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Factors influencing dairy farmers' participation in the Income Stabilization Tool: evidence from Northern Italy

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Abstract

This paper examines the factors influencing dairy farmers' participation in an Income Stabilization Tool (IST), introduced by two dairy cooperatives in the Lombardy region (Italy). Using a sample representative of dairy cooperative members of the area, our results show that higher perception of input price volatility is significantly associated with a higher probability of IST uptake. Farmers' prior experience of coupled payments, as well as of mutual funds that compensate for production losses due to adverse climatic events or animal diseases is negatively correlated with their probability of participating in this IST. In addition, farmers who are sole traders or have attained post-secondary education are significantly linked to a lower participation rate in the IST. In contrast, female farmers are more likely to adopt IST. Our results are robust across various model specifications. The findings suggest that the role of risk management tools should be re-evaluated in relation to indirect support measures, such as coupled payments and subsidies, in order to reduce perceived overlap among these tools, improve IST adoption, and enhance overall policy effectiveness. The intensive dairy farming practices in the Lombardy region and its essential role in the Italian dairy sector make our analysis informative for understanding the dynamics of IST adoption in areas of concentrated livestock operations.

Keywords: Income Stabilization Tool (IST), risk management, dairy farming, farmer participation

JEL codes: Q12, Q18

1. Introduction

In sectors with high production specialization, such as permanent crops and dairy farming, the industry faces increased exposure to income downside risk (Antón and Kimura 2011; Finger and Lehmann 2012; Finger et al. 2018; De Salvo et al. 2019; Rippo and Cerroni 2023). Hence, understanding the specific risk factors faced by farmers that are unique to each sector and the influence of policy support on the income stabilization can help clarify differences in their income stabilization adoption decisions (Finger et al. 2022). One such instrument that has gained attention in this context is the Income Stabilization Tools (ISTs), a type of mutual funds designed to compensate for losses in farm income. This distinguishes IST from other mutual funds, which compensate farmers for their yield losses rather than income losses.

The IST was first introduced in Pillar II of the 2014 Common Agricultural Policy (CAP) reform, in the Article 39 of EU Regulation No 1305/2013 (European Commission 2013). Farmers pay annual contributions to the fund, which compensates up to 70 per cent of income losses when such losses exceed 30 per cent compared to a baseline income.[1] To encourage farmers to adopt this tool, CAP subsidizes up to 65 per cent of the IST operating costs.[2], [3] In addition, the 2017 Omnibus Regulation introduced sectorial IST funds for specialized sectors such as dairy, apples, and grapes, which provide greater flexibility (European Commission 2017). Unlike general IST, sectorial IST calculates income loss at sector level, with activation triggered by a 20 per cent sector-wide income loss instead of the previous 30 per cent threshold. CAP support for sectorial IST funds has also been increased to cover up to 70 per cent of IST eligible costs.

Several studies have demonstrated the efficacy of operating mutual funds to compensate for farmers' income losses rather than yield losses in the face of systemic risks (Meuwissen et al. 2013; Capitanio et al. 2016; El Benni et al. 2016; Trestini et al. 2018; Severini et al. 2019; Giampietri et al. 2020; Finger and El Benni 2021; Louhichi and Merisier 2024).[4] IST offers several advantages over private insurance and other mutual funds for yield losses. In particular, IST addresses income variability and systemic risks not covered by multi-peril insurance. In addition, IST considers broader factors such as output market prices and input costs. Both general IST and sectorial IST are designed to mitigate adverse selection by including both high- and low-risk farms, ensuring participation by farmers who are less aware of their on-farm risks (Meuwissen et al. 2013). However, despite these benefits, sectorial ISTs especially may face limitations in accessibility and attractiveness, as their implementation depends on formal membership in cooperatives, consortia, or producer organizations, and compensation is tied to sector-wide income triggers (Rippo and Cerroni 2023).

So far, only two countries and one autonomous region have adopted the tool, including Italy, Hungary, and Castilla y León (autonomous community of Spain), among which Italy has been the only EU member adopting exclusively the sectorial ISTs, addressed in the sub-measure 17.1 of the 2014–2020 National Rural Development Programme (MASAF 2023). This approach is favoured due to the relative simplicity of implementing and designing sectorial IST, as it leverages established knowledge of risks specific to sectors.[5] The sectorial IST activation system in Italy allows its participants to request compensation in advance from their respective fund in the event of a predetermined trigger event. For instance, in the case of dairy sectorial IST used in our analysis, the trigger event is predetermined based on the milk price database of its region, Lombardy, managed by the CLAL Italian Dairy Economic Consulting firm (https://www.clal.it/). For dairy farms, the sectorial income loss threshold used for the trigger event is relaxed to an average drop at sectorial level of 15 per cent using the baseline of sector-level income average over the preceding three consecutive years.

In Italy, national subsidization to sectorial ISTs accounts for 2.1 per cent of the total budget allocated to support to risk management tools (National Rural Networks 2023). About 2,000 farms are participating in nine different active sectorial IST funds, including four for the dairy sector, three for the fruit and vegetables sector, one for the sugar beet sector, and one for the rice sector (European Commission 2021; MASAF 2023). The low uptake of IST in recent years has resulted in a lack of *ex-post* studies due to a scarcity of data and the fact that the IST trigger event has not taken place in most ISTs, preventing the observation of treatment effects. One exception is Rippo and Cerroni (2023), which assesses the importance of the factors influencing farmers' participation in the sectorial IST. Their study focused on the apple sector and found that understanding farmers' risk management strategies and socio-economic characteristics can support the development of an effective sectorial

IST operating system. The feasibility of implementing IST is further explored through *ex-ante* studies, suggesting the need for a holistic approach to analysing farmers' decisions to adopt risk management tools, such as IST, to better design risk management strategies and public support to farmers (Sherrick et al. 2004; Capitanio et al. 2016; El Benni et al. 2016; Trestini et al. 2018; Severini et al. 2019; Čop et al. 2020, 2021, 2023; Zinnanti et al. 2023; Louhichi and Merisier 2024).

Our study builds on the work of Rippo and Cerroni (2023), which applied the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate farmers' participation in the Italian apple sectorial IST. Similarly, we adopt the UTAUT framework to select variables in our sample and examine the factors associated with farmers' participation in the dairy sectorial IST.

Given that sectorial ISTs in Italy are currently conducted through cooperatives or consortiums, we focus on a sample of non-organic dairy farms that are members of cooperatives where the IST is offered as a voluntary risk management tool. An empirical analysis is conducted on 66 dairy farms from two cooperatives in Brescia province (Lombardy region), namely Milk Producers Cooperative of the Municipality of Brescia (*Cooperativa Produttori Latte del Comune di Brescia*) and Cooperative of Milk Producers in the Province of Brescia (*Cooperativa Produttori Latte Indenne della provincia di Brescia*). The two cooperatives have operated a dairy sectorial IST since 2019. To receive public subsidies for the IST operation, the number of farmers voluntarily participating in this tool are committed to adopt the IST for the period between 2019 and 2024. During this period, the number of participants remains fixed, with no entries or exits allowed. The cooperative-based structure and high IST participation rate (74.24 per cent) make it an informative case for understanding the mechanisms behind IST adoption in specialized dairy systems.

Our analysed sample combines data from three main sources: (1) a farm survey capturing perceived risks correlated with dairy farming; (2) secondary data on farm structure provided by the cooperatives; and (3) station-based weather information. Specifically, all cooperative members participated in the survey, giving our survey a response rate of 100 per cent. In terms of weather data, we incorporated the station-based weather information, retrieved from Agri4cast, into our dataset by matching the nearest spherical weather station to each farm location.[6] This ensures a more precise representation of the weather conditions occurring at each farm (Schlenker and Roberts 2009).

We carefully address this topic in a specific context of cooperatives. Our results show that farmers' perception of input price volatility is positively correlated with a higher IST participation rate, while sole trader status is negatively associated with the adoption of this IST. Furthermore, farmers' experience with existing policy instruments, such as coupled payments and mutual funds, poses important challenges to increasing IST adoption, as they are significantly linked to a lower probability of IST subscription. Moderating factors, such as female farmers, are correlated with a higher probability of participating in this IST, while farmers who have pursued post-secondary education are associated with a lower IST participation rate.

In the following sections, we present a detailed conceptual framework addressing factors influencing farmers' acceptability of participating in the IST, which is used as our motivation to design our survey and select relevant variables for our empirical analysis. It is then followed by methods, results and discussion. Finally, the paper concludes with a conclusion.

2. Conceptual framework

Following Rippo and Cerroni (2023), our study investigates factors influencing dairy farmers' participation in the dairy sectorial IST using the UTAUT developed by Venkatesh et al. (2003) as the underlying behavioural framework. The framework is adapted to reflect the

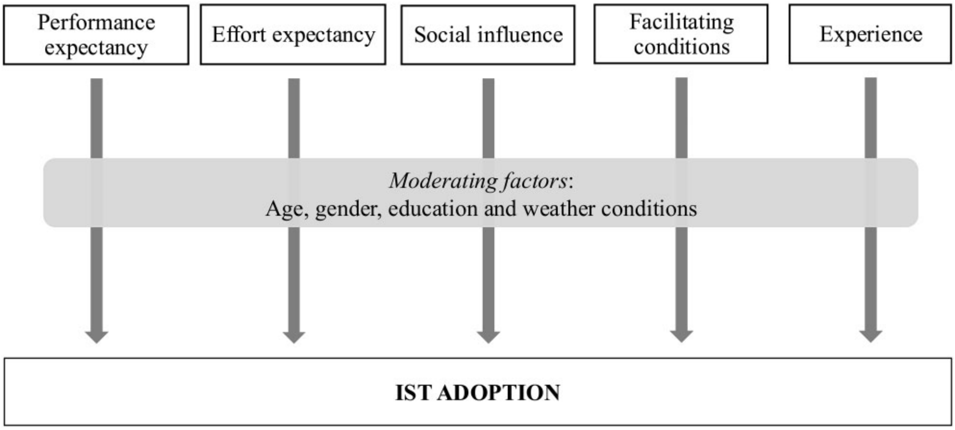


Figure 1. The UTAUT model developed by Venkatesh et al. (2003) adapted to this study.

specific context of the Italian dairy sector and guides both the design of our survey and our empirical analysis.

The UTAUT framework has been increasingly adopted in different topics to explain individuals' attentions to adopt new technologies or systems (Li et al. 2020; Rübcke Von Veltheim et al. 2022; Rippo and Cerroni 2023; Michels et al. 2024). Given the limited *ex-post* literature on IST adoption, UTAUT provides a structured approach to model the relationships between four latent constructs, that is, *performance expectancy, effort expectancy, social influence, and facilitating conditions*. These constructs elucidate significant associations between several farm structural, socio-economic, and risk factors with the adoption of the IST. In addition to the four latent constructs, the UTAUT framework incorporates three key moderating variables, including *age, gender, experience*, and *voluntariness of use*.

In particular, *performance expectancy* indicates individual beliefs in the improvements of their farm performance because of adopting a particular innovation. *Effort expectancy* captures perceived ease of use to of the innovation. *Social influence* reflects the extent to which individuals perceive that cooperatives and advisory services play importance roles in influencing them to adopt the new system. *Facilitating conditions* illustrates the perceived availability of infrastructure, resources, and institutional support necessary to implement and effectively use the innovation.

Compared to the original structure of the framework by Venkatesh et al. (2003), Rippo and Cerroni (2023) adapted the model to the context of sectorial IST schemes in Italy, where participation is restricted to members of specific producer organizations such as apple growers in the Consortium for the Defence of Agricultural Products in Trento, Italy. This modification helps address selection bias, since farmers within such organizations tend to share similar structural and operational characteristics such as farm size, farm specialization, and years of experience.

Within this organizational context, we further adapt the framework to reflect farmers' acceptability of IST (see Fig. 1). First, following Venkatesh et al. (2003), we keep *social influence* as one of the constructs as the dairy sectorial IST allows members of two separate cooperatives to participate. Differences in the administrative operations, social norms, and leadership of the cooperatives can influence their members to adopt this tool. Second, following Rippo and Cerroni (2023), we treat *experience* as one of the latent constructs rather than a moderating variable, defined not by years in dairy farming but prior engagement with similar risk management tools and income support instruments, such as mutual funds, coupled payments, and private insurance. Third, we exclude the moderator indicating *voluntariness of use* as IST participation is voluntary to all farmers.

In addition to age and gender, we consider education and weather conditions to be moderators. In particular, education can moderate the relationship between performance expectancy and IST adoption by influencing how farmers interpret and evaluate the potential benefits of a new tool such as the IST (Savage 1993; Dohmen et al. 2011; Lefebvre et al. 2014; van Winsen et al. 2016). We include weather conditions as a moderator in the UTAUT framework to capture environmental heterogeneity across farms more effectively, acknowledging that the adoption process may vary depending on the extent of weather stress experienced by farms (Lefebvre et al. 2014; Finger et al. 2018; Vroege and Finger 2020; Quiédeville et al. 2022). Further elaboration of survey and data collection as well as justification of variables selected based on this framework is explained in the next section.

3. Methods

3.1. Survey design and data collection

The data used in this study refers to the year 2022 and combines secondary data with additional information collected through a questionnaire. The primary data were collected with the collaboration of two dairy cooperatives operating in the province of Brescia (Lombardy region), located in the Po Valley of Northern Italy. The questionnaire was administered between March and June 2023 to all farms of the two cooperatives. The managers of the cooperatives distributed and explained the survey directly to their farmers during two routine cooperative meetings. The final dataset comprises 66 valid responses, representing 100 per cent of the cooperative members at the time of data collection. Of these, 49 farmers participated in the IST, corresponding to a participation rate of 74.24 per cent.

Questions in the survey focus on four key areas: (1) social-demographic characteristics, (2) farm structure and performance, (3) experience with risk management tools and coupled payments, and (4) perceived impact of market risks (e.g. milk and input price volatility). The final section of the questionnaire includes an open-ended question allowing farmers to share their opinions or suggestions for improving the sectorial IST (see supplementary Appendix A).

The survey was introduced to farmers during two scheduled cooperative meetings. Farmers were first provided with a brief overview of the research objectives, including its focus on risk management practices and perceptions related to the IST. Participation was entirely voluntary, and informed consent was obtained prior to data collection. Farmers were assured of the anonymity and confidentiality of their responses to encourage open and honest participation.

Primary survey responses were subsequently integrated with two additional data sources: (1) farm-level data provided by the cooperatives, matched using anonymized farm identification numbers; and (2) daily weather data from Agri4cast, linked to each farm based on geographic location (Schlenker and Roberts 2009). The farm-level data provided by the cooperatives includes information on IST adoption, their utilized agricultural area, livestock unit, and milk deliveries. The weather data includes key meteorological variables such as daily temperature, rainfall, and vapour pressure.

3.2. Variable mapping based on UTAUT framework and sample description

We elaborate our selection of explanatory variables for the empirical analysis based on the adapted UTAUT conceptual framework. Selected variables are presented in Table 1.

In terms of *performance expectancy*, since IST is designed to mitigate the impacts of income shocks, we proxy this construct using farmers' perception of milk price and input price volatility. These variables reflect farmers' assessments of how strongly milk and input

Table 1. Descriptive statistics of variables.

Variables	Description	Mean (SD)[a]	Min	Max
IST	1 = participated in dairy IST, 0 = otherwise	0.74	0	1
Performance expectancy				
Perceived milk price	Perceived impact of milk price volatility on farm business on a Likert scale of 5	4.26 (0.66)	3	5
Perceived input price	Perceived impact of input price volatility on farm business on a Likert scale of 5	4.05 (0.67)	3	5
Effort expectancy				
Milk per LSU	Cow milk produced per livestock unit (LSU) in 2022 (1,000 litres/LSU)	7.68 (1.77)	2.62	10.56
Top_producer	1 = farm is among the top milk-quality producers in the cooperatives	0.15	0	1
Social influence				
Cooperative	1 = farm is member of Milk Producers Cooperative of the Municipality of Brescia, 0 = farm is member of Free Milk Producers Cooperative of the Province of Brescia	0.23	0	1
Facilitating conditions				
Sole_trader	1 = farmer is a sole trader, 0 = otherwise	0.20	0	1
Livestock density	Number of livestock units (LSU) divided by the utilized agricultural area (LSU/ha)	5.09 (2.51)	0.61	17.26
Experience				
Coupled_payment	1 = received coupled payments, 0 = otherwise	0.67	0	1
Insurance	1 = purchased insurance for their dairy farm, 0 = otherwise	0.86	0	1
Mutual_fund	1 = participated in other mutual funds to compensate farmers for yield losses, 0 = otherwise	0.41	0	1
Moderating factors				
Age	Farmer's age (years)	61.11 (13.13)	37	97
Female	1 = female, 0 = male	0.06	0	1
Education	1 = pursued post-secondary education (>13 years of schooling), 0 = otherwise	0.56	0	1
Weather_stress	Average number of days per year between 2015 and 2018 for which the THI index was equal to or greater than 72 (days/year)	103.27 (6.43)	90.75	109.25

[a]We only report standard deviations of continuous variables.

price fluctuations affect their business (Assefa et al. 2017; Giampietri et al. 2020; Knapp et al. 2021). On a 5-point Likert scale, the average perceived impact of milk price volatility is 4.26 (SD = 0.66), while the input price volatility is similarly high at 4.05 (SD = 0.67). For both variables, the lowest score is three, indicating strong awareness of market risks among farmers. In addition, the *t*-test shows that, on average, IST participants perceive input price volatility as having a significantly greater impact on their farm business compared to non-participants (see Table C1 in the supplementary Appendix C). Since the IST is specifically designed to mitigate farmers' income loss caused by market volatility, we expect that farmers who perceive higher exposure to price risks are more likely to see IST as useful (Kuethe and Morehart 2012; Atta and Micheels 2020).[7]

Regarding *effort expectancy*, Rippo and Cerroni (2023) consider proxies related to both time and financial costs to reflect farmers' perceived ease of use of the IST. In this context, the IST functions as an annual subscription, and income compensation is activated where the sectorial income falls by more than 20 per cent. Given this automatic activation and integration within the cooperative system, we assume that the time cost for farmers is minimal. However, the financial cost remains relevant. The IST requires farmers to pay an annual fee, which is calculated based on farm profitability (see the supplementary Appendix B). Since farm profit is determined by both the quantity and quality of milk delivered, we include *Milk per LSU* as a proxy for productivity and operational efficiency, and *Top_producer*, a binary indicator for farms ranked among the top milk-quality producers within their cooperative. These variables capture both output capacity and adherence to quality standards, which may impact the expectation on efforts required to comply with IST rules. In our sample, the average milk production per livestock unit is 7.68 thousand litres per unit and approximately 15 per cent of farms are ranked as top milk-quality producers.

Social influence is captured by the dummy variable *Cooperative*, which indicates membership in one of the two cooperatives involved in the IST. This variable allows us to explore whether being in a particular organizational environment, where peer norms, communication flows, or leadership endorsement may differ, affects farmers' participation in the IST. In particular, about 23 per cent of farmers are members of the Milk Producers Cooperative of the Municipality of Brescia (variable *Cooperative* = 1), with the remainder belonging to the other cooperative. Since both cooperatives administer the same IST programme but may vary in their internal dynamics, this variable provides insights into the role of peer and institutional influence in shaping behavioural intention and actual adoption of the IST (Venkatesh et al. 2003).

We include two variables to reflect *facilitating conditions*. *Sole_trader* captures whether the farm is operated by a sole proprietor, which may be correlated with lower access to administrative or technical assistance compared to enterprises (Lefebvre et al. 2014). In our sample, 20 per cent of farmers are sole traders and the average number of sole traders among the IST participants are significantly lower than that of non-participants (according to the *t*-test—see Table C1 in the supplementary Appendix C). *Density*, defined as the number of livestock units per hectare, indicates production intensity and may be associated with greater resource use. Farms in the sample have an average livestock density of 5.09 LSU per hectare, with a standard deviation of at 2.51. These variables reflect the farms' structural and organizational characteristics typically associated with large-scale dairy farms.[8]

We include three binary variables under the *experience* construct to account for prior experience to risk management practices in the last 5 years. *Insurance* identifies whether a farmer has purchased insurance for their dairy farm, which reflects familiarity with formal risk mitigation. Recent CAP reforms have positively impacted farmers' adoption of insurance and IST, suggesting that policy changes can enhance risk management instrument uptake (Giampietri et al. 2020). *Coupled_payment* indicates whether the farmer received coupled payments for their dairy farm, which can influence the dependence on public support and reduce the perceived need to additional tools. In our sample, approximately 67 per cent of farmers have received coupled payments, with IST participants showing a significantly lower rate of couple payment receipt than non-participants, as confirmed by the *t*-test (see Table C1 in the supplementary Appendix C).

On the other hand, the variable *Mutual_fund* captures whether farmers have participated in mutual funds that provide compensation for yield losses. These yield-based mutual funds offer compensation for production losses due to adverse climatic events or animal diseases

(MASAF 2023). When annual production drops by at least 20 per cent due to such causes, the funds compensate farmers up to a maximum of 70 per cent of the marketable value of the production losses. In the sample, approximately 40.91 per cent of farmers have joined this type of mutual funds. However, the adoption rate of these funds is significantly lower among IST participants than among non-participants (see Table C1 in the supplementary Appendix C). We expect that farmers with prior experience in yield-based mutual funds are positively associated with participation in the IST, due to the common use of mutual funds in the cooperative (Santeramo 2018; Rippo and Cerroni 2023).

Regarding *moderating factors*, the average age of farmers are approximately 61 years old with a standard deviation of 13.13 years. Older and more experienced farmers tend to exhibit lower likelihood of adopting income risk mitigation tools and technological innovations (Mishra and Goodwin 2003; Venkatesh et al. 2003; Flaten et al. 2005, 2006; Ogurtsov et al. 2009; Frosch 2011). Furthermore, in our sample, only 6 per cent of farmers are female. Female farmers demonstrate a lower innovation uptake, which may be attributed to higher levels of risk aversion compared to male farmers (Eckel and Grossman 2002; Venkatesh et al. 2003, 2008; Cerroni 2020; Rippo and Cerroni 2023). In our sample, about 6 per cent of farmers have completed post-secondary education. However, the share of IST participants with post-secondary education is significantly lower than that of non-participants (see Table C1 in the supplementary Appendix C).

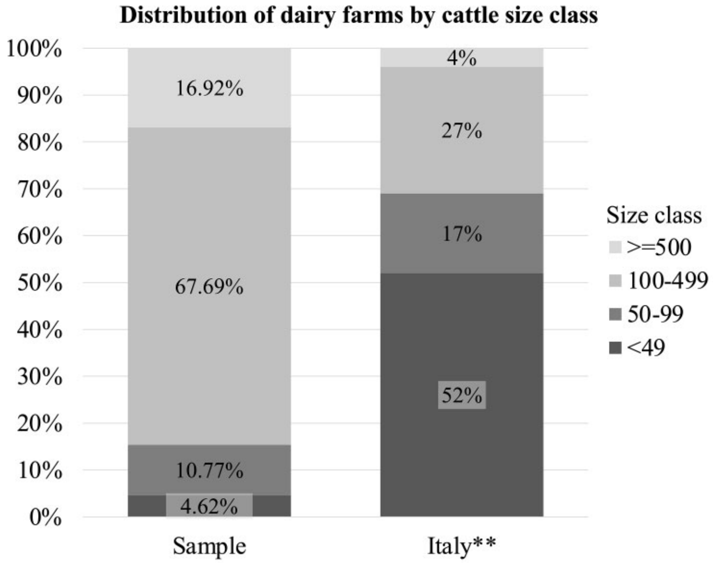
We include a weather indicator *Weather_stress*, which captures the average number of days per year between 2015 and 2018 that farms experienced heat and humidity stress. This indicator is based on the daily temperature–humidity index (THI), where values above 72 indicate potential heat and humidity stress in dairy cows, subsequently affects cow productivity (Thom 1959; Oliveira and Esmay 1982).[9] The selected period (i.e. 2015–2018) reflects the years following the inclusion of the IST in the CAP Pillar II in 2014 and preceding its adoption by cooperative members in our sample in 2019. According to Table 1, on average, farms experienced approximately 103.27 days per year of heat and humidity stress (SD = 6.43) between 2015 and 2018, with values ranging from 90.75 to 109.25 days per year.

3.3. Representativeness of the sample

We compare the structural characteristics of the farms in our sample with those at the provincial, regional, and national levels to illustrate that our sample is representative only of dairy farms belonging to dairy cooperatives.

Farms in the sample differ significantly from the national farm structure and are likely to represent larger and more commercially oriented farms rather than small farms that dominate the country. Our sample consists mainly of large farms, with an average UAA of 68.45 hectares, above the national average of 10.97 hectares and the Lombardy regional average of 22.39 hectares (ISTAT 2020). According to the ISMEA classification of dairy farms (ISMEA 2022), in our sample, only 6.07 per cent of farms are small (less than 20 cows), 10.61 per cent are medium and 83.33 per cent are large (more than 100 cows).[10]

Most farms in the sample are medium or large-scale operators (see Fig. 2). The average number of livestock units per farm is 333.43 units, which is higher compared to the provincial, regional, and national average of 300.40, 307.60, and 106.00 per farm, respectively (Lombardy Region and UCSC 2023). The mean density of livestock in the sample is 5.09 units per hectare, slightly lower than the density observed in the Lombardy region (5.57 units per hectare) and much higher than the average Italian livestock density (3.32 units per hectare). Farmers that are sole traders make up one-fifth of the sample, significantly lower than the national average of 93.5 per cent for farm types (ISTAT 2020). In our sample, the average volume of milk produced per livestock unit in 2022 is 7.68 thousand litres/cow/year, which is a notably higher value than the regional and national averages.



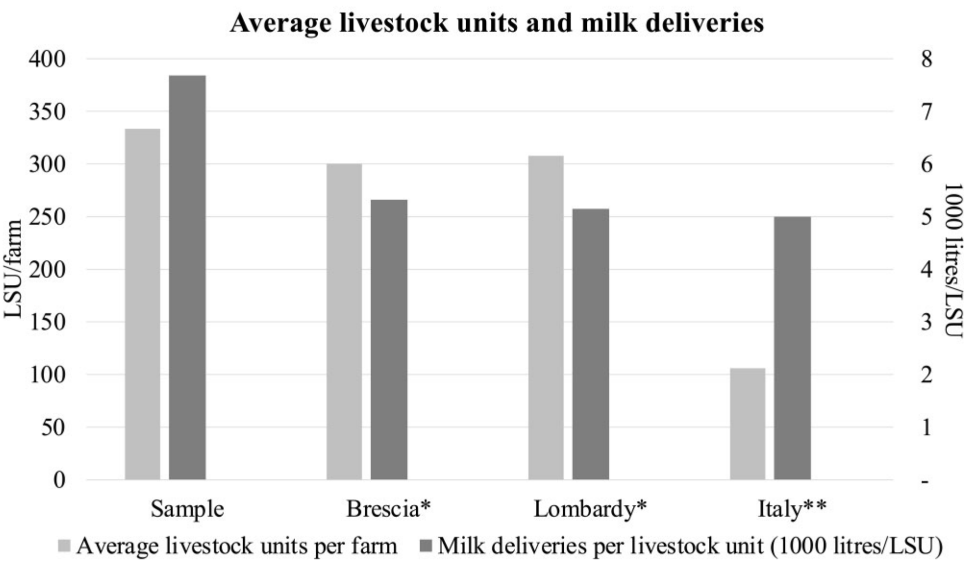


Figure 2. Comparison of cooperative farms in the sample with provincial, regional, and national averages. (*) We report dairy farms at the provincial and regional levels in the year 2022 (Lombardy region and UCSC 2023). (**) The most recent national report on dairy farms was in 2021 (ISMEA 2022).

4. Empirical approach

4.1. Econometric implementation

Following Angrist and Pischke (2009) and Breen et al. (2018), we employ a linear probability model (LPM) to examine the factors associated with IST participation. The LPM is particularly appropriate given our small sample size and the predominance of medium and large farms. LPM is a viable alternative to logit and probit models due to its interpretability and robustness, especially given that our sample structure increases the risk of perfect separation problems in logit and probit estimations. LPM has been increasingly adopted for the analysis of binary outcomes (Möhring and Finger 2022; Bucheli et al. 2023; Wang et al. 2023; Zachmann et al. 2024). The LPM to estimate farmers' participation in the IST is denoted as follows:

$$\Pr(IST_i) = \beta_0 + \sum_{k=1}^{10} \beta_k X_{ki} + \sum_{l=1}^{4} \gamma_l Z_{li} + \varepsilon_i \qquad (1)$$

where IST_i is the binary dependent variable, representing IST participation of farmer *i*. X_{ki} indicates 10 independent variables ($k = 1, \ldots, 10$) belonging to the five UTAUT construct groups and Z_{li} ($l = 1, \ldots, 4$) consists of four moderators. We refrain from identifying causal relationship between variables, but we rather interpret the results as associations. The coefficient β_k ($k = 1, \ldots, 10$) captures the change in probability of IST participation associated with a unit change in the corresponding explanatory variable X_k. We use the robust standard errors to correct for heteroskedasticity and serial correlation.

4.2. Robustness checks

Given the observational nature of the data, the issue of endogeneity may raise. While the UTAUT framework and the inclusion of perceived price risks, education, and farm performance indicators help capture a range of relevant factors, unobserved characteristics such as farmers' trust in institutions may influence both the decision to adopt IST and the explanatory variables used. In addition, reverse causality could also be a concern, especially if participation in IST influences how farmers perceive price risks or adjust their production strategies.

To ensure the validity and stability of our regression results, we conduct robustness checks, including comparisons with other LPM, logit, probit specifications, multicollinearity diagnostics, and bootstrap resampling. The robustness checks aim to assess whether the estimated relationships between the independent variables and IST participation remain consistent under different modelling approaches and data perturbations. We proceed the robustness checks as follows.

First, we estimate multiple models with different subsets of explanatory variables. Specifically, we re-estimate several LPM models, each excluding a set of variables belonging to a UTAUT construct. For example, the LPM model without *performance expectancy* or the LPM model without *effort expectancy*. Further than estimating an LPM, we also estimate logit and probit models for comparison. The logit and the probit models are estimated multiple times with different subsets of variables from the five groups of UTAUT constructs. This approach allows us to identify whether certain sets of determinants are robustly correlated with IST participation, while ensuring that our results are not driven by any particular model specification.

Second, given the relatively small sample size, we perform bootstrap resampling with 1,000 replications to assess the stability of our estimates (Efron 1979). Bootstrap standard errors are calculated for LPM, logit, and probit models to assess whether the results remain consistent across different resampled datasets. Bootstrap standard errors are obtained using the *boot* package in R (Davison and Hinkley 1997). Very large bootstrap standard errors relative to the original LPM, logit, and probit models indicate high variability in coefficient estimates, suggesting that the original regression may already be unstable due to the issues listed above.

Third, to diagnose the presence of perfect separation, we estimate a Firth's penalized logistic regression models, which uses penalized likelihood estimation to reduce small sample bias and address separation issues (Firth 1993; Heinze and Schemper 2002). This regression method has been applied to analyse the determinants of adopting agricultural innovations at the farm level, such as Souza Monteiro and Caswell (2009). We compare the results of Firth's regression results with our results from the LPM, logit, and probit models to support our decision of choosing LPM as our main regression model.

Finally, besides sample size and separation problems, unstable regression model can be due to multicollinearity. To detect this issue between independent variables, we calculate the variance inflation factor (VIF) for all explanatory variables in the LPM models (Wooldridge 2020: 92). For each independent variable X_k, we run a linear regression Ordinary Least Squares (OLS), treating X_k as the dependent variable and regressing it on all other independent variables. Using R_k^2 from each regression model, VIF is calculated for each independent variable as: $VIF_k = \frac{1}{1-R_k^2}$. The VIF measures how much the variance of an estimated regression coefficient increases due to collinearity with other regressors. A VIF greater than 10 indicates severe multicollinearity, while values between 5 and 10 indicate moderate collinearity, which may require further investigation.

5. Results and discussion

5.1. Empirical results

Table 2 shows the estimates for six LPMs, including our main model (*LPM full model*) and five additional models for robustness checks (*Models 2–6*). Our results show that *performance expectancy*, *facilitating conditions*, and *experience* constructs are significantly associated with IST participation probability. We present the empirical results alongside corresponding discussions.

Regarding *performance expectancy* construct, coefficient for perceived impact of input volatility (*Perceived input price*) ranges from 0.156 to 0.226, indicating that farmers who perceive higher volatility in input prices are significantly associated with an increase of approximately 16–23 per cent in the IST participation rate. In contrast, we do not find a significant estimate for perceived impact of output price volatility (*Perceived output price*). This suggests that farmers are more responsive to the cost component rather than the revenue component of the income risk. In addition, while milk prices are often partially stabilized through cooperative pricing mechanisms and long-term contracts, input prices (e.g. feed, energy, and fertilizers) are largely beyond farmers' control and are subject to market fluctuations. Hence, our finding supports the hypothesis that higher perception of input price volatility influences farmers' adoption of risk management tools (Kuethe and Morehart 2012; Atta and Micheels 2020).

In terms of *facilitating conditions*, being a sole trader (*Sole_trader*) is statistically correlated with 22–30 per cent decrease in the probability of IST subscription. Although all farmers in the sample are members of cooperatives, being a sole trader implies full responsibility over administrative and financial decisions. This can influence their engagement with risk management tools such as the IST. The significant negative association between *Sole_trader* and IST participation rate suggests that independently operated farms may face greater constraints in adopting a new risk management tool. These constraints may include limited administrative capacity, time constraints, or scepticism about the benefits of participation, even when cooperative support is available. The result is in line with previous literature on the uptake of risk management tools (Lefebvre et al. 2014; Rippo and Cerroni 2023), which show that enterprise type can influence adoption behaviour due to differences in perceived complexity, cost-benefit considerations, and risk attitudes.

The *experience* construct is particularly relevant in explaining farmers' decision making to adopt the IST. Farmers having received the coupled payments (*Coupled_payment*) show a significant association with 23%–25% decrease in the IST adoption rate. This finding is

Table 2. Results of linear probability models.

	LPM full model (Model 1)	Robustness checks				
		Model 2	Model 3	Model 4	Model 5	Model 6
Performance expectancy						
Perceived milk price	−0.050 (0.084)		−0.070 (0.080)	−0.054 (0.073)	−0.075 (0.077)	−0.103 (0.084)
Perceived input price	0.161* (0.090)		0.156* (0.084)	0.156** (0.077)	0.164* (0.089)	0.226*** (0.082)
Effort expectancy						
Milk per LSU	0.004 (0.027)	0.013 (0.027)		0.004 (0.026)	0.003 (0.028)	−0.004 (0.025)
Top_producer	0.188 (0.169)	0.180 (0.176)		0.188 (0.167)	0.034 (0.156)	0.158 (0.181)
Social influence						
Cooperative	0.019 (0.172)	−0.095 (0.127)	0.007 (0.165)		0.022 (0.178)	0.145 (0.163)
Facilitating conditions						
Sole_trader	−0.302** (0.129)	−0.295** (0.142)	−0.229 (0.137)	−0.303** (0.128)		−0.291** (0.134)
Livestock density	−0.018 (0.014)	−0.023 (0.016)	−0.018 (0.015)	−0.018 (0.014)		−0.006 (0.017)
Experience						
Coupled_payment	−0.234** (0.097)	−0.242** (0.097)	−0.236*** (0.086)	−0.233** (0.095)	−0.251** (0.099)	
Insurance	0.107 (0.135)	0.078 (0.134)	0.108 (0.144)	0.111 (0.129)	0.119 (0.134)	
Mutual_fund	−0.207* (0.118)	−0.272** (0.117)	−0.191 (0.117)	−0.212* (0.106)	−0.145 (0.117)	
Moderating factors						
Age	−0.005 (0.004)	−0.006 (0.004)	−0.004 (0.004)	−0.005 (0.004)	−0.004 (0.003)	−0.003 (0.004)
Female	0.232** (0.107)	0.213 (0.117)	0.252** (0.110)	0.230** (0.107)	0.268** (0.125)	0.259* (0.136)
Education	−0.242** (0.102)	−0.283** (0.103)	−0.218** (0.102)	−0.241** (0.101)	−0.243** (0.102)	−0.202* (0.112)
Weather_stress	0.003 (0.009)	0.002 (0.008)	0.004 (0.008)	0.003 (0.008)	0.007 (0.010)	0.000 (0.008)
Constant	0.600 (0.947)	1.358 (0.971)	0.567 (0.958)	0.638 (0.939)	0.203 (1.072)	0.608 (0.870)
Adj R-squared	0.193	0.180	0.201	0.208	0.139	0.096

Each of the five models for robustness checks (Models 2–6) excludes variables measuring a construct. In particular, Model 2 excludes *performance expectancy* factors, Model 3 excludes *effort expectancy* factors, Model 4 excludes *social influence* factors, Model 5 excludes *facilitating conditions*, and Model 6 excludes *experience*. Robust standard errors in parentheses. Signif. codes: '*' 0.1, '**' 0.05, '***' 0.01.

consistent with the literature on the interaction between private insurance and coupled payments, which suggests that coupled payments act as a form of income insurance, reducing the need for additional risk management tools (Finger and Lehmann 2012; Möllmann et al. 2019).

Farmer being a member of a yield-based mutual fund (*Mutual_fund*) illustrates a significant negative correlation with 15%–27% of IST adoption probability. This result of the mutual fund is in contrast with previous study on the Italian apple-sectorial IST by Rippo and Cerroni (2023), where mutual fund participation is positively associated with IST uptake. In the context of dairy farming, yield-based mutual funds provide compensation for production losses due to adverse climatic events or animal diseases (MASAF 2023). The observed negative correlation suggests that farmers do not always perceive complementarities between yield-based mutual funds and the IST. Instead, they may see them as substitutable tools, particularly if they are unfamiliar with how IST addresses broader income-related risks besides yield losses. For cooperatives, this indicates that familiarity with risk management tools, such as mutual funds for yield losses, does not necessarily translate into additional adoption of a novel risk management tool, such as the ISTs.

Our results show that being female farmers are positively associated with a higher likelihood of IST adoption, with the estimated probability ranging from 21 per cent to 27 per cent. This finding is in contrast with a previous study by Rippo and Cerroni (2023) which found a negative association between female farmers and apple-IST adoption. While this study emphasizes the role of gender as a moderating factor affecting behavioural intention and adoption of innovations, we add another layer to the explanation of our result. In particular, we explain the farmer risk aversion based on their gender, which may be the cause of inconsistency in the gender estimates across different contexts (e.g. apple sectorial IST and dairy sectorial IST). Our observed negative relationship between female farmers and IST adoption can be explained by evidence from dairy farming studies suggesting that female farmers are more risk-averse than male farmers and therefore more inclined to adopt tools that stabilize income in the face of market and production volatility (Flaten et al. 2005; Eckel and Grossman 2008).

Regarding education, we find that farmers with post-secondary education are correlated with a decrease of 20%–28% in IST participation rate. We acknowledge that the finding is challenging to interpret definitively. One possible explanation is that farmers with less education may perceive market and production risks as more severe or uncertain (Savage 1993) and therefore perceive the IST as a valuable solution for income risk mitigation. In contrast, farmers with higher education level may be more confident in managing risks through alternative strategies, such as market-based instruments, business planning, or cooperative support (Dohmen et al. 2011; van Winsen et al. 2016).

Finally, the estimate for weather conditions (*Weather_stress*) is positive but not statistically significant across all model specifications. Within our sample of cooperative dairy farmers, exposure to weather-related stressors alone does not significantly influence the likelihood of IST adoption. As all farms in our sample are located within the same province and plain terrain, the limited spatial variation may constrain the exploratory power of the weather variable, as within-province differences in exposure to heat and humidity stress are likely to be small.

5.2. Robustness checks

According to Table 2, the significant estimators identified in the *LPM full model,* that is, *Perceived input price, Sole_trader, Coupled_payment, Mutual_fund, Female*, and *Education*, maintain consistent signs, magnitude, and statistical significance across most specifications (*Models 2–6*). Although the statistical significance of *Female* and *Mutual_fund* weakens in Model 2 (i.e. excluding *performance expectancy* construct) and Model 3 (i.e. excluding *effort expectancy* construct), respectively, the direction and magnitude of their coefficients remain stable. Hence, the loss of significance is likely due to the omitted relevant constructs (i.e. *performance expectancy* construct or *effort expectancy* construct) rather than model instability.

Due to space constraint, we report the results of the same specifications estimated for the logit and probit models in Tables C2 and C3 in the supplementary Appendix C. The key estimators identified in the *LPM full model* also show consistent signs, magnitudes, and statistical significance in both logit and probit models, strengthening the robustness of the LPM estimates.

Nevertheless, the bootstrap results show that the logit and probit models suffered from excessively large standard errors, reinforcing concerns about perfect separation. In contrast, LPM standard errors remained more stable, suggesting that LPM provides more reliable inference (see the supplementary Appendix C Table C4). Even with Firth's logistic regression, the logit standard errors remain large, indicating that separation remained a persistent problem (see the supplementary Appendix C Table C4). Given that over 96 per cent of the farms in the sample are medium or large farms, and that all farmers are members of the two cooperatives, the structure of the dataset is likely to have contributed to this issue. This further supports the decision to rely on LPM, which does not suffer from separation-related estimation problems. Furthermore, the VIF analysis shows that the independent variables do not exhibit excessive collinearity in all LPM models (VIF values < 5) (see the supplementary Appendix C Table C5). Hence, we conclude that our results from the LPM are robust.

6. Conclusions

Income variability in agriculture has gained significant attention from farmers and policymakers in recent years due to increasingly volatile economic, environmental, and political conditions. This paper contributes to the ongoing discussion on the effectiveness of financial risk management tools by exploring the factors associated with farmers' participation in the IST, which is one of three key risk management tools subsidized under the CAP Pillar II. Unlike insurance and mutual funds, which compensate farmers for yield losses, IST specifically addresses income losses. Our study focuses on the case of dairy sectorial IST currently implemented for dairy cooperatives in Brescia, Italy, a province that operates one of the nine sectorial ISTs in the entire country. Until now, Italy is the only EU Member State to have implemented sector-specific ISTs, demonstrating its pioneering role in support novel agricultural risk management tools in the EU.

Our paper discusses closely with Rippo and Cerroni (2023) on Italian apple sectorial IST as *ex-post* studies on this topic remain scant. To investigate factors associated with the adoption of the IST at the farm level, we adopt the UTAUT conceptual framework to explain the acceptability of the IST among dairy farmers based on factor groups regarding *performance expectancy, effort expectancy, social influence, facilitating conditions*, and *experience*. Our results show that the perceived impact of input price volatility is positively associated with the probability of IST participation, while sole trader status, coupled payments, and mutual funds are significantly associated with a lower adoption rate of IST. Moderating factors, such as being a female farmer, are positively correlated with the IST participation rate, while farmers having post-secondary education are negatively correlated with the probability of IST adoption. Our results are robust across various model specifications.

In the context of risk management in cooperatives, income risk mitigation should focus on either direct income support (i.e. coupled direct payments) or risk management tools (i.e. insurance, mutual funds for yield losses, and ISTs for income losses), rather than implementing both simultaneously (Popp et al. 2021). This insight is relevant for policy makers and cooperative organizations seeking to tailor risk management strategies to the needs of different farmer profiles and to improve the accessibility and effectiveness of IST.

As coupled payments have been projected to decline, especially for large farms, in the coming years, reducing farmers' dependence on coupled payments will be essential to ensure a smooth transition to adopting risk management tools that meet their needs. Cooperatives implementing sectorial ISTs should focus on improving the accessibility of the ISTs to members that have not adopted mutual funds nor received financial support from coupled payments to increase the tool adoption rate. In addition, the allocation of public funds for risk management tools should consider the forementioned determinants, to ensure that policies are effectively targeted at those farmers most in need of support. Factors such as perceived administrative burden or confidence in IST effectiveness plays an important role that requires further investigation (Vigani et al. 2024).

Our paper faces some limitations. As farm size in our sample is higher than the national average, results from this sample may not be representative at the regional and national levels. Our sample consists entirely of farmers within two cooperatives in the region of Lombardy, Italy, rather than including both cooperative and non-cooperative members. We acknowledge that the identified factors may partially reflect cooperative influence rather than purely individual preferences. Hence, if the sample included both cooperative and non-cooperative farmers, we might have observed stronger effects of farm structure and risk management experience, as non-cooperative farmers are likely to have greater variability in risk exposure and financial insecurity (Trestini et al. 2018). Given that the current sectorial ISTs operated in Italy is strictly limited to cooperatives or consortia, and given the robustness of our results within the sectorial IST established by two cooperatives, our findings remain informative with regards to factors influencing farmers' adoption of this novel tool.

We recommend that future research on the adoption of risk management tools take a holistic approach, considering the perspectives and roles of all key stakeholders, including public authorities, cooperatives in high-value agricultural sectors, and individual farmers (Arata et al. 2023; Vigani et al. 2024). A comprehensive understanding of how these actors engage with different risk management strategies and tools is essential for designing a coherent policy framework that minimizes overlaps and inefficiencies between policies (Finger et al. 2022; Arata et al. 2023). Italian farmers' preferences for specific features of risk management tools remain an underexplored area in the literature. Hence, examining which features drive adoption and which barriers hinder participation represents an important step towards understanding farmers' adoption of these tools. In addition, further research should investigate the mechanisms underlying the negative correlation between education and IST adoption. Future studies should also involve broader geographic coverage or higher resolution weather database, such as satellite data, to provide further insights into the role of climatic conditions in IST participation decisions. As IST funds continue to expand and evolve, we expect that future empirical studies with larger sample sizes will provide more robust findings and strengthen the evidence base for more targeted and effective policy interventions.

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Supplementary material

Supplementary data are available at *Q Open* online.

Conflict of interest

None declared.

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Data availability

Due to confidentiality agreements with the cooperatives involved in the survey, the underlying data cannot be made publicly available. The survey questionnaire and all analysis code are provided in the supplementary material.

End notes

1 The calculation of IST contribution fee in Italy can be found at https://www.masaf.gov.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/14340 (in Italian) and is elaboratively explained in the supplementary Appendix B.
2 Operating costs include administrative costs spread over 3 years and compensation for farmers' loss of income. IST fund must be financed entirely by contributions from farmers.
3 The income baseline can be computed in two ways: (1) an average of the farm's income over the preceding three consecutive years; or (2) an average of farm income from any 3 years within the preceding 5-year period, excluding the highest and lowest entry ('the Olympic baseline').
4 Systemic risks refer to the potential failure of an agricultural system caused by the interlinkages of its components—such as extreme cold weather that reduces the quantity and quality of cow milk, increases the cost of energy for heating, and causes shortages in milk supply—can lead to high price volatility in the market and affect farmers' income (Bernard De Raymond et al. 2021).
5 According to Decree No. 10158 released on 5th May 2016 by the Italian Ministry of Agriculture, Food, and Forestry Policies (MASAF 2016), each sectorial IST fund must be run for a minimum duration of 5 years, and participants must be members of the IST fund for at least 3 years.
6 Agri4cast data is available on https://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx.
7 Unlike Rippo and Cerroni (2023), we did not have information on farm-level insurance indemnification used as a proxy for the *performance expectancy* construct. Instead, we include an insurance dummy in the *experience* construct, which we elaborate later, to explain farmers' experience with similar risk management tools.
8 In the following sub-section (3.3), we compare the farm structure of our sample with that of dairy farms at the provincial, regional, and national level.
9 THI is calculated following the formula THI $= T_g + 0.36T_{dp} + 41.2$, where T_g is the black globe temperature (°C) represented by the maximum temperature within the recorded day (Thom 1959; Oliveira and Esmay 1982). T_{dp} is the dewpoint temperature (°C): $T_{dp} = \frac{100-RH_{percent}}{5}$, where $RH_{percent}$ the relative humidity percentage defined as $RH_{percent} = \frac{Vapour\ pressure\ value}{es_{magnus}} \times 100$. The es_{magnus} estimates the saturation vapour pressure of water at a given temperature T_{max}, defined as: $es_{magnus} = 6.1094 \times \exp(\frac{17.625\times T_{max}}{243.04+T_{max}})$ (Huang 2018).
10 ISMEA (2022) classifies dairy farm scales in Italy into small (<50 heads), medium (50–100 heads) and large (>100 heads) based on the number of cow heads on the farm.

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