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Factors influencing the simultaneous adoption of risk management instruments in Mediterranean irrigated agriculture

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Abstract

Agriculture is highly impacted by different sources of risk. There is a wide variety of management instruments that farmers can use to cover these risks. The objective of this paper is to analyze the explanatory variables for the simultaneous adoption of a large set of risk management instruments. The main innovation is the methodological approach: first, we apply a hierarchical cluster analysis to identify the groups of instruments whose adoption is correlated; second, we use multivariate probit models to analyze the influence of different factors on the simultaneous adoption of the instruments included in each cluster. The explanatory variables capture farmers' socio-demographic features, risk aversion and subjective perception of past risk experience; farms' technical-economic characteristics; and local-level climate change. The results reveal significant differences in the variables influencing the adoption of the risk management instruments. The findings can support farmers, risk management service providers, and policymakers.

Keywords: adoption decisions; cluster analysis; multivariate probit; risk perception; risk preferences

1 Introduction

Agriculture is an economic activity that is characterized by its high exposure to risk (Hardaker *et al.* 2004); many different sources of risk may negatively affect farmers' income and well-being (OECD 2011). The most widely-accepted classification of agricultural risks (Komarek, De Pinto, and Smith 2020) differentiates between: i) *production risks,* which can derive from extreme meteorological events (e.g., hail, frosts or droughts), pests and diseases, or other yield-limiting factors related to the obsolescence of technology, all of which cause a reduction in agricultural outputs; ii) *market risks*, arising from fluctuations in the market prices for inputs and/or outputs, or from farmers' uncertainty regarding the purchase conditions imposed by buyers in the value chain; iii) *financial risks*, particularly associated with interest rate volatility, which can raise the cost of the debt assumed by farmers, or the uncertainty regarding access to credit when needed or the value of financial assets; iv) *legal and institutional risks*, related to changes in agricultural policies and regulations; and v) *other risks*, such as those linked to farmers' civil liability or those derived from accidents or other unexpected events (e.g., fires, theft, etc.) that may occur on the farm.

In Spain, farming is especially vulnerable to production and market risks. First, agricultural areas in southern and eastern Spanish regions (the most important regions in the country in terms of farming activity) are particularly affected by production risks arising from meteorological factors. This is due to their Mediterranean climate, with a high frequency of adverse events such as irregular precipitations; i.e., droughts, floods, frosts, or hail storms (Antón and Kimura 2011). In this regard, it should be noted that future climate change projections indicate a higher frequency and intensity of adverse climatic events (mainly droughts) in the near future in these Mediterranean-climate regions (EEA 2019). The resulting increase in water scarcity will exacerbate the vulnerability of agricultural systems that are highly dependent on water resources, such as irrigated agriculture. Second, circumstances such as progressive trade liberalization, stronger international competition in agricultural markets (i.e., production specialization), and increased market speculation due to the greater involvement of institutional investors (the so-called "financialization" of agricultural markets) inevitably generate higher volatility in agricultural prices. These conditions lie at the core of the serious market risks for Spanish farmers (Antón and Kimura 2011). The predicted future trend is that, far from diminishing, market risks are likely to remain high in the coming years (OECD and FAO 2020; Degiannakis *et al.* 2021).

In this highly uncertain environment, farmers—as risk-averse economic agents (Just and Pope 2013)—usually respond by adopting a portfolio of different risk management instruments in order to reduce their exposure to risk and help stabilize their agricultural incomes (Velandia *et al.* 2009). Notable examples of such instruments include crop diversification, crop insurance, and precautionary savings (a complete list of instruments available to farmers, as well as a description of each one, is provided in Section 2.1).

In this respect, a recurrent question raised in the related literature concerns the factors that influence farmers' adoption of the various risk management instruments (e.g., socio-demographic variables such as farmers' age; technical-economic features such as farm size; farmers' risk perception; or farmers' risk attitude—these variables are detailed below in Section

2.2). However, despite the extensive literature analyzing the factors determining the adoption of risk management instruments in agriculture, the results to date have not been conclusive. As such, more research on the topic is needed.

Moreover, much of the earlier research focused on the adoption of specific risk management instruments, but considering the decisions to adopt different risk management tools as independent of one another (e.g., Asravor 2019; Khan *et al.* 2020). Some studies have considered the simultaneous adoption of several risk management tools available to farmers, but including a very small set of instruments in the analysis (only two or three) (e.g., Velandia *et al.* 2009; Ullah *et al.* 2015; Lu, Latif, and Ullah 2017; Akhtar *et al.* 2019). The reality is that farmers can choose from many risk management instruments (Pennings *et al.* 2008); therefore, the analysis of farmers' risk management decision-making should consider the whole portfolio of these alternatives, taking into account the interrelationships among all the instruments available to farmers. Surprisingly, however, there are very few studies that do so (Meraner and Finger 2017).

Thus, the main objective of this paper is to analyze the factors that may influence the simultaneous adoption of risk management instruments, taking into account the real set of such tools available to farmers and the possible relationships among them. In particular, the analysis considers factors usually accounted for in the literature related to farmers' socio-demographic variables, farms' technical-economic characteristics, subjective perception of risk (relative importance of the different sources of risk for each farmer), risk aversion, and past risk experience. In addition, farmers' perceptions about climate change are also taken into account, since production risks related to climate change are especially relevant in the case study selected for the empirical research, i.e., the irrigated agriculture in the province of Córdoba, a Mediterranean-climate region in southern Spain.

For this empirical study, we collect primary information from a representative sample of irrigation farmers operating in the case study area, gathering data about each producer's adoption of the different risk management instruments available. In a first stage, we apply a hierarchical cluster analysis to identify the groups of instruments whose adoption is closely correlated. In a second stage, we use multivariate probit models to analyze the influence of the different factors on the adoption of different risk management instruments within each cluster, thus taking into account the correlations among the adoption decisions. To the authors' knowledge, this two-stage approach is a methodological innovation in the field of agricultural risk.

The results of this paper contribute to the understanding of the demand for risk management instruments in Mediterranean irrigated agriculture, an agricultural system that remains underexplored. This new knowledge is useful for farmers, risk management service providers, and policymakers. First, this study provides constructive information that can be used in decision-making processes related to the selection of portfolios of risk management instruments for farming. Second, the results of this paper could also help firms providing risk-bearing services to understand the current and potential demand for risk management instruments by farmers (i.e., insurance, off-farm investments, etc.). And third, this study provides valuable insights for policymakers, supporting their decisions regarding the design of policy instruments to promote appropriate risk management in the agricultural sector.

The remainder of the paper is structured as follows. After this introduction, a brief literature review is presented, describing the different risk management instruments analyzed in this paper and the existing evidence on the factors explaining their adoption by farmers (Section 2). Next, the materials used and the methods implemented in this study are explained (Section 3). We then detail the results from the cluster analysis and the multivariate probit models (Section 4), before discussing them (Section 5). Finally, we summarize our conclusions in the last section of the paper (Section 6).

2 Risk management instruments

2.1 Typology of risk management instruments

There is a large set of instruments available to farmers to help them manage the risks they face. These instruments are usually classified as follows (Meraner and Finger 2017):

- *On-farm agricultural risk management instruments*. This category includes: i) technological optimization, i.e., the employment of productive technologies that make it possible to increase the efficiency of the farm, minimizing the negative effects of production risks (e.g., optimal irrigation programming and adjustment of fertilizer doses); ii) good management practices, which are production methods designed to enhance the use of resources on the farm and appropriately manage production risks (e.g., implementation of integrated pest management or conservation tillage systems); iii) use of seed varieties resistant to stressful situations such as droughts or specific pests; and iv) crop diversification to reduce downside yield risk derived from production and market risks related to particular crops.

- *On-farm non-agricultural risk management instruments*. This group comprises: i) forward contracts, i.e., agreements between the seller (farmer) and the buyer (any firm in the value chain) that set the conditions for the sale of the agricultural production (price, quantity, or delivery date) to protect the farmer from market risks; ii) sales through cooperatives, whereby being a member of a cooperative and using its sale channel helps the farmer to deal with market risks; and iii) precautionary savings, i.e., the maintenance of a certain level of cash reserves by smoothing consumption to be prepared for any kind of contingency that could entail farm income losses.
- *Off-farm risk management instruments*. Within this category, the following instruments can be highlighted: i) agricultural insurance, a risk-transfer mechanism designed to cover economic damage on the farm that may be caused by meteorological events such as frost or hail (production risks) and/or agricultural price crises (market risks); ii) other insurance schemes, including civil liability, life, health, or fixed assets insurance; iii) contribution to a private pension fund so that the farmer receives a supplement to the public pension when he/she retires; iv) off-farm employment; and v) off-farm investments—the latter two instruments are strategies to increase and diversify farm household income.

Overall, these risk management instruments may reduce farmers' exposure to risk, minimizing their vulnerability, and helping to stabilize farm household income. Selecting the best portfolio of these risk management instruments is one of the most complex decisions that a farmer has to make (Pennings *et al.* 2008). Nevertheless, under the current context of growing risks due to climate change, this decision-making is becoming more and more important, and key to successfully adapting to a changing future (Varela-Ortega *et al.* 2016; EEA, 2019).

2.2 Factors explaining the adoption of risk management instruments

There is extensive literature focusing on the factors influencing farmers' adoption of risk management instruments (for a recent state-of-the-art review, see Duong *et al.* 2019). However, as stated previously in the Introduction section, most research is based on the individual adoption of specific risk management instruments.

Previous research works analyzing farmers' decision-making regarding the adoption of these instruments take into account the following categories of influential factors (van Winsen *et al.* 2014; Meraner and Finger 2017): i) farmers' socio-demographic characteristics; ii) farms' technical-economic variables; iii) farmers' risk perception; iv) farmers' risk attitude; and v) farmers' past risk experience.

First, farmers' socio-demographic characteristics include variables such as their age, level of education, household size, farming experience, or household income (e.g. Velandia *et al.* 2009; Asravor 2019; Adnan *et al.* 2020). Second, farms' technical-economic variables typically comprise farm size, farm output, crops grown, and land ownership (van Asseldonk *et al.* 2016; Akhtar *et al.* 2019). In this study we have also considered additional variables such as the habitat (urban vs. rural) or the percentage of non-family labor over total farming labor.

Third, farmers' risk perceptions have also been taken into account as variables measuring their subjective interpretation of the probabilities of risk exposure, which are influenced by their culture, beliefs, value systems, and the objective risk the decision-maker is facing (Meraner and Finger 2017; Asravor 2019). The theoretical basis of the concept of risk perception lies in the subjective expected utility (SEU) theory, which states that when individuals make decisions under uncertainty (e.g., choosing risk management instruments), they take into account their subjective risk perceptions because the objective risk measures are unknown.

Fourth, as proposed by the expected utility theory (EUT), risk attitude (i.e., risk aversion) may also play a key role in understanding farmers' decision-making regarding the adoption of risk management instruments (Akhtar *et al.* 2019; Khan *et al.* 2020). Risk-averse farmers could be expected to show more intense preferences for less risky alternatives, although they imply forgoing some income. Thus, risk aversion may favor the adoption of risk management instruments.

Finally, farmers' past risk experience—that is, experiences related to relevant income losses suffered in the recent past as a consequence of the different sources of risks—is another variable often posited to be an influential factor on farmers' decision to adopt risk management instruments (Meraner and Finger 2017).

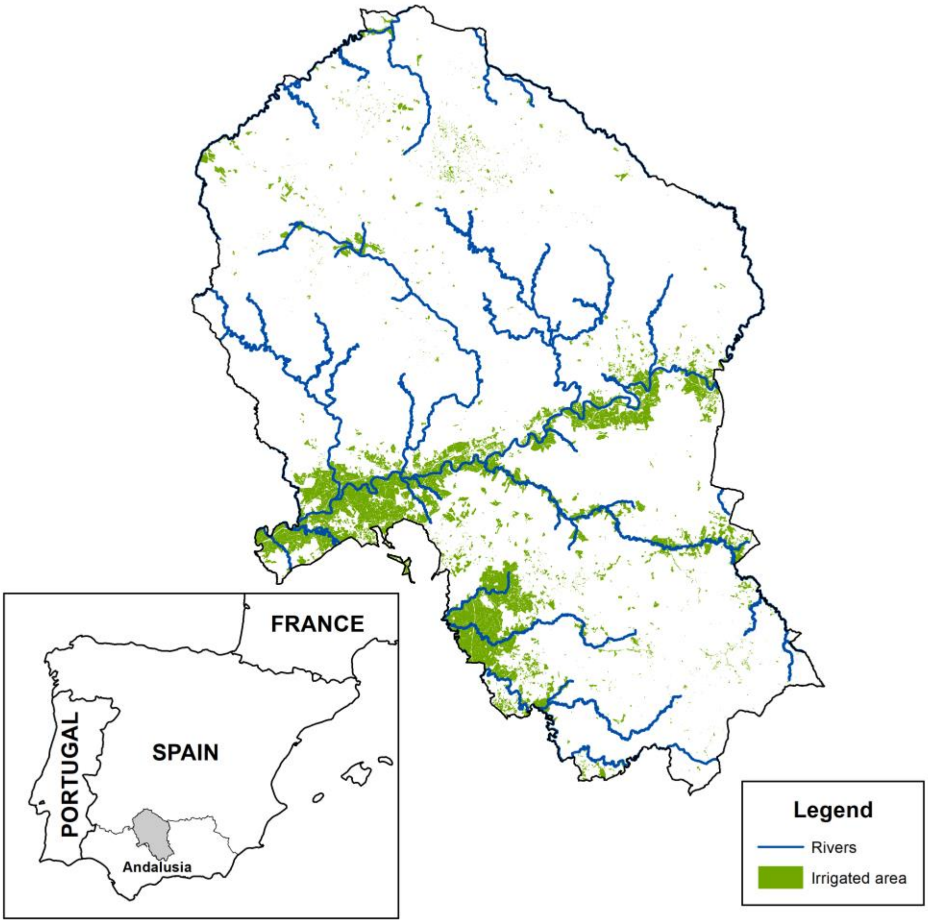
Overall, the analysis of influential factors on the adoption of risk management instruments in agriculture has been broadly addressed in the literature. However, research to date is inconclusive regarding how those factors affect farmers' decision-making. Moreover, as stated above, there is a dearth of studies analyzing the simultaneous adoption of multiple risk management tools from the whole set of instruments available to farmers. In this paper, we attempt to fill this research gap.

3 Material and methods

3.1 Case study

The irrigated agriculture of the province of Córdoba (see map in Figure 1) is used as a case study in this paper. According to data from the last agricultural census, this agricultural system is managed by a population of 3,369 farmers working 111,451 irrigated hectares. The main crop grown in this case study is olive (44.6% of the irrigated area), followed by cereals, oilseeds, and protein crops (wheat, corn, and sunflower, with 30.1% of the irrigated area), other ligneous crops (mainly orange, with 14.3%), other extensive herbaceous crops (mainly cotton, with 6.6%) and horticultural crops (e.g., potatoes, garlic, or onions, 4.4%).

Figure 1. *Study area: irrigated agriculture in the province of Córdoba (Spain)*.



As in many other Mediterranean and semi-arid climate regions, irrigators in the province of Córdoba must cope with a high level of risk, with production and market risks being the major sources of uncertainty. Among the production risks, the risk of drought (i.e., irrigation water shortage) is the most serious threat in this agricultural system (Quiroga and Iglesias 2009), since the water allotments that farmers receive each irrigation season are highly uncertain and depend on the availability of water in reservoirs. According to the most recent assessments, under the current climate scenario, Cordoban irrigators have a 26.9% probability of being granted irrigation water allotments that are less than 70% of the volume needed to fully satisfy their crop needs (Gómez-Limón 2020). As previously mentioned in the Introduction section, climate change predictions in the Mediterranean basin show that, in the coming years, there will be a gradual decline in rainfall, a progressive increase in temperatures, and a greater frequency and intensity of drought periods. These predicted conditions will have a very negative impact on irrigated agriculture in Southern Spain (Garrote *et al.* 2015), as they imply an increased demand for irrigation water (because of the higher crop water needs), lower availability of water in reservoirs, and a higher frequency of irrigation water supply gaps (because of hydrological droughts). Under these circumstances, there is growing concern among farmers that climate change may jeopardize the future viability of irrigated agriculture in this region. Consequently, farmers need to adopt risk management tools, which may even be considered as climate change adaptation measures (Varela-Ortega *et al.* 2016).

Market risks are equally relevant in this agricultural system, especially affecting farmers growing crops with high price volatility such as fruits and vegetables (perishable products with an inelastic short-term supply), or olives (olive oil competes with other vegetable oils leading to price-elasticity, which is combined with variable annual yields −output production− depending on the crop year).

The joint effect of the various different sources of risk can lead to important income losses for the farmers operating in the case study area. In fact, it is estimated that more than 35% of the farmers in this agricultural system suffer from annual income losses of over 30% (MAPA, 2019), a significantly greater share than the European average (EC, 2017). All of this justifies the choice of irrigated agriculture in the province of Córdoba as an interesting case study for this research.

3.2 Data collection and sample description

In order to collect the data required for the empirical work, a survey of a representative sample of farmers from the case study was carried out. The selected farmers were interviewed face-to-face to complete the questionnaire designed for this study.

The questionnaire was structured in five parts. In the first part, we focused on gathering information about the main characteristics of the farm: size, crop pattern, and labor employed on the farm, among others. In the second, we collected all the data necessary to estimate farmers' subjective perception of the different sources of risk (production, market, financial, institutional and legal, and other risks), as well as the data to calculate the level of individual farmers' risk aversion. In the third part, we explored farmers' past experiences regarding each source of agricultural risk and their perception of climate change locally. In the following section, we included questions regarding the adoption of each of the 12 risk management instruments available to the irrigation farmers in the case study area, grouped according to Meraner and Finger (2017), as shown in Table 2. Finally, we asked about socio-demographic variables, such as gender, age, educational level, and economic dependence on farming, among others.

The farmers' perceptions regarding each source of agricultural risk were measured using the best-worst multicriteria decision-making method (Rezaei 2015), estimating their relative importance as weights summing up to one. Five sources of risk were initially considered: production, market, financial, institutional, and other sources of risk. Since the first three sources of risk were considered the most relevant, accounting for an aggregate weight of more than 75%, they were the only ones included in the quantitative analysis subsequently conducted.

Individual farmers' level of risk aversion was measured by the constant relative risk aversion (CRRA) coefficient, elicited through the lottery-choice task method proposed by Eckel and Grossman (2008). For this purpose, we assume that farmers' attitude to risk can be modeled relying on EUT, using a utility function defined as $U(\pi_i) = ({\pi_i}^{1-CRRA_i})/(1 - CRRA_i)$, where $CRRA_i$ is the Arrow-Pratt coefficient of relative risk aversion ($CRRA_i = -\pi\, U''(\pi)/U'(\pi)$) for farmer *i*, and π_i is the profit from farming activities also for farmer *i* (Moschini and Hennessy 2001). According to existing evidence (e.g., Gollier 2004, p. 31), CRRA typically varies between 0.5 (slightly risk-averse) and 4.0 (extremely risk-averse). Further details about the implementation of this experimental method to the case study considered can be found in Gómez-Limón, Guerrero-Baena, and Sánchez-Cañizares (2020).

The questionnaire was tested on a subsample of 20 farmers to ensure that filling it in did not take more than 30 minutes (to avoid survey fatigue) and that all the questions were easily understood by farmers. On average, it took 25 minutes to fill in the questionnaire, and interviewees affirmed that they understood the questions posed; only minimal changes had to be made to the wording of the initial cheap talk introducing the risk management instruments considered.

To obtain a representative sample of irrigators from the province of Córdoba, a two-phase sampling method was implemented. First, once the size of the sample had been set (n=200), we determined the number of farmers to be interviewed from each of the 21 irrigation districts of the province, using quota sampling based on the size of each irrigation district. Second, the farmers to be interviewed in each irrigation district were selected following a random procedure. The implementation of this second stage was supported by the water user associations (WAUs) operating in Córdoba. They are non-profit organizations that locally manage the water allotments annually granted by the River Basin Agency. The whole population of irrigators analyzed belongs to the same WAU. From their own records, each WAU drew a random subsample of farmers with the size requested by the authors and contacted them to encourage their participation in the survey. This way of approaching the farmers eased the interviewer's introduction to chosen irrigators and meant that only a very few refused to take part in the survey, thus diminishing the risk of selection bias. The survey was administered between October and December 2018, a period that was specifically selected to ensure a high response rate (during these months irrigators have a very low workload). The survey fieldwork was done by a single interviewer hired full-time and specifically trained for this task, ensuring the consistency of the interviews. The final result of this process was 204 completed and validated questionnaires.

Tables 1 and 2 show the descriptive statistics for the variables considered in the study (metric and categorical variables, respectively). As can be seen, the average farmer in the sample is 54.8 years old and manages an agricultural holding of 46.8 hectares with the following crop pattern: 41.2% of the area is cultivated with olive groves, 21.2% with other ligneous crops, 21.0% with cereals, oilseeds, and protein crops, 9.4% with other extensive herbaceous crops, and 7.2% with horticultural crops.

These variables capturing the farmer's age, farm size, and crop pattern were used to assess the representativeness of the sample. When the distributions of the sample were compared with the distributions of the population using chi-square tests, the null hypothesis of equality of distributions was not rejected, except for the case of farm size (census average of 33.1 hectares vs. sample average of 46.8 hectares). However, it is worth pointing out that the exception of farm size does not necessarily indicate a biased sample, but rather may reflect the difference between the legal definition of 'farm' used in the agricultural census and the economic interpretation used in the survey carried out for this paper. While the census records one farm for each individual legally holding a farm, in our survey the farm was defined as the agricultural management unit. This means that many 'economic farms' registered in our survey could be made up of more than one 'legal farm' (i.e., recorded in the census) when they are actually managed by a single farmer (e.g., when both members of a married couple each legally own a farm, but the two farms are managed by just one of them).

Table 1. *Descriptive statistics for metric variables*.

Variable	Measure	Mean	Std. dev.	Min	Max
Farmers' characteristics					
Age	Years	54.8	12.3	21.0	83.0
Household size	Number of people	2.5	1.1	1.0	6.0
Agricultural income over total income	Percentage	62.4	29.2	5.0	100.0
Farm characteristics					
Farm size	Hectares	46.8	85.1	1.0	732.0
Farm gross margin	€/ha	2,013.3	1,872.6	420.4	8,552.0
Variance of farm gross margin	(,000 €/ha)^2	1,815.7	2,634.7	18.7	8,669.1
Non-family labor over total labor	Percentage	63.4	35.8	0.0	100.0
Cultivated area of ligneous crops	Percentage	63.3	43.5	0.0	100.0
Risk perception and risk aversion					
Perception of production risks	Percentage	29.2	15.0	4.3	65.7
Perception of market risks	Percentage	35.7	15.6	4.0	64.7
Perception of financial risks	Percentage	10.4	8.5	2.7	46.7
Constant relative risk aversion coefficient (CRRA)	Adimensional	2.7	2.0	0.3	5.5
Past experience and climate change perception					
In the last 5 years, I suffered important losses because of production risks	Likert 1: strongly disagree to 5: strongly agree	2.1	1.3	1.0	5.0
In the last 5 years, I suffered important losses because of market risks	Likert 1: strongly disagree to 5: strongly agree	2.6	1.4	1.0	5.0
In the last 5 years, I suffered important losses because of financial risks	Likert 1: strongly disagree to 5: strongly agree	1.3	0.7	1.0	5.0
I think that climate change is occurring locally	Likert 1: strongly disagree to 5: strongly agree	3.3	1.4	1.0	5.0

Other relevant socio-economic variables (not included in census data) relate to the farmers' educational level and the percentage of their income that comes from the agricultural activity. Sample data show that the average farmer in the case study area has a low-to-medium educational level (two-thirds of the sample have completed secondary education) and that farming is the main source of income (62.4% of total income).

It is observed that farmers in the sample perceive market risks (average of 35.7% of total perceived risk) and production risks (average of 29.2% of total perceived risk) to be the most relevant. The average CRRA coefficient is 2.7, so farmers in the sample are medium-to-high risk-averse. In addition, most of the interviewed farmers agree that the impacts of climate change are occurring locally.

Table 2. *Sample descriptive statistics for categorical variables*.

Variable	Category	Number of farmers	Percentage
Farmers' characteristics			
Gender	1 = Male	201	98.5
Educational level	0 = Primary	67	32.8
	1 = Secondary	62	30.4
	2 = University	75	36.8
Habitat	1 = Rural (<10.000 population)	118	57.8
Adoption of on-farm agricultural risk management instruments			
Technological optimization	1 = Yes	179	87.7
Resistant seed varieties	1 = Yes	140	68.6
Good management practices	1 = Yes	204	100.0
Crop diversification	1 = Yes	92	45.1
Adoption of on-farm non-agricultural risk management instruments			
Forward contracts	1 = Yes	93	45.6
Sale through cooperatives	1 = Yes	145	71.1
Precautionary savings	1 = Yes	172	84.3
Adoption of off-farm risk management instruments			
Crop insurance	1 = Yes	107	52.5
Other insurance	1 = Yes	163	79.9
Pension funds	1 = Yes	48	23.5
Off-farm employment	1 = Yes	82	40.2
Off-farm investments	1 = Yes	82	40.2

3.3 Analyzing simultaneous adoption of risk management instruments. The agglomerative hierarchical clustering (AHC) method

As the main objective of this paper is to analyze the factors explaining the simultaneous adoption of risk management instruments, the application of a multivariate regression model is needed to account for the potential correlations of adoption decisions. However, the inclusion of all the instruments analyzed together in a single regression model would require the estimation of a large number of coefficients or parameters. Taking into account the limitation of the total valid questionnaires obtained (n=204), such a high number of parameter estimations is simply not feasible, thus ruling out the implementation of a single multivariate regression model with all these instruments as endogenous variables simultaneously. For this reason, an approach is suggested which makes it possible to identify groups of highly correlated instruments that can be evaluated simultaneously in a single regression model; that is, each group comprises a maximum of 3-4 risk management instruments, permitting a robust estimation of the parameters considered.

To explore the correlations among the adoption decisions, the Spearman's rank-order correlation coefficients among the instruments were calculated, revealing statistically significant correlations between many pairs of instruments. Having confirmed this, the analysis of the explanatory factors of simultaneous adoption strategies follows a two-step methodological approach: first, a clustering technique to group instruments with similar characteristics; second, a multivariate regression model to analyze the influence of exogenous variables within the previously identified clusters.

In order to group the risk management instruments analyzed into highly correlated sets of instruments, agglomerative hierarchical clustering (AHC) has been applied. AHC is a clustering method which builds a hierarchy of clusters through a procedure whereby each observation/variable starts in its own cluster, and the two "closest" clusters are then merged successively to form larger clusters, until the final cluster contains all the observations/variables (Nielsen 2016; Hair *et al.* 2018).

The decision about which clusters should be combined is based on a measure of dissimilarity between sets of observations. In the AHC method, this measure is obtained through a specific metric which determines the distance between pairs of observations. After calculating these distances among all pairs of observations, a linkage criterion is defined to establish the dissimilarity as a function of the pairwise distances of observations (Rokach and Maimon 2005).

The most commonly-used metrics in AHC are the Euclidian distance, square Euclidian distance, and the Chebychev, Mahalanobis, Manhattan, and Minkowski distances. The choice of the metric influences the number and structure of the clusters. In this study the metric selected was the squared Euclidian distance:

$$\|a-b\|^2 = \sum_i (a_i - b_i)^2 \quad (1)$$

Among the different options for the linkage criterion (complete/single/unweighted average/weighted average -linkage clustering, etc.), Ward's minimum variance criterion was selected (Ward 1963). This option minimizes the total within-cluster variance, by implementing recursively the Lance-Williams algorithm, where each step entails finding the pair of clusters that leads to a minimum increase in total within-cluster variance after joining (Szekely and Rizzo 2005).

The hierarchical clustering achieved by this AHC procedure is represented graphically through a dendrogram, which depicts it in the form of a tree, with the linkage distance measure on the horizontal axis.

Determining the final number of clusters to adopt is a subjective process. Despite the development of sophisticated methods or algorithms to evaluate cluster solutions, the final decision on the number of accepted clusters usually falls to the researchers (Nielsen 2016; Hair *et al.* 2018). In our case study, the chosen clusters must include fewer than 3-4 instruments to later allow robust estimations of the multivariate regression models.

3.4 Factors explaining simultaneous adoption. The multivariate probit (MVP) regression

After defining the clusters of risk management instruments, the influence of exogenous factors on the simultaneous adoption of the instruments included in each cluster can be modeled through multivariate regression models to minimize the estimation biases due to correlated adoption decisions. At the same time, the error structure of the system should be allowed to be freely correlated to avoid biased estimates. For this purpose, we use multivariate probit (MVP) regression, a popular modeling approach applied to dichotomous correlated data to investigate interdependent strategy adoption decisions (e.g., Velandia *et al.* 2009).

The MVP model is a simultaneous system of *m* binary probits to estimate both the observed and unobserved influence on dependent dichotomous variables by *k* independent variables. It is based on the multivariate normal distribution and is recommended when the endogenous variables are very closely linked and seem to be influenced by the same factors (Mullahy 2016). The general specification according to Greene (2003) can be expressed as:

$$Y_{ij}^{*} = \beta_i X_{ij} + \varepsilon_{ij} \tag{2}$$

where Y_{ij}^{*} (*j*=1,…, *m*) is the dichotomous variable related to the adoption of risk management instrument *j* by farmer *i* (*i* = 1,..., *n*), X_{ij} is a 1 × *k* vector of the observed factors that affect the decision to adopt risk management instrument *j* by farmer *i* (explanatory independent variables), β_i is a *k* × 1 vector of unknown coefficients to be estimated, and ε_{ij} is the vector of unobserved error terms normally distributed with zero mean and constant variance, where the variance-covariance matrix is given as follows:

$$R = \begin{bmatrix} 1 & \cdots & \rho_{1m} \\ \vdots & \ddots & \vdots \\ \rho_{m1} & \cdots & 1 \end{bmatrix} \tag{3}$$

The off-diagonal elements in this matrix ρ_{ij} represent the unobserved correlation rho between the stochastic latent utilities.

The system of equations of the MVP models is estimated using simulated maximum likelihood methods through the *mvprobit* command in Stata 14.0 (Cappellari and Jenkins 2003).

To determine the goodness of fit of the MVP models, two statistics have been calculated: the Wald test and the likelihood ratio (LR) test of correlation coefficients rho. On the one hand, the Wald test approximates the log-likelihood test, testing a null hypothesis where all the parameters in the model are simultaneously equal to zero. This test generates a chi-square value where the degree of freedom is equal to the number of parameters in the full model. If the associated *p*-value is below the significance level, the null hypothesis can be rejected, indicating that the coefficients of the explanatory variables are not simultaneously equal to zero and the inclusion of these variables means a statistical improvement in the fit of the model. On the other hand, the LR test of rho (correlation coefficients between the residuals of each of the *m* binary probits estimated in the MVP model) tests the null hypothesis where these rhos are simultaneously equal to zero, i.e., the error terms are independent. If this null hypothesis is not rejected, each instrument should be estimated in a single individual probit. By contrast, if the *p*-value associated with the chi-square value obtained in the LR test is below the selected significance level, the result supports the use of an MVP model as there is mutual interdependence among the risk adaptation strategies.

4 Results

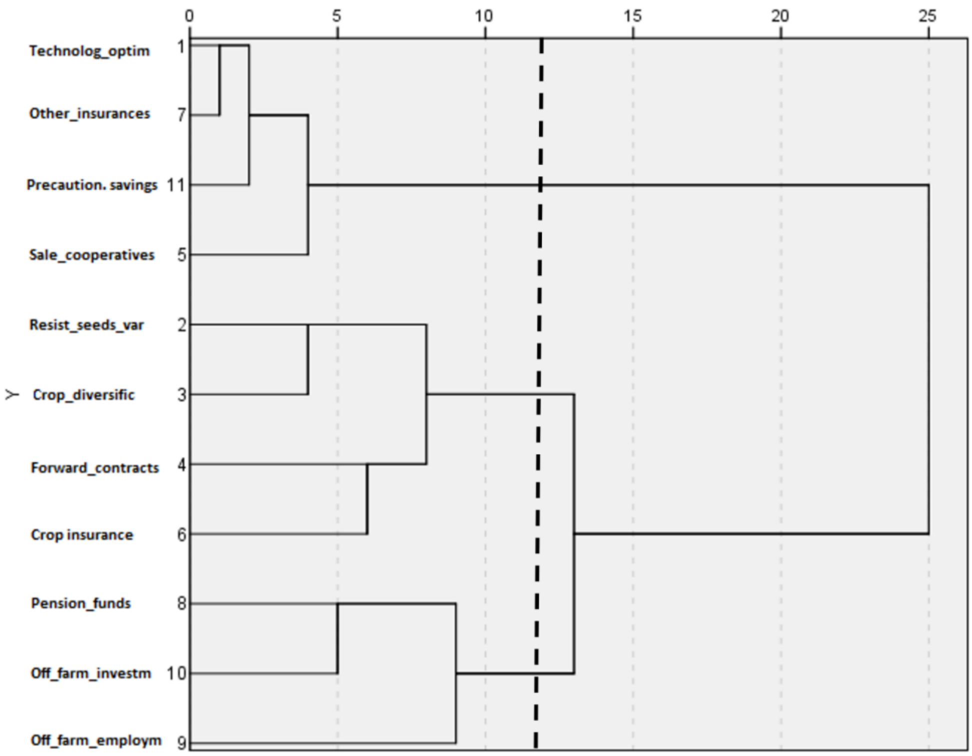
Table 2 shows the adoption rates of the different management instruments analyzed. First of all, it is worth mentioning that all farmers surveyed declared that they use good management practices. For this reason, this instrument is not included in the AHC and regression analyses since there is no variability in the adoption decisions. Other tools that are used by most farmers are technological optimization (87.7%), precautionary savings (84.3%), other insurance (79.9%), sale of products through cooperatives (71.1%), resistant seed varieties (68.6%), and crop insurance (52.5%).

4.1 Clusters of instruments

The clustering procedure explained above yielded the dendrogram shown in Figure 2, depicting the hierarchal classification of risk management instruments. As indicated by this dendrogram and the research needs (clusters should include a small number of instruments to allow robust estimations of the resulting MVP models), the 11 instruments considered (excluding the use of good management practices for the reason stated above) have been grouped into the following three clusters:

- Cluster 1: Technological optimization, other insurance, sale through cooperatives, and precautionary savings.
- Cluster 2: Resistant seed varieties, crop diversification, forward contracts, and crop insurance.
- Cluster 3: Pension funds, off-farm investments, and off-farm employment.

Figure 2. *Dendrogram (hierarchical classification of risk management instruments)*.



Each of these three clusters includes highly correlated instruments that merit joint analysis. Thus, it is reasonable to analyze the factors explaining the simultaneous adoption of risk management tools by considering three MVP regression models, one for each cluster.

4.2 Probit regressions

Table 3 presents the results obtained from estimating the MVP models for the instruments included in Clusters 1 to 3. First, it is worth noting that the Wald test for the three MVP models shows significant chi-square values, thus rejecting the null hypothesis that all the parameters in the model are simultaneously equal to zero. Moreover, the values of the LR test of rho for these three models also show significant chi-square values, allowing us to reject the null hypothesis that the correlation rho ρ_{ij} are simultaneously equal to zero (i.e., the error terms are independent). The latter results justify the joint estimation of the instruments included in each of the three clusters considered through multivariate probit models, given that there is a mutual interdependence among these risk adaptation strategies. Overall, the parameter estimates show that there are differences in the variables influencing the adoption of each risk management instrument. The results obtained from the MVP models are described below.

4.2.1 Farmers' socio-demographic variables

First of all, the results in Table 3 show that older producers are more likely to adopt technological optimization, but less likely to choose precautionary savings and off-farm employment. Second, the education variables (dummies related to secondary and university education, considering primary education as the reference category) are positively associated with many risk management instruments. Farmers who have secondary or higher education tend to use the risk management instruments included in Cluster 1 (technological optimization, sale through cooperatives, other insurance, and precautionary savings) more than those who only have primary education. Moreover, the most educated farmers—those who have a university degree—are more likely to adopt crop insurance, pension funds, and off-farm employment.

Third, the habitat variable (1. Rural) is found to be positively associated with the adoption of technological optimization, sale through cooperatives, and the use of resistant seed varieties, and negatively associated with crop insurance. In other words, producers who live in rural areas (villages with fewer than 10,000 inhabitants) are more likely to adopt the first three on-farm risk management instruments, while those who live in semi-urban or urban areas (towns and cities with more than 10,000 inhabitants) tend to rely more on the use of crop insurance, an off-farm risk management instrument.

Fourth, the variable related to the size of the farmers' household only influences (positively) the adoption of off-farm investments. And fifth, it is easy to see why an increase in the percentage of agricultural income over total income encourages farmers to use technological optimization, other insurance, forward contracts, and crop insurance, but discourages the use of off-farm instruments not related to agricultural activity (off-farm employment and off-farm investments).

Table 3. *Multivariate probit estimates for risk management instruments*.

Variable	MVP Cluster 1				MVP Cluster 2				MVP Cluster 3		
	Technol. optimization	Sale coop.	Other insurance	Precaut. savings	Resistant seed var.	Crop diversif.	Forward contracts	Crop insurance	Pension funds	Off-farm employ.	Off-farm invest.
Constant	-0.351	1.687	1.302	**3.463** **	0.821	-0.080	0.151	-0.304	**-4.768** ***	**2.167** **	1.204
Age (years)	**0.024** *	-0.003	-0.009	**-0.031** **	-0.009	0.001	-0.015	-0.004	0.016	**-0.038** ***	-0.006
Educational level (1. Secondary)	**0.758** **	**0.662** **	**1.061** ***	0.102	0.001	0.443	-0.432	0.360	0.266	-0.245	-0.202
Educational level (2. University)	0.346	-0.288	0.402	**1.598** ***	-0.114	0.123	0.244	**0.779** **	**0.545** *	**0.693** **	0.025
Habitat (1. Rural)	**0.561** *	**0.488** **	-0.287	-0.249	**0.468** *	-0.142	-0.318	**-0.684** ***	-0.047	0.012	0.141
Household size (num. people)	0.005	0.009	0.100	-0.207	-0.140	-0.059	-0.050	0.117	0.089	0.149	**0.161** *
Agricultural income over total income (%)	**0.011** **	0.006	**0.009** **	-0.001	-0.002	0.006	**0.008** *	**0.012** ***	-0.003	**-0.018** ***	**-0.020** ***
Farm size (ha)	0.001	-0.001	**0.012** **	0.000	0.003	**0.003** **	0.001	0.001	0.000	**-0.006** **	0.001
Farm gross margin (10^3 €/ha)	0.000	0.000	0.000	0.000	**0.252** *	0.184	**-0.364** ***	**-0.321** ***	-0.057	0.067	-0.026
Variance of farm gross margin (10^6 €/ha)^2	-0.032	-0.079	0.074	0.095	**-0.207** ***	-0.007	**0.320** ***	**0.252** ***	0.090	0.098	0.007
Non-family labor over total labor (%)	0.001	0.000	0.003	0.000	0.007	**0.007** *	0.004	**0.006** *	-0.002	**-0.007** *	**0.012** ***
Cultivated area of ligneous crops (%)	**0.009** *	0.005	-0.001	**-0.008** *	**-0.015** ***	**-0.020** ***	**-0.017** ***	**-0.010** ***	0.122	-0.050	-0.029
Perception of production risks (%)	-0.166	**-0.078** **	0.070	-0.029	0.007	0.001	**0.016** *	0.011	**0.030** **	-0.002	0.000
Perception of market risks (%)	-0.070	-0.012	-0.146	-0.043	0.005	0.001	**0.022** **	0.004	**0.029** **	0.007	-0.006
Perception of financial risks (%)	0.007	-0.107	-0.213	-0.264	0.012	**-0.057** **	0.000	0.019	**0.040** **	0.008	**-0.034** **
Constant relative risk aversion (CRRA)	-0.081	-0.079	0.058	0.033	-0.055	0.018	-0.003	-0.054	**0.105** *	-0.018	**-0.126** **
I suffered substantial production risks (1-5)	-0.015	-0.021	-0.014	-0.012	-0.151	-0.099	**0.168** *	**-0.211** **	-0.112	0.040	-0.037
I suffered substantial market risks (1-5)	0.004	-0.014	-0.017	0.013	**0.237** **	**0.279** ***	0.064	0.089	**0.157** *	-0.029	0.040
I suffered substantial financial risks (1-5)	-0.019	-0.012	0.003	0.028	**0.579** **	-0.078	-0.169	-0.207	-0.222	0.108	0.190
I think that CC is occurring locally (1-5)	-0.086	-0.027	0.020	0.096	**-0.151** *	-0.047	-0.075	-0.015	0.022	0.083	**-0.149** *
No. of observations	204				204				204		
LR test ρ_{ij}=0, $\chi^2(6)$ C1 and C2, $\chi^2(3)$ C3	**13.916** **				**11.496** *				**25.771** ***		
Log-likelihood value	-299.78				-373.59				-272.29		
Wald $\chi^2(76)$ for C1 and C2, $\chi^2(57)$ for C3	**115.20** ***				**213.08** ***				**136.94** ***		

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively.

4.2.2 Farms' technical-economic characteristics

As can be seen in Table 3, a larger farm size positively affects the adoption of other insurance and crop diversification, while it dissuades farmers from implementing off-farm employment choices.

Regression coefficients also show that farmers who obtain higher farm gross margins per hectare are more likely to use resistant seed varieties, but they do not tend to adopt either forward contracts or crop insurance. The variance of farm gross margin, which quantifies the variability of profitability due to both production and market risks, is also statistically significant in the adoption of the three mentioned risk management instruments, but with opposite signs.

With respect to the variable of non-family labor over total farming labor, a higher proportion of outside employees encourages the adoption of crop diversification, crop insurance, and off-farm investments, and discourages off-farm employment.

Finally, the cultivated area of ligneous or permanent crops (olive and orange trees in the case study area) positively affects farmers' decision to adopt technological optimization, but negatively influences the use of the whole set of instruments in Cluster 2 as well as precautionary savings.

4.2.3 Farmers' perception of risks, past experience, and perceptions about climate change

Results suggest that the adoption of the pension funds instrument is positively influenced by the perception of production, market, and financial risks. Besides, the use of forward contracts is positively affected by the perception of the first two types of risks. At the same time, farmers' perception of the existence of production risks was found to negatively affect the choice of the sale through cooperatives instrument, and the perception of financial risks negatively influences the adoption of crop diversification and off-farm investments.

Our findings confirm that the coefficient of constant relative risk aversion only affects the adoption of pension funds (positively) and off-farm investments (negatively). Thus, the more risk-averse farmers are more willing to adopt pension funds and less likely to implement off-farm investments.

Regarding the results for subjective past experience, it should be highlighted that farmers who claimed to have suffered substantial losses due to production risks are more likely to adopt the use of forward contracts, but less likely to adopt crop insurance. Past experiences related to market risks and financial risks are positively associated with the use of resistant seed varieties, and the former also has a positive influence on both crop diversification and pension funds.

Finally, it is worth commenting that the variable capturing farmers' perceptions of climate change is associated with only two risk management instruments (resistant seed varieties and off-farm investments)—negatively in both cases.

5 Discussion

5.1 Farmers' socio-demographic variables

First, regarding the farmer's age, its negative relationship with the adoption of precautionary savings is also reported by Ullah *et al.* (2015) and Adnan *et al.* (2019). These authors suggest this result may be due to the fact that older farmers have more family expenses (e.g., paying for the university education of their children), so they are not able to allocate financial resources to precautionary savings. Likewise, McNamara and Weiss (2005) also provide evidence that as the age of the farmer increases, job opportunities outside the farm decrease, so older farmers are less likely to find other employment. However, the positive association found between age and technological optimization contradicts previous research (e.g., Tambo and Abdoulaye 2012). In any case, we noted that older farmers in our case study tend to prefer fine-tuning the existing technologies on their farms (e.g., deficit irrigation) rather than investing in new technologies yielding long-term economic returns.

Second, the results found show that the education variables considered are positively associated with many risk management instruments. This result may be explained by the fact that more educated farmers can access more information and are better able to identify the benefits of risk management tools, as previously reported by Adnan *et al.* (2019). Indeed, it is usually posited that agricultural producers with higher education tend to adopt sophisticated risk management instruments (Velandia *et al.* 2009), such as crop insurance, an idea that is confirmed in our findings.

Third, a novel result worth noting is that farmers who live in rural areas prefer on-farm tools such as technological optimization, sale through cooperatives, or the use of resistant seed varieties. There is a practical reason for this: producers who live closer to their farms are able to manage these instruments more accurately. By contrast, producers who live in semi-urban or urban areas tend to rely more on the use of off-farm instruments. This is the case with crop insurance: farmers living in semi-urban or urban areas prefer this tool because of their proximity to insurance dealers, who mainly operate in urban areas.

Fourth, there is previous evidence that farmers with larger families are more likely to engage in on-farm non-agricultural strategies (Benjamin and Kimhi 2006). However, our results seem to support the idea that such farmers, who require higher incomes to cover their families' economic needs, are more likely to adopt off-farm investments, not only as a risk management instrument, but also as a way to stabilize expected returns and supplement their agricultural incomes.

5.2 Farms' technical-economic characteristics

This study confirms that farm size is positively associated with crop diversification, as previously reported by Asravor (2019): as farm size increases, crop diversification becomes more technically feasible, because this instrument can only be efficiently implemented in larger farms. It is also obvious why farm size was found to have a negative influence on the adoption of off-farm employment, in line with findings from previous research (e.g., Akhtar *et al.* 2019): larger farms require more complex management and monitoring, which dissuades farmers from applying for other jobs.

The positive influence of the variable farm gross margin per hectare on the adoption of resistant seed varieties also corroborates the findings of previous research (Khan *et al.* 2020). In this regard, it is worth noting that the farmers in our case study who obtain higher farm gross margins per hectare are those who cultivate vegetables (the most profitable crops), and they are better able to afford the higher cost of resistant seed varieties. For these crops, farmers usually opt for traditional market transactions (outright purchase and down payments), while forward contracts are rarely used because of technical difficulties related to the standardization of these products and their high price volatility. Furthermore, crop insurance is not used by vegetable growers because this risk management instrument covers only production risks (yield losses), whereas these farmers primarily face market risks.

The trade-off between expected profitability (farm gross margin) and the risk borne by farmers (variance of farm gross margin) explains the opposite signs of the latter's influence on the adoption of the instruments resistant seed varieties, forward contracts, and crop insurance.

Producers who run their farms using a higher proportion of non-family labor (generally, more qualified workers) are more able to diversify their crops since the adoption of this risk management instrument entails varied and more complex tasks. Nevertheless, the complexity involved in the management of a farm employing a high proportion of non-family labor dissuades the producer from searching for a job outside the farm.

Finally, with regard to the variable cultivated area of ligneous or permanent crops, it should be highlighted that technological optimization (e.g., deficit irrigation programming or fertigation) is a suitable risk management instrument for these growers. However, instruments in Cluster 2, as well as precautionary savings, are not technically feasible for them (e.g., resistant seed varieties or crop diversification cannot be used for these permanent crops) or are not well suited to these farmers' risk management requirements (e.g., olive and orange are usually traded using traditional market transactions and the currently available insurance schemes are not appropriate for these crops).

5.3 *Farmers' perception of risks, past experience, and perceptions about climate change*

An interesting finding regarding the influence of the variables related to farmers' perception of risks is that pension funds and forward contracts are positively affected by these influential factors. These results differ from those reported by Lu, Latif, and Ullah (2017) and Adnan *et al.* (2020) for the case of forward contracts. It may be that farmers in our case study consider pension funds and forward contracts to be a useful way of coping with the main risks in this irrigated farming system, in both the long (pension funds) and the short term (contract farming).

The result indicating that the more risk-averse farmers are more willing to adopt pension funds and less likely to implement off-farm investments may be explained by the different level of risk associated with the management of these two instruments: quite low for the former but much higher for the latter. In any case, the results obtained show that risk aversion does not influence the adoption of on-farm risk management instruments in this case study, in contrast to previous evidence, such as that reported by Meraner and Finger (2017).

Regarding the influence of the variable subjective past experience on the adoption of risk management instruments, the results obtained are rather counterintuitive. For instance, forward contracts are employed to offset market risks, but our results show that those who have suffered significant losses due to production risks are more likely to adopt forward contracts. Similarly, crop insurance is used to cover production risks, but farmers in the case study who have suffered significant losses due to production risks are less likely to adopt it. This may imply that insured farmers do not have such a strong perception of the production risks, probably because they have been using crop insurance over the years and this instrument has satisfactorily covered the existing production risks.

Finally, despite the fact that most of the farmers in the sample believe that climate change is occurring locally, this perception does not prompt them to adopt specific risk management instruments to face this new source of production risk. Likewise, Hamilton-Webb *et al.* (2017) found in their study that concern about climate change was not a significant motivation for a risk management behavioral response.

6 Conclusions

The main objective of this paper was to analyze the influence of a series of explanatory variables on the joint adoption of risk management instruments by farmers. To that end, the irrigated agriculture of a Mediterranean-climate region in southern Spain was used as a case study. The main innovation of this paper lies in the methodological approach followed. Due to the difficulty of regressing the large number of risk management instruments available to farmers in a single model, we first categorized them in smaller groups according to the correlations among the adoption choices, using a hierarchical clustering technique. We subsequently modeled the simultaneous adoption of the instruments included in each cluster using multivariate probit regressions.

The results of the hierarchical clustering show a classification of instruments primarily based on their suitability for managing existing risks according to the farms' technical features and farmers' socio-demographic characteristics. The first cluster of instruments contains technological optimization, sales through cooperatives, other insurance, and precautionary savings. According to the multivariate probit estimates, the adoption of these instruments is preferred by full-time irrigated farmers (high proportion of agricultural income as a percentage of total income) growing permanent crops (olive and orange in this case study), and living close to their holdings (rural inhabitants), since these instruments are the most suitable for managing their farming risks. The reasons behind this are that the other on-farm risk management instruments cannot be implemented in farms specialized in permanent crops (e.g., crop diversification or resistant seeds), they are not well suited to these crop requirements (e.g., crop insurance, explaining the very low adoption rates in the olive and citrus sectors), and they are not compatible with common sale practices through producers' cooperatives (e.g., forward contracts). The second cluster of instruments comprises resistant seed varieties, crop diversification, forward contracts, and crop insurance. As shown by regression estimates, this is the most suitable set of instruments for full-time irrigated farmers (high percentage of agricultural income) growing annual crops (both extensive crops, such as wheat, cotton, or corn; and vegetables, such as potatoes, garlic, or onions). Finally, the third cluster is formed by the three off-farm risk management instruments: pension funds, off-farm employment, and off-farm investments. These are more complex tools requiring greater knowledge and skills, making them more suitable for those farmers with university education. Moreover, the adoption of these instruments is positively correlated with part-time farming since they are mainly implemented by farmers with significant non-farm income.

The results of the probit regressions reveal other explanatory variables worth noting. First, higher educational levels are positively related to more complex instruments in addition to off-farm instruments, such as crop insurance. Second, older producers are less likely to use off-farm employment and precautionary savings but more inclined to adopt technological optimization. Third, a larger farm size encourages the adoption of crop diversification and a higher farm gross margin per hectare supports the use of resistant seed varieties. Fourth, farmers adopting the risk management instruments are satisfactorily hedging their main sources of risk, since our results do not reveal a significant positive association between the perception of risk and the adoption of the risk management instruments (excluding forward contract and pension funds).

It is also worth mentioning that farmers' risk aversion and their perception about climate change at a local level have little influence on the adoption of the various risk management instruments, contrary to what was initially expected.

As stated at the beginning of this paper, these results provide useful information to support the decision-making process for three main stakeholders: farmers, providers of agricultural risk management instruments, and policymakers. First, the analysis carried out is relevant for farmers as it can guide their decision-making on the joint use of risk management instruments based on their socio-economic characteristics, type of agricultural holding, and their perception of the risks they bear. Second, regarding the firms providing risk-bearing services, the outcomes of the models are valuable because they could help inform the design of new combinations of risk management instruments better targeted to specific farmer profiles. And third, this study can support policymakers in the design of future policy strategies aimed at promoting better risk management within the agricultural sector. On this matter, it is worth remarking that the valuable insights gained here could feed into the current debate regarding the reform of the European Common Agricultural Policy (CAP) for the next programming period 2021-2027, with a special focus on the most suitable risk management tools to address risks, crises and natural disasters that agriculture may face. Moreover, as climate change is expected to get worse in the near future, the analysis performed yields practical information for agricultural risk management (both production- and market-related risks) under this predicted scenario, in order to improve the adaptability of farming activities to this challenge.

Finally, the results of this study point to a future research line in this field. Further analyses are needed to determine farm typologies based on the portfolio of risk management instruments adopted, allowing assessments of different farm profiles (e.g., combinations of farm size, crop pattern, production technology, etc.) with similar risk management demands. The information provided by this paper and the proposed analyses could be fruitfully combined in order to design more targeted and efficient instruments for managing risk in the agricultural sector.

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