cost}}$. This corresponds to the WTA to move from the status quo category of attribute k to category l .

The WTA estimates presented in Table 6 are calculated using the RPL models shown in Table 5. The estimated standard deviations and CIs around the mean of the WTA estimates are obtained using the delta method at a 95% confidence interval. WTA estimates are similar using the RPL with or without interactions, which shows that our estimates are rather robust; thus, we focus on the RPL with interactions when interpreting the results. No WTA is computed for *i*) the “*Health and environmental impacts*” attribute for respondents thinking pesticides do not impact the environment, and *ii*) the “*Charter*” level, because neither coefficient is statistically significant at the 5% level in the RPL model with interactions.

Farmers in our sample need to receive approximately 90 euro per hectare per year (€/ha/yr), on average, to accept one additional year out of 10 of the risk of large production losses due to pests.¹⁹ In addition, they need to receive 132 €/ha/yr to accept two additional years of that risk. The production risk attribute is clearly a dominant criterion in our respondents’ decisions. Farmers express high preferences for not bearing any additional risk of large production losses, as shown by the high associated WTAs. Furthermore, when considering the mean estimates of both WTAs, this attribute does not seem to be linear, in the sense that farmers need to receive more for the first additional year of risk than they do for the second year.²⁰ For our respondents, the unique fact of having an increased risk of large production losses, rather than the extent of the risk increase, seems to influence their decisions most.

For “*Administrative commitment*,” all else being equal, farmers need to re-

¹⁹Note that this attribute is measured for a given profit level (the cost attribute) and, thus, only measures the distaste of the additional risk of large production losses.

²⁰This nonlinearity in the effect of increased risk of large production losses is even more significant given that the maximum value of the CI of the WTA for the one-year level is higher than the minimum value of the CI for the two-year level.

	RPL Model	RPL Model with interactions
	Mean (95% CI)	Mean (95% CI)
. Attributes		
.Production Risk :		
+ 1 year	96.84 [32.10 ; 161.58]	90.25 [32.72 ; 147.78]
+ 2 years	158.46 [74.33 ; 242.59]	132.14 [68.74 ; 195.53]
.Administrative commitment :		
Charter	-	-
Contract	93.67 [13.34 ; 174.00]	98.08 [22.26 ; 173.90]
Certification	128.71 [35.74 ; 221.68]	136.29 [46.28 ; 226.31]
.Health & Environmental Impacts (HEI)		
for respondent thinking pesticides do not impact the environment	-	-
for respondent thinking pesticides impact the environment	-	-3.75 [-7.08 ; -0.42]

Table 6: WTA estimates for the Random Parameter Logit models

568 ceive, on average, 98 €/ha/yr to sign agri-environmental contracts with public
569 authorities, and 136 €/ha/yr to commit to a certification. The WTA for a char-
570 ter commitment is not significant at the 5% level. Unsurprisingly, respondents
571 need to receive more to enter a certification process than an agri-environmental
572 contract, which itself requires more compensation than a charter. This is intu-
573 itive, because a certification includes rigorous specifications and controls, whereas
574 a charter is very weakly constraining. Signing an agri-environmental contract with
575 public authorities, such as an Agri-Environmental Scheme, usually implies controls
576 and specifications that are less constraining than a certification associated with a
577 label. See, for instance, Sutherland (2011) on the difficulties of adopting a certifi-
578 cation, with an example of English farmers and the organic label.

579 Respondents who believe that pesticides affect the environment (65.4% of the
580 sample) are significantly willing to pay almost 4 €/ha/yr to reduce by 1% the
581 impacts of pesticides on health and environment. In contrast, those who do not
582 believe that pesticides impact the environment are, on average, not willing to pay
583 for health and environment improvements.

584 5 Conclusion and policy implications

585 Our study investigates farmers' motivations and obstacles related to reducing their
586 use of pesticides. We use a quantitative approach based on a discrete choice
587 experiment to measure the relative weight of various factors that influence farmers'
588 decisions. We value farmers' WTA for several nonmarket components of their
589 decisions, such as the administrative framework of a practice change, the resulting
590 reduction of the impact of pesticides on health and the environment, and the
591 additional risk of large production losses. For the latter attribute, because farmers
592 use pesticide as an insurance device to limit production losses, without necessarily
593 increasing the total mean income (Menapace et al., 2013; Pedersen et al., 2012),
594 we expected this risk would be a major component explaining farmers' reluctance
595 to reduce pesticides, something barely examined by the quantitative literature on
596 this topic.

597 We find that most respondents in our sample do not consider the administrative
598 framework that may accompany changes in agricultural practices as an opportunity
599 for support or integration in a network, but rather as a burden. In particular, on
600 average, Agri-Environmental Schemes taking the form of a contract with public
601 authorities are valued negatively, which is consistent with the literature (Ruto
602 and Garrod, 2009; Christensen et al., 2011). All else being equal, farmers in our
603 sample would need to receive, on average, 98 €/ha/year to sign such a contract.
604 In addition, on average, the farmers in our sample would need to receive 136
605 €/ha/year to join a certification on pesticide reduction.

606 With regard to the effect on production risk, our results show that farmers
607 dislike increased risk of large production losses, regardless of the effect of the
608 practice change on the level of mean profit. We can relate this result to the
609 fact that the yield is an objective *per se* for many farmers. The risk of a large
610 production loss due to pests is a prominent obstacle to the reduction in the use of
611 pesticides. All else being equal, farmers in our sample need to receive on average
612 90€/ha/year to accept one additional year, over 10 years, of large production
613 losses due to pests. This amount is not very much higher for two additional
614 years (132€/ha/year), showing that they perceive this risk more qualitatively than
615 quantitatively. According to these results, our respondents tend to experience a
616 psychological cost from the risk of large production losses, independently of the
617 financial outcome.

618 The impact of agricultural practices on the environment and human health
619 plays a subtle role in the decisions of our respondents. At first glance, this attribute
620 does not seem to be decisive for the interviewed population. However, when taking
621 into account respondents' awareness of the environmental impacts of pesticides, we
622 understand this behavior better. Respondents who believe that pesticides affect
623 the environment (about 65% of the sample) are significantly willing to pay to
624 reduce pesticide impacts. They are, for example, willing to pay 75 €/ha/year to
625 reduce the health and environmental impacts of pesticides by 20%.

626 Two other results are worth mentioning. First, it seems that the existence
627 of outside revenue is a determining factor in farmers' willingness to change prac-
628 tices. Farmers with low, insecure incomes may be locked into pesticide intensive
629 practices, and lump-sum subsidies that are independent of farming activities could
630 help them to adopt riskier low-pesticide practices. Second, respondents who be-
631 lieve that yields cannot be maintained while reducing pesticides seem reluctant to
632 change their practices. Thus, it is necessary to increase informational campaigns
633 on alternative farming practices that, in some cases, do allow to maintain satisfac-
634 tory yields and reduce pesticides (as demonstrated by Lechenet et al., 2017, among
635 others). Education campaigns on farm accounting and composition of profit could
636 also help farmers understand that aiming at a high yield can be a misleading
637 objective.

638 Our results shed some light on suitable agri-environmental policies. Sufficiently
639 high payments are required to compensate for a reduction in the use of pesticides,
640 for three main reasons. Farmers may need i) significant incentives to overcome
641 their distaste of the increased risk of large production losses (“production-risk
642 premium”), and ii) an “administrative burden premium” to accept changing their
643 current practices, whereas iii) environmental and health improvements may not
644 be a sufficient motivation for some farmers. In addition, the high heterogeneity
645 of preferences observed in our sample favors differentiated payments by farmer

646 type, when possible. Measures should be taken to reduce these necessary pre-
647 miums. With regard to production risk, the Income Stabilization Tools (IST)
648 discussed within the European Common Agricultural Policy or the Agricultural
649 Risk Coverage (ARC) proposed within the Farm Bill 2014 in the United States
650 could be useful. In addition, ensuring farmers have access to reliable and af-
651 fordable production-risk insurance is advised. With regard to the administrative
652 burden, simplified formalities are necessary. Dedicated studies would be useful to
653 understand which administrative tasks trouble farmers the most. Free and easily
654 accessible assistance for these tasks should also be generalized.

655 Because outside revenues favor adoption, area-based payments (as the direct
656 payments in the successive Farm Bills in the United States or in Pillar 1 of the
657 European Common Agricultural Policy), which are independent of production lev-
658 els, could increase sure income. They could be conditional on pesticide reduction
659 and even be combined with additional payments for those who go beyond legal
660 requirements. In addition, contrary to the recent guidance tendency, result-based
661 payments (e.g., conditional on biodiversity indicators) could be less favorable to
662 pesticide reduction than management-based payments that are more certain. A
663 remuneration of low-pesticide practices through the market via higher prices is less
664 satisfying than the above mentioned direct payments on this point, because it is
665 correlated to the production level.

666 Our study has several limitations. Our sample, although representative on sev-
667 eral criteria, is rather small and over-representative of large farms from the center
668 of France. As discussed previously, a small sample size is a common drawback
669 in the DCE literature targeting farmers, especially when treating such sensitive
670 issues as pesticide reduction. To overcome this limit, we limited blocking to two
671 blocks in our experimental design, inducing a reasonable number of respondents
672 per block, as explained in Section 2.2. In addition, according to Greiner (2016),
673 using a D-efficient experimental design, as we do, requires a much smaller sample
674 size than a random orthogonal design. As stated by this author, “a systematic
675 review of discrete choice experiments based on design features and sample size by
676 Bliemer and Rose (2011) and Rose and Bliemer (2013) supports the assertion.”
677 Our results should, however, be interpreted with caution, and are not necessarily
678 directly applicable to the whole population of French farmers.

679 Further research is needed to understand the drivers of the adoption of practices
680 that reduce pesticide use. In particular, our work is a first attempt to measure
681 the role of production risk in farmers’ behavior. Other studies of this type would
682 be useful to confirm, reject, or refine the obtained values using other samples. As
683 mentioned in Chevassus-au Louis et al. (2009), the accumulation of many small
684 local studies, yielding a database of monetary values, is needed to support public
685 decision-making. Moreover, complementary choice experiments among farmers

686 could help us to understand the relative weight of other factors, such as the need for
687 technical training on new practices, role of network and neighborhood connections,
688 and the impact of a practice change on farmers' work schedule.

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899 **A Appendix**

900 **A.1 Descriptive sheets of attributes presented to respon-**
901 **dents**

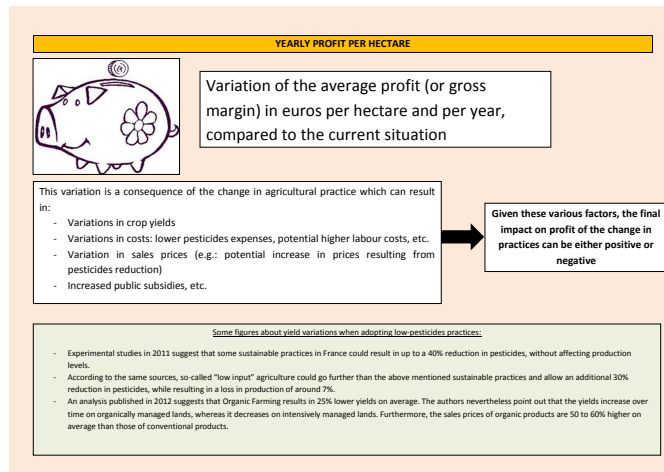


Figure 2: Description of the profit attribute

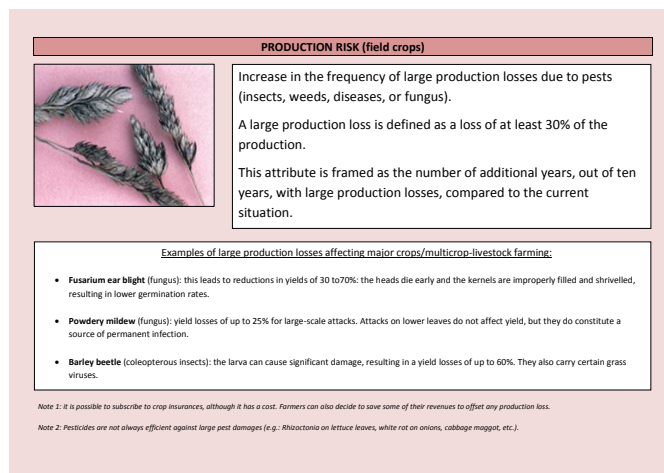


Figure 3: Description of the production risk attribute (field-crops version). There were other versions adapted to various farming activities.

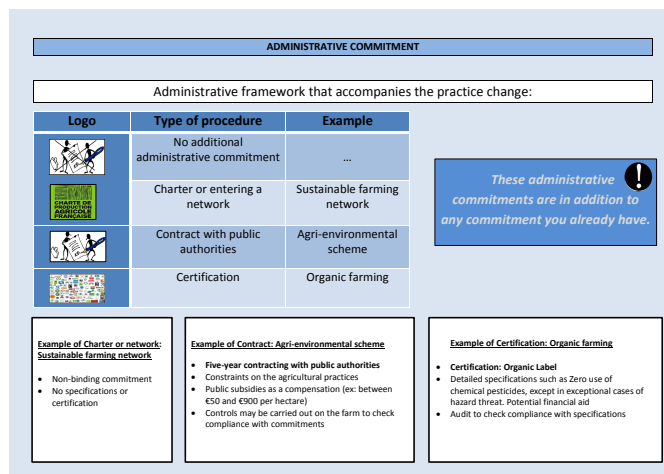


Figure 4: Description of the administrative framework attribute

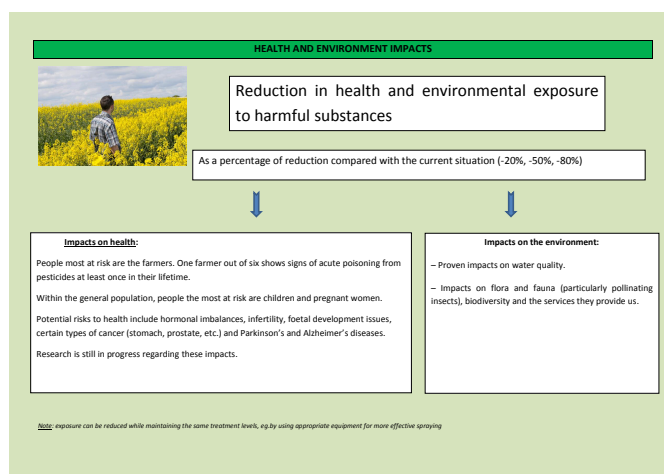


Figure 5: Description of the health and environmental impacts attribute

902 **A.2 Additional descriptive statistics and results of qualita-**
 903 **tive questions**

	Our Sample		French farmers
French Region			
Auvergne-Rhône-Alpes	7	9%	9%
Bourgogne-Franche-Comté	7	9%	6%
Bretagne	3	4%	4%
Centre-Val de Loire	17	23%	8%
Grand Est	9	12%	9%
Hauts-de-France	2	3%	9%
Île-de-France	16	21%	2%
Normandie	1	1%	5%
Nouvelle-Aquitaine	4	5%	19%
Occitanie	3	4%	19%
Pays de la Loire	5	7%	4%
Provence-Alpes-Côte d'Azur	1	1%	5%
Cropland type			
Field crops	59	79%	-
Market gardening	5	7%	-
Wine-growers	7	9%	-
Mixed crop and livestock	4	5%	-

Table 7: Descriptive Statistics

	Nb	%
Do you see agri-environmental schemes as a constraint?		
Yes	57	76,0%
No	18	24,0%
Do you think reduced pesticides is compatible with constant yields?		
Yes	30	40,0%
No	39	52,0%
I don't know	6	8,0%
Do you think pesticides impact health?		
Not at all	5	6,7%
A little	17	22,7%
Significantly	33	44,0%
Very significantly	15	20,0%
I don't know	5	6,7%
Do you think pesticides impact the environment?		
Not at all	2	2,7%
A little	23	30,7%
Significantly	32	42,7%
Very significantly	17	22,7%
I don't know	1	1,3%

Table 8: Sensitivity to administrative commitment and to health and environmental exposure

904 **A.3 (Not for publication, or For online publication only)**
 905 **Comparing the RPL model with the CL and the LC**
 906 **models**

907 Different discrete choice models are obtained from various assumptions on the dis-
 908 tribution of the random terms. We tested three types of models: conditional logit
 909 (CL), random parameter logit (RPL), and latent class (LC). The RPL, which we
 910 retained as the more suitable formulation, is presented in the main text. This ap-
 911 pendix presents the CL and LC models, and discusses why we chose an RPL model.

912
 913 We run CL estimations with the same specifications as those in our RPL model,
 914 where (the “*profit*” and “*health and environmental impacts*” attributes are specified
 915 as continuous variables, and the “*production risk*” and “*administrative commit-*
 916 *ment*” attributes are modeled as effect-coded dummy variables), with and without
 917 interactions with socioeconomic variables. Although the estimates are similar in
 918 their order of magnitude, in both cases, the RPL models are preferable to the
 919 CL models, owing to the higher values of their log-likelihood functions, and be-
 920 cause the standard deviations in the RPL model are highly significant. We also
 921 performed the test proposed by Hausman and McFadden (1984) to test the *IIA*
 922 assumption. If this property is rejected, then the CL model is not appropriate.
 923 The results of this test for both CL models, with and without interactions with
 924 socioeconomic variables, are presented in Table 9.

Alternative dropped	CL model without interactions			CL model with interactions		
	Chi2	D.o.f.	P-Value	Chi2	D.o.f.	P-Value
Practice A	8.50	8	0.3866	15.53	13	0.2756
Practice B	10.10	8	0.2580	11.40	13	0.5771
Practice C (status quo)	19.20	8	0.0138	37.78	13	0.0003

D.o.f. : Degrees of freedom of the Hausman and McFadden (1984) test for the *IIA* property.

NB : The statistic of this test follows a Chi-squared distribution. *Chi2* corresponds to the *Chi-squared value* of this test.

Table 9: Test of independence of irrelevant alternatives (*IIA*)

925 The null hypothesis of the Hausman test stipulates that there is no significant
 926 difference between the full model and a model with one alternative less. According
 927 to Table 9, the Hausman tests lead to the result that the null hypothesis must be
 928 rejected at the 5% and the 1% levels for the CL models, without and with inter-
 929 actions, respectively, when the alternative status quo is dropped. Because both
 930 CL models violate the *IIA* property, they are not suitable for modeling farmers’
 931 preferences belonging to this sample.

933 Another way to take the heterogeneity in respondents' preferences into account
 934 would have been to analyze the sample using a latent class (LC) model. In this
 935 model, respondents are sorted into classes C , in which preferences are assumed
 936 to be homogeneous in their attributes. In contrast, preferences are allowed to be
 937 heterogeneous between classes, thus partitioning the population. Table 10 shows
 938 that, regardless of the number of classes considered, the RPL model outperforms
 939 the LC model in terms of the *Bayesian information criterion* (*BIC*) and the *con-*
 940 *sistent Akaike information criterion* (*CAIC*), because models with lower *CAIC*
 941 and *BIC* measures are preferable to models with higher measures.

Number of classes	Parameters (P)	Log likelihood	AIC	CAIC	BIC
- (RPL)	15	-540.19	1110.38	1160.14	1145.14
2	17	-563.62	1161.24	1217.64	1200.64
3	26	-553.72	1159.44	1245.70	1219.70
4	35	-523.07	1116.13	1232.25	1197.25
5	44	-510.51	1109.03	1255.00	1211.00

. AIC (Akaike Information Criterion) = $-2LL + 2P$

. CAIC (Consistent Akaike Information Criterion) = $-2LL + P[(\ln N) + 1]$

. BIC (Bayesian Information Criterion) = $-2LL + P[\ln(N)]$

Table 10: Criteria for comparing RPL and LC models