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Time discounting and implications for Chinese farmer responses to an upward trend in precipitation

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Abstract

This paper studies Chinese grape growers' time discounting and its implications for the adoption of technology that can reduce the negative effects of increasing precipitation. Using primary data collected in Xinjiang Province, we undertook a contingent valuation of rain covers that protect fruit from rain and estimated a discounted utility model using these data. Using a hierarchical Bayesian approach, we find that local grape growers discount the future very heavily, with a discount rate of 0.17 per year, which is almost four times higher than the Chinese market interest rate. Farmers also tend to underestimate the benefits of adopting covers, with their purchase decisions appearing to largely depend on their past actual losses rather than future anticipated losses. These findings have broader implications for policies promoting proactive adaptation in response to likely increased rainfall in the region. Targeting farmers who give lower weight to events far off in the future and understanding that many farmers may tend only to make adoption decisions that have strong short-term benefits could improve the efficacy of climate policies that target agricultural technologies.

KEYWORDS

China, contingent valuation, grape, hierarchical Bayesian approach, increased rainfall, technology adoption, time discounting

JEL CLASSIFICATION

C11; D22; O13; Q12; Q16

1 | INTRODUCTION

Grape production is particularly vulnerable to precipitation. Good growing conditions require 'rain at the right moment'. In particular, precipitation during veraison (the stage from berry growth to ripening), and during harvest, increases the likelihood of fungal disease and causes grapes to rot and mould, affecting yield and market acceptability (Agosta et al., 2012).

Xinjiang, the study area of this paper, has the highest grape yields and planted areas among all of China's provinces (National Bureau of Statistics, 2017). According to meteorological data from NOAA (National Oceanic and Atmospheric Administration), regional precipitation has been increasing in frequency and intensity since 1951 (NOAA, 2019). This trend threatens local farmers' livelihoods. For example, rain showers in August 2018 caused over 60% of grapes to rot in Huangtian, as reported by Xinjiang Production and Construction Crops Thirteenth Division of Government Affairs (2018).

Since 300 BC, farmers in Xinjiang have traditionally grown grapes in open irrigated fields, due to the relatively low annual rainfall (Jiang et al., 2009). Thompson Seedless is the leading variety planted in Xinjiang, and it has long been popular in the region, in part because the environmental conditions there have historically been particularly suitable. However, this variety is highly susceptible to fungal diseases which spread easily in warm and humid environments (Satisha et al., 2008). Currently, the main methods farmers choose to deal with such diseases are to plant alternative cultivars, spray pesticides, and pick out rotten fruits after rainfall. Yet these strategies already have limitations, and they may become less viable as climatic conditions gradually become warmer and wetter (Piao et al., 2010). New cultivars usually need at least three years before they produce fruit, and therefore growers do not have revenue during that time. The pesticides that are currently used by farmers are not particularly effective and may have potential negative impacts on consumers' health and environmental pollution (Mesnage & Séralini, 2018). Farmers do not necessarily take account of these externalities when making their decisions. For example, some interviewees who complained about the efficacy of pesticides suggested adding oil to the pesticide. This can help to repel water from the grape and so reduce damage, yet it makes it more difficult for consumers and companies to clean the grapes before consumption. Finally, removing rotten fruit is costly and labour-intensive.

Rain covers have proven to be more effective than fungicide sprays with respect to reducing losses, and improving yields and profits (Du et al., 2015). They also reduce the negative health externalities caused by pesticides, though they can increase plastic pollution (Chavarria et al., 2007; Li et al., 2014). The current market price of rain covers is around 700–800 yuan/mu (£0.12/m^2–£0.13/m^2). To encourage uptake, the local government is currently providing a rain cover subsidy of 500 yuan/mu (about £0.08/m^2) to the first 2000 adopters of rain covers in the region. Yet despite the proven effectiveness and subsidisation of these covers, few farmers are using this new technology and few have taken up the government's offer.[1]

We seek to determine why adoption rates of rain covers are so low, despite their effectiveness, and what policies might be implemented to promote greater adoption. The existing literature highlights a number of factors that are likely to influence farmers' willingness to take measures to adapt to weather variability. These include demographic factors (Deressa et al., 2011; Fosu-Mensah et al., 2012; Le Dang et al., 2014); resource availability (Bryan et al., 2009; Falco et al., 2014); and social barriers (Adger, 2003; Vulturius & Gerger Swartling, 2015). Some researchers have also demonstrated that psychological factors, such as climate change beliefs, risk perceptions, attitudes toward innovation (Mase et al., 2017); attitudes toward risk (Alpizar et al., 2011); and the psychological distance of risk (Azadi et al., 2019), may also affect farmers' actions.

[1]Personal correspondence with lead author during data collection, 2019.

Adaptation is an intertemporal behaviour. Farmers often need to act now to be prepared for climate events that will take place in the future (Bernedo & Ferraro, 2017). Therefore, it is important to consider individuals' discount rates. Though few studies explore the relationship between farmers' time preference/discounting and their response to anticipated future weather variability, we can still gain some knowledge from the limited existing literature. For example, Stein and Tobacman (2016) found that people with higher discount rates have higher willingness-to-accept weather insurance. Ngoma et al., (2019) found farmer impatience was negatively related to the likelihood of adopting climate-smart agriculture.

We contribute to the literature in two ways. First, we have designed a novel experiment to elicit individual farmers' discount rates. This format is linked more closely to the research context than the typical method of binary choice lists applied in most studies using individual time discounting. Our design also considers the temporal nature of the problem, which has been largely ignored or framed as a static problem in the majority of contingent valuation or choice modelling studies. Secondly, we explore the extent to which farmers underestimate the benefits from future adaptive strategies and whether this inhibits the promotion of adaptive technologies, especially those that require relatively large initial investment.

The rest of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 builds the utility model and describes the design of the experiment and methods for data analysis. Section 4 states the empirical results. Section 5 discusses the main findings and provides possible policy suggestions.

2 | LITERATURE REVIEW AND HYPOTHESES

There is limited literature that explores the links between individuals' discount rates and their adoption of proactive measures to respond to future weather variability. However, we get some insights from research in energy efficiency, that addresses the relationship between preference and behavioural factors and the adoption of energy-efficient technologies. For example, households may discount future energy savings, which is one of the internal barriers to adopting energy-efficient technologies (Newell & Siikamäki, 2015).

To reduce the influence of cognitive bias, some researchers have explored how more effective policies can be designed to encourage more successful adoption. De Groote and Verboven (2019) suggest that promoting the adoption of solar photovoltaic systems should be through subsidies for future electricity production rather than through subsidies for upfront investment. Langer and Lemoine (2018) designed a subsidy schedule that is informed by consumers' characteristics. If households are myopic, the subsidies can increase strongly over time; if households have rational expectations, the time profile of the efficient subsidy will be flatter.

Although the adoption of adaptive strategies to changing rainfall patterns has some similarities with investment in energy-efficient technologies, there are also differences. Individuals' decisions over whether to take proactive or reactive measures closely depend on the external environment, in this case, rainfall patterns. However, due to the complexity of natural and anthropogenic process (Pachauri et al., 2014), it is hard for farmers to predict how, and to what extent, future weather and climate patterns will evolve. Compared with energy-saving technologies, the benefits of adaptation are more uncertain. Uncertainty can augment individuals' discount rates, and this can partly explain the high discount rates found in other empirical studies (Wilkinson & Klaes, 2012). Motivated by these findings from the literature, we arrive at our first hypothesis:

Hypothesis 1: A grape grower in Xinjiang is likely to heavily discount the benefits from the adoption of rain covers.

We judge whether the discount factor is high by comparing the value of the farmer's discount rate to the market interest rate. Adopting rain covers is an intertemporal investment with a relatively high upfront cost. The purchasing farmer must decide whether or not to make a one-time upfront investment based on the predicted accumulated utility value over the covers' lifespan. The utility value from covers comes from reduced crop damage. However, farmers may be budget constrained, or they may not have sufficiently valued the benefits (Gong et al., 2014; Weber & Chapman, 2005). Farmers with higher discount rates might be expected to be less likely to make long-term investments, all other things constant, choosing alternative management approaches that provide more immediate benefits and that have lower upfront costs (Hallegatte et al., 2012), such as spraying pesticides or pruning rotten grapes. Therefore, Hypothesis 2 states:

Hypothesis 2: Farmers with higher discount rates are less likely to adopt rain covers.

3 | METHODOLOGY

Methods to elicit individuals' discount rates can broadly be divided into two categories: experimental studies and field studies (Frederick et al., 2002). In experimental studies, researchers generally apply the method of classic binary choice lists, as initially designed by Coller and Williams (1999) and Harrison et al., (2002). Respondents are required to choose from a smaller but more immediate payoff or a larger but more delayed payoff (Bezabih, 2009). In field studies, discount rates are inferred from people's intertemporal economic decisions in real-world scenarios rather than hypothetical choices (Frederick et al., 2002).

It has been argued that experimental studies seem to get more precise results compared with field studies because they abstract from and simplify the complexity of real-world decisions, and control other important factors that may influence discount rates (Frederick et al., 2002). However, the experimental design needs to conform to a particular research domain and background, because even for the same individuals, different goods and services may be discounted at different rates (Frederick et al., 2002).

To design an experiment that is closer to the real-world experiences of farmers, we designed hypothetical scenarios that are reasonable representations of the real decisions that farmers in Xinjiang make. Instead of making farmers choose from a number of options with different payoffs at different times, in our experiment, farmers are told about the characteristics of rain covers and future rainfall conditions, and they respond with how much they are willing to pay for rain covers according to specific scenarios. To elicit a more precise willingness-to-pay (WTP) for each farmer, we incorporate the design into a multiple-bounded contingent valuation framework. Multiple-bounded questions have been shown to help to provide more statistical information than other contingent valuation approaches with single or double-bounded questions (Roach et al., 2002).

3.1 | Maximum WTP model.

We make the following assumptions. First, farmers optimise their discounted returns from using rain covers over the lifespan of the covers. The utility functions are linear in anticipated profit and cost. This strong assumption implies farmers are only concerned with the maximum of profit and cost minimisation, while other attributes such as the ease of installation and management, or leisure time, do not determine their choices. Second, we do not consider the role of risk and uncertainty. Instead, we assume that farmers are able to fully anticipate profits and rotting rates given a set number of rainy days. The consideration of risk and/or uncertainty would require a more complex treatment of the utility and value of using rain covers. The curvature of the utility functions and the introduction of probabilities would be required, along with the elicitation of farmers' subjective probability distributions. While the simultaneous treatment of time and uncertainty remains an interesting and potentially fruitful one, it would also require many additional assumptions about the shape of the utility functions, and probability weighting functions if prospect theory was followed. Third, we assume that there are no economic losses due to rain after the adoption of rain covers. With regard to the anticipated losses there is also an assumption that there is a linear (though discounted) loss in utility with respect to these anticipated losses, which might also be challenged.

Finally, we assume the anticipated profits from grapes after using covers and not using covers are the same when there is no rainfall in a given period, and both can be represented by π_i. Several papers (Lim et al., 2014; Permanhani et al., 2016) do show that the use of rain covers may affect fruit quality, and hence the price and profit obtained from the fruit. However, during the fieldwork, no farmers mentioned that a change in quality was a reason for non-adoption.

A farmer's utility, under adoption, is defined as the discounted anticipated profit over the life of the cover, less the cost of adoption, as follows:

$$U_{cover,i} = \pi_i \sum_{t=1}^{T} \left(1 + r_i\right)^{-t} - C_T \tag{1}$$

where:

- π_i is the ith farmer's anticipated profit from one mu of area planted to grapes (one mu is a Chinese farmland unit, equal to approximately 666.67 m^2) in one period if there is no rain;
- T is the lifespan (in years) of plastic rain covers;
- t is the tth year;
- r_i is the time discount rate of the ith farmer;
- C_T is the upfront cost, incurred in period 0, of sufficient rain covers, that last the full T years, for one mu of farmland planted to grapes.

If a farmer does not adopt rain covers, their grapes may rot. We introduce the time invariant parameter δ_i, which represents farmer *i's* 'rotting rate' for a rainy day, which is assumed to be known to each farmer, but not fixed across farmers.

The farmer's utility, if they do not buy rain covers, is therefore:

$$U_{no-cover,i} = \pi_i \sum_{t=1}^{T} \left(1 + r_i\right)^{-t} \left(1 - \delta_i\right)^{y_{i,t}} \tag{2}$$

where $y_{i,t}$ is the number of rainy days in a given period experienced by the ith farmer at time t. For a given value of $y_{i,t}$, $\left(1 - \delta_i\right)^{y_{i,t}}$ is the farmer's share of their annual profit they will lose each year without the protection of rain covers.

We did not ask the farmers to estimate the number of rainy days. Rather, this was set within the scenario offered to them. The 'rotting rate' is that which individual farmers know according to their particular situation. For example, farmers with other alternative measures, such as spraying pesticides, may have a smaller δ_i, because the net loss from not using rain covers will be lower.

When $U_{cover,i} \geq U_{no-cover,i}$, the farmer is better off purchasing the rain covers. Formally: Let $V_i = U_{cover,i} - U_{no-cover,i}$. Then the farmer will purchase rain covers if $V_i \geq 0$:

$$\begin{aligned} V_i &= \pi_i \sum_{t=1}^{T} \left(1+r_i\right)^{-t} - C_T - \pi_i \sum_{t=1}^{T} \left(1+r_i\right)^{-t} \left(1-\delta_i\right)^{y_{it}} \\ &= \pi_i \sum_{t=1}^{T} \left(1+r_i\right)^{-t} \left(1-\left(1-\delta_i\right)^{y_{it}}\right) - C_T \end{aligned} \tag{3}$$

Therefore, when $\pi_i \sum_{t=1}^{T} \left(1+r_i\right)^{-t} \left(1-\left(1-\delta_i\right)^{y_{it}}\right) \geq C_T$, farmers will be willing to pay for rain covers, and the maximum willingness to pay ($MWTP$) is:

$$MWTP_i = \pi_i \sum_{t=1}^{T} \left(1+r_i\right)^{-t} \left(1-\left(1-\delta_i\right)^{y_{it}}\right) \tag{4}$$

The $MWTP$ function asserts that farmers' preferences are determined by three properties: lifespan of covers (T); their cost ($MWTP$); and the subjective future number of rainy days (y) through time. We naturally assume that farmers accept the conditions provided by scenarios in terms of the number of rainy days and the cost of the covers. We focus on the price of covers acceptable to farmers (shown in the Appendix S1, Figure A1), and do not explicitly account for other possible costs, such as labour and installation. This simplified the scenarios and made them easier for farmers to understand. Farmers are likely to have implicitly factored in these costs when making their decisions, and would ultimately have embedded the costs in the final estimates of their $MWTP$. If farmers were unable to accurately factor in these other factors, this may bias the results.

3.2 | Identification of attribute levels.

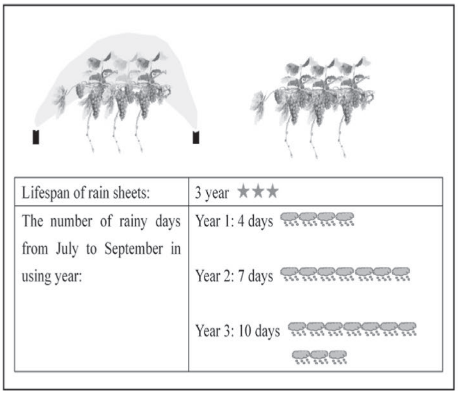
To identify the attributes and levels we considered both theoretical underpinnings and farmers' experiences, the latter determined through focus group discussions with three local farmers. After establishing the attributes (the numbers of rainy days through time, the life span of rain covers and the cost of covers), the next step was to assign attribute levels. First, according to data from NOAA (2019), the average number of rainy days (rainfall is equal or above 0.01 inches) in the study area during July to September from 2008 to 2012 was 7.2 days $\left(\frac{10+6+7+6+7}{5}\right)$. Based on these historic data, explicitly including the possibility of zero rainfall days, we assigned six levels for each year that the rain covers last: 0 days, 2 days, 4 days, 7 days, 10 days, and 13 days. Secondly, we considered four different time periods T for the lifespan of the rain covers: T = 1, 2, 3, and 4. Thirdly, from the Xinjiang Production and Construction Crops Thirteenth Division of Government Affairs (2018), the cost of covers with about a 3-year lifespan was about 700–800 yuan per mu. Thus, we set starting prices for 1 year, 2 years, 3 years and 4 years, respectively, to be 400 yuan, 600 yuan, 800 yuan and 1000 yuan.

3.3 | Design of the choice tasks.

As the design process (Appendix S1, Figure A2), initially, we designed 40 choice cards: 8 cards with 1-year lifespan rain covers, 8 cards with 2-year lifespan rain covers, 12 cards with 3-year lifespan rain covers, and 12 cards with 4-year lifespan rain covers. Next, we divided these cards equally into four groups according to the lifespan. In the third step, we randomly chose the number of rainy days from the six predetermined levels, and for cards in which the lifespan is more than 1 year, we designed two scenarios to present to each respondent: an upward trend of rainy days over time; and a downward trend of rainy days over time.

To ensure the appropriateness of the questions, and that farmers could understand the process, we undertook a pilot in April 2019. We first asked three local grape growers to do the survey separately, and then brought them together to talk about potential improvements to the questionnaire. We found that two of the farmers were not happy with the length of time the whole process took. Therefore, to avoid farmer fatigue, we reduced the number of cards each farmer was shown from 10 to 7, and the total number of cards from 40 to 28. Consequently, 7

Scenario Card Provided for Farmers:



Price Card Provided for Interviewers:

Cost (yuan/mu)	Accept/Not accept
200	
400	
600	
800 (starting point)	
1000	
1200	
1500	

FIGURE 1 Example of a scenario card and a corresponding price card

cards were assigned to each person, comprising one card for covers with a 1-year lifespan, two cards for covers with a 2-year lifespan, two cards for covers with a 3-year lifespan, and two cards for covers with a 4-year lifespan. An example of one prospect for a 3-year lifespan cover is shown in Figure 1.

For the choice tasks, each farmer was first given a ‘starting price’ according to the covers’ lifespan. Specifically, the ‘starting price’ for covers with 1-year, 2-year, 3-year and 4-year lifespan was 400 yuan, 600 yuan, 800 yuan and 1000 yuan, respectively. Then, the farmer indicated whether they would buy the rain cover for that price. Next, depending on the farmer's answer, the interviewer increased (if the farmer indicated they would buy the cover) or decreased (if the farmer indicated they would not buy the cover) the price. This was done in increments of 200 yuan or 100 yuan. Finally, the interviewer recorded the respondent's maximum WTP on the price card (shown in Figure 1). This process can be described using a bidding tree, one example of which is provided in the Appendix S1, Figure A3.

Our questionnaire also included a section with demographic questions. The average completion time for each person was approximately 30 minutes. Farmers were each given 30 yuan (about £3.30) as compensation for their time spent doing the choice experiment.

3.4 | Study site and data collection.

The study area is in Liu Shuquan town in Hami city in Xinjiang Uygur Autonomous Region, northwest corner of China. Hami is in the Turpan-Hami basin, where almost 95% of China's total raisin crop is grown (Ward & Inouye, 2018). Since 1951, the amount of annual precipitation and the number of days of rainfall (equal or above 0.01 inches) in Hami had exhibited an upward trend (shown in the Appendix S1, Figure B). The formal fieldwork started in May 2019. In the survey, the interviewer first required farmers to complete the WTP tasks, before asking them additional questions (see Appendix S1, Figure A1).

To obtain our sample of participants, with the help of the village heads, we first obtained a list of local grape growers and their contact information from the local government. Then, we randomly selected from the name list, with each grower having the same probability of being sampled to reduce differences between the sample and a general population sample. Our final sample comprised 155 farmers and 1085 observations, of which 52.26% were male, and 48.39% were between 40 and 50 years old. The median income per year for a family was between about 30,000 and 50,000 yuan.

3.5 | Statistical analysis.

To estimate the key parameters, the empirical specification outlined in Equation (4) was specified in log form:

$$\ln(MWTP_i) = \ln\left(\pi_i \sum_{t=1}^{T} \left(1+\gamma_i\right)^{-t}\left(1-\left(1-\delta_i\right)^{y_{it}}\right)\right) + e_i \tag{5}$$

where e_i is assumed to be iid normal with mean zero. This model is non-linear in parameters, which allows for individual farmer effects. Using classical statistical methods, this model could in principle be estimated as a random or mixed-effects model to allow for farmer heterogeneity, whereas a standard Bayesian approach would be to treat it as a hierarchical model. In the hierarchical Bayesian approach, the estimated parameters are treated as randomly distributed for distributions that are governed by their means and variances, but are not the same for each subject (as in the case of classical random effect models). Here we employ this Bayesian approach. Specifically, each of the key structural parameters was estimated as a bounded parameter using transformations of underlying parameters as follows:

$$\delta_i = \frac{e^{\alpha_i}}{1+e^{\alpha_i}};\gamma_i = \frac{e^{\beta_i}}{1+e^{\beta_i}};\pi_i = e^{\gamma_i}$$

$$\sigma_e^2 = Var\left(e_i\right)$$

There was a hierarchical prior structure of the form:

$$\alpha_i \sim N\left(\alpha, \sigma_\alpha^2\right);\sigma_\alpha^{-2} \sim Gamma\,(1,1);\alpha \sim N(0,1)$$

$$\beta_i \sim N\left(\beta, \sigma_\beta^2\right);\sigma_\beta^{-2} \sim Gamma\,(1,1);\beta \sim N(0,1)$$

$$\gamma_i \sim N\left(\gamma, \sigma_\gamma^2\right);\sigma_\gamma^{-2} \sim Gamma\,(1,1);\gamma \sim N(0,100)$$

$$\sigma_e \sim TN(0,100)\ \text{(Truncated above zero)}$$

This is a relatively diffuse set of priors. Increasing the variance of each of the parameters ten-fold delivered results that were not substantively different to those presented below.

Because of the complexity of high-dimensional integrals, often it is not practical to compute the deterministic approximation of posterior distributions, in which case a more applicable Markov Chain Monte Carlo (MCMC) method is used instead, in which a series of samples is drawn from probability distributions using Markov chains to converge into a target distribution (Hoffman & Gelman, 2014). Here, a form of MCMC called Hamiltonian Monte Carlo (HMC) was employed using the Stan software.

This approach has higher performance for hierarchical models (Betancourt & Girolami, 2015). In practice, HMC's performance is highly sensitive to three tuning parameters: discretisation time, mass matrix, and the number of leapfrog steps (Stan Development Team, 2019). An automatic parameter tuning approach of HMC called No-U-Turn Sampler (NUTS) is adopted to avoid inappropriate parameter setting of the number of steps and reduce the correlation between successive samples (Hoffman & Gelman, 2014). Posterior inference in this paper

TABLE 1 The distributions of the mean value of estimated means for (γ, δ, π)

	Discounted rate(γ)	Rotting rate(δ)	Anticipated profit (yuan/mu) (π)
Average	0.17	0.55	532.04
Standard deviation	0.03	0.06	28.05
Minimum value	0.07	0.37	434.18
Maximum value	0.30	0.84	642.92
Observations	16,000	16,000	16,000

is based on 16,000 samples after discarding 24,000 samples in the warm-up phase. The RHAT convergence stats produced by Stan were used and they showed all models converged well.

4 | RESULTS

4.1 | Farmers' willingness to pay

The contingent valuation survey revealed that the average MWTP for rain covers is 884 yuan/mu (about £0.15/m^2), and the median value is 800 yuan (about £0.13). The MWTP varies considerably from 50 to 3800 yuan/mu (£0.008/m^2–£0.63/m^2). In such a relatively small rural area, the reason for the apparent heterogeneity is worthy of further study. Perhaps not surprisingly, covers with longer life expectancies are more attractive to farmers. For covers with a 1-year, 2-year, 3-year, or 4-year lifespan, farmers' average maximum payment price per unit of farmland was 449 yuan (£0.07/m^2), 735 yuan (£0.12/m^2), 972 yuan (£0.16/m^2), and 1162 yuan (£0.19/m^2) respectively.

4.2 | Farmers' time discounting

Table 1 displays the distributions of estimated mean values for (γ, δ, π). From the results, the sampled local grape growers can be seen to have a positive average discount rate of approximately 0.17 per year. This value is considerably higher than the Chinese average interest rate of government bonds net of inflation at about 0.03, and average central bank lending rate net of inflation at around 0.05 (Li et al., 2013), thus supporting Hypothesis 1. Compared with other studies across the globe, the rates far exceed the estimates at 0.001 for West African farmers discounting financial rewards (Liebenehm & Waibel, 2014), and 0.078 for Vietnamese villagers (Tanaka et al., 2010). However, they are lower than for Indian farmers at 0.23 (Bauer & Chytilová, 2013), and US farmers, around 0.28 (Duquette et al., 2011). The high rate suggests that local grape farmers discount the future heavily, tending to pay more attention to the present. We return to this point below.

From the other two estimated parameters, δ and π, we find the average value of the rotting rate to be 0.55. Readers should recall that this value represents farmers' beliefs about their economic losses from one rainfall event, and implies that farmers believe that the negative effects of rain between July to September on their harvest to be relatively high. This high rotting rate possibly reflects farmers' beliefs about the weather conditions. According to Menapace, Colson et al., (2015), individuals who believe that the climate is changing tend to feel that adverse weather may cause larger future crop losses. In terms of this study, 91% of farmers believed the amount of precipitation has increased, and 87.1%

TABLE 2 The estimated parameters' (γ_i, δ_i, π_i) distributions for all farmers

	Discounted rate	Damaged rate	Anticipated profit (yuan/mu)
Mean	0.22	0.53	601.87
Standard deviation	0.11	0.14	262.64
Minimum value	0.06	0.07	183.21
Maximum value	0.58	0.75	1414.00
Observations	155	155	155

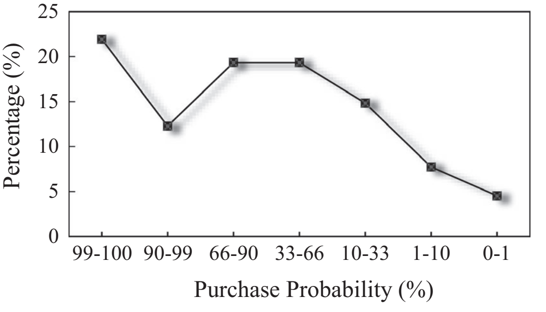


FIGURE 2 The distribution of purchase probability for covers in the next 5 years

believed the number of rainy days has increased. Most local grape growers can perceive the increasing trend in precipitation. This belief may increase their concerns about fruit losses and thus increase their beliefs about the larger economic losses from rainfall. The averaged anticipated annual net profit per year in the absence of rain is estimated to be 532 yuan/mu (£0.09/m^2).

Our results suggest that individual discount rates (γ), farmers' beliefs of losses (δ), and anticipated profit (π) exhibit considerable heterogeneity. Figure C in the Appendix S1 visualises how the three estimated parameters are distributed across farmers, and Table 2 displays the mean, minimum value and maximum value for these parameters by the individual. While these should be (and are) similar to the results reported in Table 1, there can be a divergence between the distribution of individual estimate mean values drawn from the sampler if the empirical distribution of the individuals does not perfectly conform to the assumptions underpinning the hierarchical model. The long-tailed distributions reflect that individuals' parameters disperse widely, and this can also be concluded from the large standard deviations. The range between the maximum and minimum are also wide due to the existence of extreme values. These results show the diversity for the three parameters among farmers, which may relate to individuals' demographic characteristics, experiences, and management levels of vineyards.

4.3 | The relationship between time discounting and adoption intention

Next, we consider whether growers' time-discounting characteristics influence their choice over adapting to increasing precipitation in the future. When, during the survey, farmers were asked whether they were likely to purchase rain covers to protect their grapes in the next

TABLE 3 Factors that influence farmers' possibilities to adoption

Variables	Estimates	*Z*-test statistic
Discount rate	0.94 (0.79)	1.19
Age	0.19** (0.09)	2.18
Education	–0.09 (0.10)	−0.89
Gender	0.27 (0.19)	1.46
Gender of the main decision-maker in the household	0.05 (0.21)	0.28
Losses from the rain last year	–0.14* (0.07)	–1.85
Vineyard area	–0.03 (0.11)	–0.25
General income from grapes	–0.02 (0.08)	–0.27
Log-likelihood	–278.45	
Pseudo R^2	0.03	
Observations	155	

Notes: Numbers in parentheses are standard errors.

*, ** represent significance levels p = 10%, 5%, respectively.

5 years, over one-fifth of the farmers said they were 99%–100% sure that they would (Figure 2). In contrast, just over 12% reported less than a 10% likelihood.

We conducted an ordered probit regression to explore potential linkages between farmers' personal time preferences and future adoption possibilities. In the regression analysis, individual-level time preference is found to be a key explanatory variable, given that personal adoption probability (in percentage terms) over the next 5 years was the (ordinal) dependent variable. This statistical method is a relatively standard approach. For example, Azra Batool et al., (2018) used the same approach to explore the influence of demographic variables on economic empowerment.

The results in Table 3 suggest that only age and prior experience of losses are related to farmers' intentions to purchase, while discount rate, education level, gender, the gender of the main decision-maker, area of the vineyard, and general income from grapes are not statistically significant. It is noteworthy that we obtain the prior experience of losses from farmers' self-reports. We asked them this question: 'Has your vineyard suffered profit losses from rainfall between July to September last year?', and if they said yes, they chose the range in which the losses fall.

According to our findings, even though farmers tend to potentially underestimate future benefits of using covers, this does not greatly influence their self-reported likelihood to adopt them. Meanwhile, those farmers in our sample who had greater losses in the past year tended to have a higher probability of using covers. This important finding suggests that local farmers place less weight on future benefits of adopting adaptive measures and, rather, their purchasing decisions largely depend on their recent prior experience. Given that there is an upward trend in precipitation predicted in the future, it is problematic if farmers make their adoption decisions based on past rainfall patterns rather than future rainfall patterns. The government could make efforts to increase famers' beliefs about the effectiveness of adaptation strategies, especially for those who have low trust in the utility of covers.

Another factor that influences a farmer's purchasing decision is their age. Older farmers are found to have lower probabilities of purchasing rain covers. Possible reasons are that elders are accustomed to their traditional farming practice and trust their past experience. They may also consider that it would take more physical effort to install and use covers.

5 | DISCUSSION AND CONCLUSION

We found high discount rates for our Chinese grape farmers. These discount rates imply that farmers are very focused on the short term and may not take sufficient action to adapt to the negative implications of weather variability in 10 or 20 years' time, even if they are provided with evidence that these future events will take place for certain.

There are at least two sets of reasons that might explain the high discount rates estimated in this paper. First, the difference between real values and stated values may reflect hypothetical bias (Penn & Hu, 2018). Although farmers appeared to understand the attribute levels, and these attribute levels were set broadly in line with reasonable projections, it is possible that farmers were swayed by their beliefs and/or knowledge about the cost of covers and/or the likely number of rainy days when making their decisions. Here, degrees of trust in the investigators and the scenarios may also play a role. For example, if farmers doubt that the rain covers can last as long as those presented in the scenarios, they may state that they would pay less for longer lifespans, thus increasing their apparent discount rates. Second, the estimates were derived from a model that did not explicitly take account of the impacts of risk and uncertainty. Instead, we assumed farmers were able to fully anticipate profit (in the absence of rain) along with the rotting rate (should rain occur). In reality these would be stochastic, thus being subject to uncertainty. If farmers reason that values further off in the future are more variable, then uncertainty/ambiguity aversion may also make the certainty equivalents for equivalent payoffs larger in the short run. This would mean that the discount rates measured here conflate strict time preferences with uncertainty/ambiguity aversion. Having said this, the central finding that farmers are very focused on the short run would not fundamentally change.

With regard to rain covers specifically, the current local market costs of covers are about 700–800 yuan/mu. Our results suggest that the average and median of maximum willingness to pay for these covers are 884 yuan and 800 yuan respectively and, as such, at least half of the interviewed farmers would accept the market price. However, the actual adoption rate is less than 2%, (3/155), even with government subsidies for early adopters. This suggests that there are other factors that inhibit farmers from adoption, not just price, so the government should consider other approaches to encouraging adoption.

Our results further suggest that recent losses partly determine farmer perceptions of future benefits. If farmers make decisions informed primarily by their past experience, this is likely to lead to sub-optimal uptake of new technologies and methods, particularly in the context of climate change, where the future is likely to be different from the past in the context of precipitation-induced crop damage. It may therefore be necessary for policy makers and extension agents to put more effort into ensuring that farmers are aware of the implications of changing precipitation patterns, and thus the future benefits of adaptive strategies. Additionally, since farmers have considerable heterogeneity in both their willingness to pay and discount rates, policies may need to target those who have higher discount rates and lower anticipated benefits from adoption. Similar policy suggestions have been made by Olivier and Frank (De Groote & Verboven, 2019).

As we discussed earlier, uncertainty can augment individuals' apparent discount rates, resulting in them discounting the future more highly. This in turn would make these individuals more willing to adopt short-term technologies than long-term technologies. Farmers' doubts about the effectiveness of covers may increase their perceived uncertainty of their effectiveness, thereby affecting the adoption rate of rain covers. Therefore, building trust in the benefits of covers may have a positive effect on adoption rates. One way to increase farmers' beliefs about the benefits may be to use particular farmers or areas as pilots to adopt rain covers and demonstrate their success and cost effectiveness. Currently, there are only a few effective cases showing on the local government website. The scope of transmission is limited, and only farmers who have access to the internet can see these examples. Local government might provide finance for these pilot regions. And, finally, the government could regulate the manufacturing and sales market of rain covers so as to require the manufacturers to indicate the predicted lifespan to reduce farmers' uncertainty.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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