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Improving the understanding of farmers' non-compliance with agricultural policy regulations

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ABSTRACT

To reduce the negative impacts of agricultural production, Switzerland and the EU introduced environmental and animal welfare regulations in their direct payment policy schemes. Compliance with these regulations is monitored, and fines are imposed if deficiencies in implementation are identified. Non-compliance with these regulations reduces the effectiveness of direct payment measures and creates public and private administrative transaction costs. Therefore, a better understanding of the reasons behind farmers' non-compliance with direct payment regulations can help the government develop targeted measures to increase the effectiveness of direct payment policies. We used data on self-reported compliance with direct payment regulations from a survey of 808 Swiss farmers to develop a framework that explains the likelihood of receiving penalties based on the following influencing factors: (1) knowledge of rules, (2) acceptance of rules, (3) costs and benefits of non-compliance, and (4) farmer and farm characteristics. We found that 28% of the participants had experienced receiving penalties because of non-compliance with direct payment rules. Based on a hierarchical binary logistic regression model, our findings revealed that better knowledge of inspection measures, higher educational levels, and higher acceptance of entrepreneurial restrictions associated with direct payment regulations significantly reduced the likelihood of receiving penalties as a result of non-compliance. We further found that non-compliance with direct payment rules could hardly be explained by farm size or farm types. Information about the reasons for farmers' non-compliance with direct payment regulations can help the government develop targeted measures to increase the effectiveness of policy measures.

1. Introduction

To reduce the negative environmental impacts of agricultural production on land use and enhance animal welfare, agricultural policies in Switzerland and the EU introduced cross-compliance standards in their direct payment schemes in 1999 and 2005, respectively (Bartolini et al., 2012). Since then, Swiss farmers have received direct payments only if they comply with environmental regulations (i.e. restrictions on fertiliser and pesticide use and a minimum ecological focus area of 7% of the agricultural area used) (Ritzel et al., 2020; El Benni et al., 2022). In addition to the cross-compliance system, a number of voluntary agri-environmental programmes have been introduced in the last 20 years to preserve biodiversity on farmland or landscape quality or to promote animal welfare. The farmers participating in these programmes receive agri-environmental payments provided that they meet specific requirements (i.e. observing regulations on fertiliser and pesticide use and the mowing of grassland beyond the cross-compliance standards) and provide proof of eligibility (Mack et al., 2021). To ensure that farmers comply with direct payment regulations, governmental authorities monitor farmers by conducting regular on-farm inspections, for which farmers need to (i) provide various forms of documentation and (ii) accompany inspectors during visits (Mack et al., 2019a,b; El Benni et al., 2022). If non-compliance with regulations is identified, it typically results in a fine that includes a reduction in direct payments. Non-compliance with direct payment regulations is not only a civil offence but also of political interest because farmers who receive direct payments without meeting environmental regulations reduce the effectiveness of policy measures and may cause harm to the environment and to animals. Non-compliance also increases administrative transaction costs for governmental authorities and farmers because of follow-up inspections.

According to Elffers et al. (2003, p. 410), non-compliance with any

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law might be caused by two reasons: 'errors, whether due to lack of knowledge or concern, or deliberate or wilful non-compliance'. Information about the reasons why farmers do not comply with direct payment regulations would help the government develop targeted measures to increase the effectiveness of policy measures and reduce public and private administrative costs. To the best of our knowledge, there is no literature investigating the factors influencing farmers' non-compliance with agricultural policy regulations. A better understanding of the reasons for farmers' non-compliance is important to increase the effectiveness of direct payment measures, minimise the negative environmental effects of agricultural land use, and reduce public and private administrative transaction costs.

The aim of this study, therefore, is to improve the understanding of farmers' non-compliance with direct payment regulations. We discuss the implications of our findings for governmental authorities so that they can effectively address the motives behind non-compliance. We used data on self-reported compliance with direct payment rules from a paper-and-pencil survey of 808 randomly chosen Swiss farmers in 2019 (Mack et al., 2019a,b). Secondary census data on farm structure and participation in voluntary direct payment programmes were linked to the questionnaire data at the individual farm level.

Previous research focusing on the reasons for non-compliance with regulations in the agri-food sector can be grouped into two strands. The first strand has focused on non-compliance with organic farming regulations (Zorn et al., 2010, 2013; Lippert et al., 2014; Gambelli et al., 2014a, 2014b) and nitrate pollution regulations (Lunn et al., 2020), using data from control bodies or official statistics from enforcement agencies to predict non-compliance. Researchers have concluded that data availability should be extended to examining the personal characteristics of farmers as well as to explaining the risk factors of non-compliance (Gambelli et al., 2014a, 2014b). The second strand of research has focused on non-compliance in the context of pesticide application regulations (Elffers et al., 2003), irrigation regulations (Greiner et al., 2016; Loch et al., 2020), or conservation rules (Solomon et al., 2015) and used self-reported survey data from mostly face-to-face interviews. In this context, researchers are aware that directly asking whether people do or do not comply on the basis of self-reports is difficult (Davis et al., 2019; Moore and Rutherfurd, 2020; Cerri et al., 2021) because they may be reluctant to admit illegal or socially undesirable behaviours. Therefore, researchers have developed specific question techniques that particularly protect respondents' privacy. An overview of the determinants influencing non-compliance based on this strand of literature is provided in Section 2.

Our contribution to these two strands of research is twofold. First, we provide insights into the reasons for farmers' non-compliance with direct payment regulations. Second, we present recommendations regarding the measures that governmental authorities could take to increase the effectiveness and efficiency of direct payment policy measures.

The remainder of this paper is structured as follows. The second section describes the framework of our study and the hypotheses developed. Section 3 shows the data basis and the statistical model, and Section 4 presents the results and discusses them. Finally, Section 5 concludes the paper.

2. Conceptual framework and hypotheses explaining non-compliance

We first provide an overview of relevant factors that influence non-compliance with regulations in the context of agriculture. Second, we describe the influencing factors considered in our study to investigate non-compliance behaviour and justify the exclusion of certain aspects. Based on this, we present the conceptual framework used in the study and build our hypotheses.

The broad literature on factors that influence environmental non-compliance in the context of agriculture has been summarised by various researchers (Greiner et al., 2016; Zorn et al., 2010, 2013; Lippert et al., 2014; Gambelli et al., 2014a, 2014b). However, there is a lack of an integrated and internally consistent compliance theory that could account for the economic, emotional, and normative dimensions of non-compliance (Etienne, 2011; cited in Greiner). As an analytical framework for analysing compliance behaviour, the so-called Table of Eleven (T11) questionnaire was used by some researchers (Elffers et al., 2003; Greiner et al., 2016). T11 considers 11 influencing factors and was developed by Dutch regulators to analyse reasons for non-compliance to improve regulations (Ruimschotel et al., 1996; Elffers and Ruimschotel, 1997). Elffers et al. (2003) described T11 as a systematic list of elements that form part of a valuation function for comparing compliance and non-compliance options with regulations that are not specific to agriculture. According to Greiner et al. (2016), T11 is conceptually consistent with the literature and includes six influencing factors (T1–T6) representing intrinsic motivators and social compliance forces, and five factors encompassing enforcement dimensions (T7–T11). T11 explains non-compliance behaviour based on knowledge and familiarity with rules (T1), costs and benefits of compliance versus non-compliance (T2), extent of acceptance of the policy/legislation—acceptance of its objective and its effects (T3), respect for official authority (T4), social control (T5), likelihood of being reported by somebody other than the official authorities (T6), likelihood of inspections by the official authorities—both actual and perceived (T7), perceived other likelihood of detection on the basis of an inspection (T8), selectivity (or targeting), i.e., the perceived likelihood of selective inspection following a violation (T9), perceived likelihood of a penalty (fine or other) being issued following detection (T10), and severity of the penalty—in terms of amount of financial damage or damage to reputation (T11).

Researchers, including the developers of the T11, have been well aware that questions on illegal or socially non-desirable behaviours are difficult to ask not only in face-to-face interviews (Brittain et al., 2020) but also in surveys in which there is no direct human interaction (Baruh et al., 2017). Therefore, specific question techniques, such as randomised response techniques, were developed to protect respondents' privacy (Elffers, 2003; Cerri et al., 2021). Based on this knowledge, we developed a leaner approach that considers three influencing factors (T1–T3) from T11 and combines some of the sensitive questions with other questions to draw the participants' focus away from the sensitive context. Specifically, we used a survey of farmers' administrative burden, which was not entirely sensitive in terms of illegal or socially non-desirable behaviours (Mack et al., 2019, 2021; Ritzel et al., 2020). Following the rationale to include only very few sensitive questions, we did not include all 11 items from T11 but instead focused on T1–T3, which capture knowledge, costs and benefits, and acceptability of rules. We further included items on farmer characteristics as proxy variables for farmers' risk aversion and general skills and items on farm characteristics as proxies for opportunity costs of environmental regulations. Items on social control (T5), likelihood of being reported (T6), and enforcement dimensions (T7–T11) were not asked and thus not considered in our study.

We asked only the less-sensitive question of whether non-compliance was ever detected; we did not ask questions on non-detected non-compliance. Following this rationale, we also did not ask for the number and kind of penalties farmers had experienced in the past. The participants were assured full anonymity and data privacy in the cover letter of the survey.

Thus, in this study, we explain the likelihood of receiving penalties through the influencing factors presented in Fig. 1.

First, an important requirement regarding farmers' compliance with direct payment regulations is that they know the policies and rules. A lack of knowledge (T1) can increase the likelihood of receiving penalties due to errors (Elffers et al., 2003). We considered three items to measure farmers' knowledge and familiarity with rules: their knowledge of agricultural policy measures, their knowledge of record obligations, and their knowledge of inspection measures (Table 1). Knowledge of record

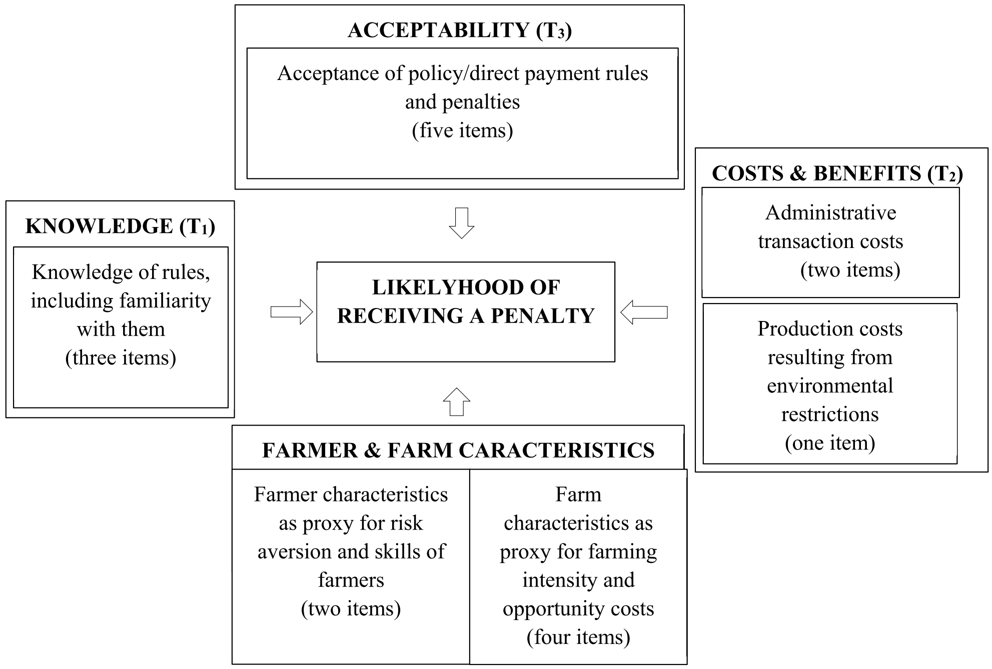

Fig. 1. Conceptual framework of the factors influencing the likelihood that farmers receive penalties.

obligations is crucial for farmers because they have to prove that they meet environmental and animal welfare standards (Mack et al., 2021). For instance, Swiss farmers must annually fill out nutrient balance sheets and biodiversity area reports. Furthermore, they have to provide land plot plans and crop rotation reports. Therefore, we assumed that the better the knowledge of record obligations, the lower the likelihood of receiving a penalty (H1b, Table 1). Knowledge of inspection measures includes farmers' knowledge of the procedure of farm visits by inspectors and the knowledge of the required documentation for on-farm inspections. In Switzerland, site inspections take place at least every four years, during which farmers must provide various forms of documentation and accompany the inspectors to check inspection points. If non-compliance is detected, the government increases the number of on-farm inspections. We assumed that a better knowledge of the procedure of on-farm inspections might decrease the likelihood that farmers receive penalties, because farmers will focus on the restrictions that are monitored during the farm visit (H1b, Table 1). Thus, knowing all the inspection points during the farm visit might not only decrease the likelihood of receiving a penalty but also increase the non-detected non-compliance because farmers are better informed about cheating possibilities. However, because we focused on the less sensitive question of detected non-compliance, this hypothesis could not be tested.

Costs and benefits (T_2) affect non-compliance behaviour. A possible motivation for farmers' non-compliance with environmental regulations might be to avoid the higher production costs associated with the restrictions (Mack and Huber, 2017; Kuhn et al., 2019). Therefore, we considered one item measuring farmers' production costs resulting from environmental restrictions (Table 1). We used the variable 'number of adopted voluntary agri-environmental programmes by farmers' as a proxy for the production costs associated with environmental restrictions, assuming that the higher the adoption rate of agri-environmental programmes, the higher the incentive for farmers to non-comply with regulations. Furthermore, direct payment programmes lead to administrative transaction costs (Coggan et al., 2022). High transaction costs might also lead to non-compliance. For this category, we considered two variables measuring administrative workload (work preparatory to direct payment inspections and workload involving the use of e-government services) (Table 1). Accordingly, we tested H2a–2c, which assumed that the higher the costs of one of the items, the higher the likelihood of receiving a penalty (Table 1).

Third, we considered the acceptability of rules and penalties (T_3). We captured the acceptability of direct payment regulations through five variables measuring the acceptance of agricultural policy, record obligations, inspection measures, entrepreneurial restrictions, and penalties (Table 1). Based on the assumption that it is easier for individuals to follow rules that they consider reasonable (Elffers, 2003), we tested H3a–H3e, which assumed that the higher the acceptance of rules and penalties, the lower the likelihood of receiving a penalty (Table 1).

We further considered the socio-demographic characteristics of the farm managers (i.e. age and educational levels) as proxies for farmers' risk aversion and general skills (Table 1). The discourse on age is mixed. One argument is that the likelihood of receiving penalties because of unintentional errors is higher for older farmers because they have more difficulties coping with the bureaucratic workload and e-government services (Mack et al., 2019a,b, p. 16). Another perspective is that older farmers are more risk-averse and more cautious than younger ones, which leads to a higher likelihood of receiving penalties (Mather et al., 2012). Due to the mixed discourse on age, we suggest a two-sided hypothesis for H4 on age (Table 1). H5 on educational levels assumed that a higher educational level might lead to a lower likelihood of receiving penalties because of fewer unintentional errors due to better administrative and bureaucratic skills, which are of crucial importance for farmers (Forney, 2021). Therefore, we formulated H4 and H5 (see Table 1).

Finally, we included farm characteristics as a proxy for farming intensity and opportunity costs. We assumed that the higher the farming intensity, the higher the opportunity costs of agri-environmental programmes, and thus, the higher the incentive to non-comply with

Table 1
Overview of the tested hypotheses.

H1a	The better the knowledge of record obligations the lower the likelihood of receiving a penalty
H1b	The better the knowledge of inspection measures the lower the likelihood of receiving a penalty
H1c	The better the knowledge of agricultural policy measures the lower the likelihood of receiving a penalty
H2a	The higher the workload for inspections the higher the likelihood of receiving a penalty
H2b	The higher the e-government workload the higher the likelihood of receiving a penalty
H2c	The higher the number of agri-environmental programmes adopted the higher the likelihood of receiving a penalty
H3a	The greater the acceptance of agricultural policy measures the lower the likelihood of receiving a penalty
H3b	The greater the acceptance of inspection measures the lower the likelihood of receiving a penalty
H3c	The greater the acceptance of record obligations the lower the likelihood of receiving a penalty
H3d	The greater the acceptance of entrepreneurial restrictions the lower the likelihood of receiving a penalty
H3e	The greater the acceptance of penalties the lower the likelihood of receiving a penalty
H4	The higher the age the higher the risk aversion resp. the lower administrative skills the higher the likelihood of receiving a penalty
H5	The higher the educational level the lower the likelihood of receiving a penalty
H6	The greater the farm size the higher the likelihood of receiving a penalty
H7	The likelihood of receiving a penalty is higher for combined farms than for specialised farms
H8	The likelihood of receiving a penalty is lower the higher the agricultural zone
H9	The likelihood of receiving a penalty is higher for conventional farms than for non-organic farms

regulations. We considered farm characteristics such as farm size, farm type, organic farming, and agricultural zone (Gambelli, 2014a; El Benni et al., 2022). Farm size might affect compliance costs because the larger the farm, the more complex it is, and the more costly it will be to meet all direct payment regulations. Therefore, we considered H6. We also included farm type, assuming that more specialised farm types (arable crop farms, vegetable/orchard/viticulture farms, dairy farms, suckler cow farms, other cattle farms, horse/sheep/goat farms, and specialised pork/poultry farms) have a lower likelihood of receiving a penalty than combined farm types (combined dairy/arable crop farms, combined pig/poultry farms, and other farms) because the environmental regulations and administrative tasks might be more complex in combined farms than in specialised farms.

Furthermore, we included the variable agricultural zone as a proxy for farming intensity, reflecting that natural and climatic production conditions play an important role in farming intensity. The definition of variable agricultural zones relies on the official Swiss agricultural zone classification, which divides Swiss agricultural land into six zones: plain, hill, mountain I, II, III, and IV (FOAG, 2020). This classification is based on climatic conditions (in particular, length of growing season), accessibility, and land slope (FOAG, 2020). In mountain zones, the natural conditions for agricultural production are more difficult, with a higher zone number. Therefore, farming intensity and opportunity costs for complying with environmental regulations are substantially lower in mountain zones than in plains. Thus, we assumed that the higher the agricultural zone, the lower the incentive for non-compliance with environmental regulations. Finally, we considered organic and conventional farms to be influencing variables, hypothesising that the incentive for non-compliance with environmental regulations is higher in conventional farms.

3. Data basis and methods

Data from a paper-and-pencil questionnaire and census data were used to explain farmers' non-compliance with direct payment regulations. A hierarchical binary logistic regression model was estimated to explain farmers' non-compliance with these regulations. Based on the significance of the estimated parameters, the nine hypotheses were tested. The following sub-sections describe the survey and census data and the specification of the regression model in detail.

3.1. Survey and census data

A paper-and-pencil survey of 2000 randomly selected Swiss farmers was conducted from February 2019 to April 2019. Farmers' contact information was provided by the Swiss Federal Office for Agriculture, which maintains a database of all farm households receiving direct payments, comprising about 98% of all Swiss farms. The farmers received a paper-and-pencil questionnaire via postal mail. The response rate was approximately 40% (N = 808). Our sample of 808 farms is almost representative of the total Swiss farm population in terms of agricultural region, farm type, farm size, farmer's age, and farmer's educational level, suggesting that the distribution of these items in the sample is similar to that of the total farm population (Mack et al., 2019a, b). Secondary census data from 2018 on farm structure and participation in voluntary direct payment programmes were linked to the questionnaire data at the individual farm level.

3.2. Description of the variables

Farmers' non-compliance with direct payment regulations is the binary dependent variable. Accordingly, the survey participants were asked whether they had experienced being penalised because of regulatory non-compliance (i.e. 1 = yes, received a penalty; 0 = no). A total of 798 of the 808 participants responded with either yes or no, with 28% stating that they had experienced receiving penalties (Table 2). Data on the farmers' knowledge of direct payment regulations (T_1) were collected by asking the survey participants to rate three statements capturing different elements of the regulation scheme on a seven-point Likert scale (Table 2). To estimate the administrative effort associated with the direct payment scheme, in the survey, we asked the farmers how much time they had to spend in preparing for the inspections and asked them to rate their workload in the context of e-government services. To investigate farmers' acceptance of direct payment regulations and penalties, we asked them to rate five statements on a seven-point Likert scale (Table 2). To compute the variables of organic production, agricultural zone, farm size, farm type, and participation in voluntary agri-environmental programmes, secondary census data were used.

3.3. Group comparisons

We compared complying (have not received penalties) and non-complying (have received penalties) farmers in terms of their knowledge, acceptance of rules, and farmer and farm characteristics based on

Table 2
Summary statistics of the dependent and independent variables.

			M	SD	%	N	Missing Values
Binary dependent variable: Detected non-compliance with direct payment regulations							
1	Penalty	Have you ever received a penalty because of non-compliance with direct payment rules?				798	10
		Yes = 1			28	223	
		No = 0			72	575	
Independent variables							
Knowledge of regulations, including familiarity with the rules (T_1) [a]							
1	Record obligation	I am informed about current record obligations to provide proof of eligibility for direct payments.	4.8	1.3		797	11
2	Inspection measures	I am well informed about monitoring and inspection measures of direct payment rules.	4.6	1.4		797	11
3	Agricultural policy	I am well informed about the current agricultural policy system.	4.6	1.3		796	12
Costs and benefits (T_2)							
1	Workload inspections[b]	How much time (minutes) do you spend annually to provide all the necessary documents for the inspections?	131	57		801	7
2	E-government workload[c]	How much has the administrative workload changed because of the switch from paper to electronic forms?	4.2	1.5		786	22
3	Agri-environmental programmes	Uptake of voluntary agri-environmental programmes (number)	7.1	2.3		808	
Acceptance of policy/direct payment rules (T_3) [a]							
1	Agricultural policy	I identify myself with the federal direct payment system.	3.6	1.6		792	16
2	Inspection measures	I believe that the current monitoring and inspection measures of the direct payment system are important'	4.2	1.6		793	15
3	Record obligations	I consider current record obligations to provide proof of eligibility for direct payments appropriate.	3.9	1.6		797	11
4	Entrepreneurial restrictions	I do not feel restricted in my entrepreneurial freedom by the current direct payment monitoring and inspection system.	4.5	1.9		797	11
5	Penalties	The penalties in case of non-compliance with direct payments rules are justified.	3.8	1.7		783	25
Farmer characteristics							
1	Age	Years	50	10		796	12
2	Educational level[d]	Educational level	3.6	1.7		784	24
Farm characteristics							
1	Farm size	ha	24.1	18		808	0
2	Farm type (dummy)	Arable crops (Reference)			7.2	58	
		Vegetable/orchard/viticulture			4.5	36	
		Dairy			23.6	191	
		Suckler cows			8.42	68	
		Other cattle			8.8	71	
		Horses/sheep/goats			5.8	47	
		Specialised pork/poultry			3.5	28	
		Combined dairy/arable crops			5.1	41	
		Combined suckler cows/arable crops			3.1	25	
		Combined pigs/poultry			14.7	119	
		Other farms			15.2	123	
3	Organic (dummy)	Production system: organic farming yes = 1			16.5	808	
		No = 0					
4	Agricultural zone (dummy)	Plain zone = reference			45.5	368	
		Hill zone			14.5	117	
		Mountain zone I			11.4	92	
		Mountain zone II			17.8	144	
		Mountain zone III			7.7	62	
		Mountain zone IV			3.1	25	

Notes.
[a] Measured on a seven-point Likert scale from 1 (not correct at all) to 7 (fully correct).
[b] Measured in minutes.
[c] Measured on a seven-point Likert scale from 1 = has become much lower to 7 = has become much higher.
[d] No vocational education and training = 0; Training = 1; Vocational education and training (VET): federal VET certificate = 2; Vocational education and training (VET): federal VET diploma = 3 Federal diploma of professional education and training (PET) = 4 Advanced federal diploma of professional education and training = 5; Higher technical college = 6 University degree = 7.

group mean values. We also tested whether there were significant differences between these two groups using a Wilcoxon rank-sum test (also called the Mann–Whitney *U* test). This was used because it is a nonparametric test that allows for the comparison of two groups without assuming that the values are normally distributed. The test finds significant differences between the two groups for a specific variable without controlling for other variables.

3.4. Hierarchical binary logistic regression model

To test H1–H9 (Table 1), we used a binary logistic regression model. We further applied hierarchical regression to test whether the stepwise implementation of items from T1, T2, T3, and socio-demographic items led to a significant improvement in the model fit (see Wilson and Lorenz, 2015). The latter was measured using the likelihood ratio (LR) test [Pr > LR] when adding additional blocks with variables in the logistic regression model. A *p*-value of 0.05 or lower provides evidence that the model with the additional block of variables performs better than the model without the additional block. We further provided the comparative model fit criteria—Akaike information criterion (AIC) and Bayesian information criterion (BIC). The independent variables were grouped into five blocks.

Table 3
Comparison of farmers with and without penalties for all independent variables: mean values (standard deviations in parentheses), *p*-values, and significant differences based on the two-sample Wilcoxon rank-sum test (also called the Mann–Whitney *U* test) for ordinally scaled variables and based on the chi-square test for dummy variables.

	Farmers without penalties	Farmers with penalties	*p*-values|
No. Of farms	**566**	**221**	
Record obligations	**4.84 (1.27)**	**4.72 (1.29)**	**0.200**
Inspection measures	4.65 (1.33)	4.31 (1.42)	0.004***
Policy measures	4.62 (1.36)	4.57 (1.31)	0.467
Workload inspections	127.7 (53.0)	140.31 (57.9)	0.002***
E-government workload	4.16 (1.53)	4.39 (1.51)	0.039*
Voluntary agri-environmental programmes	7.1 (2.41)	7.3 (2.21)	0.413
Policy measures	3.67 (1.65)	3.42 (1.58)	0.075
Inspection measures	4.26 (1.53)	4.01 (1.65)	0.060
Record obligations	3.96 (1.61)	3.73 (1.67)	0.090
Entrepreneurial restrictions	3.6 (1.86)	3.1 (1.87)	0.000***
Penalties	4.03 (1.71)	3.36 (1.73)	0.000***
Age	49.4 (10.57)	50.7 (9.02)	0.231
Educational level	3.7 (1.55)	3.4 (1.39)	0.007***
Farm size	23.5 (17.9)	25.8 (18.4)	0.016*
Farm type			
Arable crops	0.06 (0.24)	0.09 (0.29)	0.174
Vegetable/orchard/ viticulture	0.05 (0.22)	0.03 (0.16)	0.109
Dairy	0.23 (0.42)	0.23 (0.42)	0.745
Suckler cows	0.08 (0.27)	0.09 (0.28)	0.790
Other cattle	0.09 (0.28)	0.09 (0.28)	0.981
Horses/sheep/goats	0.07 (0.26)	0.02 (0.14)	0.005***
Specialised pork/poultry	0.04 (0.19)	0.02 (0.14)	0.206
Combined dairy/arable crops	0.05 (0.22)	0.05 (0.21)	0.973
Combined suckler cows/ arable crops	0.03 (0.17)	0.03 (0.18)	0.689
Combined pigs/poultry	0.13 (0.34)	0.18 (0.38)	0.075
Other farms	0.14 (0.35)	0.16 (0.37)	0.529
Organic	0.18 (0.02)	0.14 (0.02)	0.150
Plain zone	0.43 (0.02)	0.51 (0.03)	0.045*
Hill zone	0.15 (0.01)	0.13 (0.02)	0.407
Mountain zone I	0.11 (0.01)	0.13 (0.02)	0.347
Mountain zone II	0.19 (0.02)	0.14 (0.02)	0.076
Mountain zone III	0.08 (0.01)	0.05 (0.02)	0.132
Mountain zone IV	0.03 (0.07)	0.04 (0.01)	0.689

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

- Block I: Variables on knowledge (T_1)
- Block II: Variables on costs and benefits (T_2)
- Block III: Variables on acceptance (T_3)
- Block IV: Variables on farmer characteristics
- Block V: Variables on farm characteristics

For the hierarchical logistic regression model, we used the nestreg logit command in Stata. The nestreg command fits nested models by sequentially adding blocks of variables and then reporting the comparison tests between the nested models (StataCorp, 2021). The variables of T_1 (knowledge), T_2 (costs and benefits), and T_3 (acceptance) were not aggregated to a latent construct because we were interested in estimating the influence on single items. We tested for multicollinearity among the independent variables by calculating the variance inflation factor (VIF) based on a linear regression model. This is possible because multicollinearity does not depend on the nature of the model; rather, it relies on the covariance matrix of the predictor variables. The VIF for all variables was below 4. This is below the commonly recommended threshold of 10 for multiple regression analysis (e.g. Chatterjee and Hadi, 2012), suggesting that multicollinearity was not an issue.

4. Results

4.1. Differences between farmers with and without penalties based on group comparisons

Table 3 provides the mean values of the farmers with penalties and without penalties for all independent variables and the significant differences based on the Wilcoxon rank-sum test for ordinally scaled variables and the chi-square test for dummy variables. In total, 28% of the respondents stated that they had received penalties because of non-compliance with direct payment requirements in the past.

The group comparisons showed that self-reported knowledge regarding inspections was significantly lower in the non-complying group than in the complying group, whereas no difference was found for knowledge regarding record obligations and agricultural policy. These results indicate that errors resulting from a lack of knowledge regarding inspections might play a role in receiving penalties. We further found that non-complying farmers required significantly more time (on average, 13 min more) to prepare documents for direct payment inspections. In addition, the non-complying group perceived the administrative workload resulting from the change to e-government services as significantly higher than the complying group did. However, we did not find any differences in the uptake of voluntary agri-environmental programmes between the two groups.

Regarding the acceptance of agricultural policy, inspections, and record obligations, we did not find a significant difference between the two groups. By contrast, we found that non-complying farmers had significantly more problems accepting the restrictions to their entrepreneurial freedom resulting from the direct payment system and its penalties. This finding indicates that compared with the group of farmers not receiving penalties, the group receiving penalties might perceive the direct payment system as more restrictive. Although no difference in age was observed, farmers who had received penalties in the past were, on average, significantly less educated than farmers without penalties. We also found that non-complying farms tended to be larger, while no differences could be found for most of the farm types considered. Only one farm type (horses/sheep/goats) received significantly fewer penalties.

We found no difference between farms with and without penalties regarding the percentage of organic farms. However, farms in the plain region seem to have received significantly more penalties, whereas for

Table 4
Results of the hierarchical binary logistic regression model: Model fit measured by Pr > LR chi square when adding additional blocks into the logistic regression model (dependent variable: penalty = yes/no).

Block	LL	LR	df	Pr > LR	AIC	BIC
Block I: Knowledge (T1)	−421.17	11.09	3	0.0113	850.35	868.61
Block II: Costs and benefits (T2)	−414.73	12.9	3	0.0049	843.45	875.41
Block III: Acceptance (T3)	−407.00	15.45	5	0.0086	838.00	892.79
Block IV: Farmer characteristics	−402.57	8.86	2	0.0119	833.14	897.05
Block V: Farm characteristics	−392.42	20.29	17	0.2597	846.84	988.37

LL: Log likelihood; LR: Likelihood ratio (LR) test, df: Degree of freedom; Pr > LR: *p*-value, which is compared with a critical value to determine whether the overall model is statistically significant. Blocks I–IV are statistically significant because the *p*-value is less than 0.05. Block V is not statistically significant.

the other regions, we did not find a significant difference.

4.2. Predictors of the likelihood that farmers receive penalties

The results of the model fit of the hierarchical binary logistic regression models are shown in Table 4. Five different blocks were tested for their contributions to non-compliance with direct payment requirements. When only items of Block I (knowledge) were used, the hierarchical binary logistic regression model was statistically significant at the 0.05 level compared with the intercept-only model (Table 4). When items of Block II (costs and benefits) were added to the model, the overall model was statistically significant at the 0.001 level compared with Model I. When items of Block III (i.e. items of T3) were added, the overall model was statistically significant (compared with Model II, including Blocks I and II), indicating that Block III led to an improvement in the model fit. Furthermore, adding Block IV (farmer characteristics) items led to an improvement in the model fit, whereas adding Block V (farm characteristics) items could not improve the model fit (compared with a model with Blocks I–IV).

The parameters estimated for the different farm and farmer characteristics of the hierarchical binary logistic regression are provided in Table 5. For the interpretation of the model estimates, we report the average marginal effects of the independent variables. We used Stata's margin command to obtain the average marginal effect for the independent variables. In general, the average marginal effect is the expected difference in outcome probability associated with a 1-unit increase in the independent variable, adjusted to the sample distributions of all the variables in the model. A positive marginal effect signifies an increase in the probability, whereas a negative marginal effect signifies a decrease in the probability, with a 1 unit increase in the independent variable. The interpretations for dummy and continuous variables differ slightly. For dummy variables, margins actually calculate the outcome values at the values of the independent variables that differ by 1 and take their differences. For continuous variables, margins estimate the first partial derivative of the probability with respect to the independent variable. Table A1 in the Appendix shows estimated coefficients of the logistic regression and standard errors of the binary logistic regression model. The magnitude and significance of the marginal effects did not substantially change when an additional block of variables was included in the model. This implies that the estimated marginal effects were robust.

We found that knowledge of the procedure of farm visits by inspectors significantly reduced the probability of receiving a penalty, whereas knowledge of record obligations to provide proof of eligibility for direct payments or knowledge of current agricultural policy measures did not influence the likelihood of receiving a penalty. More precisely, if knowledge of inspection measures increases by one unit, the likelihood of receiving a penalty is significantly reduced by four to five percentage points (Table 5).

Within Block II (costs), we found that farmers' administrative workload to prepare documents for on-farm inspections significantly increased the likelihood of non-compliance. An increase in the administrative workload by 10 min increases the likelihood of non-compliance by ten percentage points. The results of the binary logistic regression show that if the acceptance level for entrepreneurial restrictions increased by one unit, the likelihood of receiving a penalty was significantly reduced by 1.8–1.9 percentage points (Table 5); however, an increase in the acceptance of penalties had an even higher negative effect on non-compliance (−3.4 percentage points).

Introducing the fourth block on farmer characteristics revealed that a higher educational level reduced the likelihood of non-compliance. By contrast, we did not find a statistically significant effect of age on the likelihood of receiving a penalty. Introducing the fifth block revealed that farm size did not have a significant effect on the likelihood of receiving a penalty. We also found that in combined farm types (combined dairy/arable crops; combined suckler cows/arable crops, combined pigs/poultry) the likelihood of receiving a penalty is not significantly higher than in specialised farms.

We did not find that organic farming and agricultural zones influence the likelihood of receiving a penalty. We found that only Mountain zone II had a significantly lower likelihood of receiving a penalty than in the plain region.

5. Discussion and limitations of the study

Almost one third of the respondents (28%) stated that they had previously received a penalty. This relatively high number of self-reported (detected) non-compliance indicates that either the farmers did not perceive this question on penalties as sensitive or they trusted the data privacy policy of the study. The results are in line with those of 2016, in which 16% of Swiss farms were sanctioned by authorities (Forney, 2021).

The significant negative effect of knowledge on inspection measures on the probability of receiving a penalty can be explained by the fact that inspectors decide on penalties based on the results of on-farm inspections. Moreover, during visits, farmers are often informed about the reasons they receive penalties. Thus, improving knowledge of inspection measures and penalties may not only reduce errors but may also have deterrent effects. These results are in line with those obtained by Greiner et al. (2016), who found in interviews with Australian farmers that better knowledge of penalties helps to reduce non-compliance. Accordingly, we cannot reject H1b, which states that better knowledge of inspection measures lowers the likelihood of receiving a penalty (Table 6). However, one limitation of our study is that we could not investigate the influence of the knowledge of inspection measures on the non-detected non-compliance rate.

We also cannot reject H2a, which posits that farmers' administrative workload to prepare documents for on-farm inspections increases the likelihood of receiving a penalty. These results also indicate that farmers with penalties were less informed about the documents required for inspections and thus required significantly more time to prepare them. However, the results imply that a higher workload for e-government services and the adoption of more agri-environmental programmes do not lead to a higher probability of receiving a penalty; therefore, H2b and H2c were rejected.

Further, our results support H3d and H3e, indicating that the higher the acceptance of entrepreneurial restrictions and penalties, the lower the likelihood of non-compliance. The results might also indicate that farmers' detected non-compliance is associated with a legitimacy problem of the regulatory authorities. Against this background, the results reveal that penalties cannot serve as deterrents for all farmers. An increase in penalty intensity may be necessary to address this challenge. Similarly, H5 remains valid, as a higher educational level was associated with a lower likelihood of non-compliance. The results indicate that errors in the implementation of direct payment obligations, which lead to penalties, might be relevant and that targeted administrative training for less educated farmers could reduce penalties.

However, we have to reject the two-sided hypothesis of age. Introducing the fifth block showed that farm characteristics could not explain the non-compliance of farmers. These results are in line with those of previous research (Gambelli et al., 2014a), indicating that non-compliance with organic production rules could hardly be explained by farm characteristics.

A limitation of our research is that we did not consider the different subject matters of non-compliance (i.e., incorrect carry-over of a value instead of use of a chemical in excess of the permitted limit). Consequently, we could not link these topics to the factors included in our research. However, this might be a starting point for further research.

An overview of the rejected and non-rejected hypotheses is shown in Table 6.

Table 5
Results of the hierarchical binary logistic regression model (average marginal effects). Dependent variable – Penalty: yes = 1/no = 0.

Variables	Model I	Model II	Model III	Model IV	Model V
Block I: Knowledge of regulations					
Record obligations	0.018	0.021	0.021	0.022	0.029
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Inspection measures	−0.054***	−0.050***	−0.041**	−0.040**	−0.043**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Agricultural policy measures	0.009	0.004	−0.003	7.95e-05	−0.005
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Block II: Costs and benefits					
Workload inspections		0.001***	0.001**	0.001***	0.001**
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
E-government workload		0.013	0.005	0.002	0.003
		(0.011)	(0.012)	(0.012)	(0.015)
Agri-environmental programmes		0.005	0.004	0.007	−0.001
		(0.007)	(0.007)	(0.007)	(0.009)
Block III: Acceptance					
Agricultural policy measures			−0.009	−0.012	−0.005
			(0.011)	(0.011)	(0.011)
Record obligations			0.012	0.011	0.009
			(0.013)	(0.013)	(0.013)
Inspection measures			0.007	0.011	0.012
			(0.014)	(0.014)	(0.014)
Entrepreneurial restrictions			−0.018*	−0.019**	−0.019**
			(0.010)	(0.010)	(0.010)
Penalties			−0.034***	−0.034***	−0.033***
			(0.011)	(0.011)	(0.011)
Block IV: Farmer characteristics					
Educational level				−0.029**	−0.033***
				(0.012)	(0.012)
Age				0.002	0.002
				(0.002)	(0.002)
Block V: Farm characteristics					
Farm size					0.001
					(0.001)
Vegetable/orchard/viticulture					−0.103
					(0.105)
Dairy					−0.038
					(0.074)
Suckler cows					−0.002
					(0.090)
Other cattle					0.019
					(0.089)
Horses/sheep/goats					−0.255**
					(0.123)
Specialised pork/poultry					−0.164
					(0.122)
Combined dairy/arable crops					−0.069
					(0.091)
Combined suckler cows/arable crops					0.032
					(0.107)
Combined pigs/poultry					0.000
					(0.073)
Other farms					−0.007
					(0.072)
Organic					−0.002
					(0.052)
Hill zone					−0.064
					(0.053)
Mountain zone I					−0.022
					(0.059)
Mountain zone II					−0.102*
					(0.058)
Mountain zone III					−0.098
					(0.078)
Mountain zone IV					0.030
					(0.101)
Constant	−0.339	−1.441***	−0.461	−0.671	−0.137
	(0.367)	(0.531)	(0.626)	(0.762)	(0.863)
Observations	710	710	710	710	710
LR chi square	11.09	23.98	39.43	48.3	68.59
Pr > LR chi square	0.0113	0.0005	0.0000	0.0000	0.0001
Pseudo R2 (McFadden R2)	0.013	0.0281	0.0462	0.0566	0.0804

Standard errors of average marginal effects in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 6
Overview of the hypotheses that were rejected and not rejected.

H1a	The better the knowledge of record obligations the lower the likelihood of receiving a penalty	H1a rejected
H1b	**The better the knowledge of inspection measures the lower the likelihood of receiving a penalty**	**H1b not rejected**
H1c	The better the knowledge of agricultural policy measures the lower the likelihood of receiving a penalty	H1c rejected
H2a	**The higher the workload for inspections the higher the likelihood of receiving a penalty**	**H2a not rejected**
H2b	The higher the e-government workload the higher the likelihood of receiving a penalty	H2b rejected
H2c	The higher the number of agri-environmental programmes adopted the higher the likelihood of receiving a penalty	H2c rejected
H3a	The greater the acceptance of agricultural policy measures the lower the likelihood of receiving a penalty	H3a rejected
H3b	The greater the acceptance of inspection measures the lower the likelihood of receiving a penalty	H3b rejected
H3c	The greater the acceptance of record obligations the lower the likelihood of receiving a penalty	H3c rejected
H3d	**The greater the acceptance of entrepreneurial restrictions the lower the likelihood of receiving a penalty**	**H3d not rejected**
H3e	**The greater the acceptance of penalties the lower the likelihood of receiving a penalty**	**H3e not rejected**
H4	The higher the age the higher the risk aversion resp. the lower administrative skills the higher the likelihood of receiving a penalty	H4 rejected
H5	**The higher the educational level the lower the likelihood of receiving a penalty**	**H5 not rejected**
H6	The greater the farm size the higher the likelihood of receiving a penalty	H6 rejected
H7	The likelihood of receiving a penalty is higher for combined farms than for specialised farms	H7 rejected
H8	The likelihood of receiving a penalty is lower the higher the agricultural zone	H8 rejected
H9	The likelihood of receiving a penalty is higher for conventional farms than for non-organic farms	H9 rejected

6. Conclusions and policy implications

To reduce the negative environmental impacts of agricultural production on land use, Switzerland and the EU introduced environmental regulations in their direct payment policy schemes. Non-compliance with agricultural direct payment regulations reduces the effectiveness of policy measures and creates public and private administrative transaction costs. Therefore, improving the understanding of the reasons why farmers do not comply with direct payment regulations can help the government develop targeted measures to increase the effectiveness of direct payment policies and reduce administrative transaction costs. Based on self-reported survey data, we identified the factors influencing non-compliance with direct payment regulations using hierarchical logistic regression.

Our study of Switzerland provided various levers for reducing the likelihood of receiving penalties associated with non-compliance with direct payment regulations. Our findings initially indicated that improving farmers' knowledge of on-farm inspections would significantly reduce the likelihood of receiving penalties. Therefore, providing farmers with detailed information regarding on-farm inspection measures and the reasons for penalties would help reduce these penalties. Overall, this should lead to greater effectiveness and efficiency of the direct payment policy. Second, we found that farms that had more difficulties with the administrative workload related to the preparation for on-farm inspections were more likely to receive penalties. Thus, another starting point would be to simplify the necessary administrative requirements and provide specific support for farmers who encounter difficulties with administrative tasks. Third, our results indicate that the likelihood of receiving penalties could be reduced if farmers consider entrepreneurial restrictions reasonable for protecting the environment. Thus, authorities (e.g. agricultural schools and extension services) should always provide explanations of why restrictions are relevant and important to protect the environment. Fourth, investing in higher education can also reduce the probability of receiving penalties, thus decreasing private and public administrative transaction costs. The results of this study are relevant not only for Switzerland but also for the EU, where non-compliance with direct payment regulations might also play a role.

Author statement

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere. We also did not use AI for writing the text.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We understand that the Corresponding Author is the sole contact for the Editorial process. He/she is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

Appendix

Table A1
Results of the hierarchical binary logistic regression model: Estimated coefficients of the logistic regression, standard errors in parentheses.
Dependent variable – Penalty: yes = 1 / no = 0

Variables	Model I	Model II	Model III	Model IV	Model V
Block I					
Record obligations	0.089	0.104	0.107	0.115	0.156
	(0.089)	(0.090)	(0.091)	(0.092)	(0.096)
Inspection measures	*−0.267****	*−0.253****	*−0.213***	*−0.211***	*−0.234***
	(0.087)	*(0.087)*	*(0.091)*	*(0.092)*	*(0.095)*
Agricultural policy measures	0.047	0.019	−0.014	0.000	−0.026

(*continued on next page*)

Table A1 (*continued*)

Variables	Model I	Model II	Model III	Model IV	Model V
	(0.076)	(0.077)	(0.078)	(0.080)	(0.083)
Block II					
Workload inspections		*0.005****	*0.004***	*0.004****	*0.004***
		(0.002)	*(0.002)*	*(0.002)*	*(0.002)*
E-government workload		0.068	0.024	0.012	0.017
		(0.057)	(0.060)	(0.060)	(0.062)
Agri-environmental programs		0.024	0.020	0.038	−0.004
		(0.036)	(0.037)	(0.038)	(0.048)
Block III					
Agricultural policy measures			−0.045	−0.063	−0.024
			(0.056)	(0.057)	(0.060)
Record obligations			0.063	0.055	0.046
			(0.069)	(0.070)	(0.072)
Inspection measures			0.036	0.056	0.064
			(0.072)	(0.073)	(0.075)
Entrepreneurial restrictions			*−0.093**	*−0.101***	*−0.102**
			(0.051)	*(0.051)*	*(0.052)*
Penalties			*−0.178****	*−0.178****	*−0.178****
			(0.059)	*(0.059)*	*(0.062)*
Block IV					
Educational level				*−0.151***	*−0.176****
				(0.061)	*(0.066)*
Age				0.011	0.011
				(0.009)	(0.009)
Block V					
Farm size					0.005
					(0.005)
Vegetable/orchard/viticulture					−0.550
					(0.567)
Dairy					−0.202
					(0.396)
Suckler cows					−0.011
					(0.481)
Other cattle					0.104
					(0.476)
Horses/sheep/goats					−1.370**
					(0.664)
Specialised pork/poultry					−0.883
					(0.659)
Combined dairy/arable crops					−0.369
					(0.487)
Combined suckler cows/arable crops					0.174
					(0.572)
Combined pigs/poultry					0.00125
					(0.394)
Other farms					−0.037
					(0.384)
Organic					−0.012
					(0.279)
Hill zone					−0.343
					(0.286)
Mountain zone I					−0.118
					(0.314)
Mountain zone II					−0.550*
					(0.311)
Mountain zone III					−0.528
					(0.421)
Mountain zone IV					0.160
					(0.543)
Constant	−0.339	−1.441***	−0.461	−0.671	−0.137
	(0.367)	(0.531)	(0.626)	(0.762)	(0.863)
Observations	710	710	710	710	710
LR chi2	11.09	23.98	39.43	48.3	68.59
Pr > LR chi2	0.0113	0.0005	0.0000	0.0000	0.0001
Pseudo R2	0.013	0.0281	0.0462	0.0566	0.0804

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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