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Towards a holistic approach to sustainable risk management in agriculture in the EU: a literature review

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Abstract. Agriculture is one of the sectors most exposed to a plethora of risky phenomena such as weather, pests and diseases, changes in prices and government policies, instability of global markets. We review the literature on risk management (RM) in agriculture focusing on five key issues: i) why evidence on RM is often controversial; ii) how farmers behave in selecting among available RM instruments; iii) why some of these instruments are underutilised; iv) how to assess the impacts of innovative RM tools to (further) improve their design; v) how agricultural policy measures aimed at increasing the environmental sustainability of the sector could affect RM choices. We address all these issues to get a holistic vision of RM, and point at areas where further analyses are needed.

Keywords: risk management choices, behavioural factors, adoption of risk management tools, use of chemicals, feasibility studies.
JEL Code: Q12, D81, D83, O31.

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1. INTRODUCTION

Although risk concerns all economic activities, agriculture is one of the most concerned sectors, due to its exposure to a plethora of risky phenomena such as weather, pests and diseases, changes in prices and government policies, instability of global markets, and other factors (Moschini and Hennessy, 2001; Hardaker et al., 2015; Komarek et al., 2020). Furthermore, the multifaceted risks farmers must cope with are very likely to occur simultaneously, producing a compounded negative effect (Hardaker et al., 2004).

Risk in agriculture causes wide volatility in farmers' income and well-being and in turn it influences the decision-making process. Experiencing negative events reduces farmers' willingness to invest and innovate (Sckokai and Moro, 2009). This, in turn, may negatively affect farms' productivity and

competitiveness (Vigani and Kathage, 2019) and push farms out of the business. The negative consequences may also be reflected in the value chain (Cafiero, 2008) and transferred to all stakeholders of the agro-food system. Major and unexpected events such as the COVID-19 pandemic and the food/energy crises induced by the war in Ukraine have unrevealed the vulnerability of the global food supply. By threatening the status of global food security, these major shocks have induced unprecedented policy responses in all advanced economies, as well as in developing countries (European Parliament, 2022; OECD, 2020; Santeramo and Kang, 2022). Over the years, risk in agriculture has been increasing in width and depth, unveiling the need for improving Risk Management (RM), as recognized by the European Commission (2017) "[...] *it is important to set up a robust framework for the farming sector to successfully prevent or deal with risks and crises, with the objective of enhancing its resilience and, at the same time, providing the right incentives to crowd-in private initiatives*". RM refers to the actions taken to manage potential problems induced by risky events, to reduce their detrimental consequences, and to increase the chances of success of the business (Kahan, 2013). In this sense, RM can be a key factor in enhancing the resilience of farms and related farming systems (Spiegel et al., 2020) and several scholars call for improving and enlarging the scope of RM to do so (Finger et al., 2022). Unfortunately, the state of knowledge on RM in agriculture is still incomplete, and the current approaches to RM are too simple, partial, and inappropriate to successfully help cope with multi-faced global challenges: changes in climate, more frequent extreme weather events, unstable and volatile markets, food security and food safety threats. Improving the state of knowledge on RM is important: successfully managing risks helps in finding the right balance among productivity, environmental care, market resilience to climate change, and capability to secure safe and quality food.

This paper reviews the extant literature on the analyses of agricultural RM, highlights progress and gaps, and advices on promising areas of research. This exercise is *per se* a very useful contribution to developing a holistic approach to analysing RM. More generally, we hope this piece will stimulate the debate on this relevant topic. While we are aware that some recent literature reviews exist, especially on specific topics (e.g., Komarek et al., 2020), we believe that our paper makes a twofold contribution to the extant debate. First, our overview of the literature focuses on five research questions: i) why evidence on RM is often controversial; ii) how farmers behave in selecting among available RM instruments; iii) why some of these instruments are underutilised; iv) how to assess the impacts of innovative RM tools to (further) improve their design; v) how agricultural policy measures aimed at increasing the environmental sustainability of the sector could affect risk and, consequently, RM choices. These questions are answered in the subsequent sections. This review also highlights areas where further analyses are needed. Second, we use a holistic approach to the topic. Since RM in agriculture is a complex phenomenon, several RM actions are available, and farmers' decisions are affected by spatially and temporally heterogeneous factors, a holistic approach seems needed (Figure 1). RM decisions are strongly influenced by the context in which farmers operate. Several dimensions are relevant to define the context, including not only farm structural and productive characteristics, but also the markets and the environment in which farmers operate. Regarding the markets, the complexity and interconnection of the global agri-food sector have imported new risks into the sector or emphasized old ones. Regarding the environment, there is a vast literature pointing out the effect of climate change on the risks farmers are facing (e.g., Sorvali et al., 2021). A growing body of literature has also shown that farmer's behavioural factors do affect the farmer's RM choices and therefore such factors cannot be ignored. Furthermore, the farm sector in the EU is heavily affected by policies. On the one hand, EU rural development policies support the adoption of specific RM tools providing subsidies to reduce the cost of adoption. On the other hand, farm production is constrained by pieces of legislation aimed at reducing the use of inputs with a harmful effect on the environment. However, often these inputs (e.g., pesticides in the case of pests, and irrigation in the case of drought) have also an effect on agricultural risk, thus their imposed reduction is likely to influence RM choices. The policy context is evolving in this area: the recently released Farm-to-Fork strategy (F2FS) and the CAP reform (European Commission, 2018) have set very ambitious environmental targets for EU agriculture (reduction of 50% and 20% in the use of pesticides and fertilisers respectively, by 2030). This will have consequences on the risk faced by farmers because the use of chemicals is intimately related to risk in agriculture and its management (Möhring et al., 2020). Studying the impact of policies targeted to environmental objectives on the farmer's risk and the uptake of RM tools is worthy to be addressed. Farmers are the ultimate decision-makers in terms of risk management strategies. As economic agents they can take several actions to manage risk including the adoption of specific RM tools (Santeramo, 2019; Cai, de Janvry and Sadoulet, 2020), changes in production mix and diversification, subscription of

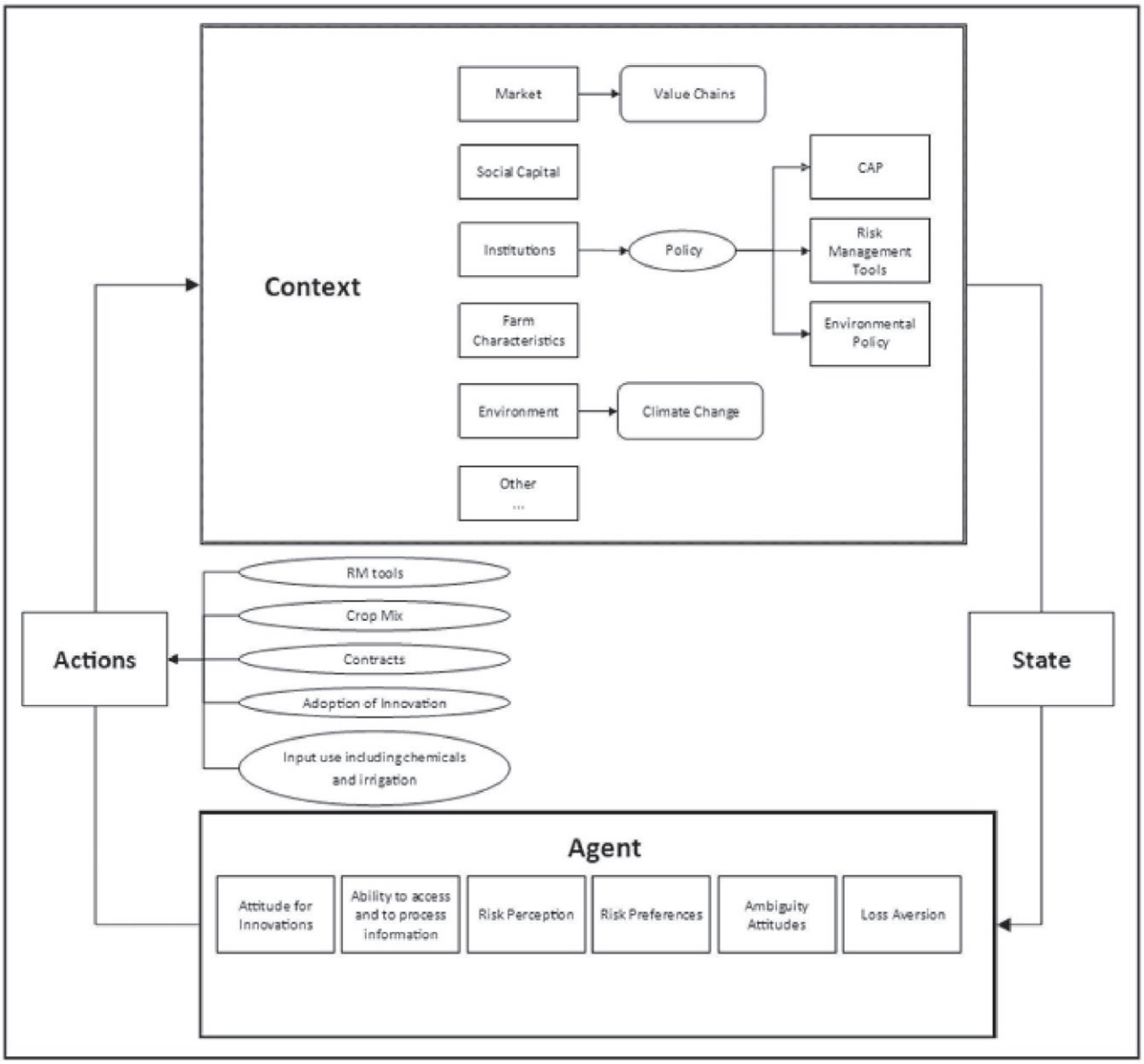

Figure 1. Graphical representation of the environment in which RM takes place. Source: Own elaboration.

production contracts, use of risk decreasing input such as pest control chemicals and irrigation (Cerroni, 2020). Their actions are however influenced by risk preferences (Iyer et al., 2020), and other behavioural factors. The literature on the influence of other behavioural factors (i.e., subjective probabilities, risk perception and preferences, ambiguity attitudes, loss aversion and time preferences) on farmers' decisions to uptake RM tools (Colen et al., 2016) is scant (Coletta et al., 2018; Cerroni, 2020; Čop et al., 2023). Similar considerations apply to the attitude toward innovations and the ability to gather and process information.

In the end, this oversimplified framework (and logical flow) advocates for a holistic approach to the analysis of RM also realizing that the current state of agricultural RM is constantly evolving, and it needs to be adapted to novel challenges. Our literature review is an attempt to approach the study of RM by adopting a holistic view: the methods adopted in the analysis of RM in agriculture, the behavioural factors affecting RM adoption, innovative RM tools, the relationship between agricultural risk and input use and between different policies directly or indirectly affecting risk and RM in agriculture.

These topics were selected because they are important in influencing the choice of RM strategies. Furthermore, on these issues there have been significant advances in the literature but still some aspects require further study. Although the emphasis is on EU RM, the review considers analyses carried out also in non-EU countries. These are included to report approaches of analyses that could be replicated in the EU context and to better position the possible strategic choices of the EU with respect to the international context.

Section 2 gives an overview of the methods available in the literature to study the adoption of RM in agriculture and it also summarises risk types whose frequency is increasing in the agricultural sector. Section 3 focuses on the behavioural factors, specifically the subjective probabilities, risk and uncertainty preferences, affecting the farmer's decision to adopt insurance products (either traditional insurance or weather-based index insurance). Section 4 provides a picture of innovative RM tools, such as the mutual funds for catastrophic events (introduced by the last CAP reform) and the weather-based index, together with their pros and cons compared to traditional insurance products. Section 5 reports on the studies related to the impact of pesticide and fertiliser use on agricultural risk as well as on the effect of insurance product adoption on this use. The section also highlights potential synergies and trade-off among different EU agricultural policies.

The last section concludes by summarizing the main points raised by the literature review. Here, special attention is paid to identify the areas where further improvements in the research on farm risk management are needed.

2. EXPLAINING RISK MANAGEMENT CHOICES

To cope with the large array of risks the farm sector is facing, the European Union (EU) decided to emphasize the role of new RM tools (Meuwissen et al., 2018) by structurally supporting not only crop insurance products, but also mutual funds (MF). These can cover yield losses and, by means of the Income Stabilisation Tool (IST), can help farmers cope with income drops (El Benni et al., 2016), enlarging the type of risks covered by subsidized tools. Despite the pervading exposure to risks for farmers (Trestini et al., 2017), the advantages that these instruments provide to farms (Enjolras et al., 2014; Severini et al., 2019) and the confirmed trend in the reduction of decoupled direct payments, the expenditure foreseen since 2014 in the CAP for the Risk Management Toolkit involves only 12 over 28 Member States (Chartier et al., 2017). Among these, Italy, the leading country in terms of allocated budget, still records a limited uptake of risk management tools (Ismea, 2022). The application of CAP is further pushing in the direction to improve the development and the support for risk management solutions by confirming actual tools and introducing in the Italian Strategic Plan of the CAP, from 2023, the new catastrophic risk coverage called Agricat, built as a mutual fund.

All this offers farmers the opportunity to get access to a wide set of RM solutions. This availability of innovative tools (i.e. mutual funds, IST and Agricat) together with the limited diffusion of traditional ones (i.e. insurance), impose understanding determinants of the diffusion of both traditional and innovative RM tools to allow farmers to maintain and improve their resilience and competitiveness under the new orientations of CAP. Understanding the factors that influence the adoption of RM tools allows, from the point of view of policy maker, to evaluate the effectiveness of RM policies and to guide their design. While, from the perspective of insurance company or mutual fund, it provides a better understanding of farm preferences by driving the development of RM tools that can promote farm resilience.

The review of the research methodologies applied to understanding the adoption of RM tools by farmers allows to identify research gaps and suggest potential future studies. The adoption of risk management tools is extensively investigated in the literature (Harrison and Ng, 2019), yet the behavioural factors of this adoption is often neglected (see Section 3 for a detailed discussion on this point). In the EU, a growing body of studies about yield insurance and mutual fund adoption is observable (Enjolras and Sentis, 2011; Liesivaara and Myyrä, 2017; Meuwissen et al., 2018; Santeramo, 2018; Santeramo et al., 2016; Was and Kobus, 2018). Index-based insurance tools, marginally adopted in the EU, are mainly investigated in developing countries (e.g., Bucheli et al., 2021; Jensen et al., 2018) with some applications in the EU (Vroege et al., 2019).

In order to understand RM behaviour and assess the probability of farmers' adoption of available and innovative tools, it is worth considering different determinants simultaneously within an effective conceptual framework. In fact, the determinants of the adoption of RM tools are widely discussed in the literature, whereas practical application aiming to understand the interaction of different determinants is much less explored (Holt and Laury, 2002; Franken et al., 2017). Indeed, risk and ambiguity preferences may affect risk behaviour directly (Menapace et al., 2013; Čop et al., 2023). Furthermore, risk attitude explains risk behaviour, being

indirectly affected by socio-economic and individual characteristics (Dohmen et al., 2011; Donkers et al., 2001). Complex interrelations can be simplified by multivariate statistical analysis such as the so-called Structural Equation Modelling (SEM) (Ullman and Bentler, 2003). SEM allows for testing complex models that imply both direct and indirect effects, allowing to solve limitations of traditional regression models. Furthermore, SEM allows researchers to distinguish between observed and latent variables, testing a wider variety of hypotheses compared with most traditional approaches (Kline, 1998). This approach is quite recent among agricultural economists, with one of the first examples incorporating risk components proposed by Pennings and Leuthold's (2000). In recent applications, risk behaviour has been investigated focusing on risk perception and risk attitude (Van Winsen et al., 2016), and on farm socio-economic and individual characteristics of risk attitude (Franken et al., 2017), also incorporating the role of trust and perceived barriers (Giampietri et al., 2020). A first attempt to apply a defined framework to understand the participation to RM tools has been applied by Rippo and Cerroni (2023) using the Unified Theory of Use and Acceptance (Venkatesh et al., 2003). Beside these attempts to build a framework able to understand and support the diffusion of available and innovative tools, any shared conceptual framework is, to our knowledge, applied in the literature.

Literature proposing the analysis of determinants of diffusion and/or adoption of innovation at SMEs including farms is extensive and well formalized. Many other methodologies should be tested also for the case of RM tools adoption. To do so, we should consider the organisational profile of farms and the role of individuals, especially in family farms. At first glance, when evaluating family farm choices, the theory of planned behaviour (TPB) (Ajzen, 1985; 1991) and technology acceptance model (TAM) (Davis, 1986) appear to be the most appropriate frameworks. This is because the two frameworks include constructs such as "Subjective norms", in the case of the TPB, or the perceived usefulness, in the case of the TAM, which strictly refer to the individual evaluation of the choice or to the perceived social pressure to engage or not to engage in a behaviour. When the farm adopts a structure in which wage labour becomes prevalent by assuming a corporate structure with division and delegation of responsibilities, the process of choice moves from being individual or dependent on family needs and relationships to being the result of an organizational choice. In this case, diffusion of innovation theory (DOI) (Rogers, 1995), and the technology–organization–environment (TOE) framework (Tornatzky and Fleischer, 1990) are suitable. These methodologies analyse the adoption process at the organizational level, including among determinants of specific adoption choice variables like the compatibility with the company, in the case of DOI, and formal/informal organisational link, in the case of TOE.

Besides deterministic approaches, Machine Learning solutions start to be applied to further understand factors affecting the adoption of RM strategies. Few applications can be retrieved from the current literature considering application of insurance contracts in Romania and Italy (Mare et al., 2022; Biagini et al., 2022a) and mutual funds for pest diseases in the North of Italy (Höschle et al., 2023).

At present, there is a growing interest in the management of new and/or growing risks: among these, it is worth to mention the need to manage growing systematic abiotic risks (e.g., drought and frost) and emerging biotic threats (pests and diseases). As regards the latter, the need for better-tailored risk management tools becomes more urgent given the orientation of agricultural policy towards the significant improvement of production environmental standards (e.g., F2F Strategy), often not sufficiently supported by alternative solutions in pest management. In the case of extreme and systematic weather risks, a country-wide event cannot be covered under indemnity insurance schemes because the costs for the physical damage assessment in the field often outweigh the benefit for the insured farm (Vroege et al., 2019) and the systemic nature of the event may expose insurance sector to unsustainable costs. Concerning biotic threats, the availability of insurance is rare as it is often unsuitable for the insurance market, due to both their unpredictable spread, linked to an epidemic dynamic, and agents' behavioural reasons, mainly moral hazard (Norton et al., 2016). To face the limitations of insurance, some pioneering initiatives of mutual funds to manage such risks have been locally developed in Italy, both with private and public support (Giampietri et al., 2020; Höschle et al., 2023), but the availability of such tools is below the expected demand.

To design a better-tailored RM tool offering protection against pests and diseases that are appealing to farmers, the first important step is to investigate farmers' preferences for the characteristics of such innovative tools. Until now, farmers' preferences for insurance contract characteristics remain mostly unaddressed, despite being of utmost importance for designing new insurance contracts, extending them to other crops, and increasing participation rates. To this purpose, the discrete choice experiment (DCE) approach has proved to be useful. Based on the Lancaster's (1966) theory of

consumer and the Random Utility Theory, demand is defined over the characteristics of goods, rather than over goods themselves. In DCE respondents are thus asked to choose between different bundles of goods (e.g., RM tools) described in terms of their characteristics (e.g., price, level of maximum indemnity). DCE has been largely employed to elicit consumers' preferences and policy design (Colombo et al., 2005). More recently, this approach has also been used to investigate farmers' preferences for agro-environmental scheme designs (Ruto and Garrod, 2009) and contract farming configurations (Abebe et al., 2013). Furthermore, discrete choice experiments have been used to investigate farmers' preferences for insurance contract characteristics. While there are several DCE carried out in developing countries addressing farmers' preferences for insurance characteristics (Akter at al., 2016; Reynaud, Nguyen, Aubert, 2017; Ward and Makhija, 2018; Ali et al., 2021; Tang et al., 2022), there are only few that concern European farmers (Mercadé et al 2009; Liesivaara and Myyrä, 2017; Möllmann et al., 2019; Doherty et al., 2021; Čop et al., 2023) and there are no applications on Italian farmers. In conclusion, the literature review highlights the lack of a general framework to support the development of effective policies to promote RM solutions in agriculture. A comparison of different frameworks can improve the understanding of farmers' behaviour and evaluate the most suitable approach depending on the organizational profile. These studies should support policy design based on the joint study of farmers' preferences and behaviour towards RM strategies. Furthermore, there is a need to carry out policy impact assessments in terms of farmer uptake of RM innovations and effects in reducing risks and increasing farm resilience. Finally, it may prove useful, as RM solutions for farmers increase, to better understand the interactions and possible trade-offs between the different tools.

3. BEHAVIOURAL FACTORS INFLUENCING FARMERS' ADOPTION OF RISK MANAGEMENT TOOLS

From a behavioural perspective, the economic framework that is generally used to understand and predict farmers' decisions to cope with agricultural risks is rooted in expected utility theory (EUT) (von Neumann and Morgenstern, 1947). However, some fairly recent empirical applications have demonstrated that farmers' decisions to insure their production often depart from standard EUT. Non-standard economic theories, such as prospect theory, explain farmers' choice behaviour more parsimoniously (e.g., Babcock, 2015; Dalhaus et al., 2020; Feng et al., 2021). These empirical findings determined the development of a small but growing research that investigates the extent to which behavioural factors such as farmers' probabilistic beliefs, probability weighting, risk and uncertainty preferences, and loss aversion influence farmers' decisions to purchase an insurance product (e.g., Fezzi et al., 2021) and participate to mutual funds (Rippo and Cerroni, 2023; Čop et al., 2023). These behavioural factors are generally elicited using experimental methods, while their ability to explain and predict farmers' choice behaviour is tested by combining data from economic experiments with primary data obtained using stated preference surveys or available secondary data on actuarial farmers' purchasing decisions (Iyer et al., 2019). In this section, we mainly focus on the literature related to subjective probabilities, risk and uncertainty preferences.

Subjective probabilities are considered to be important predictors of farmers' behaviour because farmers, like any other economic agent, base their decisions on their beliefs or expectations when the decision context is highly uncertain. If expressed in a probabilistic fashion, these beliefs or expectations are defined as subjective probabilities (e.g., Hardaker and Lien, 2010). The literature looking at the role of subjective probabilities in explaining farmers' behaviour is scant, and only a very small number of studies examined how subjective probabilities influence farmers' decision to purchase an insurance product (see Cerroni, 2020; Čop et al., 2023; Cerroni and Rippo, forthcoming for recent reviews). There are a couple of noticeable exceptions. Čop et al. (2023) found that subjective probabilities are important predictors of farmers' decisions to enrol on a sector-specific IST related to grapevine. Fezzi et al. (2021) found that farmers' subjective probabilities regarding production losses due to extreme climatic events are not in line with objective measures of risk. Hence, policy interventions geared to reduce this gap could have important policy implications regarding insurance subsidization. One potential drawback of these studies is the elicitation of subjective probabilities using hypothetical methods that are not incentive-compatible and therefore do not induce farmers to elicit truthful beliefs. However, the literature on decision analysis provides several incentive-compatible methods that are able (in theory) to elicit truthful beliefs under a proper incentive scheme. These methods could be used to elicit more accurate subjective probabilities related to uncertain agricultural outcomes (see Cerroni and Rippo, forthcoming for a review). More accurate probability assessments should have in theory a higher degree of external validity and explain farmers' choice behaviour more parsimoniously.

Risk preferences have been shown to be an important driver of farmers' decision-making processes, especially those related to the adoption of new technology and crops (e.g., Liu, 2013; Barham et al., 2016). However, only a few studies have investigated whether these preferences can play a role in explaining farmers' decision to purchase insurance products. Recent research indicates that risk preferences are poorly correlated with the decision to purchase traditional insurance products (Menapace et al., 2016; Coletta et al., 2018; Rommel et al., 2019; Čop et al., 2023). These results may be driven by some confounding factors that have been recently identified in the related literature. First, risk preferences appear to be highly context-dependent (Finger et al., 2022) and therefore their ability to explain farmers' choice behaviour may be context-dependent too. Second, a wide range of approaches exists to elicit risk preferences (see Cerroni, 2020, and Cerroni et al., forthcoming for recent reviews), and, unfortunately, empirical evidence suggests that different elicitation techniques provide inconsistent measures (e.g., Reynaud and Couture, 2012). Once again, the elicitation technique used may have an impact on the ability of elicited preferences to explain choice behaviour. Some practitioners advocate that adding an agricultural context to standard monetary lotteries can improve the external validity of elicited preferences, thus boosting the predictive power of elicited risk preferences. On the other hand, contextualization may lead farmers to use heuristics that undermine the internal validity of experimental data (see Cerroni, 2020 for an application of contextualized field experiments and a discussion on strengths and limitations).

If farmers' risk preferences are extensively researched in the related literature, uncertainty and ambiguity preferences are not. There are only very few studies eliciting farmers' uncertainty and ambiguity preferences (e.g., Beharam et al., 2014, Bougherara, 2017; Cerroni, 2020). None of these studies attempt to use such preferences to explain farmers' behaviour when purchasing insurance products. In this section, we use the terms uncertainty and ambiguity interchangeably, however, we have to acknowledge that the distinction between risk, uncertainty and ambiguity is far from being clear in the decision analysis literature (see Cerroni and Rippo, forthcoming for a discussion).

The most popular approach to disentangling these concepts is the frequentist. Here, risk refers to situations where definite numerical probabilities are known and can be objectively measured, while uncertainty refers to situations where definite numerical probabilities are unobservable (Knight, 1921). However, other paradigms exist, such as the subjectivist, under which subjective probabilities play a key role under both conditions of risk and uncertainty (Ramsey, 1931; de Finetti, 1931, Savage, 1954). Furthermore, there are other schools of thought that try to differentiate uncertainty from ambiguity. For example, according to Harrison (2011), uncertainty refers to situations when the agent can form a unique and well-defined subjective probability distribution, while ambiguity refers to situations when the agent is not capable of doing so.

This brief discussion on the role that subjective probabilities, risk and uncertainty preferences can have on farmers' decisions to use risk management tools allows to highlight a few key points relevant in the case of the use of insurances. First, the literature exploring the extent to which these behavioural factors affect these decisions is almost non-existent. The literature focusing on standard agricultural insurances and mutualistic solutions is limited. While common sense suggests that subjective probabilities, risk, and uncertainty preferences can affect the uptake of risk management tools, the extent of these impacts and the underlying behavioural mechanisms are unclear and under researched. Second, there is still an open discussion in the decision analysis literature regarding the most appropriate way to elicit these behavioural factors. Many methods are available to elicit subjective probabilities, risk and uncertainty preferences in the literature and empirical evidence suggests different methods lead to different results. This may have an influential impact on the role these behavioural factors play in explaining farmers' insurance decisions. The horse race to truthful probabilistic beliefs, risk and uncertainty preferences is not over yet. Exploring the internal and external validity of results obtained via different elicitation methods appears to be the only strategy to shed light on these issues. Third, behavioural factors can be useful also to predict farmers' choice behaviour. A new stream of research is emerging that seeks to incorporate these behavioural factors into simulation models to enhance their ability to explain and predict choice behaviour (e.g., Huber et al., 2022). This line of research definitively contributes to build a more holistic view about. sustainable risk management in agriculture.

4. INNOVATIVE RISK MANAGEMENT TOOLS

The previous sections have focused on RM behaviour and choices of RM tools mainly referring to already existing tools such as crop insurance schemes that have a long history in Italy, and date back to the early 2000s (Cafiero et al., 2007; Santeramo and Ramsey, 2017). The transition has been motivated by drawbacks associat-

ed with the ex-post compensation, such as its financial unsustainability (Goodwin and Smith, 1995; Goodwin and Mahul, 2004; Mahul and Stutley, 2010; Santeramo et al., 2016), as compared to crop insurance and revenue insurance schemes.

Despite this, the public crop insurance scheme has not been a story of success, as testified by low and heterogeneous participation and retention (Santeramo et al., 2016). This has been motivated by the lack of tradition with subsidized schemes, as well due to the necessity to serve a relatively little market, with many (highly differentiated) crops and a majority of small-size firms (Santeramo et al, 2016) and has suggested to implement ameliorative reforms to overcome the complexity of the policy environment (Severini et al., 2017). Two major reforms were implemented in 2013 and 2015; the former removed subsidies to the mono-risk insurance contracts; the latter replaced the multi- and pluri-risks contract schemes with "packages" covering a set of adversities (Santeramo et al., 2022). Both reforms had negligible effects on insured acreage (as high as three percent) and insured values (estimated to be lower than one percent), casting doubts on their effectiveness. Finally, farmers are often coping with risks which are not covered by traditional insurance schemes, or that are extraordinary in terms of expected damages (i.e., due to so called catastrophic events).

Because of these reasons, it seems relevant to consider innovative RM tools because these may overcome the issues encountered by the traditional insurance products. Indeed, the new Common Agricultural Policy is continuing to reform by enlarging the support for innovative risk management interventions and strategies. Here we focus on two of themes: mutual funds for the so-called catastrophic events and the index-based insurance schemes. These options are precisely meant to complement traditional insurance schemes but are not the only innovative instruments[1]. While the ex-post approach tries to limit the potential additional damages that may occur after a catastrophic event, and to promote the restoration of the damaged structures, alternative mechanisms may help share the costs associated with extreme events and catastrophes. The use of insurance tools to cope with extreme and catastrophic events is dated (Michel-Kerjan, 2010) but still very debated, especially in agriculture (Bucheli et al., 2020). The rationale is simple: due to the increasing amount of available data on weather conditions and the higher frequency of extreme events and natural disasters (both systemic in nature and with high impacts on the sector), coping more directly with these events is not only possible, but also necessary to avoid the default of many farms. The catastrophic bonds and the catastrophic reinsurance may help cope with disasters as they are bet on the occurrence of a disaster, in which case an indemnity is paid. Another possibility, being explored in Italy, is the use of a mutual fund to cover losses from high impactful events.

In Italy the new risk management interventions have been defined by the National Strategic Plan (NSP) 2023-2027 of the CAP. Besides confirming support to (production) insurance schemes, (production) mutual funds (for plants, animal production, farm structures and livestock farms), and (income) mutual funds (for selected sectors such as poultry, sugar beet, durum wheat, cow and sheep milk, olive, fruit and vegetable, rice, and pig), it also establishes a mutual fund (the Agricat) for catastrophic event. The latter covers farmers against specific weather events (frost, drought, and flood) defined as potentially catastrophic. The indemnities are triggered by production losses due to one of the three events, as certified by randomly executed expert reports. The economic sustainability of the newly established fund is unclear, and depends on the design of the fund, on the rating of the premia, and on the effectiveness of the damage reports. In 2022 the Ministry of Agriculture has started a pilot study in thirteen provinces (both in the North and in South), for twelve products (apples, pears, durum wheat, corn, almonds, oranges, apricots, actinidia, wine grapes, oil olives, peaches, and industrial tomatoes). ISMEA has released preliminary results on peaches, concluding that about sixty percent of insured farms have incurred in losses below the (20%) damage or (30%) deductible thresholds, whereas the remaining share of farms has incurred in losses as high as fifty percent in one out of four cases. The findings are of undoubted interest, but also worrisome compared to the US system, in which indemnities worth 14.9% of insured liability are considered to be excessively high in that the median value is as low as 2% of crop insurance liabilities (DeLay et al., 2022). Such a high level of indemnities points at precise future goals, which can be summarised in four priorities: i) improve the accuracy of existing data to map and monitor high-impacts weather events; ii) increase the penetration of the program, and farm retention; iii) mitigate and reduce repetitive losses to lower operating expenses; iv) strengthen the financial sustainability of the program by designing optimal participation rates. These points translate into research questions worth investigation.

Another innovation, barely adopted in developed countries, is the use of index-based insurances: the

[1] For sake of brevity, we do not discuss other innovative instruments such as, for instance, the Income Stabilization Tool (cfr. Giampietri et al., 2020, and Zinnanti et al., 2022, for recent assessments).

scheme indemnifies farmers, who have likely incurred losses, when the index exceeds a threshold (Abdi et al., 2022). A practical example may help in understanding the rationale behind this scheme. Assume a set of farms are exposed to potentially detrimental events (e.g., excessive rain): when the event occurs with a certain magnitude (e.g., the daily volume of precipitation is three times larger than the average precipitation) the likelihood that the farm experiences a loss is high. In this situation, while collecting data on precipitation for each single farm may be costly and inappropriate to determine the incurred losses, relying on the index may be a second-best solution. The operation of an index-based insurance consists of indemnifying all farms when the index exceeds a threshold. The scheme of an index-based insurance has *pros* and *cons*, and is not the ultimate solution (Carter et al., 2017): on one hand it may reduce (or eliminate) moral hazard and adverse selection issues; on the other hand, it may be ineffective if the correlation between triggered pay-outs and the occurrence of loss events is rather low. This potential fallacy is referred to as "basis risk" and defined as "the risk that a protection buyer's own losses exceed the payments under a risk transfer mechanism structured to hedge against these losses." (Ross and Williams, 2009). The basis risk has serious impacts on the functioning of index insurance (Clement at el., 2020) and calls for a deep understanding of the phenomena aimed to be coped against.

The basis risk is a three-dimensional concept, defined by time, space and design of the index. The three dimensions correspond to the temporal, spatial and design basis risks, which are inversely correlated with the informative content of the information being used. For instance, an index-insurance built on hourly data for weather events provides lower temporal basis risks with respect to the same index built on annual data. Similarly, an index built on state level data will have higher spatial basis risk than a similar index relying on municipality level data. As for the design basis risk, the lower the flexibility (and complexity) of the index, the higher the design basis is likely to be. Differently, highly informative datasets allow good performance, in terms of correlation between agricultural data and weather statistics (e.g., Cheng et al., 2017). In a recent paper, Stigler and Lobell (2023) decompose, from a theoretical point of view, the basis risk of the index insurance schemes. Their empirical analysis uses linear and quantile regressions, coupled with richly informative datasets, to derive effective indexes.

Index-based insurance is still underutilized in developed countries, whereas there are several applications in developing countries: "more than fifteen developing countries have offered individual-level index insurance schemes […], and some twenty have offered it at the institutional or geographical level." (Carter et al., 2017, p. 423). The low uptake of index-based insurance calls for a better understanding of the challenges that prevent participation. In particular, Carter et al. (2017) indicate four areas of improvement on (a) the design of the contract; (b) the measurement of risks; (c) the quality of insurance schemes, and (d) the use of other risk coping interventions.

These areas of improvement should be approached by promoting empirical studies that explore the informative content of the large datasets, through a holistic lens capable of merging knowledge from different disciplines (e.g. climatology, agronomy, statistics, economics, management) . For instance, promising research may be conducted by analysing the correlation in the tails of the yield and weather data distribution[2] (e.g., copula-based models, quantile regressions) as well as using quantitative methods capable of synthesising large sets of variables[3] (e.g., machine learning, shrinkage estimators). However, none of those techniques would be sufficient without a better understanding of the fundamentals of the economics and management of risks, topics that should remain a priority in the research agenda.

5. AGRICULTURAL RISK, INPUT USE AND RELATED POLICIES

The previous sections have considered the potential role of RM strategies and tools without accounting for the fact that other policies exist and affect farmers' behaviour. Indeed, some policies not targeted to risk in agriculture may have an unintended effect on RM behaviour and choices. A holistic view to the risk analysis cannot ignore the synergies and trade-off across policies directly or indirectly affecting the agricultural risk. This section refers to the literature that has shown that there exists a relation between the farmer's use of fertilisers and pesticides and the risk farmer faces. Thus, any policy aimed at constraining the use of chemicals in agriculture has an indirect effect on the risk the farmers must cope with.

This branch of analysis fits with the EU F2F Strategy, which has defined a set of objectives and guidelines to drive the European agri-food system toward a fair,

[2] See for instance applications by Goodwin and Hungerford (2015), Conradt et al. (2015), Bokusheva (2018), among others.

[3] A good discussion on recent methodological advances to model insurance is provided by Ali et al. (2020) who discuss the potentiality of machine learning, as well as of artificial intelligence.

healthy, and environmental-friendly transition. Among the targets of the Strategy, two are specifically addressed to fertilisers and pesticide use. The Strategy aims at reducing the overall application of chemical pesticides in agriculture by 50% as well as of the more hazardous ones by 50% by 2030. The Strategy also envisages a reduction in fertiliser application of 20% by 2030 and a reduction of the nutrient losses in the soil of 50% over the same time horizon. Along this line, in June 2022 the Commission made a proposal (European Commission, 2022) to revise the directive on the sustainable use of pesticides (2009/128/EC) and to switch the legal framework from a directive to a regulation. The proposal aims at meeting the F2F Strategy targets in terms of pesticides and has received criticism from many Member States which particularly blame the "flat rate" pesticide cut proposed by the Commission. In order to implement the fertiliser goal of the Strategy, a new digital tool is being developed, the Farm Sustainability Tool for Nutrients (FaST). FaST will combine data from different sources and will provide detailed *ad hoc* recommendations on the application of crop fertilisation and plant protection products. This should improve the efficiency in fertiliser use and, consequently, should help to comply with the target on the fertiliser use reduction and losses. Finally, measures related to the pesticides and fertilisers targets are contained in the National Strategic Plans of the Common Agricultural Policy (CAP) 2023-2027, specifically in the eco-schemes and in the enhanced conditionality of the first CAP pillar as well as in the agri-environmental-climate measures of the second CAP pillar. The effect of a policy targeted at the reduction of chemicals is likely to affect farm input decisions and the corresponding farmers' expected utility in two ways. First, it would directly constrain the amount of chemical application in the farmer's decision process. Second, as literature has shown that pesticides and fertilisers use often changes the level of agricultural risk and farmers are usually risk-averse, the policy imposed on these inputs alters the level of risk the farmers face and, as a consequence, is likely to affect farmer's decision on the use of other inputs related to the chemicals (may they be substitutes or complementary inputs).

The use of agricultural inputs, including pesticides and fertilisers, is affected by the degree of risk aversion of the farmer (Bontemps et al., 2021). For example, according to the model adopted (either the Expected Utility or the Cumulative Prospect Theory (Tversky and Kahneman, 1992)) it has been shown that from 4% to 19% of the pesticide expenditure on farms is explained by farmer risk aversion behaviour (Bontemps et al., 2021). Therefore, the higher the risk aversion of the farmers the higher will be the impact on farmer's decisions and, in turn, on the effectiveness of a policy that restricts chemicals use. The estimation of the farm risk aversion behaviour is partially dependent on the theoretical model adopted. For instance, Rommel et al. (2022) in a study on farmer's risk preferences in 11 EU countries have shown that the Cumulative Prospect Theory explains the preferences better compared to the Expected Utility framework.

Möhring et al. (2020a) provide a deep literature review on the relationship between pesticide use and farm risk. They show that around half of the papers that so far have assessed this issue find a risk-increasing effect of the pesticides (e.g., Serra et al., 2006 and 2008), around half report a risk-decreasing effect (e.g., Koundouri et al., 2009; Antle, 2010; Gardebroek et al., 2010) and only one paper finds no effect (Hurd, 1994). Besides the heterogeneity of the agricultural products and of the countries analysed in the papers, another reason to explain such opposite effects found in the literature is the heterogeneity of the indicators used to measure pesticide application across papers. Möhring et al. (2020a) show that the impact of pesticide use on farm risk depends on the pesticide indicators and on the pesticide type considered. Unfortunately, in most of the countries the national FADN datasets contain data of poor quality related to pesticide quantity and this prevents from using that type of information in this type of research. If no better-quality data are available, the only option is to use pesticide expenditure as a proxy for pesticide quantity. Indeed, most of the studies cited above use pesticide expenditure. Improving the data quality concerning pesticides in the EU is of paramount importance to inform evidence-based policy making. The F2F Strategy also acknowledges the need to overcome the data gaps by changing the 2009 Regulation concerning statistics on pesticides. In addition, the Commission announced its intention to convert the FADN dataset into the FSDN (Farm Sustainability Data Network) which would include more detailed information on the environmental practices of the farms and would introduce data on their social practices (European Commission, 2021).

When it comes to fertilisers, literature (Paulson and Babcock, 2010; SriRamaratnam et al., 1987) agrees that fertilisers are risk-increasing and it highlights the "fertilisers paradox". Indeed, although fertilisers are risk-increasing, risk averse farmers oversupply them. This happens because, under production uncertainty, due to for example unpredictable weather conditions or uncertainty in the amount of nutrients available to the crops, the overapplication of fertilisers is used by farmers as

a form of self-protection (Babcock, 2001; Paulson and Babcock, 2010). Therefore, when modelling farmer fertiliser use it is important to account for the uncertain conditions the agricultural production faces which affect farmer's decisions about fertilisers.

When analysing the relationship between chemical use and agricultural risk some issues must be addressed from a methodological viewpoint. First, there may be some simultaneity in the chemical use decision and agricultural risk. Indeed, usually chemicals are applied multiple times in the cropping seasons and the number of applications as well as the amount of chemicals applied in each application are decided by the farmers based on how the season is going in terms of weather and pests and how the crop is growing. If throughout the cropping season, the farmer observes an increase in agricultural risk compared to his initial expectation, he may adjust the planned fertiliser and pesticide application consequently. In addition, the past year agricultural risk is likely to affect the current year input decisions. This consideration makes relevant the use of a sequential decision-making production model as proposed by Antle (1983a) to account for the possible feedback effect, i.e., the farmer adjusts his decision on variable input use based on the output observed or on the adjustment in the output expectations. Second, the analysis of risk in agriculture needs to account not only for the mean and variance of the crop yields and of farmer's revenue, but also for higher moments of the yield and revenue distribution (Finger et al., 2018) as farmers are often downside risk averse (Di Falco and Chavas, 2006). Indeed, it is likely that farmer decisions are more affected by variations of crop yield and farm revenue below the average than by variations above the average. Specific econometrics approaches exist to address higher moments of the distribution such as the moment-based approach (Antle, 1983b) recently applied to Italian farm data by Biagini et al. (2022b) and its updated version that uses partial moments (Antle, 2010).

Another important topic only partially addressed in the literature is the relationship between RM tools adoption and chemical application. RM tools change the agricultural risk faced by farmers and consequently, they may impact the use of risk-increasing and risk-decreasing input when the farmer is not risk-neutral. For example, the adoption of insurance may induce farmers to adopt moral hazard behaviour which in turn influences the pesticide and fertiliser use decisions (Mishra, 2005). As stated earlier, pesticides are risk-increasing or risk-decreasing according to the type of crop, the country and the pesticide indicator considered, and therefore the direction of the relationship between pesticides and farm insurance remains an empirical question. Second, insurance may induce farmers to change land allocation among crops, e.g. by growing more risky crops, and this also affects chemical use. Analysing whether insurance and chemicals are substitutes, complements or independent goods from the producer's perspective is a worthy issue. Indeed, this assessment would outline the interaction and the spillover effects among two policies: the one pointing at reducing chemicals application in agriculture and the one pointing at increasing the adoption of RM tools among farmers. Although this research branch is rather explored in the US where studies reveal a positive, a negative and a zero effect of insurance uptake on input use, Möhring et al. (2020b) is one of the few examples applied to European agriculture. The study is focused on two countries (France and Switzerland) and it shows that the adoption of insurances increases the application of pesticides.

6. CONCLUSIONS

The agricultural sector is, by its nature, exposed to several risks, and farmers have a long-lasting tradition in coping with them. Yet the rising complexity and interconnection of the global agri-food sector have introduced new risks into the sector, calling for more and more frequent policy interventions. In the European Union, the interventions on risk management have been fragmented and managed at the national level and slow is the introduction of innovative tools. In the context of a CAP with a declining budget, oriented toward environmentally-friendly and sustainable production models, risk management becomes a relevant strategy to lower income uncertainty and favour the resilience of the agri-food system. Given the low uptake rate of RM tools in the European Union, studying the determinants of the uptake referring to both the farm and farmer's characteristics as well as to the RM tool design is crucial to set up effective innovative RM tools and to refine the traditional ones. Studies on the determinants of farmers' behaviour towards risk management tools are rather limited in number. Equally, literature on innovative tools, such as index-based and the catastrophic insurance schemes is scant.

The role of behavioural factors in explaining farmers' risk management decisions is often neglected in the literature. However recent studies suggest that behavioural factors should be incorporated into models to explain and predict farmers' adoption and use of risk management tools (e.g., Babcock, 2015; Dalhaus et al., 2020; Feng et al., 2020; Tack and Yu, 2021). Those stud-

ies have stimulated a growing stream of research that has mainly focused on the elicitation of farmers' risk preferences using experimental methods. Empirical results show that further research is needed in several dimensions. First, preference elicitation methods appear to have an important impact on the magnitude of elicited preferences, therefore further research is needed to identify the methods that provide more robust measures in terms of internal and external validity. Second, empirical evidence indicates that risk preferences are context-dependent. Hence, it is still unclear whether risk preferences elicited using monetary lotteries are fully able to explain farmers' choice behaviour, or whether practitioners should move to the use of contextualized lotteries that may improve the external validity of elicited preferences. Third, while farmers' risk preferences have been widely investigated in the literature, there are only a few studies focusing on the role that subjective beliefs, ambiguity attitudes and time preferences may have on farmers' decisions in general, and more specifically, regarding the uptake of different RM tools. Finally, a holistic approach to the study of risk management cannot ignore the interrelation between farmer's input not specifically targeted to risk management and the agricultural risk. This is key to discover possible synergies and trade-offs among different policies. The policies aiming at reducing the fertiliser and pesticide use in agriculture indirectly affect the agricultural risk because fertilisers and pesticide impact the risk level. Results reported by the literature on this impact are controversial and depend on the crop, country and indicator considered and there is often the issue of poor data quality. A more sustainable use of chemicals in agriculture and a better management of risk in the sector are two forefront topics in agricultural economics. Hence, efforts towards gathering better quality data are required. In addition, given the importance of framing consistent and effective EU policies, the investigation of the relationship between the RM tools adoption and the farm application of chemicals needs to be addressed. This investigation would shed light on whether two apparently independent policies, namely the policy restricting the use of chemicals in agriculture and the one promoting the adoption of RM tools, have the same or opposite direction.

Besides briefly mentioning what the literature has already provided and which methods have been investigated, we conclude this paper with a few priorities to orient future research: efforts should be devoted to improve the use of the large amount of available data, to improve the financial mechanisms that may ensure the financial stability of the RM schemes, and to increase the interconnection (and complementarity) of the RM instruments. In short, the search for innovation in RM should be not only oriented toward a sophistication of the strategies, but also (and mainly) toward a better exploitation of the informative content of the existing data, as well as of the holistic nature of the approaches. In addition, the results of this literature review suggests that the theoretical framework used so far in the literature for understanding farmer behaviour in terms of RM is not unique: different models have been applied sparsely, and often without accounting for the complex nature of the issue at stake. Therefore, it seems necessary to commit research efforts to carrying out a comparative evaluation of methods and hypotheses used in empirical analyses, also including behavioural variables towards risk. This latter calls for developing new tools to investigate farmers' preferences, with particular attention to the characteristics of the tools and their interaction with other strategies. Similarly, because farmers' behaviour is affected by several policies, including those aimed at reducing the use of potentially harmful inputs, it seems important to analyse RM choices under a more articulated policy scenario. Fostering the analyses in these directions is expected to better understand how farmers select among available RM instruments including the most innovative ones on which they have not a large experience. The results of these analyses could provide insights that could be used to increase the uptake of already existing RM tools, facilitate the design and introduction of the new ones and, indirectly, allow the EU farm sector to become more resilient.

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