

Climate Change Beliefs and Perceptions of Agricultural Risks: An Application of the Exchangeability Method

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Abstract

Using the exchangeability method, we elicit Italian farmers' short- and long-run perceptions of agricultural risks related to climate change. We consider four sources of crop loss risk: powdery mildew and hail for grape growers and apple dieback and hail for apple farmers. We find that perceived crop loss risks tend to be greater in the long run than in the short run. Controlling for a variety of factors (past experiences with crop losses, farming experience, numeracy, interactions with other producers, and farm characteristics), we identify climate change beliefs as a critical factor explaining the short- vs. long-run difference in risk perceptions: those who believe in climate change project larger future crop losses. Additionally, prior direct experience with crop losses helps explain why certain farmers perceive greater risk. Our results suggest that outreach services should offer field days providing first-hand exposure to crop losses and adopt a segmented approach that considers farmers' climate change beliefs.

Keywords: Climate change, Exchangeability method, Subjective risk perceptions

JEL: Q10

1. Introduction

Much of the concern surrounding climate change stems from the potential for negative effects on agricultural productivity and farmers' welfare worldwide (Dinar and Mendelsohn, 2011; Gornall et al., 2010). Changes in rainfall patterns and temperatures affect mean yields and yield variance directly as well as indirectly due to increased susceptibility to pests and diseases (Mendelsohn and Dinar, 2009). Negative effects of climate change have been projected for open field crops (Porter et al., 2014), including high-value perennial crops such as apples (Stöckle et al., 2010), cherries (Lobell and Field, 2011), and grapes (Jones et al., 2005).

The economic impact of climate change on agricultural profitability depends partly on farmers' willingness and ability to respond to new climatic conditions by adopting adaptation

strategies (Howden et al., 2007; Reidsma et al., 2010; Di Falco, Veronesi, and Yesuf, 2011). These strategies might include changing farm production practices (e.g., planting and harvesting times, crop protection methods, irrigation and fertilizer control, tillage practices, and cultivar selection) or farm financial management (e.g., insurance purchases) (Smit and Skinner, 2002; Nicholas and Durham, 2012). Applying adaptation strategies to the cultivation of perennial crops can be particularly challenging, however, due to their long lifecycle, with many perennials being planted only once every 25 or more years (Lobell et al., 2006).

Farmers' decisions regarding adapting their farming practices hinges critically on their perceptions (i.e., subjective beliefs) of the agricultural risks related to climate change. As postulated by the theory of planned behavior (Ajzen, 1991), subjective beliefs form the information base that generates attitudes and intentions, ultimately culminating in behavior. Hence, investigating risk perceptions is fundamental for understanding adaptation. Knowledge of risk perceptions can also help enable policymakers and outreach professionals to target information or to “de-bias” incorrect subjective beliefs (Patt and Schröter, 2008; Arbuckle et al., 2013; Dohmen et al., 2009).

There is a growing literature investigating farmers' beliefs regarding climate change and their perceptions of climate change-related risks (see Arbuckle et al., 2013 and references therein). Previous research has found that farmers have varying levels of concern with regard to climate change-related risks, as reviewed in the following section. However, due to the methods used in previous research to elicit risk preferences, three critical questions remain open. First, do farmers perceive an increase in climate change-related agricultural risks even when they are not prompted to think about climate change? Second, are differences in long- and short-run risk perceptions attributable to farmers' personal beliefs regarding climate change? Third, what is the magnitude of this difference in perceptions of agricultural risks due to climate change?

This study aims to answer these questions through a unique investigation of farmers' perceptions using the exchangeability method (EM) (Baillon, 2008). The EM is a method for indirectly eliciting subjective risk perceptions that produces cardinal measures of perceived risk without directly asking respondents to make difficult probability statements. Crucially, in our implementation of the EM, we do not mention climate change. In contrast to previous research, our approach thus avoids *priming* subjects—that is, we do not “push” farmers to think in terms of climate change when assessing agricultural risks.

This study contributes to the climate change literature by providing a set of measures of Italian farmers' short- and long-run perceptions of climate change-related agricultural risks. Specifically, we focus on subjective beliefs concerning crop losses due to agricultural threats that are particularly relevant for perennial-crop farmers: apple dieback, grape powdery mildew, and hail. By combining the EM-derived measures of farmers' short- and long-run crop loss expectations with stated beliefs about climate change, we provide quantitative evidence on the role of climate change beliefs in the development of farmers' risk perceptions over time.

2. Literature review: Climate change beliefs and agricultural risk perceptions

A growing body of literature has emerged investigating (i) farmers' beliefs about the existence and drivers of climate change, (ii) farmers' concerns (risk perceptions) related to climate change, (iii) the relationship between climate change beliefs and risk perceptions, and (iv) the relationship between climate change beliefs and farmers' willingness to adapt. Prior studies have focused on diverse groups of farmers in both developing and developed countries. Table 1 provides an overview of this literature, which is discussed in more detail in the remainder of this section.

Table 1. Key findings of previous studies on farmers' climate change (CC) beliefs, risk perceptions, and adaptation.

Study	Location	Key Findings
Diggs (1991)	North Dakota & Colorado, U.S.A.	<ul style="list-style-type: none"> • 29.5% of Colorado and 41.4% of North Dakota farmers believe that the climate is changing. • Farmers with less farming experience are more likely to believe that droughts are becoming more frequent and severe.
Weber (1997)	Illinois, U.S.A.	<ul style="list-style-type: none"> • 53% of farmers do not expect significant future changes in climate. • Farmers who believe in CC are more likely to take adaptive measures.
Hogan (2011)	Australia	<ul style="list-style-type: none"> • Believing in CC does not explain farmers' intentions to adopt sustainable agricultural practices. • Farmers who noticed physical evidence of CC are less likely to undertake risk management strategies.
Safi (2011)	Nevada, U.S.A.	<ul style="list-style-type: none"> • 61.3% of farmers agree that CC is currently taking place. • 28.9% and 26% of farmers, respectively, believe that human activity is playing a significant role in CC and that CC is a cause of drought in Nevada. • Farmers who believe that human activities have played a significant role in CC and that CC is a possible cause of drought in Nevada perceive more severe risks from CC.

Haden et al. (2012)	California, U.S.A.	<ul style="list-style-type: none"> • 54.4% of farmers agree that the global climate is changing. • 35% of farmers believe that human activities are an important cause of CC. • Farmer willingness to adopt mitigation practices is positively related to CC beliefs.
Safi, Smith, and Liu (2012)	Nevada, U.S.A.	<ul style="list-style-type: none"> • Less than 15% of farmers rate the expected impact of CC on themselves or their families as a great deal. • Farmers' aggregate risk perception is positively affected by beliefs that human activities have played a significant role in causing CC.
Barnes and Toma (2012)	Scotland	<ul style="list-style-type: none"> • 47.7% of farmers agree or strongly agree that average annual temperatures will likely increase in the future. • 51.5% of farmers agree or strongly agree that input costs will increase because of CC.
Barnes and Toma (2013)	Scotland	<ul style="list-style-type: none"> • 45% of farmers agree or strongly agree that CC will lead to increasing productivity losses due to diseases and pests. • Farmers' perceptions of risk from CC are influenced by different sources of information and by the messages provided by these different channels.
Niles, Lubell, and Haden (2013)	California, U.S.A.	<ul style="list-style-type: none"> • 43% of farmers believe that local water availability has decreased over the course of their farming career. • Farmers' perceptions of decreasing water availability positively influence CC beliefs and perceived risk.
Arbuckle, Morton, and Hobbs (2013a)	Iowa, U.S.A.	<ul style="list-style-type: none"> • 68% of farmers believe in CC. • 35% of farmers agree or strongly agree that they are concerned about the potential impact of CC on their farm operations. • CC believers are more likely to undertake adaptive steps and to support government mitigation actions.
Arbuckle, Morton, and Hobbs (2013b)	Iowa, U.S.A.	<ul style="list-style-type: none"> • CC beliefs are positively associated with perceived CC risks to agriculture.
Arbuckle et al. (2013)	U.S. Corn Belt	<ul style="list-style-type: none"> • 65.5% of farmers believe in CC. • 41% of farmers believe that CC is caused by human activity. • Farmers who believe CC is caused by human activity are more likely to be concerned about CC impacts and to support adaptation/mitigation actions.
Rejesus et al. (2013)	Mississippi (MS), North Carolina (NC), Texas (TX), and Wisconsin (WI), U.S.A.	<ul style="list-style-type: none"> • 24.1% of MS, 36.3% of NC, 24.6% of TX, and 25.8% of WI farmers believe that CC is scientifically proven. • 36.7% of MS, 47.4% of NC, 25.9% of TX, and 41.6% of WI farmers believe that human activities are causing CC. • 72.6% of MS, 72.3% of NC, 68.9% of TX, and 71.1% of WI farmers believe that average yields will neither increase nor decrease by more than 5% because of CC. • Farmers' CC beliefs are influenced by age, willingness to accept risk, off-farm employment, and farm assets.
Wheeler, Zuo, and Bjornlund (2013)	Australia	<ul style="list-style-type: none"> • 32% of farmers believe that CC poses a risk to their region. • A belief in CC affects farmers' willingness to undertake certain adaptation strategies (e.g., changing crop mixes).

Esham and Garforth (2013)	Sri Lanka	<ul style="list-style-type: none"> • The mean score for the perceived risk of being exposed to and affected by CC is 2.39 out of 3 (from 1 = no risk to 3 = high risk). • CC and risk perceptions significantly affect actual adaptation actions.
Le Dang et al. (2014)	Vietnam	<ul style="list-style-type: none"> • Farmers are more concerned about the impact of CC on production than on other dimensions of their life (e.g., income or physical health). • Information and experience with CC-related events increase farmers' perceived CC risk.

Farmers' beliefs about the existence of climate change and its causes have been elicited using Likert scales (expressing degree of agreement with statements), dichotomous (yes/no) questions, open-ended questions, and closed multiple-option questions. A review of these studies reveals that the share of farmers who believe in climate change varies significantly by location. For example, Haden et al. (2012) find that in 2011, 54.4% of California farmers believed or strongly believed that the global climate was changing. Arbuckle, Morton, and Hobbs (2013a) find that in 2011, 68% of Iowa farmers believed that climate change was occurring. Rejesus et al. (2013) find that in 2009, approximately 24-25% of farmers in Mississippi, Texas, and Wisconsin and about 36% of farmers in North Carolina believed or strongly believed that climate change had been scientifically proven.

Farmers' perceptions of agricultural and non-agricultural risks related to climate change have typically been elicited using Likert scale-type questions or risk assessment scales. Of the two components of risk - magnitude and likelihood of harm (Patt and Schröter, 2008) - most past studies have focused on climate change's effect on the perceived *magnitude* of negative outcomes while ignoring the effect on the perceived *likelihood* of negative outcomes. These studies consider a variety of different dimensions of risk, ranging from general effects of climate change on a farmer's own farming operation (Arbuckle, Morton, and Hobbs, 2013a; Rejesus et al., 2013) to specific effects of climate change on drought occurrence or heat stress (Arbuckle et al., 2013); they have also specified various different levels and targets of risk (e.g., individuals, farming communities, or future generations) (Safi, Smith, and Liu, 2012). For example, Arbuckle et al. (2013) use a four-point Likert scale to assess Midwestern U.S. farmers' concerns about the impact of climate change on drought, heat stress, extreme rain, and saturated soil as threats to their farm operations and find that only drought and heat stress concern more than half of farmers. Barnes and Toma (2012) and Barnes, Islam, and Toma (2013) use five-point Likert scales to assess Scottish dairy farmers' perceptions of the effect of climate change on their standard of living, input

costs, productivity losses due to crop diseases and pests, and ability to invest in their business. These studies find that the majority of farmers are concerned that climate change will negatively affect input costs and productivity.

Two studies of risk perceptions stand out for considering both the magnitude and likelihood of harm. Rejesus et al. (2013) use an interval scale with three levels (0% - 5%, 5% - 10%, > 10%) to assess U.S. farmers' expectations for the impact of climate change on mean yields and yield variability. They find that most producers (roughly 70%) do not believe that climate change will affect either average yields or average yield variability by more than 5%. In another key contribution, Le Dang et al. (2014) assess Vietnamese farmers' expectations for the probability and severity of climate change impacts using a seven-point Likert scale. They calculate perceived climate change risks as manifesting in different dimensions of farmers' lives (i.e., physical health, income, physical assets, production, social relationships, anxiety about personal loss, and happiness) by multiplying the perceived probability by the perceived severity. They find that, among all dimensions considered, the highest perceived risk was to agricultural production, with the highest mean scores for both expected probability and expected severity (5.71 and 5.04, respectively, out of 7).

A few studies investigate the relationship between climate change beliefs and risk perceptions. Safi, Smith, and Liu (2012) regress a risk perception index (based on eight different risk dimensions and levels) against a set of potential factors, finding that climate change beliefs are strong determinants of risk perceptions. Arbuckle, Morton, and Hobbs (2013b) and Le Dang et al. (2014) also find significant direct effects of a belief in climate change on the severity of perceived climate change-related risks.

Finally, several of the cited studies investigate how farmers' beliefs in climate change and risk perceptions impact their plans to engage in adaptation, and most of them find a positive significant relationship (one exception is Hogan et al., 2011). For example, Haden et al. (2011) find a positive relationship between U.S. farmers' beliefs in climate change and their willingness to engage in adaptation strategies. Arbuckle, Morton, and Hobbs (2013a) and Arbuckle et al. (2013) find that farmers who believe in climate change are more likely to support adaptation and mitigation actions. Weber (1997) and Rejesus et al. (2013) find similar positive relationships. In a more mixed result, Wheeler, Zuo, and Bjornlund (2013) find that climate change beliefs are related to certain adaptation strategies (e.g., improving irrigation efficiency, changing crop mixture, and

purchasing land) but not others (e.g., increasing the irrigated area). Esham and Garforth (2013) investigate actual (as opposed to intended) adaptation actions and find that perceived climate change and risk are significant drivers of farmers' decisions to adapt.

One final finding emerging from the previous literature is that past experiences play a key role in shaping farmers' beliefs about climate change, their risk perceptions, and their willingness to adapt. Examining a sample of North Dakota farmers, Diggs (1991) finds a relationship between perceptions of long-run climatic change and prior drought experience. He also finds an inverse relationship between years of farming experience and the likelihood of believing that droughts are becoming more frequent and severe. Niles, Lubell, and Haden (2013) and Le Dang et al. (2014) note similar influences of climate change experience on risk perceptions. Specifically, Niles, Lubell, and Haden (2013) find that a perceived decrease in past water availability increases farmers' concerns about future local water availability and global climate change as well as the likelihood that they will voice intentions to adopt mitigation and adaptation practices. Le Dang et al. (2014) also find a positive impact of past experience with storms, hot weather, unusual temperatures, and other climate change-related phenomena on risk perceptions.

3. Survey and methods for eliciting risk perceptions

In early 2011 (before the start of the growing season), we surveyed a sample of farmers operating apple orchards or grape vineyards in the Province of Trento, in northern Italy. With an annual production value of over 345 million Euros, apples and wine grapes are by far the two most important crops grown in the Province of Trento (Servizio Statistiche, 2007). To recruit farmers for preliminary focus groups and the final study, we collaborated with the Edmund Mach Foundation, a public institution providing local agricultural extension services in the province. This institution carries out agricultural research, promotes education and training, and provides free technical assistance and extension services to farmers. Two focus groups of 12 farmers each were conducted in 2010. The primary objectives of the first focus group were to identify a reasonable timeline for the future long-run scenarios and understand the natural way in which farmers expressed crop losses arising from the perils investigated in the study. In the second focus group, farmers provided feedback on the clarity, difficulty, and length of the survey.

Local extension service personnel provided us with farmers' contact information and informed the farmers about the research project. With their assistance, a sufficient number of

farmers were recruited to form a representative sample of the local farming population. The sample was proportionally stratified by location, main crop (apples or grapes), farmer age, and farm size. A total of 210 farmers were contacted, and 195 took part in the study, yielding a participation rate of 93%.

The in-person computer-based survey was administered by a trained enumerator. Each interview lasted an average of 30 minutes and took place in the local offices of the extension services or at the respondent's home, depending on availability. Based on feedback from the focus groups, we decided to deliver the survey using touchscreen laptops that would allow data to be entered via touch or by using a mouse, depending on the interviewed farmer's preferences. Most farmers in the region have basic computer literacy and are accustomed to using electronic recordkeeping for farming activities (e.g., pesticide use). The enumerator's role was to assist the farmer in the event of technical problems or to clarify questions if needed. To preserve privacy during the survey, the enumerator was instructed to sit so that she could not see the computer screen and to face the screen only if requested. Before starting the survey, the enumerator informed the farmer that the study's objectives were to better understand farmers' perceptions of risk and to improve outreach activities. No reference to climate change was made when introducing the study.

The computerized questionnaire was organized as follows. In the first section, we elicited agricultural risk perceptions for both the short run (the then-upcoming growing season, 2011) and the long run (the growing season 2031) using the EM, which is described in more detail in Section 3.2. Although climate change projections span a time period much longer than that considered, the focus group indicated twenty years as an ideal long-run timeframe to preserve farmers' ability and willingness to formulate beliefs about future events; a longer time horizon, it appeared, would fail to engage farmers in the task. Rejesus et al. (2013) use a similar time horizon of 25 years.

After the EM tasks, we collected information on farmers' beliefs regarding climate change. In the last part of the survey, we collected information on farm and farmer characteristics and past experience with agricultural threats. In the following subsections, we provide additional information on the agricultural risks investigated, the methods used to elicit agricultural risk perceptions, and the additional questions included in the survey.

3.1 Investigated agricultural risks

We focus on three important causes of crop loss related to weather and climate: apple dieback and hail for apple farmers and powdery mildew and hail for grape growers. We identified these agricultural perils as suitable for inclusion in the study through discussions with a group of climatologists, agronomists, and pathologists at the Edmund Mach Foundation, who collaborated with us on an interdisciplinary project, *ENVIROCHANGE* (<http://www.envirochange.eu>), seeking to assess the effects of climate change on local agriculture. As explained in more detail below, scientists have predicted an increase in the risk of crop losses due to hail (both for apples and grapes) and apple dieback, while the risk of crop losses due to powdery mildew is predicted to remain essentially unchanged despite the more mildew-favorable environmental conditions brought about by climate change.

Specifically, damage from hail is the single most important cause of revenue losses in the Trento region for apple farmers and, to a lesser degree, grape growers (CoDiPra, 2013). A recent study by Eccel et al. (2012) shows that the frequency of hail in the region has increased in the previous 35 years, and a further increase is expected in the coming years. Apple dieback is a condition in which trees die prematurely due to opportunistic pathogens that colonize trees under adverse climatic and agronomic conditions. Though prevalent in the region for only a few years and still not fully understood, this disease is projected to increase as extreme winter conditions become more frequent in the region (Dallago et al., 2011). Powdery mildew, in contrast, is a well-known fungal disease that affects grapes and can significantly reduce crop yields. Warmer and drier seasons provide ideal conditions for its spread. Although warmer temperatures and less rain are predicted for the region, a recent study by Caffarra et al. (2012) suggests that a concomitant change in plant phenology (i.e., the anticipated harvest date) will leave the severity of powdery mildew unchanged under future climate projections for the region.

3.2 Agricultural risk perception elicitation: the exchangeability method

Farmers' perceptions of risk for the 2011 and 2031 growing seasons were elicited using the EM, a technique recently proposed by Baillon (2008) and Abdellaoui et al. (2011) for eliciting subjective probabilities without asking subjects to make difficult probability statements or complete

likelihood scales. The EM is based on the idea of exchangeable events (de Finetti, 1974)—that is, events for which the assessor is indifferent to outcome permutations (Baillon, 2008). Under the EM, subjects face a series of binary choices between different prospects, and these choices are used to identify one or more points on the individual’s cumulative distribution of the probability of a given event. A key advantage of this method is that, unlike indirect techniques based on external reference events (e.g., probability wheels), the EM does not suffer from biases due to source dependence (Baillon, 2008) and is straightforward for subjects. The EM has recently been applied by Cerroni and Shaw (2012) and Cerroni, Notaro, and Shaw (2013) to elicit perceived climate change-related risks in two different contexts: undergraduate students’ perceived risk of pine beetle infestation in Texas forests and consumers’ perceived risk of pesticide residue contamination of apples in Italy.

In our study, the events considered are the province-level percentage of the apple or wine grape harvest value lost to hail, the province-level percentage of apple trees affected by dieback, and the province-level percentage of grape bunches affected by powdery mildew, in both the short and long runs. Our preliminary focus group indicated that farmers naturally express hail damage in terms of the percentage of the apple (or wine grape) crop value that is destroyed by hail, apple dieback damage in terms of the percentage of apple trees affected by the syndrome, and powdery mildew damage in terms of the percentage of grape bunches affected by powdery mildew. For all perils, the state space is constrained between 0% (no damage) and 100% (total damage); the EM implementation can thus be conveniently simplified by expressing crop damage as a percentage of crop value loss, affected trees, or grape bunches.

Note that the events investigated are expressed at the province level, not in terms of individual farm losses. We deliberately chose to elicit perceptions of a risk common to all farmers—that is, the systematic component of climate change risk for farmers in the region. An alternative would have been to elicit perceptions for the risk of crop losses on individual farms (i.e., the idiosyncratic risk from climate change). Due to different objective risks and current conditions, however, using an individual risk would have introduced confounding factors that would be difficult to control for. For example, in the case of crop diseases, the short-run objective risk perceived by an individual farmer is likely to be correlated with the current level of observed farm-level damages (i.e., the presence of pest inoculums), while the long-run objective risk is not. The presence of confounding factors affecting short-run risk perceptions but not long-run ones (or

vice versa) would have complicated our analysis of the impact of climate change beliefs on the evolution of risk perceptions over time.

The procedural steps for implementing the EM are as follows. In the first stage of the EM, the lower and upper bounds of the event space were identified for a given peril ($p \in \{hail, dieback\}$ for apple farmers, $p \in \{hail, powdery mildew\}$ for grape growers) and for a given year ($y \in \{2011, 2031\}$). As an example, Figure 1 shows the EM's first stage, identifying the bounds of the event space for the case of hail damage to apples in 2011. As can be seen, apple farmers were asked to identify their expectations for the minimum and maximum levels of damage, each expressed as a percentage of the value of apple production in the Province of Trento. The minimum and maximum percentage values were then used to specify starting values for the second stage of the EM procedure.

Give your assessment of what the percentage of the apple production value lost due to hail in the Province of Trento in the upcoming season (2011) is going to be:

Minimum damage %

Maximum damage %

Figure 1. Example of the first stage of the EM procedure, in which the event space's lower and upper bounds for hail damage to apples in 2011 are identified.

In the second stage of the EM, a series of questions akin to a binary search algorithm was used to identify the median estimated damages (i.e., the 50th percentile of the cumulative distribution of the subjective expected crop losses) caused by peril p in year y . The first question in the second stage asked farmers to choose between two alternatives (A or B), consisting of two disjoint intervals of the event space identified in stage one. For example, for peril p in year y let the minimum and maximum values identified by a farmer in stage one be \underline{v} and \bar{v} . Then the first question in stage two would ask the farmer whether he (we use the male gender pronoun as the significant majority of farmers in the study and in the region are male) expected damages due to peril p in year y to be less than/equal to (alternative A) or greater than (alternative B) a threshold

value, $T_1 = 0.5(\underline{v} + \bar{v})$. Here, T_1 corresponds to the midpoint between the minimum and maximum values identified in stage one. After the farmer selected one of the two alternatives (A or B), the second question in stage two would ask the farmer whether he expected damages due to peril p in year y to be less than/equal to or greater than a new threshold, T_2 . The value of the new threshold was calculated depending on whether the farmer selected less than/equal to (alternative A) or greater than (alternative B) in the prior question. If the farmer chose alternative A in response to the first question, the second question would ask him whether he expected the damage due to p in year y to be less than/equal to or greater than $T_2 = 0.5(\underline{v} + 0.5(\underline{v} + \bar{v}))$. If instead the farmer chose alternative B in response to the first question of stage two, the second question would ask him whether he expected the damage due to peril p in year y to be less than/equal to or greater than $T_2 = 0.5(0.5(\underline{v} + \bar{v}) + \bar{v})$. This process was repeated until the values of two thresholds were within 1% of one another.

To illustrate this procedure, Figure 2 presents the first three rounds of questions for the specific case of 2011 hail damage, assuming that the farmer identified the first-stage minimum and maximum damage levels as 25% and 75%, respectively. As Figure 2 shows, once this event space is defined, the first question in stage two asks the farmer whether he expects damages to be less than/equal to or greater than 50%. His response to this question determines the threshold value used in the second question. If the farmer selects alternative A (less than/equal to 50%), then the second question asks him to choose between less than/equal to or greater than 37.5%. If instead he selects alternative B (greater than 50%), the second question asks him to choose between less than/equal to or greater than 62.5%. This binary search process ends once the two thresholds attained from consecutive questions are within 1% of one another.

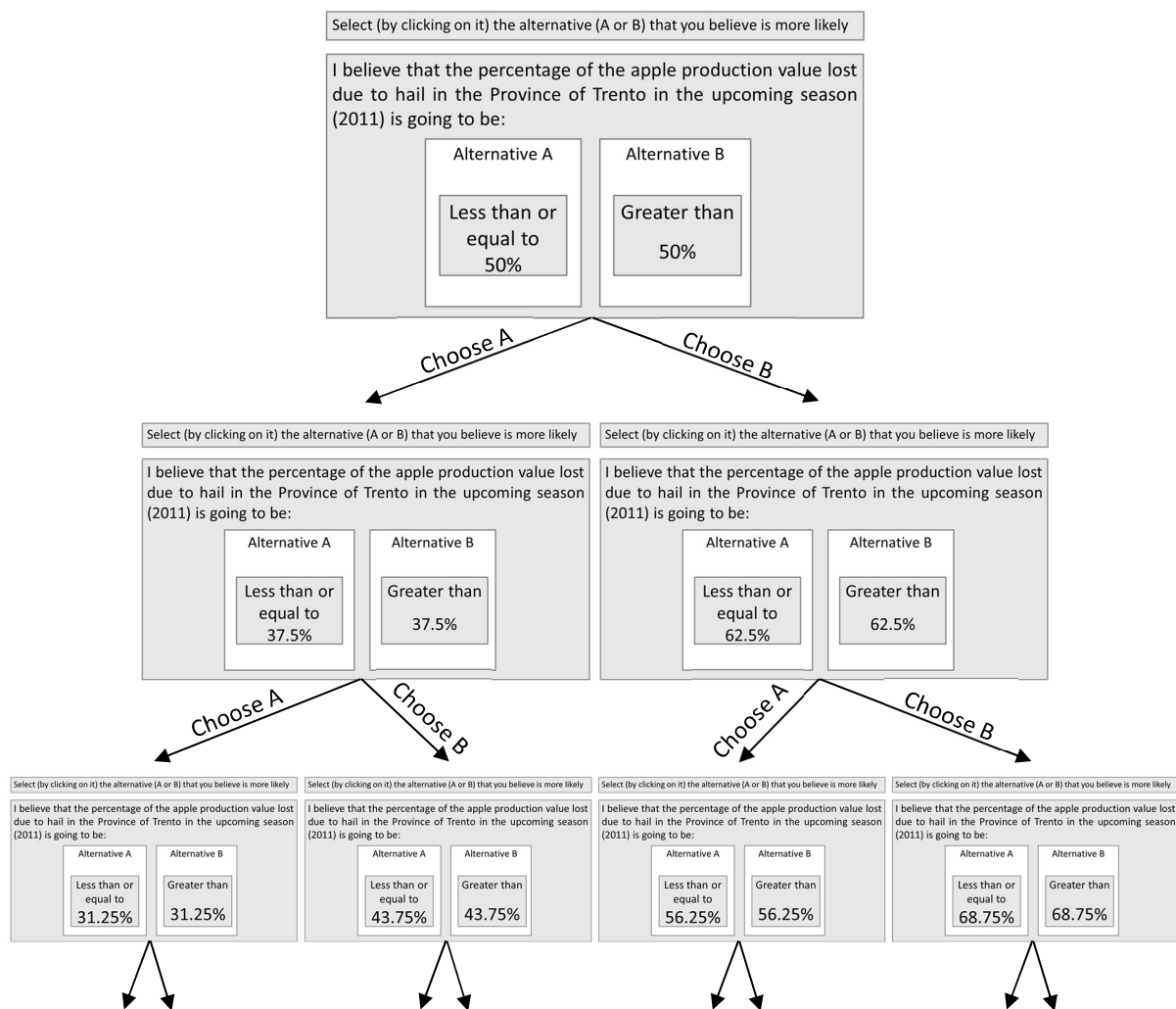


Figure 2. Example second-stage of the EM procedure for identifying a farmer’s expected median hail damage to apples in 2011.

Farmers were asked to identify themselves as an apple farmer or a grape grower, depending upon their main crop. Each farmer then completed the two stages of the EM procedure four times, once for each peril (hail and dieback for apple farmers, hail and powdery mildew for grape growers) and for each growing season, 2011 and 2031. Specifically, apple farmers performed the EM task in the following order: hail in 2011, hail in 2031, apple dieback in 2011, and apple dieback in 2031. Grape growers performed the EM task in the following order: hail in 2011, hail in 2031, powdery mildew in 2011, and powdery mildew in 2031. For each farmer the EM yielded two measures of expected damage for 2011 and two corresponding measures for 2031. The farmers

completed this exercise without problems: when asked an anonymous post-study question assessing the difficulty of the EM task, about 95% of respondents indicated that they had encountered no difficulties with understanding and performing the EM task.

3.3 Additional survey questions

The remainder of the survey elicited information on climate change beliefs, farming background, and information exposure. To capture farmers' beliefs regarding climate change, we asked the dichotomous (yes/no) question: "Do you believe in climate change?" Those who answered affirmatively were asked about the causes of climate change, as they perceived them (i.e., natural or anthropogenic factors). We also asked farmers about their direct experiences with crop losses due to the perils considered in the study. To determine a given farmer's level of interaction with other farmers in the region who could represent an additional source of information about agricultural risks, two questions about cooperative participation were also included.

Farmers then completed a set of seven probability tasks, based on which we constructed an index for numeracy (i.e., the ability to understand and use mathematical and probabilistic concepts, Peters, 2006). Two of the tasks involved the application of probability theory while the other five were adapted from Fischbein and Schnarch (1997) to assess common misconceptions regarding processing probabilistic information. Recent literature in decision science, psychology, and health has highlighted the importance of numeracy in risk perceptions (see, e.g., Reyna et al. (2009) for a health-focused literature review) and decision making in risky settings (e.g., Cokely et al., 2012).

Additionally, to facilitate a comparison between the EM results and more traditional Likert scale questions, we asked farmers to assess on an eleven-point scale how climate change would affect the risk of crop losses due to hail, powdery mildew, and apple dieback. A comparison between the EM- and Likert scale-elicited measures is provided in Appendix A.

4. Results

4.1 Descriptive statistics: Farmer characteristics and farmer risk perceptions

Table 2 summarizes the sampled farmers' characteristics, which align well with the limited data available for the population of perennial-crop farmers in the Province of Trento. According to a 2010 census conducted by the Italian National Institute of Statistics (<http://dati-censimentoagricoltura.istat.it/>), the average age of active perennial crop farmers in the Province of Trento is 49.50 (45.50 years in our sample) and the average length of education is 9.62 years (10.35 years in our sample). Also according to the 2010 census, apples and wine grapes are the main crop for 67% and 33%, respectively, of perennial crop farms (62% and 38% of farms in our sample) and the average farm size is 4.95 hectares (4.76 hectare in our sample).

The average net monthly family (farm and off-farm) income reported in our survey is 2,330 Euros. As a measure of asset liquidity, the survey asked whether the respondent would be able to pay 20,000 Euros within five days in the event of a sudden unforeseen need; 62% responded affirmatively. Considering the seven questions assessing farmers' numeracy, farmers correctly answered an average of 3.35 questions, with a standard deviation of 1.27. Given the difficulty of the questions, this indicates a fair level of numeracy.

Regarding farmers' first-hand experience with crop losses, 72% of responding apple farmers and 85% of responding grape growers stated that they had personally seen what they considered disastrous hail damage to a farm in their region in the 5 years prior to the survey. In addition, 54% of the apple farmers and 77% of the grape growers stated that they had personally seen disastrous damages due to apple dieback and grape powdery mildew, respectively. Regarding exposure to information, the farmers surveyed have been active in seeking out information about farm risks. About half of sample farmers attended the annual information session offered by Co.Di.Pr.A, the association that manages crop insurance in the region. On average, farmers read booklets or attended information sessions by local extension services 4.69 times in the previous year. Finally, the level of interaction with other farmers in the region is very high: over 90% of responding farmers are cooperative members and about a third (29%) are active in their cooperative or serve as farmer representatives involved in cooperative management.

Table 2. Model variables, sample characteristics, and survey responses.

Variable name	Variable definition	Obs.	Mean	Std. Dev.	Min	Max
<u>Dependent variables:</u> Change in Long-Run vs. Short-Run Risk Perceptions ^a						
Hail-Apples		120	5.06	8.67	-21.72	32.50
Hail-Grapes		75	5.97	7.36	-3.38	34.68
Dieback-Apples		120	1.26	8.38	-27.05	33.69
Powdery Mildew-Grapes		75	3.16	7.83	-21.32	43.38
<u>Independent variables</u>						
Climate Change Belief	1 if farmer believes in climate change, 0 otherwise	195	0.83	0.36	0	1
<u>Past experience with peril</u>						
Damage Experience (Hail-Apples)	1 if farmer has personally seen disastrous hail damage on apple farms in their region in the past 5 years, 0 otherwise	120	0.73	0.45	0	1
Damage Experience (Hail-Grapes)	1 if farmer has personally seen disastrous hail damage on grape farms in their region in the past 5 years, 0 otherwise	75	0.85	0.36	0	1
Damage Experience (Dieback-Apples)	1 if farmer has personally seen disastrous dieback damage on farms in their region in the past 5 years, 0 otherwise	120	0.54	0.50	0	1
Damage Experience (Powdery Mildew-Grapes)	1 if farmer has personally seen disastrous powdery mildew damage on farms in their region in the past 5 years, 0 otherwise	75	0.77	0.42	0	1
<u>Farm and farmer characteristics</u>						
Farming Experience	Number of years operating as a farmer	195	23.86	13.64	0	63
Full Time	1 if a full time farmer, 0 otherwise	195	0.79	0.41	0	1
Age	Years of age	195	45.50	12.76	18	79
Education	Number of years of schooling	195	10.35	2.91	5	18
Household Size	Number of members of household	195	3.38	1.21	1	6
Farm Size	Number of hectare	195	4.76	2.72	0.5	10
Cultivated/Owned	% of cultivated land that is owned	195	74.81	29.05	0	100
Income	Household monthly net farm and off-farm income (1000 Euro/month)	195	2.33	1.32	0.50	6.50
Liquidity	1 if able to pay 20,000 Euro with 5 days to cover an unforeseen expense, 0 otherwise	195	0.62	0.49	0	1
<u>Probability Numeracy and information and interaction with other farmers</u>						
Probability Test Score	# of probability questions correctly answered	195	3.35	1.27	0	7
Coop Member	1 if a member of a farmer cooperative, 0 otherwise	195	0.93	0.25	0	1
Coop Representative	1 if involved in coop management as a farmer representative, 0 otherwise	195	0.29	0.45	0	1
Co.Di.Pr.A	1 if attended an information session by Co.Di.Pr.A in 2011, 0 otherwise	195	0.53	0.50	0	1
Sessions & Articles	# of attended information sessions and articles read	195	4.69	2.24	0	8

^a Change in long-run vs. short-run risk perceptions equals the 2031 median damage minus the 2011 median damage, elicited by EM.

4.2 Farmer beliefs about climate change

Of the 195-farmer sample, 83% stated a belief in climate change. This high level appears to mirror the wider Italian population: polls have found that 89% of Italians believe that the climate has changed over the past 20 years and that 83% believe that climate change has been scientifically proven (AXA-IPSOS, 2012). The share of climate change believers in our sample is higher than has been found among farmers in other countries, such as the 65.5% reported by Arbuckle et al. (2013) for Midwestern U.S. farmers.

As shown in Table 3, 58.02% of farmers who believe in climate change stated that natural and anthropogenic factors are equally responsible for climate change. The share of farmers believing that climate change is predominantly or exclusively due to anthropogenic causes is 22.23%, nearly double the 12% of Midwestern U.S. farmers who believe that climate change is caused by human activities (Arbuckle et al., 2013). Finally, 19.76% believe that climate change is mainly or entirely due to natural factors.

Table 3. Perceived causes of climate change among farmers expressing a belief in climate change (N = 162).

Climate change is ...	Obs.	% of CC believers
Due to natural factors exclusively	9	5.56%
Due predominantly to natural factors	23	14.20%
Due to a similar extent to natural and human activity factors	94	58.02%
Due predominantly to human activity factors	31	19.14%
Due to human activity factors exclusively	5	3.09%

As has been the case for other studies focused on agricultural producers in developed counties (e.g., Weber, 1997 and Rejesus et al., 2013), farm and farmer characteristics prove to be poor predictors of climate change beliefs and unrelated to farmers' perceived causes (natural or anthropogenic) of climate change in our sample (regression analysis results are available from the authors upon request).

4.3 Farmer risk perceptions elicited via the exchangeability method

Table 4 reports summary statistics for the median damage level (our measure of perceived agricultural risk) caused by each peril in each year, as elicited via the EM. For hail in 2011, the average perceived median province-level damages are 21.17% and 12.68% for apple farmers and grape growers, respectively. This difference in perceived damages between apple farmers and grape growers corresponds with expert opinion that hail poses a greater threat to apple production than to grape production in the region (CoDiPra, 2013). For apple dieback and grape powdery mildew, the average perceived median province-level damages are lower than those for hail, equal to 10.47% and 10.12%, respectively. This also aligns to expert opinion that under current climate conditions hail poses a more significant risk to apple and grape farmers than do other perils (Olesen et al., 2011).

Table 4. Short-run (2011) and long-run (2031) risk perceptions (median crop loss).

Peril-Crop	Unit of measure	Obs.	2011 Mean (Std. Dev.)	2031 Mean (Std. Dev.)	Difference 2031-2011^a (Std. Err.)
Hail-Apples	% province-level apple value loss	120	21.17 (13.02)	26.24 (15.98)	5.07*** (0.79)
Hail-Grapes	% province-level grape value loss	75	12.68 (10.01)	18.65 (13.69)	5.97*** (0.85)
Dieback-Apples	% province-level apple trees affected by dieback	120	10.47 (11.64)	11.74 (11.86)	1.27 (0.76)
Powdery Mildew-Grapes	% province-level grape bunches affected by powdery mildew	75	10.12 (10.96)	13.27 (13.38)	3.16*** (0.90)

^a Paired t-test of difference in means between 2031 and 2011 risk perceptions for a given peril-crop, where *, **, *** denote 10%, 5%, and 1% significance levels, respectively.

The median risk perceptions for each of the four perils considered here, averaged across farmers, are greater in 2031 than in 2011. For apple farmers and grape growers, the median perceived risk levels due to hail in 2031 are 26.24% and 18.65%, reflecting increases of 5.07% and 5.97%, respectively, from 2011. A paired t-test shows that the difference in hail damage expectations between 2031 and 2011 is statistically significant, indicating that farmers perceive a substantial long-run increase in hail risk (p-value < 0.000 for both apple and grape farmers). This perception is consistent with the emerging concern among climatologists that the severity of

hailstorms in the Province of Trento, as measured by energetic indices that are directly correlated with crop damage, is increasing (Eccel et al., 2012). For apple dieback and grape powdery mildew, farmers also expect increased long-run damages, but the expected increase is less substantial. For apple dieback, the median province-level expected damage increases by an insignificant 1.27% (p-value = 0.101) while for powdery mildew the increase is 3.16% (p-value = 0.001).

Table 5 breaks down the EM results depending on climate change beliefs. Comparing the 2031-2011 change in risk perceptions between climate change believers and non-believers using one-tailed unpaired t-tests, we find that the change in perceived risk from hail is larger among climate change believers than among non-believers for both apple farmers and grape growers (p-value = 0.028 and 0.001, respectively). The same is true for apple dieback (p-value = 0.044), but the change in perceived risk from powdery mildew is not significantly different between the two groups. Overall, this unconditional analysis indicates that climate change believers anticipate more growth in climate-related agricultural risks in their region than do non-believers.

Table 5. Difference between 2031 and 2011 risk perceptions (% of province-level crop value loss) among climate change believers (CC) and non-believers (NC).

Peril-Crop	Obs.	Believers	Non-believers	Difference
		(CC) ^a	(NC) ^b	CC vs. NC ^c
		Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Err.)
Hail-Apples	120	5.67 (9.40)	2.99 (5.07)	2.68* (1.38)
Hail-Grapes	75	6.42 (7.47)	0.81 (2.81)	5.61*** (1.46)
Dieback-Apples	120	1.70 (9.35)	-0.24 (3.01)	1.95* (1.13)
Powdery Mildew-Grapes	75	3.57 (7.58)	-1.56 (9.86)	5.13 (4.13)

^a Mean (std. dev.) of the 2031 - 2011 change in risk perceptions of CC believers.

^b Mean (std. dev.) of the 2031 - 2011 change in risk perceptions of non-believers.

^c One-tailed unpaired t-test of difference in means, where *, **, *** denote 10%, 5%, and 1% significance levels, respectively.

4.4. Regression analysis of the determinants of risk perceptions

To further assess the factors affecting farmers' perceptions of hail and crop disease risks and the influence of climate change on these perceptions, this section reports results from sixteen linear regression models estimated using ordinary least squares (OLS) and controlling for a variety of factors that could influence risk perceptions. Table 6 reports results for apple farmers (Hail-Apples and Dieback-Apples regressions). Table 7 reports results for grape growers (Hail-Grapes and Powdery Mildew-Grapes regressions). In each of the regression models, the dependent variable is the change in farmers' risk perceptions (i.e., the change in expected median province-level crop damages) between 2031 and 2011, as elicited using the EM.

For each peril, we consider four model specifications (a, b, c, d), which differ in terms of independent variables. Model (a) represents the simplest model in which the only explanatory variables are farmers' climate change beliefs (*Climate Change Beliefs*) and first-hand experiences with crop losses due to the considered peril (*Damage Experience*). The *Climate Change Beliefs* variable consists of a dummy variable equal to 1 if the farmer states a belief in climate change (and 0 otherwise). The *Damage Experience* variable consists of a dummy variable that is equal to 1 if the farmer reports having personally seen recent significant crop damage due to hail (or crop disease, depending on the regression) in the region (and 0 otherwise). The *Damage Experience* variable is included based on the results of the literature review presented in Section 2, particularly the studies by Diggs (1991), Haden et al. (2012), Niles, Lubell, and Haden (2013), and Le Dang et al. (2014), who find that past experience influences risk perceptions related to climate change.

Following Diggs (1991), in model (b) we also control for any potential effects of farming experience by adding two additional explanatory variables: years of farming experience (*Farming Experience*) and a binary variable denoting whether the respondent is a full-time farmer (*Full Time*). Following the growing literature on the role of numeracy (e.g., Peters, 2008; Reyna et al., 2009; Dillingh, Kooreman, and Potters, 2013) and information (e.g., Le Dang et al., 2014) in shaping risk perceptions, in model (c) we include farmers' scores on the probability test (*Probability Test Score*) and four variables capturing interactions with local farming cooperatives and with outreach by local insurance and extension services (*Coop Member*, *Coop Representative*, *Co.Di.Pr.A*, *Sessions & Articles*). Finally, in model (d), to check the robustness of the relationship between climate change beliefs and risk perceptions, we include all available socio-demographic characteristics. A description of the explanatory variables is given in Table 2.

One feature of the modeling approach that must be considered is the potential for climate change beliefs to be endogenous, which would suggest the need for two-stage least squares estimation instead of OLS. In a related context, Wheeler et al. (2013) found that climate change beliefs were endogenous in some of their models but not others. Following Wheeler et al. (2013), we conducted Durbin and Wu-Hausman tests using as instruments weather insurance prices (which vary based on location and past weather events), altitude, and climatic normals (a climatic normal is the arithmetic average of temperature or rainfall over a prescribed 30-year interval, World Meteorological Organization, 1989), which are strongly correlated with climate change beliefs but not with the linear regression model error terms. We failed to reject the null hypothesis of exogeneity and thus report standard OLS estimation results. Tests for multicollinearity were also conducted. The variance inflation factors for all models and variables are under four, indicating that multicollinearity is not a concern. A Breusch-Pagan-Cook-Weisberg test was conducted to assess the presence of heteroscedasticity. As is common in cross-sectional studies with substantial variation in the magnitude of the dependent variable, the test indicated the presence of heteroscedasticity; Tables 6 and 7 thus report Eicker-White robust standard errors, which allow heteroscedasticity-robust inference with hypothesis tests. As in other studies of risk perceptions (e.g., Viscusi, 1991), regression results reported in Tables 6 and 7 show a large degree of unexplained individual heterogeneity in risk perceptions, resulting in overall low model fit.

Regression results suggest several key findings. The first important result concerns the *Climate Change Beliefs* variable. In the Hail-Apples, Hail-Grapes, and Dieback-Apples regressions, farmers' beliefs in climate change are found to be positive and significant predictors at standard significance levels. This result suggests that farmers who believe in climate change are indeed considering the negative consequences of a changing environment when forecasting long-term agricultural risks. Specifically, farmers who believe in climate change expect the change in median crop damages between 2011 and 2031 to be between 2.00% and 5.50% higher on average, depending upon the crop, peril, and model specification, compared to farmers who do not believe in climate change. Importantly, this result is consistent across the different model specifications (a-d), allowing us to be confident that climate change beliefs play a role in explaining risk perceptions. This finding is also consistent with Arbuckle, Morton, and Hobbs (2013b), Safi, Smith, and Liu (2012), and Le Dang et al. (2014), who all find that risk perceptions are higher among farmers who believe in climate change.

In the Powdery Mildew-Grapes regressions, however, farmers' beliefs in climate change are found to be statistically insignificant predictors, indicating that climate change believers and non-believers share similar risk perceptions concerning powdery mildew. This result is consistent with recent findings of Caffarra et al. (2012). This result might also be related to the long experience that farmers have with powdery mildew, the control of which relies on prevention through timely treatments of vineyards with fungicides (Lybbert and Gubler, 2008). In contrast, apple dieback is a relatively new and unknown peril for farmers; indeed, researchers themselves are currently trying to determine how to prevent or control the disease. It is thus conceivable that grape growers' generations-long experience fighting powdery mildew under diverse weather conditions instills in them a sense of confidence (controllability and manageability) that, as suggested in the managerial literature, dampens risk perceptions (Weber, 2002).

Consistently across all four perils and model specifications, we find that farmers with first-hand experience with significant crop damages due to hail, dieback, or powdery mildew expect future crop damages to increase significantly more than do farmers without such first-hand experience. This increase, which ranges from 2.56% to 4.78% depending on the crop, peril, and model specification, indicates that salient experience with climate-related risks affects risk expectations. This finding is consistent with several studies of risk perceptions of farmers (Diggs, 1991; Haden et al., 2012; Niles, Lubell, and Haden, 2013; Le Dang et al., 2014) and the general population (Akerlof et al., 2013).

No similar positive effect is found for the information variables included in the model (*Sessions & Articles*, *Co.Di.Pr.A.*, and the two cooperative variables). These results are consistent with the evidence captured in a recent review of 82 studies on public risk perceptions of natural hazards by Wachinger et al. (2013): the authors find that direct experience has a stronger effect than indirect experience (education, media, etc.) on risk perceptions. These results suggest that "field days," in which farmers visit a farm and gain first-hand on-farm experience with crop damages and risk management strategies, might be more effective than traditional off-farm information sessions and articles at communicating the potential risks from climate change.

Finally, a farmer's score on the probability test is the only other variable found to have significant explanatory power across the four perils, although the significance levels vary by model specification. Specifically, we find that farmers with higher scores expect larger changes in crop damage levels. This adds new evidence to the recent literature investigating the role of numeracy

in decision-making under risk. A few studies have found that individuals with poor understanding of probability are more likely to make worse decisions and have inferior economic outcomes in situations involving risk. For example, Dohmen et al. (2009) find that a poor understanding of probability increases the likelihood of overdrawing one's bank account and experiencing long-term unemployment. The literature does not reveal the channel through which a poor understanding of probability affects economic outcomes, and more research on the role of numeracy is needed. Our results suggest that the link between a poor understanding of probability and adverse economic outcomes occurs because of biased risk perceptions, a hypothesis that requires further investigation. This evidence also aligns with the findings of a health-focused literature review by Reyna et al. (2009), who report that a poor understanding of probability is linked to distorted perceptions of health risks and the benefits of medical screening.

Table 6. OLS coefficient estimates for linear models of the 2031 - 2011 change in apple farmers' risk perceptions (median crop loss).

Variable	Hail-Apples				Dieback-Apples			
	Model (a)	Model (b)	Model (c)	Model (d)	Model (a)	Model (b)	Model (c)	Model (d)
Climate Change Belief	2.966** (1.434)	2.839** (1.424)	2.857* (1.585)	3.161* (1.648)	1.999* (1.138)	2.173** (1.072)	1.940* (1.103)	2.478* (1.377)
Damage Experience ^a	4.256** (1.855)	4.207** (1.919)	3.615** (1.817)	3.480* (1.841)	3.003** (1.484)	3.25** (1.474)	3.141** (1.583)	3.364* (1.805)
Farming Experience		-0.062 (0.058)	-0.082 (0.056)	-0.069 (0.094)		0.084 (0.062)	0.058 (0.063)	0.024 (0.084)
Full Time		0.007 (2.156)	-0.437 (2.051)	0.236 (2.067)		0.971 (2.494)	0.852 (2.572)	0.314 (2.398)
Probability Test Score			1.055* (0.598)	1.111* (0.655)			0.867 (0.572)	1.039* (0.620)
Coop Member			0.038 (2.358)	-0.685 (2.404)			-2.494 (2.560)	-2.248 (2.471)
Coop Representative			1.740 (1.675)	1.326 (1.759)			1.477 (1.437)	1.697 (1.459)
Co.Di.Pr.A			2.545 (1.589)	2.904* (1.652)			2.244 (1.707)	2.010 (1.633)
Sessions & Articles			-0.398 (0.361)	-0.279 (0.407)			-0.573** (0.272)	-0.573* (0.291)
Age				-0.046 (0.100)				0.042 (0.088)
Education				0.002 (0.357)				-0.130 (0.384)
Household Size				-0.408 (0.777)				0.328 (0.776)
Farm Size				-0.492 (0.341)				0.375 (0.250)
Cultivated/Owned				0.012 (0.029)				0.020 (0.035)
Income				0.941 (0.737)				0.532 (0.684)
Liquidity				0.571				-3.957

Constant	-0.316 (1.823)	1.339 (3.769)	-1.207 (4.490)	-0.191 (7.926)	(2.238)	-1.910* (1.025)	-5.084 (3.159)	-3.835 (4.405)	(2.411) -7.508 (7.389)
Adjusted R-Squared	0.049	0.042	0.049	0.028		0.025	0.027	0.035	0.034
F test	4.65**	2.99**	1.87*	1.34		2.82*	2.90**	2.03**	1.46
Observations	120	120	120	120		120	120	120	120

Note: *, **, *** denote 10%, 5%, and 1% significance levels, respectively. Eicker-Huber-White robust standard errors in parentheses.

^aFor the Hail-Apples regressions, the *Damage Experience* variable refers to past experience with hail damage to apples. For the Dieback-Apples regressions, the *Damage Experience* variable refers to past experience with damage due to apple dieback.

Table 7. OLS coefficient estimates for linear models of the 2031 - 2011 change in grape growers' risk perceptions (median crop loss).

Variable	Hail-Grapes				Powdery Mildew-Grapes			
	Model (a)	Model (b)	Model (c)	Model (d)	Model (a)	Model (b)	Model (c)	Model (d)
Climate Change Belief	5.502*** (1.140)	5.054*** (1.055)	4.020*** (0.966)	3.802** (1.716)	5.370 (3.959)	5.423 (4.167)	5.015 (4.103)	5.902 (4.268)
Damage Experience ^a	4.749*** (1.318)	4.781*** (1.427)	3.866*** (1.292)	2.561* (1.435)	3.756*** (1.429)	3.854** (1.649)	3.518** (1.629)	4.085** (1.619)
Farming Experience		-0.024 (0.069)	-0.024 (0.062)	0.149* (0.085)		-0.016 (0.074)	0.000 (0.055)	0.086 (0.081)
Full Time		-2.977 (1.863)	-3.000 (1.963)	-1.213 (1.767)		0.281 (2.400)	-2.047 (2.388)	-0.403 (2.266)
Probability Test Score			0.794 (0.594)	0.826** (0.373)			1.173** (0.496)	1.511*** (0.504)
Coop Member			-0.460 (2.368)	0.624 (3.400)			4.598* (2.738)	3.482 (4.361)
Coop Representative			1.464 (1.786)	1.952 (1.806)			2.693 (4.152)	1.998 (2.808)
Co.Di.Pr.A			3.009* (1.645)	1.645 (1.555)			0.338 (2.329)	0.092 (2.13)
Sessions & Articles			0.790 (0.356)	0.581 (0.378)			0.452 (0.456)	0.442 (0.393)

Age				-0.036 (0.074)				-0.077 (0.095)
Education				1.236*** (0.405)				0.518 (0.405)
Household Size				-0.180 (0.552)				-0.621 (0.845)
Farm Size				-0.168 (0.316)				-0.464 (0.311)
Cultivated/Owned				-0.003 (0.028)				0.045 (0.038)
Income				0.089 (0.759)				1.782 (1.237)
Liquidity				-0.146 (1.638)				-3.443* (1.964)
Constant	-3.145*** (1.285)	-0.154 (1.979)	-4.319 (3.480)	-17.573** (7.337)	-4.69 (3.871)	-4.648 (5.115)	-13.478** (5.73)	-20.695* (10.58)
Adjusted R-Squared	0.071	0.087	0.206	0.351	0.047	0.021	0.044	0.168
F test	13.38***	10.19***	6.54***	4.12***	4.31**	2.20*	2.12**	1.92**
Observations	75	75	75	75	75	75	75	75

Note: *, **, *** denote 10%, 5%, and 1% significance levels, respectively. Eicker-White robust standard errors in parentheses.

^a For the Hail-Grapes regressions, the *Damage Experience* variable refers to past experience with hail damage to grapes. For the Powdery Mildew-Grapes regressions, the *Damage Experience* variable refers to past experience with damage due to powdery mildew.

5. Conclusion

A key area of concern regarding global climate change is its potential to negatively impact agricultural productivity and profitability. For farmers to engage in adaptation strategies to mitigate these damages, they must perceive climate change-related agricultural risks. Moreover, to design programs to help farmers manage these risks, policymakers must understand not only the impact of climate change on agricultural production but also how and to what extent farmers perceive and respond to these impacts.

This study contributes to the literature investigating farmers' perceptions of the agricultural risks associated with climate change. While previous research has elicited risk perceptions through different types of Likert scales, dichotomous questions, open-ended and closed questions, and composite indexes, we consider the median of the cumulative distribution of perceived crop losses. The elicitation is performed using the EM, an indirect method for assessing subjective risk-related beliefs that does not require difficult probability reasoning.

Among our sample of apple and grape farmers in the Province of Trento, Italy, we find that the level of long-run perceived risk of crop losses tends to be higher than the short-run level. Controlling for a variety of factors (experience with crop losses, farming experience, numeracy, interactions with other producers, and farmers' characteristics), we show that climate change beliefs help explain this long-run increase in perceived risk. Quantitatively, compared to non-believers, apple farmers who believe in climate change expect a larger increase in median crop damages due to hail and dieback (between 2.84% and 3.16% and between 1.94% and 2.48%, respectively). Similarly, grape farmers who believe in climate change expect a larger increase in median crop damages due to hail (between 3.80% and 5.50%). In the case of powdery mildew, we find no statistically significant difference in the risk perceptions between climate change believers and non-believers, which is consistent with Caffarra et al. (2012). Finally, we find that first-hand experience with crop losses positively affects risk perceptions.

The empirical evidence presented here provides insights that can help policymakers and outreach professionals better support farmers to adapt to changing agronomic conditions due to climate change. We find that a significant portion of farmers in our sample believe that climate change is occurring and also forecast increased crop losses for the future. Considering farmer assistance programs, our findings provide support for the "segmented approach" to farmer outreach suggested by Arbuckle et al. (2013), which takes into account differences in farmers'

beliefs about climate change. Whereas some farmers might benefit from general education regarding climate change and its consequences for crop losses, for others, effective outreach should focus on assistance with adopting cost-effective methods to control or mitigate the risks of which they are already aware. Moreover, given the key role that first-hand experience with past hail and/or pest damages plays in explaining risk perceptions, field days conducted by local extension services might be more effective than traditional off-farm information sessions and articles at increasing farmers' awareness of climate change risks.

References

- Abdellaoui, M., Baillon, A., Placedo, L., Wakker, P.P., 2011. The rich domain of uncertainty: source functions and their experimental implementation. *American Economic Review* 101, 695–723.
- Akerlof, K., Maibach, E. W., Fitzgerald, D., Ceden, A. Y., Neuman, A., 2013. Do people “personally experience” global warming, and if so how, and does it matter? *Global Environmental Change* 23(1), 81-91.
- Ajzen, I, 1991. The theory of planned behavior. *Organizational behavior and human decision processes* 50(2), 179-211.
- Arbuckle Jr, J. G., Morton, L. W., Hobbs, J., 2013a. Farmer beliefs and concerns about climate change and attitudes toward adaptation and mitigation: Evidence from Iowa. *Climatic Change* 118(3-4), 551-563
- Arbuckle Jr, J. G., Morton, L. W., Hobbs, J., 2013b. Understanding Farmer Perspectives on Climate Change Adaptation and Mitigation: The Roles of Trust in Sources of Climate Information, Climate Change Beliefs, and Perceived Risk. *Environment and Behavior* doi:10.1177/0013916513503832
- Arbuckle Jr, J. G., Prokopy, L. S., Haigh, T., Hobbs, J., Knoot, T., Knutson, C., Loy, A., Mase A.S., McGuire, J., Morton, L.W., Tyndall J., Widhalm, M., 2013. Climate change beliefs, concerns, and attitudes toward adaptation and mitigation among farmers in the Midwestern United States. *Climatic change* 117(4), 943-950
- Baillon, A., 2008. Eliciting Subjective Probabilities Through Exchangeable Events: An Advantage and a Limitation. *Decision Analysis* 5(2), 76-87.
- Barnes, A. P., Toma, L., 2012. A typology of dairy farmer perceptions towards climate change. *Climatic change* 112(2), 507-522.
- Barnes, A. P., Islam, M. M., Toma, L., 2013. Heterogeneity in climate change risk perception amongst dairy farmers: A latent class clustering analysis. *Applied Geography* 41,105-115.
- Caffarra A., Rinaldi M., Eccel E, Rossi V., Pertot I., 2012. Modelling the impact of climate change on the interaction between grapevine and its pests and pathogens: European grapevine moth and powdery mildew. *Agriculture, Ecosystem and Environment* 148, 89-101.

- Cerroni, S., Shaw, W.D., 2012. Does climate change information affect stated risks of pine beetle impacts on forests? An application of the exchangeability method. *Forest Policy and Economics* 22, 72-84.
- Cerroni, S., Notaro, S., Shaw, W.D., 2013. How many bad apples are in a bunch? An experimental investigation of perceived pesticide residue risks. *Food Policy* 41, 112-123.
- CoDiPra. 2013. Difesa Assicurativa Agricola Agevolata 2013, Anno XI, N.3, III Trimestre 2013.
- Cokely, E. T., Galesic, M., Schulz, E., Ghazal, S., Garcia-Retamero, R., 2012. Measuring risk literacy: The Berlin numeracy test. *Judgment and Decision Making* 7(1), 25-47.
- Dallago, G., Branz, A., Delaiti, L., Prantil, M., Prodorutti, D., Gualandri, V., Cainelli, C., Profaizer, D., Bondio, V., Culatti, P., Salvetti, M., Vittone, G., Nari, L., Asteggiano, L., Morone, C., Neri D., 2011. La moria del melo: molte cause e sintomi certi. *L'informatore agrario* 39: 44-50.
- Di Falco, S., M. Veronesi, Yesuf M., 2011. Does Adaptation To Climate Change Provide Food Security? A Micro-Perspective From Ethiopia. *American Journal of Agricultural Economics*, 93(3):829-846.
- de Finetti, B., 1974. The Value of Studying Subjective Evaluations of Probability, in C.-A. S. Staël von Holstein, ed. *The Concept of Probability in Psychological Experiments*. D. Reidel Publishing Company, Dordrecht-Holland, 2–14.
- Diggs, D.M., 1991. Drought Experience and Perception of Climatic Change among Great Plains Farmers. *Great Plains Research: A Journal of Natural and Social Sciences* 1(1),114-132.
- Dillingh, R., Kooreman, P., Potters, J., 2013. Probability Numeracy and Insurance Purchase. Working paper, available at <http://members.ziggo.nl/peterkooreman/pnip.pdf>.
- Dinar, A., Mendelsohn, R., 2011. *Handbook on Climate Change and Agriculture*. Cheltenham: Edward Elgar.
- Dohmen, T., Falk A., Huffman D., Marklein D., Sunde U., 2009. Biased probability judgment: Evidence of incidence and relationship to economic outcomes from a representative sample. *Journal of Economic Behavior & Organization* 72, 903–915.
- Eccel, E., Cau P., Riemann-Campeb K., Biasioli F., 2012. Quantitative hail monitoring in an alpine area: 35-year climatology and links with atmospheric variables. *International Journal of Climatology* 32, 503–517.
- Esham M., Garforth C., 2013. Agricultural adaptation to climate change: insights from a farming community in Sri Lanka. *Mitigation and Adaptation Strategies for Global Change* 18(5), 535–549.
- Fischbein, E., Schnarch D., 1997. The Evolution with Age of Probabilistic, Intuitively Based Misconceptions, *Journal for Research of Mathematics Education* 28(1), 96-105.
- Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., & Wiltshire, A., 2010. Implications of climate change for agricultural productivity in the early twenty-first century. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1554), 2973-2989.

- Haden, V. R., Niles, M. T., Lubell, M., Perlman, J., Jackson L. E., 2012. Global and local concerns: what attitudes and beliefs motivate farmers to mitigate and adapt to climate change?. *PloS one*, 7(12), e52882.
- Hogan, A., Berry, H. L., Ng, S. P., and Bode, A., 2011. Decisions made by farmers that relate to climate change. *Agricultural Science* 23(1), 36-39.
- Howden, S. M., Soussana, J. F., Tubiello, F. N., Chhetri, N., Dunlop, M., & Meinke, H., 2007. Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences* 104(50), 19691-19696.
- IPSOS. 2012. Individual Perceptions of Climate Risks. Survey AXA-IPSOS. Available at http://www.axa.com/lib/axa/uploads/cahiersaxa/Survey-AXA-Ipsos_climate-risks.pdf
- Jones, G.V., White, M.A., Cooper, O.R., Storchmann, K., 2005. Climate change and global wine quality. *Climatic Change*, 73(3), 319-343.
- Le Dang, H., Li, E., Nuberg, I., Bruwer, J., 2014. Farmers' Perceived Risks of Climate Change and Influencing Factors: A Study in the Mekong Delta, Vietnam. *Environmental Management*, 1-15. DOI 10.1007/s00267-014-0299-6
- Lobell, D.B., Field, C.B., 2011. California perennial crops in a changing climate. *Climatic Change* 109 (Supplement 1), 317-333.
- Lobell, D.B., Field, C.B., Cahill, K.N., Bonfils, C., 2006. Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties. *Agricultural and Forest Meteorology* 141, 206-218.
- Lybbert, T.J. Gubler, W.D., 2008. California Wine Grape Growers' Use of Powdery Mildew Forecasts. *Agricultural & Resource Economics Update* 11(4),11-14.
- Mendelsohn, R. O., and Dinar, A., 2009. Climate change and agriculture: an economic analysis of global impacts, adaptation and distributional effects. Edward Elgar Publishing.
- Nicholas, K. A., and Durham, W. H., 2012. Farm-scale adaptation and vulnerability to environmental stresses: Insights from winegrowing in Northern California. *Global Environmental Change* 22(2), 483-494.
- Niles, M. T., Lubell, M., Haden, V. R., 2013. Perceptions and responses to climate policy risks among California farmers. *Global Environmental Change* 23(6), 1752-1760.
- Olesen, J.E., Trnka, M., Kersebaum, K.C., Skjelvåg, A.O., Seguin, B., Peltonen-Saino, P., Rossi, F., Kozyra, J., Micale, F., 2011. Impacts and adaptation of European crop production systems to climate change. *European Journal of Agronomy* 34(2), 96-112.
- Patt, A. G., Schröter, D., 2008. Perceptions of climate risk in Mozambique: implications for the success of adaptation strategies. *Global Environmental Change* 18(3), 458-467.
- Peters, E., Västfjäll, D., Slovic, P., Mertz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological science*, 17(5), 407-413.
- Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., Lobell, D. B., Travasso, M.I., 2014. Food security and food production systems. In: Field, C. B., Barros, V. R., Dokken, D. J. (Eds.) Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. Contribution of working group II to the Fifth Assessment Report

- of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, 485-533.
- Reidsma, P., Ewert, F., Lansink, A. O., Leemans, R., 2010. Adaptation to climate change and climate variability in European agriculture: the importance of farm level responses. *European Journal of Agronomy* 32(1), 91-102.
- Rejesus, R. M., Mutuc-Hensley, M., Mitchell, P. D., Coble, K. H., Knight, T. O., 2013. US Agricultural Producer Perceptions of Climate Change. *Journal of Agricultural and Applied Economics* 45(4), 701–718.
- Reyna, V. F., Nelson, W. L., Han, P. K., Dieckmann, N. F., 2009. How numeracy influences risk comprehension and medical decision making. *Psychological bulletin* 135(6), 943-973.
- Safi, S., 2011. Climate change in rural Nevada: The influence of vulnerability on risk perception and environmental behavior. *UNLV Dissertation*. Paper 906.
- Safi, S. A., James Smith, W., Liu, Z. 2012. Rural Nevada and climate change: vulnerability, beliefs, and risk perception. *Risk Analysis* 32(6), 1041-1059.
- Servizio Statistica, Provincia Autonoma di Trento, La Produzione Lorda Vendibile dell'Agricoltura e della Silvicoltura in Provincia di Trento nel 2006 e nel 2007, available online at <http://www.statistica.provincia.tn.it>, accessed May 1st, 2012.
- Smit, B., Skinner, M., 2002. Adaptation options in agriculture to climate change: a typology. *Mitigation and adaptation strategies for global change* 7(1), 85–114.
- Stöckle, C.O., Nelson, R.L., Higgins, S., Brunner, J., Grove, G., Boydston, R., Whiting, M., Kruger, C., 2010. Assessment of climate change impact on Eastern Washington agriculture. *Climatic Change* 102, 77-102.
- Viscusi, W. K., 1991. Age Variations in Risk Perceptions and Smoking Decisions. *The Review of Economics and Statistics* 73(4), 577-588.
- Wachinger, G., Renn, O., Begg, C., Kuhlicke, C., 2013. The risk perception paradox—Implications for governance and communication of natural hazards. *Risk Analysis* 33(6), 1049-1065.
- Weber, E. U., 1997. Perception and expectation of climate change: Precondition for economic and technological adaptation. In: Max Bazerman, David Messick, Ann. Tenbrunsel, and Kimberley Wade-Benzoni (eds.), *Psychological Perspectives to Environmental and Ethical Issues in Management* (pp. 314–341), San Francisco, CA: Jossey-Bass.
- Weber, E. U., Blais, A. R., Betz, N. E., 2002. A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of behavioral decision making* 15(4), 263-290.
- Wheeler, S., Zuo, A., Bjornlund, H. 2013. Farmers' climate change beliefs and adaptation strategies for a water scarce future in Australia. *Global Environmental Change* 23, 537–547.
- World Meteorological Organization. 1989. Calculation of Monthly and Annual 30-year Standard Normals. WCDP-No. 10, WMO-TD/No. 341, World Meteorological Organization.

Appendix A

Appendix A briefly discusses farmers' answers to the Likert scale (LS) questions and compares them to the risk perception measures elicited via the EM. Specifically, farmers were asked: "On a scale from -5 to +5 (where -5 indicates a strong decline in damage, 0 indicates no change, and +5 indicates a strong increase in damage), how will climate change affect the average province-level crop (apple or wine grape) losses due to hail in the future (2031) compared to 2011 levels?" This question was repeated for the other two perils considered: powdery mildew and apple dieback. Similar to LS questions used in previous studies, our questions explicitly mention climate change. Table A1 summarizes farmers' responses, which suggest that farmers expect an increase in crop losses for each crop and peril.

Table A1. Expected change in average province-level crop losses in 2031 compared to 2011, elicited using a Likert scale (-5 = strong decline to +5 = strong increase).

Peril-Crop	Obs.	Mean	Std. Dev.
Hail-Apples	120	1.28	1.86
Hail-Grapes	75	1.49	1.36
Dieback-Apples	120	1.34	1.85
Powdery Mildew-Grapes	75	1.48	1.84

Examining these responses separately depending on climate change beliefs confirms significant differences in expected crop losses between the two groups. As can be seen in Table A2, a one-tailed unpaired t-test confirms that climate change believers expect larger increases in crop losses from hail for both apples and grapes (p-value = 0.035 and p-value = 0.037, respectively) and from apple dieback (p-value < 0.000). Comparing these results to the EM estimates (Table 5), we conclude that both question formats consistently capture the same statistically significant differences between climate change believers and non-believers. However, while both methods capture similar perceptions of agricultural risks, the EM has the distinct advantage of delivering a cardinal measure of the expected change in crop losses.

Table A2. Expected change in average province-level crop losses in 2031 compared to 2011, divided into climate change believers and non-believers.

Peril-Crop	Obs.	Believers (CC) ^a	Non-believers (NC) ^b	Difference CC vs. NC ^c
		Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Err.)
Hail-Apples	120	1.43 (0.20)	0.77 (1.43)	0.65* (0.35)
Hail-Grapes	75	1.55 (0.17)	0.83 (0.31)	0.72* (0.35)
Dieback-Apples	120	1.59 (0.20)	0.48 (0.25)	1.10*** (0.32)
Powdery Mildew-Grapes	75	1.55 (0.23)	0.67 (0.49)	0.88 (0.54)

^a Mean (std. dev.) of the 2031 - 2011 change in risk perceptions of CC believers.

^b Mean (std. dev.) of the 2031 - 2011 change in risk perceptions of non-believers.

^c One-tailed unpaired t-test of difference in means, where *, **, *** denote 10%, 5%, and 1% significance levels, respectively.