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Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China

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Abstract

The slow diffusion of new technology in the agricultural sector of developing countries has long puzzled development economists. While most of the current empirical research on technology adoption focuses on credit constraints and learning spillovers, this paper examines the role of individual risk attitudes in the decision to adopt a new form of agricultural biotechnology in China. I conducted a survey and a field experiment to elicit the risk preferences of 320 Chinese farmers, who faced the decision of whether to adopt genetically modified Bt cotton a decade ago. Bt cotton is more effective in pest prevention and thus requires less pesticides than traditional cotton. In my analysis, I expand the measurement of risk preferences beyond expected utility theory to incorporate prospect theory parameters such as loss aversion and nonlinear probability weighting. Using the parameters elicited from the experiment, I find that farmers who are more risk averse or more loss averse adopt Bt cotton later. Farmers who overweight small probabilities adopt Bt cotton earlier.

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1. Introduction

Poverty reduction remains one of the greatest challenges to the international community. Given the predominant role of agriculture in developing countries, advances in agricultural development are essential tools in reducing poverty and hunger. Some studies link the steady decline in poverty in Asia in the 1970s to the technological developments of the Green Revolution (Ofreneo, 2004).[1] More recently, policymakers in developing countries are pinning their hopes to the Gene Revolution, involving what are more commonly known as genetically modified organisms (GMO) (Ofreneo, 2004; Lipton, 2001, 2005; FAO, 2004). A new generation of crops that are pest and drought resistant, have higher yields, lower production costs and even contain added nutrients could be a solution to many problems in less developed countries.

Despite the profits promised by new technologies, the adoption of new innovations is often slow and even incomplete. Development economists have tried to explain the slow diffusion of new technology. Some believe it could be the key to understanding the persistent poverty of subsistence farmers in developing countries. This issue is difficult to study because many determinants such as individual risk attitudes and social learning cannot be directly observed or assessed from the standard household survey. Most empirical studies have examined the role of social learning and credit constraints in technology adoption. In this study I will focus specifically on the role of individual preferences toward risk in technology.

In the experimental economics literature, one common approach for eliciting individual risk preferences is to conduct a field or laboratory experiment in which subjects decide between a menu of pair-wise lottery choices (Holt and Laury, 2002). The design of such an experiment permits us to estimate the curvature of utility function, which is the sole parameter characterizing individual risk preferences under expected utility theory. However, since Kahneman and Tversky's (1979) seminal paper on prospect

[1] However, critics of the Green Revolution argued that its impact on poverty alleviation is either negligible or negative since commercial farmers were the main adopter of the new technologies. The Green Revolution resulted in lower product prices, higher input prices, and efforts by landlords to increase rents or force tenants off the land (de Janvry et al., 2000).

theory, several studies have found that prospect theory has more predictive power than expected utility theory under some conditions (List, 2005; Camerer, 2001). If farmers are particularly sensitive to loss below the subsistence income level, the utility function of farmers may be reference dependent, rendering expected-utility theory inadequate explaining their decisions to adopt new technologies.

In this study, I focus on farmers' adoption of genetically modified Bt cotton. Bt cotton produces a naturally occurring pesticide, Bacillus thuringiensis (Bt) toxin, which targets the cotton bollworm (*Helicoverpa amigera*). A large body of literature finds that Bt cotton is superior to conventional cotton in producing higher yields with less pesticide use (Huang et al., 2002a; Qaim and de Janvry, 2005; Qaim and Zilberman, 2003; Bennett et al., 2003). In contrast to HYV seeds, which are criticized for benefiting mostly commercial farmers, several studies depict Bt cotton as a biotechnology tailored for the poor (Lipton, 2005; ISAAA, 2006; McGloughlin, 1999; Qaim and Virchow, 2000). In 2006, Bt cotton was planted in the United States, Argentina, Brazil, India, China, South Africa, Australia, Mexico and Columbia. In China, since Bt cotton's first commercial approval in Hebei province in 1997, it has spread quickly in the Yellow River region where bollworm is the main pest.

In 2006, I partnered with the Center for Chinese Agricultural Policy (CCAP), a government-affiliated research institute in Beijing, to investigate the adoption of Bt cotton. We administered a household survey that covered information on household characteristics, outputs and inputs of each cotton plot, and the timing of Bt cotton adoption of 320 cotton farmers in four Chinese provinces during the winter of 2006. In addition, I conducted a field experiment to elicit individual risk preferences. My field experiment, which is modeled after the experiment designed by Tanaka, Camerer and Nguyen (TCN, 2006), aims to measure three parameters concerning risk preferences—risk aversion, loss aversion and nonlinear probability weighting. I use these parameters to predict the farmers' Bt cotton adoption decisions.

I find that farmers with higher risk aversion adopt Bt cotton later. Farmers who are more sensitive to loss also adopt Bt cotton later. Farmers who overweight small probabilities adopt Bt cotton earlier.

The findings are significant for couple reasons. First, this is one of the few empirical papers on technology adoption to provide some insights into how individual risk attitudes affect the timing of adoption. It is the first study to apply prospect theory to the field of technology adoption. It incorporates behavioral and psychological factors into standard development theory, and it also broadens the understanding of technology adoption decisions.[2]

Second, these findings have potential policy implications. I find that aversion to risk and fear of loss are indeed deterrents to technological advancement, as suggested by Cardenas and Carpenter (2005). Risk in agricultural production causes inefficient input allocation. From a policymaker's point of view, crop insurance can potentially be offered to hedge against the risk and fear of loss associated with the adoption of the new technology.[3] From a business point of view, as suggested in Sunding and Zilberman (2001), money-back guarantees with the seeds can be a means to persuade farmers to try the new seeds.

Lastly, this study bridges the gap between field experiments and real world behavior. There exists a long standing debate regarding the external validity of game experiments.[4] Unlike those experiments conducted in university laboratories which are used to extrapolate real world decisions, the subjects from this experiment are the same people who make the actual farming decisions. Similar to research by List (2003) and Fehr and Goette (2007), I extend game behavior to real decisions. The findings from this study suggest that game experiment results can predict the real world decisions in the case of Chinese cotton farmers.

This paper is organized as follows. Section 2 offers a review of the literature. Section 3 provides some background information on Bt cotton. Section 4 explains the design of the survey and describes the dataset from the household survey. Section 5 describes the design and procedure of the field experiment and presents descriptive analysis of the results from the field experiment. Section 6 presents a general econometric framework. Section 7 presents regression results showing the determinants of the adoption

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[2] Ashraf, Karlan and Yin (2006) and Duflo, Kremer, and Robinson (2006) also integrate components of behavior and development economics.

[3] In a series of randomized field experiments conducted in rural India, Cole, Tobacman and Topalova (2007) find higher insurance take-up rates among more risk-averse individuals. See Horowitz and Lichtenberg (1993) for the use of crop insurance in the US.

[4] See Samuelson (2005) for discussion.

decision. Section 8 discusses the threats to validity and Section 9 concludes.

2. Literature Review

In this section, I first cover the literature on determinants of technology adoption with the exception of risk preferences. This is followed by a review of the theoretical framework of the role that risk preferences play in technology adoption. Then I examine the literature on estimating risk preferences. Lastly, there are two empirical studies that also elicit farmers' risk attitudes and correlate these measures with their farming decisions.

Griliches (1957) examines the determinants of diffusion of hybrid corn in the Midwestern states in the US. He finds that the rate of adoption is an increasing S-shaped function of time during which the new innovation has been available. The exact shape of the function is determined by crop profitability and other economic variables. His seminal work paves the way for the current empirical literature on technology adoption. Technology adoption is a difficult subject to study because so many determinants are unobservable. However, after fifty years, as applied economists have scrutinized many of the possible determinants, we have a better understanding of the underlying mechanism.[5]

One factor of technology adoption that has been intensely studied is the social network. Foster and Rosenzweig (1996) set up a target input model in which there is an optimal level of fertilizers that farmers need to apply to HYV in order to achieve a high return. They find that farmers with more experienced neighbors have higher profits than those without. To further examine the role of communication and social learning in technology adoption, Conley and Udry (2003) distinguish information neighbors from geographical neighbors. They construct a detailed information network map among pineapple farmers in a village in Ghana. They find evidence that farmers imitate the choices of their information neighbor when this neighbor experiences a fruitful year in agricultural production.

It is likely that farmers hold beliefs about the return and variance of Bt cotton prior to their adoptions, and they update their beliefs as they receive new information about the Bt cotton from other Bt

[5] See Feder, Just, Zilberman (1985) for survey on earlier work in technology adoption.

cotton adopters. Unfortunately, because the objective of the CCAP is to evaluate performance of Bt cotton across several cotton-growing regions and the resources are limited, we only surveyed 20 households in a village of more than 200 households. Thus I am unable to map out the social network within a village in this study.

Many have also looked at the role of credit constraints in adoption decisions. Croppenstedt, Demeke and Meschi (2003) estimate a model of fertilizer adoption in Ethiopia. Their findings suggest that household cash resources are generally insufficient to cover fertilizer purchases. Credit constraints are less likely to bind in my case because the decision to adopt new types of seeds only increases total investment costs by a marginal amount. Adoption of Bt cotton is not an all-or-none decision. I have shown in Table 1 the share of pesticide cost in comparison to the share of cotton seeds cost for an average cotton farmer in China. The cost of Bt cotton seeds was about 100-250% more than the conventional cotton seeds in the earlier years (Huang et al., 2002b). Even if farmers do not fully anticipate the huge reduction of pesticides use from Bt cotton seeds, they can choose the intensity of Bt cotton adoption according to their credit constraint. Therefore, credit constraint alone cannot explain heterogeneity in the timing of technology adoption.

Suri (2006) tries to explain why farmers switch in and out of adoptions of hybrid maize and fertilizer in Kenya. Allowing for differences in the profitability of adoption, she concludes that providing credit can only benefit a small fraction of Kenyan farmers. Neither constraints nor irrationalities can explain the stagnation of hybrid maize adoption. The findings in this study potentially complement her findings.

The main focus of this study is on the role of individual attitudes toward risk in technology adoption. Two existing models, built by Feder (1980) and Just and Zilberman (1983), analyze how risk attitudes affect adoption decisions. Feder (1980) assumes that the modern crop entails more variability than the traditional crop and there is no fixed cost incurred for using the new technology, and his model predicts that the optimal allocation of land for modern crops declines with higher degrees of risk aversion. Just and Zilberman (1983) extend Feder's model and show that the intensity of the new technology depends on whether the technology is risk increasing or risk reducing and whether relative risk aversion is decreasing or increasing. This study is complementary to the above models but attempts to incorporate loss aversion and nonlinear probability weighting in the decision making process.

Methods of eliciting farmers' risk attitudes usually fall into two categories. One approach follows Binswanger's (1980) experimental method using risky choices with different expected payoffs and variance. The other approach uses econometric methods to estimate individual risk aversion. The econometric method first estimates the probability distribution of output given inputs and infers each farmer's risk attitude from deviations between his choice of inputs and the profit-maximizing input choice (Antle, 1987; Antle, 1988; Moscardi and de Janvry, 1977; Antle and Havenner, 1983). For example, when marginal cost exceeds the marginal profit of pesticides, Antle (1987) interprets the excessive application of pesticides as a risk premium paid by the risk-averse farmers. The econometric approach of measuring risk aversion relies on a structural model with strong assumptions. In addition, a misallocation of inputs can also be due to reasons other than risk aversion such as credit constraint or imperfect information.[6] Therefore, I decide to pursue the experimental method in this study.

There are two empirical papers similar to this study in spirit. Both of these papers try to elicit farmers risk attitudes and use this measure to explain adoption decisions. Knight, Weir and Woldehanna (2003) study the technology adoption of Ethiopian farmers. They divide farmers into risk-averse and non-risk-averse groups depending on farmers' answer to a hypothetical question. They find that risk aversion is associated with lower probabilities of technology adoptions. Engle-Warnick, Escobal, and Laszlo (2006) study the technology adoption decision of Peruvian farmers. Their experiment design is unique in that they could differentiate ambiguity aversion from risk aversion.[7] When they include measures of both ambiguity aversion and risk aversion in the probit regression, neither regressors can predict the

[6] Studies by Binswanger and Siller (1983) and Eswaran and Kotwal (1990) suggest there are two types of risk aversion. Pure risk aversion defines the utility function curvature whereas market risk aversion is the revealed risk preference which may be influenced by other constraints. The risk aversion elicited from the game should be pure risk aversion, and the econometric approach provides "market risk aversion". Throughout this paper, I am studying the relationship between pure risk aversion and farming decisions.

[7] Ambiguity aversion refers to the aversion to outcomes with unknown distribution. It is also known as uncertainty aversion.

technology adoption decision. They do find that farmers who are more ambiguity averse are less likely to diversify across different crops.

Neither of these studies has a single technology of focus. Therefore, the adoption of innovation is arbitrarily defined. In Knight, Weir and Woldehanna's study, technology adoption is a dichotomous variable which is set equal to one if a farmer has adopted at least one new agricultural input (e.g., fertilizer, pesticide, etc) and one new crop. Engle-Warnick, Escobal, and Laszlo ask farmers about the crop varieties they plant during the last twelve-month period, and technology adoption variable is set equal to one if farmers plant any modern variety. Since they use cross sectional data, it is not clear whether the diffusion of all these innovations have reached the equilibrium. Moreover, new varieties of crops may be no superior to traditional crops in the surveyed regions, so the non-adoption in the data could simply reflect that farmers do not find it profitable to plant those new varieties. In my study, Bt cotton, the technology of focus, produces higher yield than traditional cotton and by the time the survey was conducted, the Bt cotton adoption rate was 100%.

3. Background on Bt cotton

China has been one of the world's biggest cotton producers, with an estimated 46 million Chinese farmers growing cotton in recent years. 1992 was a particularly bad year for Chinese cotton farmers in the Yellow River region, due to a severe bollworm infestation. In Figure 1, we can observe a huge drop in cotton yield per hectare in 1992. Due to its vulnerability to serious pest infestations, cotton was selected by the Chinese government as a target crop in the country's biotechnology program (Huang, et al., 2004). Bt cotton was quickly developed as a result of this program. It was tested in trial fields by Chinese scientists in the mid 1990s.

Bt cotton has been approved for commercial use in Anhui, Hebei, and Shandong since 1997, and in Henan since 1999. An estimated 60 percent of cotton grown in China is Bt cotton (Pemsl, 2006). Non-Bt cotton is concentrated in the western and southern regions of China, where the bollworm pest poses less of a problem. Figure 2 shows the cumulative percentage of households that had adopted Bt cotton in the sample. Approximately 16 percent of households had adopted Bt cotton prior to the approval. According to Pemsl (2006), the black market sold Bt cotton seeds prior to the approval. My communications with farmers indicated that they were not aware of the illegality of Bt cotton seeds before 1997. Figure 3 shows the percentage of households adopting Bt cotton in each year, broken down by provinces in the sample.

According to Huang et al. (2002b), Bt cotton is an agricultural biotechnology success in China.[8] Bt cotton adopters spray pesticides 67 percent fewer times and reduce pesticide expenditures by 82 percent (Huang et al., 2002b). Fewer farmers report pesticide poisoning after adopting Bt cotton.[9] Although Bt cotton seeds cost more than non Bt cotton varieties in the earlier years (100-250 percent premium), farmers who adopted Bt cotton reduced the cost of producing a kilogram of cotton by 28 percent (Huang et al., 2002a). Besides increasing the expected value of yields, recent research on Bt crops (i.e., Bt cotton, Bt corn) indicates that they lower the risk of crop damage, thus reducing the variance of yields (Kalaitzandonakes, 2003).

4 Survey Procedure and Data Description

4.1 Survey Procedure

The Bt Cotton Survey (2006) was designed and conducted by the Center for Chinese Agricultural Policy (CCAP), Beijing, China. The CCAP is a government research institute, which has a decade of experience designing and conducting agricultural surveys. The objective of the CCAP Bt cotton survey in 2006 was to evaluate the performance of Bt cotton, so the regions were carefully chosen for this purpose. Four provinces (Henan, Shandong, Hebei, and Anhui) that have the same cotton growing season (April to October) and have high Bt cotton adoption rates were selected.[10] The CCAP randomly selected two counties per province and two villages per county. In each village, twenty households were selected

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[8] Qaim and de Janvry (2005) found similar evidence on success for Bt cotton in Argentina.
[9] In my sample, nearly 30% of farmers have had pesticide poisoning experience.
[10] See Appendix 1 for the map of China with cotton production regions and the location of survey sites.

randomly and surveyed.[11] In most cases, we interviewed the head of the household. When the head of the household does mostly off-farm work, we interviewed the family member who is the most responsible for farm work. There were a total of 320 households in the sample. Farmers were paid ten Yuan (one third of daily wage) for completing the survey.[12] Each survey took from two to three hours to complete and covered detailed information on household characteristics, individual characteristics and inputs and yield information for every cotton plot. I was involved with the survey designing process and traveled with a team of eight numerators and helped survey. It took a month to complete the entire surveying process.

4.2 Data Description

Table 2 shows summary statistics for the key variables of interest from the household survey. Fourteen percent of interviewees are female. The average interviewee in the sample has completed more than elementary school education (7.1 years) and is about 50 years old.[13]

In China, land is not privatized, and farm land is assigned to each household in villages (Brandt et al., 2002). The average household in the sample is assigned 0.59 hectares of farmland. There is neither selling nor buying of land. However, farmers can lease land from other villagers. One hundred and ten households reported leasing land and the average area leased conditional on leasing is 0.40 hectares. As the major cash crop in the region, cotton is planted on 0.54 hectares of farmland per household. Many farmers practice intercropping, growing wheat in winter and cotton during summer. Wheat and maze are the major cereal crops in the region, and they are planted on an average 0.33 hectares per household. Some farmers also grow other cash crops (fruits, vegetables, etc.) besides cotton.

Ownership of a set of durable goods is used as a proxy for wealth in 2001 and in 2006 (where the data on both were collected in 2006). For every durable good, we also asked in which year they purchased the item. If this item was purchased after 1999, we asked if they owned the same item before 1999. Given

[11] Every household in the rural area has been assigned a piece of farm land by the government; therefore, every household is a farm household.
[12] 1USD ≈ 7.54 Yuan.
[13] The sample is relatively old since migration of young men out of villages is common (Rozelle et al, 1999).

this information, I can derive the ownership of durable goods for 1999. However, one needs to approach this data with caution since this proxy for wealth in 1999 is a very noisy measure. In Table 2, I present a proxy for 2006 household wealth by estimating the total value of durable goods per capita in the household.

In this sample, only 15 out of 945 plots are reported as non-Bt cotton. All the farmers who currently use non-Bt cotton seeds had planted Bt cotton seeds in the past.[14] Therefore all farmers in the sample have experience with Bt cotton seeds, and I asked a retrospective question about the year in which they first adopted Bt cotton. Since I do not have the intensity of Bt cotton adoption over the years, the year of adoption is going to be the key measure of my analysis.

5. Field Experiment Design and Procedure

All of the farmers who completed the interview were asked to participate in a field experiment, and the goal of the experiment was to elicit farmers' preferences towards risk. In this section, I cover the design and procedure of this field experiment. Descriptive analyses of game results are presented. I briefly discuss the method of estimating individual preferences towards risk. Finally, the determinants of preference towards risk are discussed.

5.1 Design of Field Experiment

Most of the experimental procedures currently employed in the risk preference literature follow the experiment design by Holt and Laury (HL) in 2002. In HL's experiments, risk preference is simply represented by a single parameter which determines the concavity of the utility function. However, such a simple model defining risk preferences has been rejected by field data (Camerer, 2001). Several experimental studies find that individual preferences are not independent of reference points (Knetsch, 1989; Kahneman, Knetsch and Thaler, 1990). List (2003) also finds that the behaviors of inexperienced individuals are more consonant with the predictions of prospect theory whereas expected utility theory

[14] There are only five out of 320 farmers that plant non Bt cotton only.

can predict behaviors of individuals with more market experiences. Fehr and Goette (2007) elicit a measure of loss aversion among bicycle messengers and find that workers who are more prone to loss aversion are more likely to reduce their efforts in response to higher wages.

Early research in agricultural economics literature often relates farmers' utility function to the safety-first rule (Moscardi and de Janvry, 1977; Young, 1979). Under the safety-first rule, farmers maximize their expected utility subject to the constraint of minimizing the probability of disaster in which their income would drop below the subsistence level (Roy, 1952; Telser, 1955; Kataoka, 1963). If farmers hold the subsistent income level as a reference point, expected utility theory may not be the best choice for modeling farmers' technology adoption decisions. Therefore my experimental design follows the methodology developed by Tanaka, Camerer and Nguyen (TCN), which incorporates prospect theory. Following TCN, I assume a utility function of the following form:

$$U(x,p;y,q)=\begin{cases} v(y)+\pi(p)(v(x)-v(y)) & x>y>0 \; or \; x<y<0 \\ \pi(p)v(x)+\pi(q)v(y) & x<0<y \end{cases}$$

$$where\; v(\mathrm{x})=\begin{cases} x^{1-\sigma} & for\; x>0 \\ -\lambda(-x)^{1-\sigma} & for\; x<0 \end{cases} \quad and\; \pi(p)=\exp[-(-\ln p)^{\alpha}]$$

σ describes the curvature of value function for an individual: the individual is risk loving if $\sigma < 0$, risk neutral if $\sigma = 0$, and risk averse if $\sigma > 0$.[15] λ defines the curvature below zero relative to the curvature above zero. $\lambda \neq 1$ implies there is a kink in the indifference curve around zero. High λ means that an individual is more loss averse. The nonlinear probability weighting measure α is extended from a model by Prelec (1998). Probabilities are weighted by a function $\pi(p)$. If $\alpha<1$, $\pi(p)$ has an inverted S-shape, which indicates an overweighting of low probabilities and an underweighting of high probabilities (see Figure 4).

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[15] In the TCN paper, value function v(x) has the form: $v(x) = x^{\sigma}$ for $x>0$; $v(x) = -\lambda(-x)^{\sigma}$ for $x<0$. For ease of understanding and comparison with respect to the conventional form of expected utility under constant relative risk aversion (CRRA) where $u(x)=x^{1-\sigma}/(1-\sigma)$, I rewrite the value function as $v(x) = x^{1-\sigma}$

The major advantage of this design is that it still permits, under certain assumptions, the use of expected utility theory. If estimates from the experiment give us $\alpha = 1$ and $\lambda = 1$, the above model reduces to expected utility theory.[16]

5.2 Procedures of Experiment

In this experiment, participants were given three series of games that contain a total of 35 pair-wise choices. Table 3 illustrates the entire payoff matrix of the game. There are three independent series. Each row contains a choice between two lotteries, A or B.

	A	**B**
1	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	34 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩

This is how Table 3 Series 1 Line 1 was presented to the subjects. It shows that lottery A offered a 30% chance of receiving 20 Yuan and a 70% chance of receiving 5 Yuan. Lottery B offers a 10% chance of receiving 34 Yuan and 90% chance of receiving 2.5 Yuan. Each subject has to decide whether they prefer lottery A versus lottery B for each line. I followed TCN procedure putting in 10 numbered balls in a bag, using ball drawing for the randomization process. If a subject has chosen lottery B for Line 1, in this case, drawing the Number 3 ball would earn him 2.5 Yuan. However, if he had chosen A, drawing the Number 3 ball would give him 20 Yuan.

In Series 1, lottery A does not change, but as we proceed down the matrix, the expected value of lottery B increases and eventually exceeds that of lottery A. On the record sheet (presented in Appendix 2), subjects were asked at which line, from Line 1 to Line 14, would they switch from lottery A to lottery B for Series

I choose Lottery A for Line 1 to _____.
I choose Lottery B for Line _____ to 14.

[16] This functional form assuming that people are risk-loving for losses and risk-averse for gains is the major prediction from prospect theory. It is referred to as the reflection effect. See Kahneman and Tversky (1979) for more discussion. See Hershey and Shoemaker (1980), Battalio et al. (1990), and Camerer (1989) for further empirical evidences of reflection effect.

Similar questions about switching points were asked for Series 2. The more risk-averse individuals would choose A longer before switching to B than the less risk-averse individuals in both Series 1 and Series 2. By asking them one question about the switching point, I enforced monotonic switching, meaning that each subject was only allowed to switch from lottery A to lottery B once in each series. The options of never switching (always choosing A) and switching at the Line 1 (always choosing B) were also available.

In TCN's game, payoffs may be positive or negative, which allows TCN to estimate the parameter of loss aversion. Since it would be unethical to have farmers who participate in the game pay us money, at the beginning of the game, I announced that by participating, farmers would receive ten Yuan (which corresponds to roughly one-third of the average daily wage). In Series 1 and Series 2, all outcomes result in positive payoffs. However, in Series 3, there is some probability that the outcome of the game will result in a negative payoff, or the farmers will lose money, but the amount lost never exceeded ten Yuan. Questions about switching points are also asked for Series 3. The more loss-averse individual would choose to switch from A to B later or never switch (always choose A) in Series 3.[17]

Subjects were told that one of the 35 lines would be randomly chosen *ex post* and the lottery they had selected would be played for actual stakes, and their monetary payoff would be determined by the outcome of that lottery. Out of 320 farmers, five decided not to participate in the field experiment. The average payoff of the game is 30 Yuan, which is approximately a single day's wage in rural China. The highest possible payoff of the game is 850 Yuan. Holt and Laury (2002) find evidence that individuals exhibit more risk aversion in high-stakes games. Since we wish to relate the game results to their farming decisions, we employ a relatively high monetary payoff in the game to correspond more closely to the magnitude of monetary payoffs faced by farmers in production decisions, which ultimately determine their livelihoods. More details about the game procedure are provided in Appendix 3.

[17] As Camerer (1989) points out, losses that are in fact net gains, like in Series 3, may be treated differently from real losses. Therefore, the game was conducted after the long interview in hopes that the farmers would perceive the ten Yuan as part of earnings for their participation in the survey instead of windfall gains.

5.3 Descriptive Analysis of Game Results

The distributions of switching points are shown in Figure 5. The numbers next to the axes correspond to the switching point for each series. Individuals who never switch are recorded as NS in Figure 5. The size of the balls represents the percentage of individuals who choose that particular combination of switching points. The biggest ball in Figure 5, which is 5.7% of our sample, corresponds to those individuals who chose "never switching" in all three series. 7.6% of farmers in our sample chose either all lottery A or all lottery B in all three series of the game. One concern is innumeracy and its effect on the farmers' comprehension of the game. Therefore, as a robustness check in Section 7.5, I exclude individuals who chose either all lottery A or lottery B from the sample, and my results remain robust. TCN conducted the same game in Vietnam. As a comparison, the distributions of switching points from the Vietnam sample are provided in Appendix 4.

The shaded wall in Figure 5 indicates the choice sets of Series 1 and Series 2 switching points that are consistent with expected utility theory.[18] For example, individuals who choose to switch at Line 8 in Series 2 should switch at Line 14 in Series 1 according to expected utility theory. However, we observe that most of those individuals, who switch at Line 8 in Series 2, switch between Line 6 to Line 11 in Series 1 for both China and Vietnam samples. The "early" switching can be rationalized if individuals put too much decision weights on the 10% probability of winning a high prize in Series 1 lottery B. Such a finding is consistent with the findings from empirical behavioral economics literatures that suggest an inverse-S-shaped weighting function, which is concave at low probabilities and convex above some fixed probability (Wu and Gonzalez, 1996).

5.4 Estimation of Parameters

[18] Assuming constant relative risk aversion with utility function $u(x) = x^{1-\sigma} / 1 - \sigma$, the expected-utility consistent switching points combinations for Series 1 and Series 2 are (7, 1), (8, 2), (9, 3), (10, 4), (11, 5), (12, 6), (13, 7), (14, 8) and (never switch, 9). For more detail, see Tanaka, Camerer and Nguyen (2006).

Results from Series 1 and Series 2 are used to estimate the curvature of the utility function in the positive domain (σ) and to estimate the nonlinear probability weighting parameter (α) for each participant. The estimating procedure is provided in the next section.

For any subject that switches at Line N, I can conclude that he prefers lottery A over lottery B at Line (N-1) and prefers lottery B over lottery A at Line N. I can obtain a set of two inequalities from this switching point.[19] Using a combination of switching points from Series 1 and Series 2, I am able to find the ranges of (σ, α) that satisfy the set of inequalities. For example, when a subject switches from A to B at Line 7 for both Series 1 and Series 2, I know the following inequalities should be satisfied:

$$5^{1-\sigma} + \exp[-(-\ln .3)^{\alpha}]\,(20^{1-\sigma} - 5^{1-\sigma}) > 2.5^{1-\sigma} + \exp[-(-\ln .1)^{\alpha}]\,(62.5^{1-\sigma} - 2.5^{1-\sigma})$$
$$5^{1-\sigma} + \exp[-(-\ln .3)^{\alpha}]\,(20^{1-\sigma} - 5^{1-\sigma}) < 2.5^{1-\sigma} + \exp[-(-\ln .1)^{\alpha}]\,(75^{1-\sigma} - 2.5^{1-\sigma})$$
$$15^{1-\sigma} + \exp[-(-\ln .1)^{\alpha}]\,(20^{1-\sigma} - 15^{1-\sigma}) > 2.5^{1-\sigma} + \exp[-(-\ln .7)^{\alpha}]\,(32.5^{1-\sigma} - 2.5^{1-\sigma})$$
$$15^{1-\sigma} + \exp[-(-\ln .1)^{\alpha}]\,(20^{1-\sigma} - 15^{1-\sigma}) < 2.5^{1-\sigma} + \exp[-(-\ln .7)^{\alpha}]\,(34^{1-\sigma} - 2.5^{1-\sigma})$$

Parameters that satisfy the above inequalities are $0.26<\sigma<0.35$ and $0.66<\alpha<0.74$. I follow TCN's convention of approximating (σ, α) by taking the midpoint of interval to one decimal place. In the above inequalities, we would use (0.3, 0.7) as our estimates for (σ, α). After obtaining an estimate of σ, we can write out inequalities involving λ using the switching point from Series 3. Similar to σ and α, λ can only be estimated as an interval.[20] To ease the interpretation of regression results, again I use the midpoint of each interval as the point estimate of λ.[21] In this sample, the average value of λ is 3.47, which is higher than the conventional loss aversion coefficients ($\lambda \approx 2$) from studies done in developed countries (Novemsky and Kahneman, 2005). The average of σ is 0.48, indicating that people are risk averse. The average α is 0.69, meaning most people in the sample have a tendency of overweighting low probabilities.[22] The distribution of σ, α, λ parameters are shown in Figure 6. These three parameters are not highly correlated. The correlation between σ and λ is 0.16; the correlation between σ and α is 0.03; the correlation between λ and α is 0.13. As I mentioned earlier, if both $\alpha=1$ and $\lambda=1$, TCN's value function

[19] In the case of "never switch" or "switching at Line 1", I have one inequality.
[20] More details about estimation method can be found in TCN paper.
[21] The maximum value of λ is assigned as 15 instead of infinity, which is the highest range value of λ the game would imply. In robustness check, I show that regressions results are not sensitive to the way λ is estimated.
[22] TCN sample consists of people in all professions. In their farmer sub-sample, the estimates of (1-σ), which is comparable to σ in this paper, is 0.40, $\alpha=0.75$, and $\lambda=3.00$.

would reduce to the standard expected utility function. Using an F-test, I can reject the null hypotheses that $\alpha=1$ and $\lambda=1$ at 99 percent level of confidence.

5.5 Determinants of Preference Parameter

I ran regressions with each of the risk preference parameters as a dependent variable, and the results are presented in Table 4. In Column 1, σ is the dependent variable. I find that female farmers are more risk averse. The current literature on whether individual risk attitudes vary with wealth has been inconclusive.[23] In this sample, the proxy for wealth, value of durable goods per capita in 2006, can only predict risk aversion at the 10% level of significance. Wealthier individuals exhibit marginally less risk aversion. An interesting observation is that there are twelve people reported as religious in the sample. Since religious practices are usually restricted or prohibited by the government of China, having a religion and truthfully reporting it during the survey could be considered a risk-taking action of its own. Indeed, I find that self-described religious people in the sample express less risk aversion during the game as well.

λ is the dependent variable in Column 2. A higher λ represents a higher coefficient of loss aversion. Higher years of education are associated with lower coefficients of loss aversion. This result is consistent with the findings by Benjamin, Brown and Shapiro (2006). They find that individuals with higher cognitive abilities behave more in line with risk neutrality in a gamble involving both gains and losses. While wealth is not a determinant of loss aversion, having a higher share of on-farm work implies a higher loss aversion coefficient. In Column 3, the nonlinear probability weighting parameter, α, is estimated using OLS. The only determinant that can predict the nonlinear probability weighting parameter is education. The low R^2 in these regressions may suggest that these determinants are not a good predictor of the individual attitude toward risk as measured in the TCN game.[24]

In the survey we include a self-rated general risk preference measure: "How adventurous are you?

[23] See the survey by Cardenas and Carpenter (2005) for more discussion.
[24] When TCN ran a similar regression with their Vietnam sample having σ as a dependent variable, $R^2 \approx 0.07$. However, it is not unusual to get low R^2 for the experimental literature. See Benjamin, Brown and Shapiro (2006) and Dohmen et al.(2006) for more example.

(1= most adventurous…5=least adventurous)" Dohmen et al. (2006) find that a general risk question can be used to predict actual risk-taking behavior. In Figure 7, I show a box chart of the quartile level of σ and λ given the level of self-rated adventurousness measure. The self-reported risk attitude is rather a noisy measure. When I run regressions using this self-reported risk attitude on the coefficient of risk aversion (σ) and loss aversion (λ), I find that it is not correlated with the coefficient of risk aversion (σ). However, it does predict individual loss aversion (λ) at a 5% level of significance.[25]

6. Econometric Framework

6.1 Specification

In this section, the main outcome variable of interest is the timing of Bt cotton adoption. Since I have retrospective data on the year of Bt cotton adoption, hazard models provide a natural framework for modeling adoption probabilities (e.g., Hannan and McDowell, 1984).

Let t be the time elapsed from the time of first exposure to Bt cotton until adoption, $X_i(t)$ be a vector of relevant explanatory variables and β be a vector of coefficients. Denoting the cumulative density function as $F_i(t \mid X, \beta) = Prob(T \le t \mid X, \beta)$ and the density function as $f_i(t \mid X, \beta)$, the hazard function which indicates the probability of adopting Bt cotton at period t conditional upon no adoption by time {t-1} is defined as $h_i(t \mid X, \beta) = f_i(t) / [1 - F_i(t)]$. The general form of the proportional hazard function is

$$h_i(t \mid X(t), \beta) = h_o(t) \exp\{X_i'(t)\beta\}, \qquad (1)$$

where $h_o(t)$ is the baseline hazard. If the baseline hazard remains constant over time, then Equation 1 would reduce to the exponential hazard function, $h_i(t \mid X, \beta) = \exp\{X_i'(t)\beta\}$. I would like to test whether hazard is time-dependent; therefore, I use a Weibull baseline hazard specification:

$$h_i(t \mid X(t), \beta, \delta) = \delta_i t^{\delta_i - 1} \exp\{X_i'(t)\beta\} \qquad (2)$$

If $\delta = 1$, then this reduces to exponential hazard. The likelihood function for the model is:

[25] Regression results not reported.

$$L(\beta) = \prod_{i=1}^{N} f(t \mid X_i, \beta)^{c_i} (1 - F(t \mid X_i, \beta))^{1-c_i} \qquad (3)$$

where c is an indicator for the individual being censored. Since everyone has adopted Bt cotton by the time of survey, censoring would not be a concern in this sample, and the likelihood function (3) would reduce to

$$L(\beta) = \prod_{i=1}^{N} (1 - F(t \mid X_i, \beta)) \qquad (4)$$

7. Empirical Results

Time of exposure to Bt cotton is defined as the year before the first subject in the sample adopted it (1993). I estimate Equation 2 and present the results in Table 5. $\delta \approx 3.5$, which indicates that the hazard of adoption increases with time. Hence, I reject the exponential model.

7.1 Basic Specification

The main characteristic of interest is individual risk preference. To interpret the coefficients, I exponentiate coefficients reported in the table obtaining hazard ratios. For example, to interpret the coefficient of σ in Column 1, we need to exponentiate (-0.430) =0.65. This indicates that holding all else equal, the risk-averse individual with σ =1 in the sample is 35% less likely to adopt Bt cotton than the risk-neutral individual (σ =0) at any given time. In Column 2, the result suggests that being one standard deviation more loss averse than the average person in the sample would lower the probability of adoption by 15% at any given time. The sample size is smaller than the sample size in Table 3 because I dropped the households that were formed after the year of exposure (1993).[26]

One caveat about my dataset is that it is cross-sectional data and the survey was conducted after adoptions of Bt cotton have taken place. As Besley and Case (1993) argue, in cross-sectional data any *ex post* measure of covariates of interest could be affected by the adoption decision are therefore endogenous. However, some demographic variables are less likely to suffer from endogeneity because they are fixed

[26] The results were not sensitive to the inclusion of these households.

over time. I add some demographic variables that are fixed over time to my specification, and the results are shown in Columns 3, 4, 5 in Table 5. As mentioned earlier, land is assigned to each household and does not change over time. Therefore, I can simply use the size of land reported in my survey as a measure of land holdings in the past. Years of education is measured *ex post*. One might worry that it could be endogenous. However, this sample consists of adults who are on average 50 years old, and it is uncommon for adults to gain formal access to education after they start farming, especially in rural China. Therefore, it seems reasonable to assume that education is fixed over time. To my surprise, in the full model, Column 5, neither years of education nor farm size can predict the timing of adoption in the sample.[27] In Column 6, I use dummy variables indicating different levels of education, but they remain jointly insignificant.

7.2 Wealth Measure

One variable I would like to include in the specification but that is not available in this dataset is a measure of wealth prior to adoption. Wealth is expected to affect technology adoption because it is associated with credit constraints (which we did not ask about in this dataset) and greater access to resources. Ideally, I would like to include a measure of baseline wealth. The only proxy I have is information about each household's ownership of durable goods (DG) in 2001 and 1999. Durable goods asked about in the survey are a color television, black-and-white television, vcd/dvd player, stereo system/boombox, camera, washer, water heating system, gas stove, refrigerator, car, motorcycle, cellular phone, and air conditioner. I use the number of durable goods owned as a proxy for baseline wealth and the regression results are presented in Table 6 Column 1.

The coefficient on wealth is positive, but insignificant in Column 1. However, the interpretation of this coefficient requires caution. It does not tell us whether those farmers with higher initial wealth adopt Bt cotton earlier, or whether accumulating more wealth is a result of early adoption. Given this

[27] In a further investigation of education variable, I find that when I only control for village fixed effects, but not risk preferences parameters, education does predict the timing of adoption positively at the ten percent level of significance. However, once I control for risk preferences, p-value of education becomes insignificant.

concern, using the wealth measure from the earlier year should lessen the problem. As a robustness check, I use the number of durable goods owned in 1999 as a proxy for baseline wealth and the result is presented in Column 2. Comparing the results from Column 1 and Column 2, the wealth coefficient on 1999 is larger than that on 2001. If the earlier adopters accumulate more wealth over time, we should expect to find a larger upward bias in the coefficient of wealth in 2001 than wealth in 1999. This result could be an artifact of noise in the wealth measure, which is approximated by the ownership of a list of durable goods. While I do observe wide variation in wealth in 2006 as measured in the survey (i.e., the 25^{th} percentile owns, on average, 2.5 durable goods while the 75^{th} percentile owns, on average, seven durable goods), there is less variation in durable goods owned, and presumably more noise, in the earlier periods. For example, approximately one-half of respondents report that they owned only one of the durable goods on the list in 1999, which could be due to the fact that the durable goods list was created to reflect what are relevant to life in 2006, but not necessarily so in the earlier years.

Using this proxy for wealth, I implicitly give the same weight to each durable good when I measure household wealth. Certainly, there are some durable goods that are more expensive and less commonly owned, such as cars and motorcycles. Hence, I follow the procedure developed by Filmer and Pritchett (2001) and estimate a wealth index using principle components analysis. I use these wealth indexes as proxies for baseline wealth, and the regression results are presented in Columns 3 and 4.

While there is some remaining uncertainty regarding the interpretation of the wealth coefficient, the interpretations of the coefficients on σ and λ are robust to including this measure of wealth in the specification.

7.3 Nonlinear Probability Weighting

In Table 7, the nonlinear probability weighting measure (α) is included in the regressions. α defines the shape of the probability weighting function. A smaller α indicates an individual's tendency to overweight small probabilities. To ease the interpretation of the coefficient on α, I create a dummy variable, where one indicates an individual who puts excessive decision weight on small probabilities

($\alpha<1$) and zero indicates an individual who does not overweight small probabilities ($\alpha \geq 1$). The results in Columns 1 and 2 suggest that holding all else equal, individuals who overweight small probabilities are 59% more likely to adopt Bt cotton at any given time than individuals who do not overweight.[28] In Column 3, I include a direct measure of α in the regression.

In Tables 5, 6 and 7 the interpretation of the coefficients on the main variables of interests does not change when I exclude the wealth measure from the regression. Therefore, for the rest of this section, I focus on the specification without the wealth variable.

7.4 Robustness Check-Specification

In this section, I would estimate these relationships using different specifications. So far, my parametric estimates of the hazard model assume that $h_o(t)$ in Equation 1 follows a Weibull distribution. I relax this assumption by estimating the Cox proportional hazard model (Cox, 1972). Table 8 Column 1 provides the results of the Cox model. The advantage of the Cox model is that I can estimate β without directly estimating $h_o(t)$ in exchange for a loss of efficiency. The coefficient on σ is negative and significant at 90-percent level. Yet it is smaller in magnitude than the σ coefficient from the Weibull specification in Table 7, Column 3 (-0.256 and -0.430). The coefficients on λ and α both remain robust across different specifications.

In Section 7.1 and 7.2, when I assume a Weibull hazard model, I find that hazard of adoption is time dependent and it increases over time. As a specification check, I assume baseline hazard has a Gompertz specification, which is also monotonic. The baseline hazard has the form

$$h_0(t) = \exp(\theta t) \qquad (5)$$

Regression results are presented in Table 8, Column 2. $\theta \approx 0.687$. Again, it shows there is an increasing hazard rate over time. The results from σ, λ and α are not sensitive to the functional form of the baseline hazard I use.

[28] exp (0.463) = 59

One might be concerned that I impose too strong of a functional form assumption on the value function when I derive the risk preference parameters. It would be interesting to see if the experiment produces has any predictions for the adoption decision without assuming any specific functional form for the utility function. Therefore as a robustness check, I simply divide the Figure 5 into 18 different zones (See Figure 8). In the duration model, instead of using three risk preferences parameters, I replace them with 18 zone dummies. The estimated coefficients on the zone dummies are reported in Table 9, and the number of observations in each zone is reported in brackets. Zone 1, the least risk averse and the least loss averse, is the reference group, so all other coefficients should be negative, and they are. Since the individuals in Zones 10 through 18 switch later from A to B in Series 3 compared to those in Zones 1 through 9, I expect these individuals to be relatively more loss averse. Indeed, the coefficients on Zones 10 through 18 are generally more negative than those on Zones 1 through 9. An F-test rejects the null hypothesis that the zone dummies are jointly equal to zero at a 99.9% confidence level.

In a full specification model (regression results not provided), I include the seventeen zone-dummies and the three risk preferences parameters as regressors. Since the specification from Table 7 Column 3 is nested in the specification above, I can test these two competing specifications.[29] The standard likelihood ratio test reject that full specification (three risk preference variables plus zone-dummies) model in favor of the nested specification (only three risk preference variables) at a one percent significance level.

Using the result from the F-test, I can conclude that even if the functional form assumption of the value function is incorrect, the results from this experiment (represented by simply dividing them into zones) still provide some predictions for the timing of adoption.[30] Furthermore, with the result from the likelihood ratio test, I can conclude that these three risk preference parameters derived from the structured value function have already captured the essence of this game without using the non-structured zone dummy variables.

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[29] In order to run a likelihood ratio tests, the standard errors from these regressions cannot be robust standard errors.
[30] I had also tried to divide the Figure 7 into 9 zones (4 on top, 4 on bottom and 1 in the center) instead 18 zones, and the F test still rejects the null at 99% confidence interval.

7.5 Robustness Check-Other Concerns

Whether these farmers understand the game is a major concern. As mentioned earlier, 7.6% of total farmers choose either all lottery A or all lottery B in all three series. If these farmers simply did not understand the game, they add noise to the estimates. As long as their choices in the experiment are not systematically correlated with their adoption decisions, coefficients are not biased. In Column 1 of Table 10, I exclude those 7.6% of individuals from the sample. The impacts of risk aversion and loss aversion coefficients on technology adoption are even more prominent.

In this sample, twenty farmers adopted Bt cotton before it was commercialized. It is possible that these farmers who violated the law behave differently from the rest of the sample. Therefore, in Column 2, I exclude those individuals from the sample and redefine the time of exposure as 1996 for everyone in the sample. The interpretations of the coefficients do not vary too much from regression results with the full sample.

In the previous specifications, time of exposure to Bt cotton is defined as the year before the first person in the sample adopted it (1993). It is possible that Bt cotton may not be available to all farmers, especially this survey covers four provinces. I redefine the exposure date as the year before the first person adopted in each province. Results are shown in Column 3. In Column 4, the exposure date is defined as the year before first person adopted in the county. In this specification, the coefficient on σ is higher compared to the same specification with a different exposure date displayed on the right in Table 10.[31] In Column 5, I cluster the standard errors at the village level, and all the coefficients remain robust. In this section, I have shown that the coefficients of interest remain robust across alternative specifications. These results suggest that there is a strong relationship between attitudes towards risk and Bt cotton adoption decision.

7.6 Further Discussion

[31] It is not sensible to define the time of exposure as the year before the first person adopted in the village because we only surveyed 20 households in each village. It is very likely that someone had adopted earlier than the first person reported in village in the sample but was not interviewed.

Since the magnitudes of σ, λ, and α are very different, I cannot simply compare the impact of each covariate on the likelihood of adoption by looking at the magnitude of the coefficients in these tables. I can compare individuals that are one standard deviation above the mean (in each parameter) to the average person in the sample. The results from Table 7 Column 4 suggest that holding all else equal, if σ decreases by one standard deviation (becoming less risk averse), the probability of Bt cotton adoption increases by 11%. If λ drops by one standard deviation (becoming less loss averse), the likelihood of adoption will increase by 15%. If α decreases by one standard deviation, the likelihood of adoption would increase by 11%.

8. Threats to Validity

One concern regarding this study is that I only have *ex post* measures of wealth and attitudes towards risk. This situation might be problematic if risk preferences change over time. The extent to which the adoption of new technology affects individual risk preferences, or more broadly speaking, the stability of individual risk aversion over time, are topics for future research.

The lack of a baseline wealth measure may seem to pose a serious problem since it often serves as a proxy for the credit constraint faced by farmers at the time of adoption. If credit constraint is positively correlated with risk aversion, and credit constrained individuals adopt Bt cotton later, then the coefficients here suffer from upward bias. On the other hand, it is also possible that farmers can save from pesticide costs after adopting Bt cotton seeds, so the more credit-constrained farmers may have greater incentives to use Bt cotton seeds, thus adopting it earlier. Then coefficients would suffer from a downward bias. Overall, it is difficult to determine the direction of this omitted-variable bias. However, unlike other types of agricultural investments (such as buying a tractor or installing a new irrigation system), buying Bt cotton seeds does not require a large lump-sum payment because the adoption of Bt cotton is not an all-or-none decision. Although I cannot rule out that credit constraints could bias the results, we test several measures of wealth as a proxy for baseline wealth and find the results for risk preferences to be robust.

Another limitation of this study is that I am unable to distinguish risk aversion from ambiguity aversion in decision-making processes. A commonly used definition that distinguishes the two is that "risk is imperfect knowledge where the probabilities of the possible outcomes are known, and uncertainty exists when these probabilities are unknown" (Hardaker et al., 1997). In the game, the probability distribution of outcomes is known; whereas when farmers need to make the adoption decision, the distribution of cotton yields is unknown. If the decision-making process with uncertainty is different from decision-making process under risk, the external validity of field experiments relating to risk would be seriously challenged since probabilities outside of lab or field experiments are rarely known. Engle-Warnick, Escobal, and Laszlo (2006) try to differentiate ambiguity aversion from risk aversion and use both to predict adoption decisions of new technology, however, neither of the regressors appears significant. This result could suggest that risk aversion is highly correlated with ambiguity aversion.

9. Conclusion

In this paper, I find that farmers with higher risk aversion or higher loss aversion adopt Bt cotton later. Farmers who overweight small probabilities adopt Bt cotton earlier. The new technology in my study, Bt cotton, is in fact no riskier and brings higher profits than traditional cotton to farmers. Then why did risk-averse farmers adopt later? Yang et al.(2005) conducted a survey of cotton farmers in Shandong and 78% of farmers reported that they did not adopt Bt cotton in the first year of commercialization because they had doubt about the effectiveness of the resistance of Bt cotton to bollworms. Therefore, it suggests that it is not the real risk, but the risk perceived by farmers, that influence their adoption decisions. Suppose all farmers have *a priori* beliefs about the distribution of Bt cotton yields, over time farmers observe the performance of Bt cotton and update their beliefs about Bt cotton. Therefore, it will take longer (more positive signals of Bt cotton's superior performance) for more risk-averse farmers to adopt Bt cotton. Unfortunately, current dataset cannot be used to fully test this hypothesis since it does not contain enough information on farmers' social network and the learning process.

Besides Bt cotton, several varieties of disease- and insect-resistant genetically modified Bt rice have also been developed in China. These new crops are in the last phase of test trials prior to commercial approval from the Ministry of Agriculture in China. In future research, I hope to conduct a longitudinal survey of rice farmers in China, starting before Bt rice is approved for commercial use, and collect detailed *ex ante* risk preference, social network and credit constraint information. This *ex ante* information can then be related to the timing of Bt rice adoption to extend and strengthen the type of research presented in this study.

These findings suggest some policy implications worth considering. Offering insurance to mitigate the risk of failure if new crops and technology are used might expedite technology diffusion. However, the design and implementation of the insurance could be challenging since it should minimize adverse selection and moral hazard problems while remaining simple enough for farmers with low education to understand (e.g. Gine and Yang, 2007; Cole, Topacman and Topalova, 2007).

In development economics, there is a long-standing interest in understanding when farmers adopt new technologies. While the goal of this study is to shed some light on the determinants of technology adoption, the findings also suggest that agricultural productivity in developing countries increases slowly due to individual aversion to perceived risk and potential loss resulting from new technologies.

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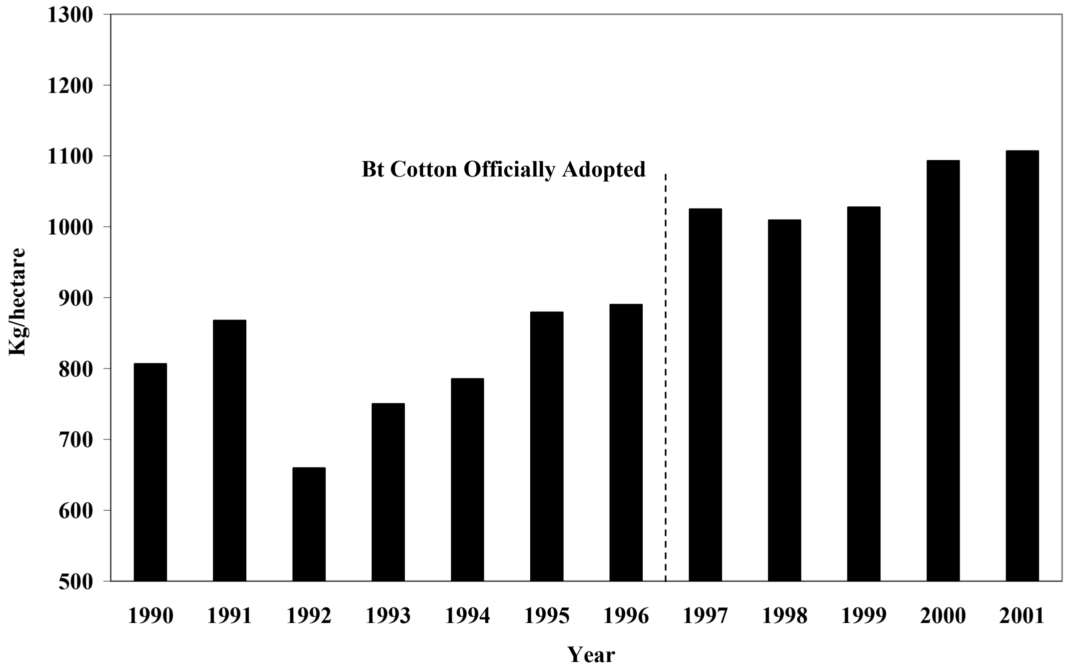
Figure 1: Cotton Yield in China



Source: China Statistical Yearbook

Figure 2: Cumulative Distribution Function of Household Adoption of Bt Cotton

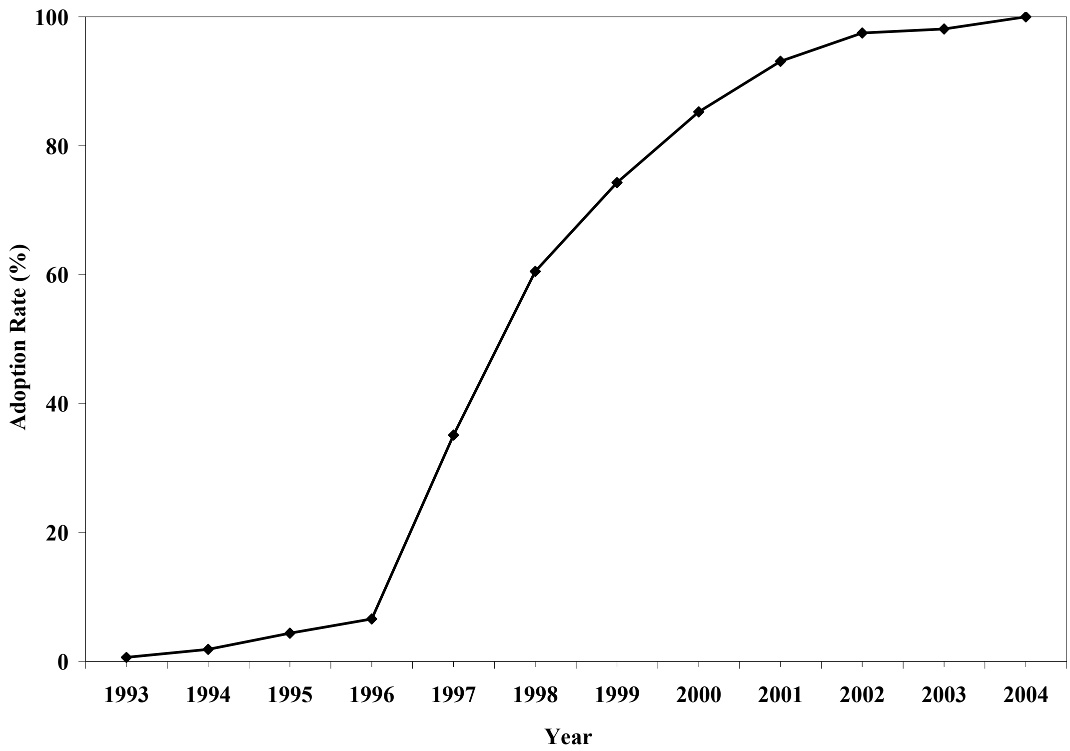


Figure 3: Percentage of Households Adopting Bt Cotton

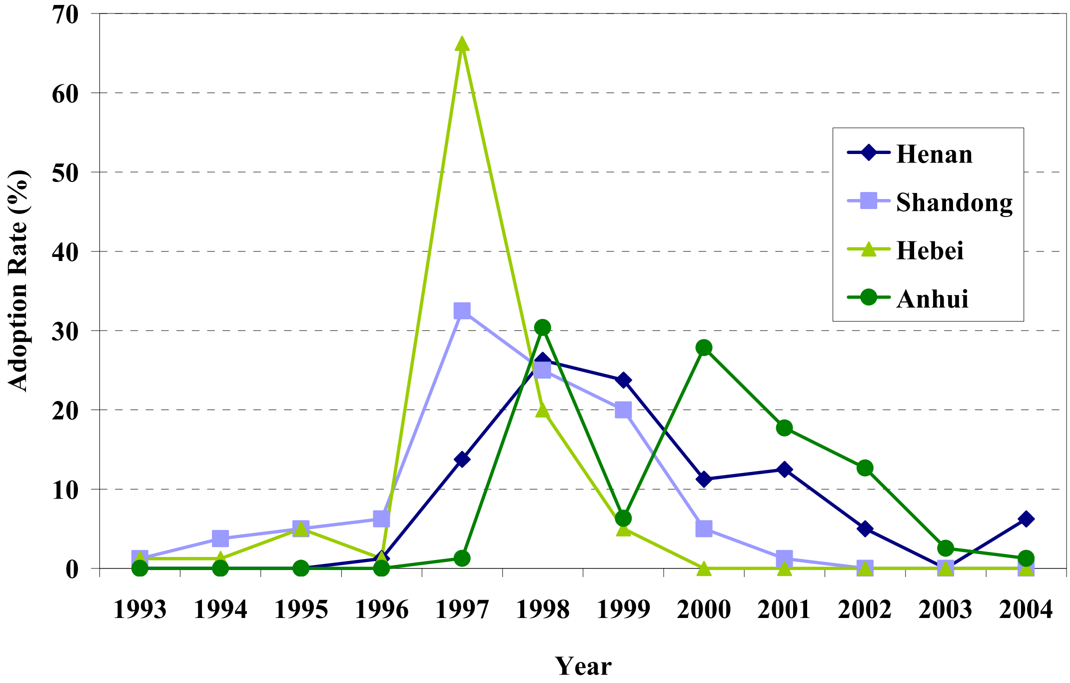
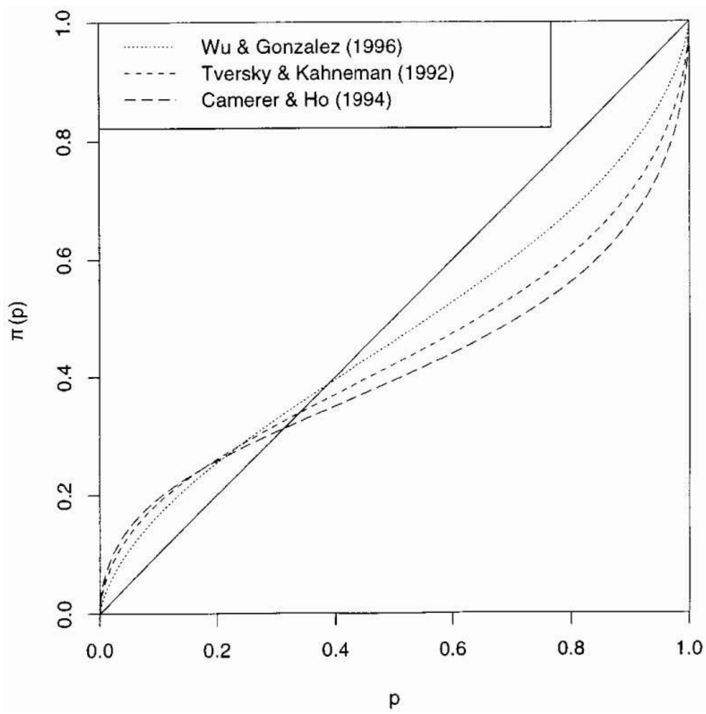


Figure 4: Weighting Functions Estimated by Camerer and Ho (1994), Tversky and Kahneman (1992), and Wu and Gonzalez (1996)



Source: Wu and Gonzalez (1999)

Figure 5: Distribution of Switching Points

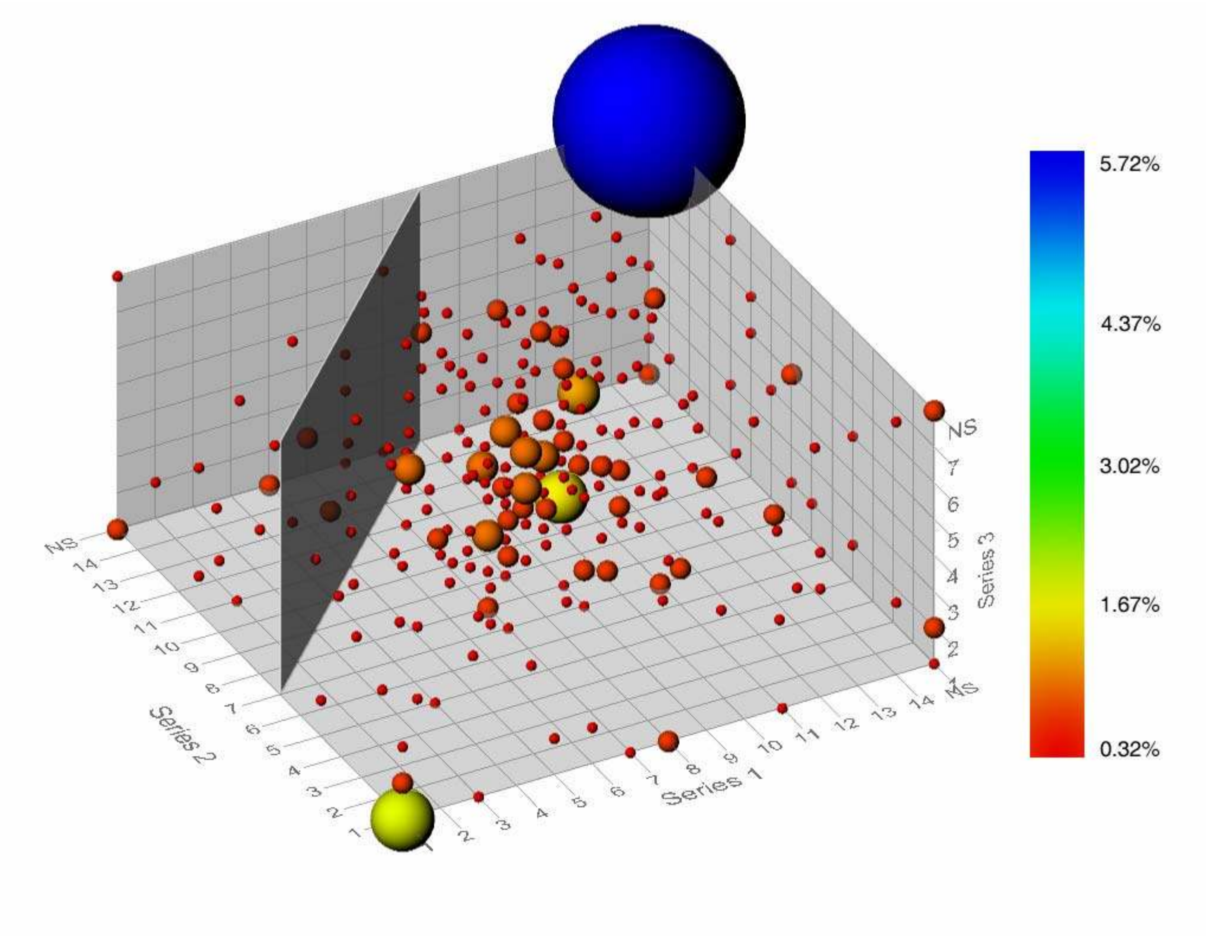


Figure 6: Distribution of Risk Preference Parameters

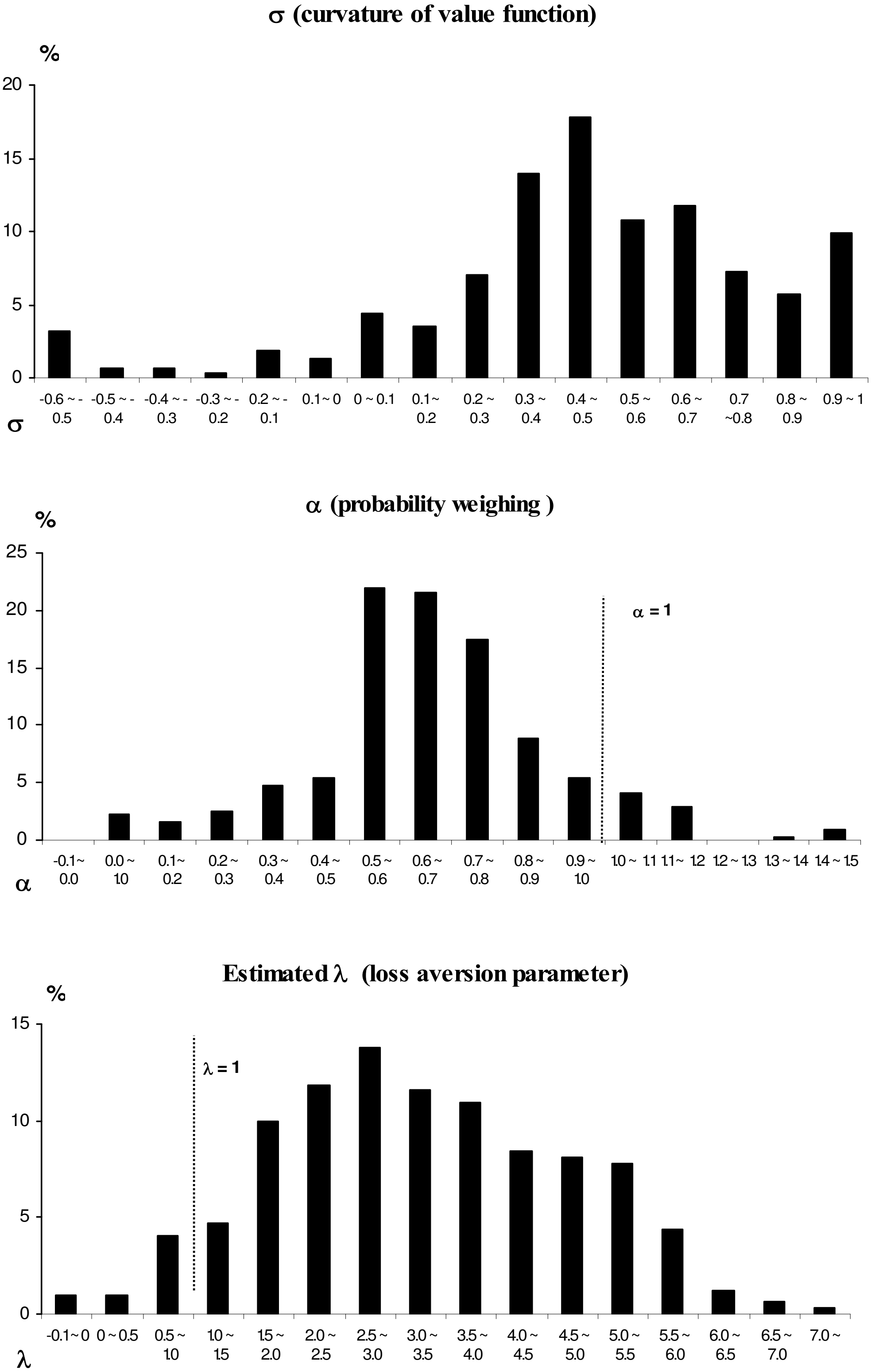


Figure 7a: Box Chart of σ

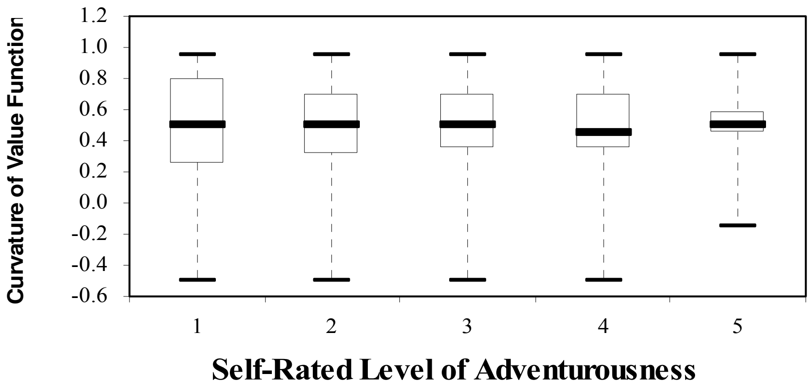


Figure 7b: Box Chart of λ

Note: For each level of adventurousness, the bottom bar corresponds to the minimum value of σ, (Figure 7a) or λ (Figure 7b), while the top bar corresponds to the maximum value. The rectangle corresponds to the 25^{th} - the 75^{th} percentile values, with the median value is represented by the bold line bisecting the rectangle.

Figure 8: Zone Division of Switching Points

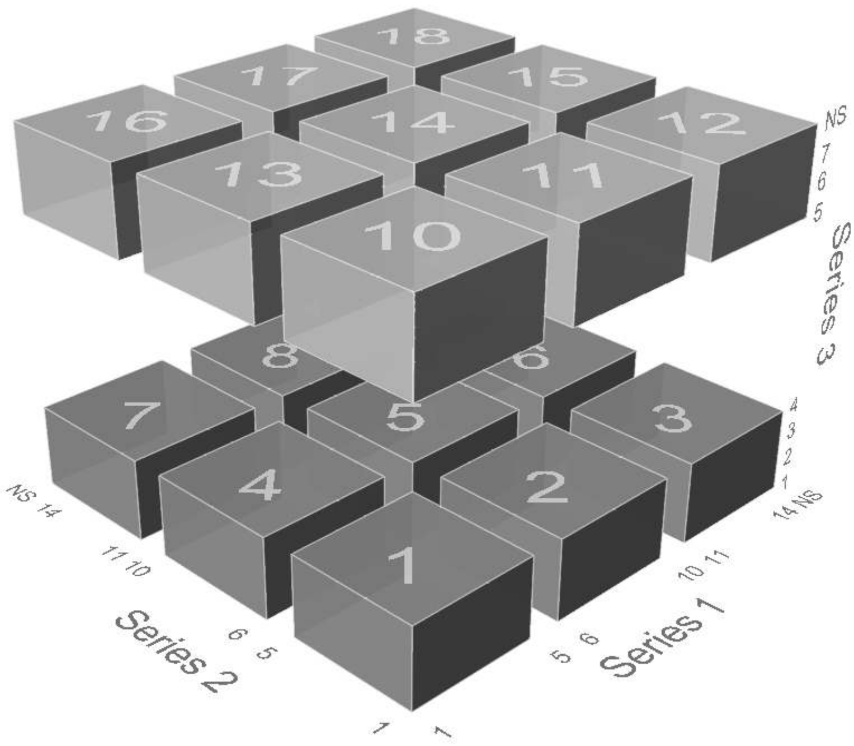


Table 1: Cost of Cotton Production

	Seed		Pesticide		Total
Year	Yuan/Ha	%	Yuan/Ha	%	Yuan/Ha
1978	29	4.70	89	14.39	619
1980	51	5.45	98	10.52	935
1985	73	5.75	182	14.25	1277
1990	106	5.86	305	16.87	1808
1991	114	5.38	344	16.29	2110
1992	105	4.79	414	18.97	2182
1993	133	5.55	454	18.98	2390
1994	174	5.50	625	19.73	3168
1995	230	5.61	834	20.32	4107
1996	238	5.63	721	17.03	4232
1997	260	6.02	728	16.83	4324
1998	271	6.15	775	17.63	4400
1999	286	7.16	611	15.28	3998
2000	283	7.25	600	15.38	3900
2001	318	8.28	554	14.42	3840
2002	320	7.92	514	12.73	4037
2003	368	8.63	567	13.29	4271
2004	466	10.44	487	10.91	4467

Source : National Production Cost Survey (2005).
Note : It is the cost of an average cotton farmer in China. The survey does not differentiate between Bt and non-Bt Cotton Farmers.

Table 2

Summary Characteristics

Age	49.52
	(8.89)
Education	7.10
	(2.96)
Female	0.14
	(0.35)
Size of Household	4.49
	(1.45)
Self-Rated Risk Attitude	2.78
(1=most adventurous, 5= least adventurous)	(0.92)
σ (Risk Aversion)	0.48
	(0.33)
λ (Loss Aversion)	3.47
	(3.92)
α (Probability Weighting)	0.69
	(0.23)
Religious (1=Yes, 0=No)	0.04
	(0.19)
Total Cotton Sown Area (Ha)	0.54
	(0.33)
Major Cash Crop Besides Cotton Sown Area (Ha)	0.12
	(0.19)
Major Cereal Crop Sown Area (Ha)	0.33
	(0.33)
Total Crop Sown Area (Ha)	1.07
	(0.58)
Total Land Owned (Ha)	0.59
	(0.29)
Cotton Yield (Kg/Ha)	3356
	(889.8)
Average Year of Bt Cotton Adoption	1998
	(1.90)
Total Value of DGs Per Capita in 2006 (Yuan)	588.40
	(9.37)
Observations	320

Note : Standard deviation are in parentheses.

Table 3: Payoff Matrix from the Experiment

Series 1	Lottery A	Lottery B
1	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 34 Yuan and 90% winning 2.5 Yuan
2	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 37.5 Yuan and 90% winning 2.5 Yuan
3	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 41.5 Yuan and 90% winning 2.5 Yuan
4	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 46.5 Yuan and 90% winning 2.5 Yuan
5	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 53 Yuan and 90% winning 2.5 Yuan
6	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 62.5 Yuan and 90% winning 2.5 Yuan
7	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 75 Yuan and 90% winning 2.5 Yuan
8	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 92.5 Yuan and 90% winning 2.5 Yuan
9	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 110 Yuan and 90% winning 2.5 Yuan
10	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 150 Yuan and 90% winning 2.5 Yuan
11	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 200 Yuan and 90% winning 2.5 Yuan
12	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 300 Yuan and 90% winning 2.5 Yuan
13	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 500 Yuan and 90% winning 2.5 Yuan
14	30% winning 20 Yuan and 70% winning 5 Yuan	10% winning 850 Yuan and 90% winning 2.5 Yuan
Series 2	Lottery A	Lottery B
1	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 27 Yuan and 30% winning 2.5 Yuan
2	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 28 Yuan and 30% winning 2.5 Yuan
3	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 29 Yuan and 30% winning 2.5 Yuan
4	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 30 Yuan and 30% winning 2.5 Yuan
5	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 31 Yuan and 30% winning 2.5 Yuan
6	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 32.5 Yuan and 30% winning 2.5 Yuan
7	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 34 Yuan and 30% winning 2.5 Yuan
8	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 36 Yuan and 30% winning 2.5 Yuan
9	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 38.5 Yuan and 30% winning 2.5 Yuan
10	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 41.5 Yuan and 30% winning 2.5 Yuan
11	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 45 Yuan and 30% winning 2.5 Yuan
12	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 50 Yuan and 30% winning 2.5 Yuan
13	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 55 Yuan and 30% winning 2.5 Yuan
14	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 65 Yuan and 30% winning 2.5 Yuan
Series 3	Lottery A	Lottery B
1	50% winning 12.5 Yuan and 50% losing 2 Yuan	50% winning 15 Yuan and 50% losing 10 Yuan
2	50% winning 2 Yuan and 50% losing 2 Yuan	50% winning 15 Yuan and 50% losing 10 Yuan
3	50% winning 0.5 Yuan and 50% losing 2 Yuan	50% winning 15 Yuan and 50% losing 10 Yuan
4	50% winning 0.5 Yuan and 50% losing 2 Yuan	50% winning 15 Yuan and 50% losing 8 Yuan
5	50% winning 0.5 Yuan and 50% losing 4 Yuan	50% winning 15 Yuan and 50% losing 8 Yuan
6	50% winning 0.5 Yuan and 50% losing 4 Yuan	50% winning 15 Yuan and 50% losing 7 Yuan
7	50% winning 0.5 Yuan and 50% losing 4 Yuan	50% winning 15 Yuan and 50% losing 5.5 Yuan

Table 4
OLS Regression of Individual Risk Preferences

	(1) σ (value function curvature)	(2) λ (loss aversion)	(3) α (probability weighting)
Age	-0.001	-0.024	0.000
	(0.002)	(0.025)	(0.002)
Education	0.000	-0.175	-0.008
	(0.007)	(0.089)*	(0.004)*
Female	0.093	0.922	-0.012
	(0.054)*	(0.634)	(0.035)
Wealth per capita (10000 Yuan)	-0.039	0.299	0.000
	(0.020)*	(0.240)	(0.015)
Religious (1=Yes)	-0.225	1.503	-0.013
	(0.090)**	(1.128)	(0.060)
% Time Spent Working On-Farm	0.095	2.174	-0.071
	(0.088)	(0.662)***	(0.069)
Village Official	0.013	-0.211	-0.014
	(0.049)	(0.573)	(0.047)
Constant	0.611	4.680	0.792
	(0.158)***	(1.929)**	(0.141)***
Observations	314	314	314
R-squared	0.09	0.17	0.06

Note: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include village fixed effects.

Table 5
Weibull Model for Duration of Time to Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
σ	-0.430		-0.465		-0.428	-0.428
(value function curvature)	(0.188)**		(0.186)**		(0.194)**	(0.197)**
λ		-0.039		-0.044	-0.041	-0.042
(loss aversion)		(0.019)**		(0.019)**	(0.019)**	(0.019)**
Age[a]			-0.01	-0.01	-0.012	-0.012
			(0.009)	(0.009)	(0.009)	(0.009)
Female			0.117	0.118	0.13	0.134
			(0.166)	(0.170)	(0.167)	(0.165)
Land owned (ha)			-0.43	-0.479	-0.464	-0.456
			(0.286)	(0.281)*	(0.291)	(0.295)
Education (years)			0.019	0.022	0.021	
			(0.020)	(0.020)	(0.020)	
Middle school[b]						0.069
						(0.134)
High school[c]						0.233
						(0.155)
Constant	-8.082	-8.177	-7.626	-7.711	-7.554	-7.477
	(0.486)***	(0.477)***	(0.586)***	(0.598)***	(0.600)***	(0.580)***
Observations	302	302	302	302	302	302

Note: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include county fixed effects. Sample exclude all households that were formed after 1993.

a. Age at time of exposure

b. Middle school equals 1 if an individual has at most some middle school education, and 0 otherwise

c. High school equals 1 if an individual has at least some high school education, and 0 otherwise

Table 6: Weibull Model for Duration of Time to Adoption
Robustness Check on Wealth Measures

	(1)	(2)	(3)	(4)
σ	-0.435	-0.429	-0.436	-0.432
(value function curvature)	(0.194)**	(0.194)**	(0.194)**	(0.194)**
λ	-0.044	-0.040	-0.043	-0.041
(loss aversion)	(0.020)**	(0.019)**	(0.020)**	(0.019)**
Age	-0.012	-0.012	-0.012	-0.012
	(0.009)	(0.009)	(0.009)	(0.009)
Female	0.139	0.112	0.140	0.112
	(0.168)	(0.171)	(0.168)	(0.172)
Land owned (Ha)	-0.478	-0.424	-0.477	-0.439
	(0.290)*	(0.284)	(0.290)*	(0.289)
Education (years)	0.023	0.015	0.023	0.015
	(0.020)	(0.020)	(0.020)	(0.020)
# of DG owned in 2001	0.010			
	(0.008)			
# of DG owned in 1999		0.078		
		(0.041)*		
Wealth index 2001[a]			0.017	
			(0.015)	
Wealth index 1999[a]				0.084
				(0.020)***
Constant	-7.614	-7.799	-7.581	-7.621
	(0.588)***	(0.602)***	(0.592)***	(0.603)***
Observations	302	302	302	302

Note: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include county fixed effects.
a. Wealth indexes are imputed using principle components analysis.

Table 7: Weibull Model for Duration of Time to Adoption
Nonlinear Probability Weighting

	(1)	(2)	(3)	(4)
σ	-0.467	-0.467	-0.43	-0.434
(value function curvature)	(0.193)**	(0.193)**	(0.192)**	(0.192)**
λ	-0.046	-0.045	-0.046	-0.045
(loss aversion)	(0.020)**	(0.020)**	(0.019)**	(0.019)**
α<1	0.463	0.426		
(probability weighting)	(0.244)*	(0.249)*		
α			-0.64	-0.632
(probability weighting)			(0.226)***	(0.229)***
Age	-0.012	-0.012	-0.013	-0.013
	(0.009)	(0.009)	(0.009)	(0.009)
Female	0.151	0.131	0.126	0.103
	(0.169)	(0.174)	(0.180)	(0.185)
Land owned (Ha)	-0.472	-0.444	-0.467	-0.442
	(0.275)*	(0.274)	(0.280)*	(0.277)
Education (years)	0.023	0.017	0.012	0.006
	(0.020)	(0.021)	(0.020)	(0.021)
Wealth index 1999		0.076		0.083
		(0.024)***		(0.022)***
Constant	-8.057	-8.078	-7.12	-7.187
	(0.617)***	(0.617)***	(0.635)***	(0.637)***
Observations	302	302	302	302

Note: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include county fixed effect.

Table 8: Different Specifications for Duration of Time to Adoption

	(1) Cox	(2) Gompertz
σ	-0.256	-0.486
(value function curvature)	(0.145)*	(0.189)**
λ	-0.034	-0.036
(loss aversion)	(0.015)**	(0.019)*
α	-0.432	-0.77
(probability weighting)	(0.169)**	(0.249)***
Age	-0.007	-0.017
	(0.007)	(0.009)*
Female	0.118	0.059
	(0.132)	(0.212)
Land owned (Ha)	-0.329	-0.454
	(0.211)	(0.296)
Education (years)	0.011	0.015
	(0.015)	(0.022)
Constant		-2.215
		(0.526)***
Observations	302	302

Note: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include county fixed effects.

Table 9: Duration of Time to Adoption
Coefficients on Zone Dummies

Zone 1	--	**Zone 10**	-0.205
	--		(0.380)
	[15]		[7]
Zone 2	-0.588	**Zone 11**	-0.747
	(0.371)		(0.381)*
	[8]		[7]
Zone 3	-0.538	**Zone 12**	-0.83
	(0.359)		(0.398)**
	[11]		[5]
Zone 4	-0.307	**Zone 13**	-0.3
	(0.391)		(0.261)
	[7]		[3]
Zone 5	-0.679	**Zone 14**	-1.196
	(0.269)**		(0.353)***
	[64]		[33]
Zone 6	-0.442	**Zone 15**	-1.568
	(0.317)		(0.405)***
	[23]		[7]
Zone 7	-1.528	**Zone 16**	-1.15
	(0.462)***		(0.424)***
	[13]		[4]
Zone 8	-1.446	**Zone 17**	-0.71
	(0.352)***		(0.311)**
	[25]		[9]
Zone 9	-0.39	**Zone 18**	-0.993
	(0.293)		(0.312)***
	[28]		[33]

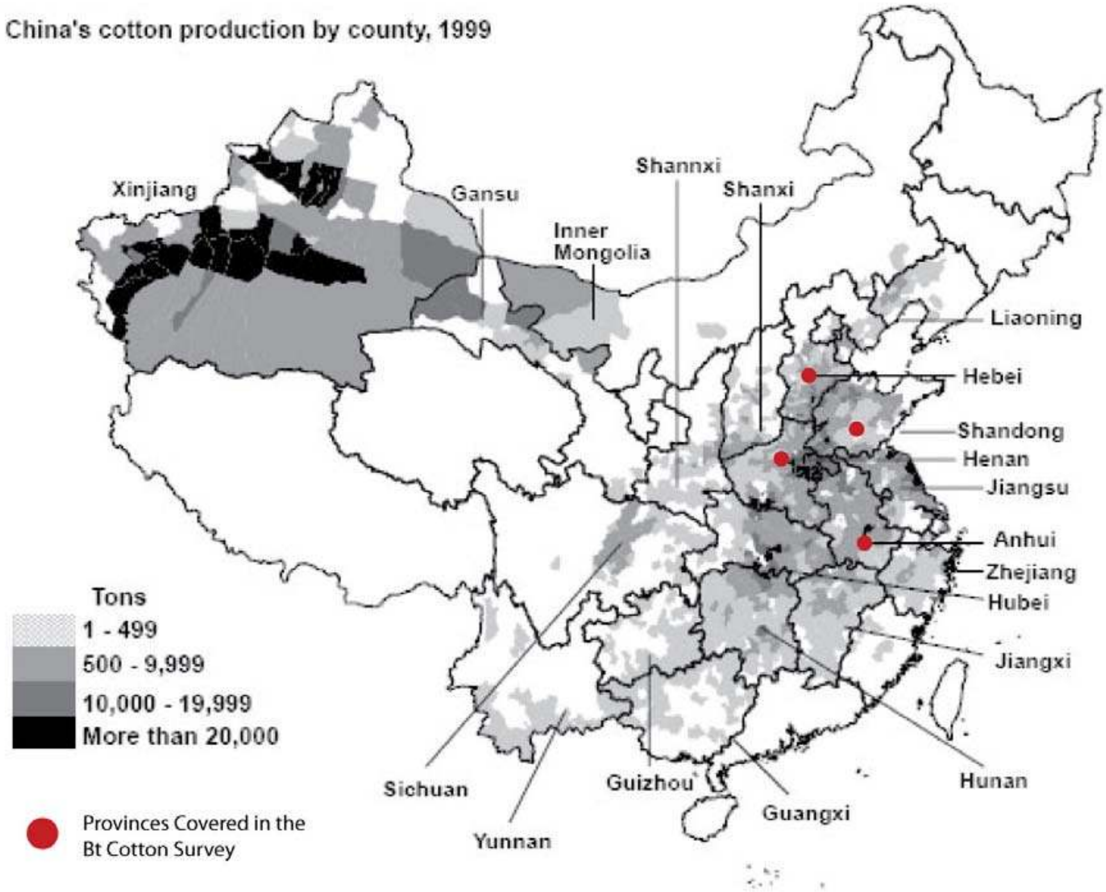
Note: Robust standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include county fixed effects. Number of observations in each zone is in brackets.

Table 10: Weibull Model for Duration of Time to Adoption
Robustness Check

	(1)[a] Drop NS	(2)[b] Drop Early Adopters	(3)[c] Province	(4)[d] County	(5)[e] Clustered	Original
σ	-0.671	-0.450	-0.511	-0.527	-0.43	-0.43
(value function curvature)	(0.217)***	(0.224)**	(0.181)***	(0.173)***	(0.230)*	(0.192)**
λ	-0.082	-0.044	-0.030	-0.023	-0.046	-0.046
(loss aversion)	(0.025)***	(0.021)**	(0.015)*	(0.014)*	(0.027)*	(0.019)**
α	-0.602	-0.501	-0.562	-0.540	-0.640	-0.640
(probability weighting)	(0.228)***	(0.230)**	(0.218)**	(0.215)**	(0.249)**	(0.226)***
Age	-0.017	-0.012	-0.018	-0.016	-0.013	-0.013
	(0.009)**	(0.009)	(0.008)**	(0.008)**	(0.011)	(0.009)
Female	0.153	0.225	0.040	0.066	0.126	0.126
	(0.184)	(0.191)	(0.191)	(0.177)	(0.167)	(0.180)
Land owned (Ha)	-0.530	-0.430	-0.273	-0.171	-0.467	-0.467
	(0.308)*	(0.308)	(0.269)	(0.246)	(0.290)	(0.280)*
Education (years)	0.017	0.002	0.014	0.011	0.012	0.012
	(0.022)	(0.021)	(0.019)	(0.018)	(0.022)	(0.020)
Constant	-8.277	0.119	-4.357	-2.740	-7.120	-7.120
	(0.681)***	(0.535)	(0.580)***	(0.506)***	(0.831)***	(0.635)***
Observations	280	282	302	302	302	302

Note: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include county fixed effects.
a. Excluding all individuals who chose only A or only B in all 3 Series.
b. Excluding all individuals who adopted Bt cotton before 1997.
c. Exposure dates are defined as the year before the first person in each province adopted.
d. Exposure dates are defined as the year before the first person in each county adopted.
e. Standard errors are clustered at the village level.

Appendix 1



Source: *China Rural Statistical Yearbook*, 2000.

Appendix 2

Record Sheet

Series 1

	A	B
1	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	34 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
2	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	37.5 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
3	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	41.5 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
4	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	46.5 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
5	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	53 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
6	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	62.5 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
7	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	75 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
8	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	92.5 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
9	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	110 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
10	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	150 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
11	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	200 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
12	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	300 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩

13	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	500 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩
14	20 Yuan if ①②③ 5 Yuan if ④⑤⑥⑦⑧⑨⑩	850 Yuan if ① 2.5 Yuan if ②③④⑤⑥⑦⑧⑨⑩

I choose lottery A for Line 1 to _____.
I choose lottery B for Line _____ to 14.

Series 2

	A	B
1	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	27 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
2	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	28 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
3	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	29 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
4	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	30 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
5	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	31 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
6	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	32.5 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
7	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	34 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
8	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	36 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
9	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	38.5 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
10	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	41.5 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩

11	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	45 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
12	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	50 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
13	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	55 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩
14	20 Yuan if ①②③④⑤⑥⑦⑧⑨ 15 Yuan if ⑩	65 Yuan if ①②③④⑤⑥⑦ 2.5 Yuan if ⑧⑨⑩

I choose lottery A for Line 1 to _____.
I choose lottery B for Line _____ to 14.

Series 3

	A	B
1	Receive 12.5 Yuan if ①②③④⑤ Lose 2 Yuan if ⑥⑦⑧⑨⑩	Receive 15 Yuan if ①②③④⑤ Lose 10 Yuan if ⑥⑦⑧⑨⑩
2	Receive 2 Yuan if ①②③④⑤ Lose 2 Yuan if ⑥⑦⑧⑨⑩	Receive 15 Yuan if ①②③④⑤ Lose 10 Yuan if ⑥⑦⑧⑨⑩
3	Receive 0.5 Yuan if ①②③④⑤ Lose 2 Yuan if ⑥⑦⑧⑨⑩	Receive 15 Yuan if ①②③④⑤ Lose 10 Yuan if ⑥⑦⑧⑨⑩
4	Receive 0.5 Yuan if ①②③④⑤ Lose 2 Yuan if ⑥⑦⑧⑨⑩	Receive 15 Yuan if ①②③④⑤ Lose 8 Yuan if ⑥⑦⑧⑨⑩
5	Receive 0.5 Yuan if ①②③④⑤ Lose 4 Yuan if ⑥⑦⑧⑨⑩	Receive 15 Yuan if ①②③④⑤ Lose 8 Yuan if ⑥⑦⑧⑨⑩
6	Receive 0.5 Yuan if ①②③④⑤ Lose 4 Yuan if ⑥⑦⑧⑨⑩	Receive 15 Yuan if ①②③④⑤ Lose 7 Yuan if ⑥⑦⑧⑨⑩
7	Receive 0.5 Yuan if ①②③④⑤ Lose 4 Yuan if ⑥⑦⑧⑨⑩	Receive 15 Yuan if ①②③④⑤ Lose 5.5 Yuan if ⑥⑦⑧⑨⑩

I choose lottery A for Question 1 to _____.
I choose lottery B for Question _____ to 7.

Appendix 3

Game Instruction

Twenty farmers from the same village are gathered in the village office at the end of the interview day. We also invite village leaders to be present in the room to witness the game, so that the farmers would trust us. The village leader first explains to the farmers that we are researchers from the Chinese Academy of Science (CCAP is a department in CAS) to conduct research on farmers who make use of genetically modified cotton. I read to the farmers the oral consent form and explain to them that everyone who agrees to participate will receive 10 Yuan to start, but they might have chance to lose all 10 Yuan or they might have chance to win up to 850 Yuan. The farmers who do not wish to participate then leave the room at this time.

We distribute an instruction sheet containing a practice question that we review with each farmer to verify that all participants understand the meanings of lottery A and lottery B. We then prepare two bags, each of a different color, that contain numbered balls. The red bag has 10 balls numbered 1 through 10 representing the probabilities mentioned in the survey questions. The green bag contains 35 balls, each representing one of 35 lines in the survey. We explain to the participants that after the completion of the answer sheet, they will draw one ball out of the green bag first. The number on that ball would determine which line out of 35 that they have answered would be played. They then draw another ball out of the red bag. Depending on the lottery they have chosen for that particular line, their payoff would be determined by the second numbered ball. I use the sample answer in the instruction sheet to demonstrate how the payoff would be determined. I repeat the demonstration five times and each time I ask participants how much the payoff would be, to ensure that most of them understand the game. We instruct them not to communicate with each other during the game. A few of participants who cannot read have special assistants to read the instruction sheet and questions to them. A cover sheet is attached to the answer sheet; therefore, participants need not worry that others would see their answers. This whole process normally takes 1 hour to 1 hour 30 minutes.

Appendix 4: Distribution of Switching Points from the TCN Vietnam Sample