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

Elaine M. Liu*

*Department of Economics, University of Houston, Houston, TX 77204 (Email: emliu@uh.edu)

I am indebted to my advisor Alan Krueger for his continuous support. I am also very grateful to Orley Ashenfelter, Roland Benabou, Anne Case, Steve Craig, Aimee Chin, Hank Farber, JiKun Huang, Chris Paxson, Ted O'Donoghue, Carl Pray, Sam Schulhofer-Wohl and Nate Wilcox for helpful discussions, and to Raj Arunachalam, Leandro Carvalho, Richard Chiburis, Angus Deaton, Molly Fifer, Jane Fortson, Ilyana Kuziemko, Jack Lin, Ashley Miller, Analia Scholosser, Tomomi Tanaka, Stephanie Wang and seminar and conference participants at Princeton University, Cornell University, Texas A&M, Rutgers University, University of Houston, National University of Singapore, National Taiwan University, HKUST, Australian National University and China Economic Summer Institute for their comments. I would also like to thank Philippe Aghion and two anonymous referees for their helpful comments. Special thanks to Raifa Hu, Zijun Wang, Liang Qi, YunWei Cui and other research staff at the CCAP for their help. Financial support from Princeton University Industrial Relations Section is gratefully acknowledged. All errors are my own.

Abstract

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 Chinese farmers, who faced the decision of whether to adopt genetically modified Bt cotton a decade ago. In my analysis, I expand the measurement of risk preferences beyond expected utility theory to incorporate prospect theory. 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.

JEL Code: O13, O14, O33, D03, D81, D83

Keywords: Technology Adoption, Risk Preferences, Prospect Theory

1. Introduction

Technological innovation drives economic development, and given technological innovation's importance in improving living standards, delays in technology adoption have always puzzled economists. The current paper examines the case of Chinese cotton farmers who were offered the opportunity to adopt genetically modified *Bacillus thuringiensis* (Bt) cotton. Upon its introduction, Bt cotton was backed by dramatic assertions from the scientific community that it would increase yields, lower pesticide costs due to its ability in eliminating pests, and was no riskier than traditional cotton crops in terms of yield risk. Given such promising scientific claims and the eventual success of neighboring farms, this begs the question: Why did some cotton farmers wait almost ten years before switching to Bt cotton?

A very extensive literature has accumulated attempting to answer the aforementioned question regarding Chinese cotton farmers' risk preferences.[1] It has been established that education (Aldana et al., 2009; Foster & Rosenzweig, 1996; Huffman, 2001), credit constraints (Croppenstedt, Demeke, & Meschi, 2003; Sunding & Zilberman, 2001; Barrett & Moser, 2003) and learning spillover (Besley & Case, 1993; Conley & Udry, 2010; Foster & Rosenzweig, 1995; Munshi, 2004) are among the main determinants of technology diffusion. However, when a group of Chinese cotton farmers were asked why they did not adopt Bt cotton when it first became available, 97% of them cited their uncertainty regarding Bt cotton's effectiveness in reducing pest infestation as the main reason (Yang et al., 2005). The farmers' perceived uncertainty regarding Bt cotton allows the individual risk preferences to play an important role in technology adoption, which is this article's main focus.

There are several reasons to focus on individual risk preferences. One, risk preferences have long been recognized by the theoretical model of technology adoption as an important factor in the technology adoption decision making process (Feder, 1980; Feder, Just & Zilberman, 1985). Omission of risk attitudes could bias the coefficient estimates of other variables that could potentially be correlated with risk attitudes (e.g., education and wealth). Two, individual risk preferences have empirically been shown to play a role in wealth accumulation and income growth in labor markets and financial markets (McInish, Ramaswami, & Srivastava, 1993; Shaw, 1996). Last, recent works by Dohmen et al. (2008) and Cesarini et al. (2009) find a intergenerational correlation of risk attitudes. If the intergenerational link of risk preferences persists over time, it could potentially explain the low level of intergenerational income mobility and the difference in wealth accumulation. However, since risk preferences are not easily assessable through a standard household survey, the extent to which risk preferences play a role in wealth accumulation is less understood from an empirical perspective.[2] The current paper is one of the first works to examine the role of risk attitudes in technology adoption decisions.

This paper uses the introduction of genetically modified Bt cotton in China as a means to examine the aforementioned issue of how risk attitudes affect technology adoption decisions. Bt cotton is a well-suited technology for the current study as it does not require a large, lump sum investment (at most, the equivalent of five to ten days of rural wages).[3] The learning curve on the part of the farmers involved with planting Bt cotton is slight because of the similarity between the planting methods of Bt cotton and traditional cotton. Bt cotton differs from traditional cotton only in that it carries the Bt gene which creates toxins that kills bollworm, the primary pest for cotton farmers in China. Bt cotton is found to produce higher yield and it is no riskier than traditional cotton seed (Crost & Shankar, 2008; Krishna, Zilberman, & Qaim, 2009). Given that Bt cotton yield is first order stochastic dominating, we know that any delay in its adoption would clearly be a non-optimal decision that could affect wealth accumulation.

In 2006, I partnered with the Center for Chinese Agricultural Policy (CCAP), a government-affiliated research institute in Beijing, to conduct a household survey and field experiment. The household survey covered information on household characteristics and the timing of Bt cotton adoption of 320 cotton farmers in four Chinese provinces. I then conducted a field experiment to elicit individual risk preferences.[4] Later I used these risk preference parameters to predict the timing of the farmers' Bt cotton adoption.

The common approach to characterize an individual risk preference is to use expected utility (EU), in which risk aversion is the sole parameter for determining the curvature of the utility function. On the other hand, in prospect theory (PT) (Kahneman & Tversky, 1979) the shape of the utility function is jointly determined by risk aversion, loss aversion (which measures one's sensitivity to loss compared to gain), and nonlinear probability weighting (i.e., the individual tendency of overweighting small (large) probabilities and underweighting large (small) probabilities). In the context of technology adoption, there are two possibilities why EU theory could be inadequate in explaining the farmers' decisions. The first possibility is that Chinese farmers have a target income level that they are trying to reach and they therefore become more sensitive to loss than gain at a target income level. Although it has not been formerly tested whether target income levels exist in agricultural settings, many studies have provided evidence of target income levels in various scenarios that could not be explained by subsistence constraints (Camerer et al., 1997; Farber, 2008; Fehr & Goette, 2007; Rizzo & Zeckhauser, 2003). The second possibility draws upon the concept of status quo bias. Status quo bias, also known as endowment effect, indicates an individual's aversion to changing from an established behavior and is found to be an implication of loss aversion. Samuelson and Zechhauser (1988) tested status quo bias both in the field and lab settings before suggesting that status quo bias could explain brand loyalty. Applying status quo bias in technology adoption could potentially explain why farmers resist change. While this idea is mentioned in Mullainathan (2004), this article is the first empirical paper to shed light on this topic.

Ex ante, both EU and PT could act as potential theories for explaining the cotton farmers' decision making processes. However, it is not clear which one is more appropriate.[5] Therefore, I use the experiment design modeled after that of Tanaka, Camerer, and Nguyen (2009; hereafter TCN). The major advantage of TCN design is that it allows one to estimate empirical specifications that nest both EU and PT; it elicit three parameters—coefficient of risk aversion, loss aversion, and nonlinear probability weighting. TCN design also allows the results from the experiment to determine whether EU or PT better fit the data. Moreover, TCN's design has been tested in Vietnam with less educated subjects. The design is simple enough for less educated subjects to follow while allowing one to estimate a sophisticated utility function.

To provide some intuition to guide us how risk preference could dictate the adoption decision, I propose a simple model of technology adoption that incorporates individual risk preferences. Considering the previous finding that uncertainty surrounding Bt cotton's effectiveness in killing pests was the main factor deterring adoption, the model allows for the subjective view of risk associated with Bt cotton to be differed from the objective risk. The model assumes that individual adoption decisions would depend on farmers' subjective belief in Bt cotton efficacy and their view of pest severity in the upcoming season. The model predicts that if farmers perceived Bt cotton as ineffective in eliminating pests, then more risk-averse and more loss-averse farmers would adopt Bt cotton later. On the other hand, the model predicts that if farmers view Bt cotton as effective in eliminating pests (as was advertised by scientists), then more risk averse and more loss averse farmers should adopt it sooner.

I use the parameters elicited from the experiment to relate to the Chinese farmers' decision to adopt the genetically modified Bt cotton. I find that farmers who behave more risk-averse, or more loss averse, in the experiment adopt Bt cotton later, whereas farmers who overweight small probabilities adopt Bt cotton earlier. These findings are consistent with the model prediction in which farmers believe that Bt cotton is risk increasing upon adoption. Over time, farmers learn the objective risk of technology.

It is important to note that the findings in this paper do not undermine the importance of learning, social networks, or credit constraints in technology adoption. The result demonstrates that risk preferences play an important role in Bt cotton technology adoption, while at the same time, complementing the existing studies on technology adoption. For example, in the studies on social learning (Conley & Udry, 2010; Foster & Rosenzweig, 1995) and social pressure (Maertens, 2009), it remains unstated as to who the initial adopter would be in a particular social network when there is no one within the network from whom to learn. A model involving risk preferences would be able to explain the differences in the timing of technology adoption. In short, the current paper's empirical results do not attempt to discount the importance of learning about Bt cotton's planting method or learning about Bt cotton with regards to it being a new technology, but instead emphasize the participants' learning process regarding the objective risks of this new technology.

This paper is organized as follows. Section 2 offers a review of the literature. Section 3 provides some background information on Bt cotton and describes the survey and dataset. Section 4 describes the design and procedure of the field experiment and presents descriptive analysis of the results from the field experiment. Section 5 uses a conceptual framework to describe the role of risk preferences in technology adoption decisions. Section 6 presents a general econometric framework to test the predictions and describes the empirical results. Section 7 concludes the paper.

2. Related Literature

Since the literature in technology adoption is vast, I will discuss the two empirical studies most relevant to my study. Both of these papers elicit farmers' risk attitudes and use this measure to explain adoption decisions. Knight, Weir, and Woldehanna (2003) study technology adoption among Ethiopian farmers by dividing 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 Peruvian farmers' technology adoption decisions. Their experiment design is unique in that they are able to differentiate Knightian uncertainty (ambiguity) aversion from risk aversion.[6] When Engle-Warnick et al. (2006) include measures of both uncertainty (ambiguity) aversion and risk aversion in the probit regression of adoption decisions when adopting the new technology would be equal to 1 and non-adoption would be equal to 0, neither regressor can predict the technology adoption decision. They do find that farmers who are more ambiguity averse are less likely to diversify across different crops.

Compared to the present article, both of these articles suffer from a shortfall that neither of these studies focus on a single technology. Therefore, the adoption of innovation is arbitrarily defined. In Knight et al.'s (2003) study, technology adoption is a dichotomous variable that is set equal to 1 if a farmer has adopted at least one new agricultural input (e.g., fertilizer, pesticide, etc.) and one new crop. Engle-Warnick et al. (2006) ask farmers about the crop varieties they had planted during the previous 12-month period, with the technology adoption variable being set equal to 1 if the farmers had planted any modern crop varieties. Since both studies use cross sectional data, and their dependent variable is a dummy variable indicating adoption, when a farmer does not adopt, it could be due to many other reasons. For example, it is unclear whether the diffusions of all these innovations have reached the equilibrium. Moreover, new varieties of crops may not be superior to traditional crops in the surveyed regions, and therefore, non-adoption in the data could simply reflect that farmers do not find it profitable to plant those new crop varieties. My paper does not suffer from the same problem because *ex post* we know that the technology of focus in my study produces higher yields than traditional cotton. By the time the survey was conducted, the Bt cotton adoption rate in the surveyed region was 100%. Therefore, we know it has reached equilibrium. This paper differs from the aforementioned studies in that it is the first empirical paper that provides evidence that PT could play a role in explaining farmers' technology adoption decisions.

3. Background on Bt Cotton and the Bt Cotton Survey

3.1 Background on Bt Cotton

In recent years, China has become both the world's largest cotton producer and consumer. However, cotton bollworm continued to destroy cotton harvests up until the late 1990s due to its ability to quickly build up resistance to pesticides (Karplus & Deng, 2008). Bt cotton, which is bollworm resistant, was developed and tested in trial fields by Chinese scientists in the early 1990s. Bt cotton has been approved for commercial use in the provinces of Anhui, Hebei, and Shandong since 1997, and in Henan since 1999. Although Bt cotton was only commercialized as recently as 1997, the earliest adoption of Bt cotton in my sample occurred in 1993; and by 2004 every farmer in my sample had tried Bt cotton (as evidenced in Figure 1).[7]

The success of Bt cotton is well documented (Bennett, Ismael, & Morse, 2005; Crost et al., 2007; Gandhi & Namboodiri, 2006; Narayanamoorthy & Kalamkar, 2006; Qaim et al., 2006).

According to Huang, et al.'s (2002a) study on Bt cotton production in China, the planting method of Bt and traditional cotton seeds are similar. Upon introduction to the market, Bt cotton was more expensive and required a bit more upfront costs (the equivalent of five to ten days of rural wages) but farmers could save nearly 28% in overall production costs through Bt cotton's lower pesticide and labor costs (Huang, et al., 2002b).

[Insert Figure 1 About Here]

If Bt cotton is such a successful product, then the natural question that arises is how to explain the 10-year lag between the first adopter and the last adopter. One might think that the Chinese government would have played some role in the farmers' decision regarding which type of cotton to plant. However, farmers are free to purchase seeds from various sources such as agricultural extension agents, seed vendors, village offices, seed companies, and other sources. If the government plays any role at all, it would likely exert its influence through village leaders or extension agents to promote Bt cotton, thus expediting the diffusion process, which still does not explain the 10-year adoption delay. Yang et al. (2005) surveyed cotton farmers in Shandong province who did not adopt Bt cotton during the first year it became available. Seventy out of the 72 farmers Yang et al. surveyed cited uncertainty about Bt cotton's efficacy as their main reason for not adopting Bt cotton. This provides more foundation to the conceptual framework used in Section 5.

3.2 Survey Procedure

The Bt Cotton Survey (2006) was designed and conducted by the Center for Chinese Agricultural Policy (CCAP) in Beijing, China. The objective of the CCAP Bt cotton survey in 2006 was to evaluate the performance of the Bt cotton seed. Therefore, four provinces (Henan, Shandong, Hebei, and Anhui) with high Bt cotton adoption rate were chosen to participate in the

CCAP Bt cotton survey.[8] The CCAP selected two counties per province and two villages[9] per county. In each village, twenty households were randomly selected and surveyed. The sample was comprised of a total of 320 households. Within each household we interviewed the family member who was most responsible for the farm work. Survey participants were paid 10 yuan (one third of the provinces' daily wage) for completing the survey.[10] Each survey covered detailed information on household characteristics and individual characteristics.

3.3 Data Description

Table 1 shows the summary statistics for the key variables of interest from the household survey. The average interviewee in the sample has completed slightly more than the equivalent of an elementary school education (7.1 years) and is about 50 years old.[11] 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. In the surveyed region, cotton is the major cash crop and is planted on 0.54 hectares of farmland per household with farmers usually practicing rotational cropping by planting cotton in the spring and wheat in the winter. Ownership of a set of durable goods (DG) is used as a proxy for wealth in 2001 and 2006. DG included in the survey include: a color television, black-and-white television, vcd/dvd player, stereo system/boom box, camera, washer, water heating system, gas stove, refrigerator, car, motorcycle, cellular phone, and air conditioner. In this sample, all the farmers have experience planting Bt cotton seeds in their plots, 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 timing between exposure to Bt cotton and adoption is treated as the outcome of interest. One thing to note is that unlike studies by Suri (2011) and Duflo, Kremer, and Robinson (2008), which find that many farmers switch between adopting and disadopting a new technology, the disadoption rate of Bt cotton in the current study is low. Only 5 out of 320 farmers disadopted Bt cotton in 2006. Therefore, it is particularly interesting to find out when farmers first start planting Bt cotton, given that their decision is rarely retracted (see Liu and Huang (Forthcoming) for information on farm and plot characteristics).

[Insert Table 1 About Here]

4. Field Experiment Design and Procedure

4.1 Design of Field Experiment

All of the farmers who completed the interview also participated in a field experiment, which elicited the farmers' preferences regarding risk. The experimental design follows the methodology developed by TCN (2009). TCN's design has two major advantages:

1. While TCN incorporates PT, it does not reject EU outright. TCN can fall back upon the use of EU theory while measuring three parameters concerning risk preferences in PT: risk aversion, loss aversion, and nonlinear probability weighting.
2. TCN has been tested on Vietnamese subjects who are at a comparable level of education to those in China. Many of the experiments used to elicit risk preferences are done in a lab setting with more educated subjects. TCN is simple enough for less educated subjects to follow and yet allows us to estimate a sophisticated utility function.

Following TCN, I assume a utility function of the following form:

$$U(x,p;y,q)=\begin{cases} v(y)+w(p)(v(x)-v(y)) & x>y>0 \; or \; x<y<0 \\ w(p)v(x)+w(q)v(y) & x<0<y \end{cases} \quad ----Eq(1)$$

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

In the proceeding utility function, x and y are the outcomes and p and q are the probability associated with these outcomes. σ describes the curvature of the value function for an individual in which the individual is risk loving if $\sigma < 0$, risk neutral if $\sigma = 0$, and risk averse if $\sigma > 0$.[12] 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 signifies 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 the function $w(p)$. If $\alpha < 1$, $w(p)$ has an inverted *S*-shape, which indicates an overweighting of low probabilities of the largest gains or biggest losses and an underweighting of high probabilities. If estimates from the experiment give us α = 1 and $\lambda \neq 1$, the above model reduces to expected utility theory.[13]

4.2 Procedures of Experiment

In the current study, participants were given three series of games that contain a total of 35 pair-wise choices. Table 2 illustrates the game's entire payoff matrix. There are three independent series, each of which contain anywhere from 7 to 14 rows, with each row containing 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

The above figure demonstrates how Series 1, row 1 in Table 2 was presented to the subjects. It shows that lottery A offers a 30% chance of receiving 20 yuan and a 70% chance of receiving 5 yuan, while 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 row within the series. I followed TCN procedure by putting 10 numbered balls in a bag and then drawing the balls out of the bag to complete the randomization process. For example, if a subject chooses lottery B for row 1 and the number 3 ball is drawn, he would earn 2.5 yuan. However, if he instead chooses lottery A, drawing the number 3 ball would earn him 20 yuan.

[Insert Table 2 About Here]

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. The record sheet (see Online Appendix available on the author's website), asked subjects at which row (anywhere from row 1 to row 14) they would switch from lottery A to lottery B for Series 1:

I choose lottery A for row 1 to _____.

I choose lottery B for row _____ to 14.

Similar questions about switching points were asked for Series 2. The more risk-averse individuals chose lottery A for a greater number of iterations before switching to lottery B than the less risk-averse individuals in both Series 1 and Series 2. Following TCN's experiment procedure, I assume rationality of subjects. Therefore, each subject is only allowed to switch from lottery A to lottery B once during each series.[14] The option of never switching (always choosing lottery A) or switching at row 1 (always choosing lottery B) were also available to all of the participants.

In order to estimate the parameter of loss aversion, payoffs were made to be positive or negative. Since it would have been unethical to have the farmers who participated in the game pay us money, at the beginning of the game I announced that by participating, the farmers would receive 10 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 (i.e., the farmers will lose money), but the amount lost was calculated to never exceeded the 10 yuan the farmers received for participating in the game. Questions about switching points are also asked during Series 3. The more loss-averse individual would choose to switch from lottery A to lottery B later in Series 3 or never switch at all (always choose lottery A).[15]

Subjects were told that one of the 35 rows would be randomly chosen *ex post* and that the lottery they had selected would be played for actual stakes, with the outcome of that lottery determining their monetary payoff. Out of the 320 farmers who completed the survey, 5 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.[16] More details about the game's procedure are provided in Online Appendix.

4.3 Descriptive Analysis of Game Results

The distributions of switching points are shown in Appendix 1. 7.6% of farmers in our sample chose either only lottery A or only lottery B for all three of the game's series. One concern that arises is that the farmers could have been innumerate and therefore did not understand how the game works.[17] Therefore, as a robustness check in Section 6.4, I excluded from the sample individuals who chose either all lottery A or lottery B and my results remain robust.

4.4 Estimation of Parameters

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 who switches at row *N*, I can conclude that he prefers lottery A over lottery B at row *N* - 1 and prefers lottery B over lottery A at row *N*. I can obtain a set of two inequalities from this switching point.[18] Using a combination of switching points from Series 1 and Series 2, I am able to find the ranges of σ and α that satisfy this pair of inequalities. For example, when a subject switches from lottery A to lottery B at row 7 for both Series 1 and Series 2, I know the following inequalities should be satisfied:

$$5^{1-\sigma} + \exp\,[-(-\ln 0.3)^{\alpha}](20^{1-\sigma} - 5^{1-\sigma}) > 2.5^{1-\sigma} + \exp\,[-(-\ln 0.1)^{\alpha}](62.5^{1-\sigma} - 2.5^{1-\sigma})$$

$$5^{1-\sigma} + \exp\,[-(-\ln 0.3)^{\alpha}](20^{1-\sigma} - 5^{1-\sigma}) < 2.5^{1-\sigma} + \exp\,[-(-\ln 0.1)^{\alpha}](\,75^{1-\sigma} - 2.5^{1-\sigma})$$

$$15^{1-\sigma} + \exp\,[-(-\ln 0.9)^{\alpha}](20^{1-\sigma} - 15^{1-\sigma})$$
$$> 2.5^{1-\sigma} + \exp\,[-(-\ln 0.7)^{\alpha}](32.5^{1-\sigma} - 2.5^{1-\sigma})$$

$$15^{1-\sigma} + \exp\,[-(-\ln 0.9)^{\alpha}](20^{1-\sigma} - 15^{1-\sigma}) < 2.5^{1-\sigma} + \exp\,[-(-\ln 0.7)^{\alpha}](34^{1-\sigma} - 2.5^{1-\sigma}).$$[19]

Parameters that satisfy the above inequalities are 0.26 < σ < 0.35 and 0.66 < α < 0.74. I follow TCN's convention of approximating σ and α by taking the midpoint of the interval to one decimal place. In the above inequalities, we would use 0.3 and 0.7 as our estimates for σ and 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, and I use the midpoint of each interval as the point estimate.[20] For the ease of interpretation, again I use the midpoint of each interval as the point estimate of λ. In this sample, the average of λ is 3.47.[21]

The average of σ is 0.48, indicating that people are risk averse. The average of α is 0.69, meaning that most people in the sample have a tendency of overweighting low probabilities.[22] The distribution of σ, α, and λ parameters are shown in Figure 2. The correlation between σ and λ is 0.16; the correlation between σ and α is 0.03; and the correlation between λ and α is 0.13. As mentioned earlier, if both $\alpha = 1$ and $\lambda = 1$, TCN's value function would reduce to the standard EU function. Using an *F*-test, I can reject the null hypotheses that $\alpha = 1$ and $\lambda = 1$ at the 1% level. Thus, I can conclude that with the TCN experimental setup, PT could describe the Chinese farmers' decisions better than the standard EU function.[23]

[Insert Figure 2 About Here]

4.5 Determinants of Preference Parameter

Table 3 reports the OLS regression result using each of the risk preference parameters as a dependent variable. The explanatory variables I use are age, years of schooling, gender, wealth, religion, time spent on the farm, and land owned. Column 1 presents results using σ as 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.[24] In this sample, the proxy for wealth (i.e., the value of DG per capita in 2006) can predict risk aversion at the 5 percent level. An interesting observation is that twelve people within the sample self-reported as being religious. Since religious practices are typically restricted or prohibited by the Chinese government, truthfully reporting one's religious faith during the survey could be considered a risk-taking action of its own. Indeed, as suggested by Column 1, self-described religious individuals in the sample also express less risk aversion during the game. The coefficient of loss aversion, λ, is the dependent variable in Column 2. A higher λ represents a higher coefficient of loss aversion. Spending more time working on the farm could also predict a higher coefficient loss aversion coefficient. In Column 3, the nonlinear probability weighting parameter, α, is estimated using OLS. The only determinant that can marginally predict the nonlinear probability weighting parameter is education.

[Insert Table 3 About Here]

5. Conceptual Framework

This section introduces a simple conceptual framework through which to understand the role of risk preference parameters in the technology adoption decision process. In the case of Bt cotton planting, there are a few sources of uncertainty that could influence farmers' technology adoption decisions. First, the *ex ante* pest severity during each season is unknown when farmers make their decision about whether or not to grow Bt cotton. Second, although scientific evidence shows that Bt cotton is superior to traditional cotton, for various reasons, the subjective view of yield risk of Bt cotton could be different.[25] For example, farmers might believe that the performance of Bt cotton is plot-specific, or farmers could be skeptical about the extension agents' claims about Bt cotton efficacy since extension agents' salaries are tied to the sales of farming inputs (Huang et al., 2002a).

For simplicity, assume that there is only one type of pest, cotton bollworm. I normalize the sales price of cotton yield as 1 yuan per hectare,[26] and the cost of Bt cotton seeds (per hectare) is C^{BT} yuan; the cost of traditional cotton seeds (per hectare) is C^{T} yuan. The difference in seed price between Bt cotton and traditional cotton is $M = C^{BT} - C^{T}$.

Suppose there are two states of the world, the normal pest level state, in which farmers spray b yuan worth of pesticide per hectare with probability (q) and the severe bollworm infestation state ($1 - q$), in which farmers spray $2b$ yuan worth of pesticide per hectare. I can express the profit of traditional cotton as a lottery, L^{T}, described below:

$$L^T = \begin{cases} \Pr(1-b-C^T) = q \\ \Pr(1-2b-C^T) = 1-q \end{cases}.$$

To capture the uncertainty farmers have about Bt cotton efficacy, as suggested by Yang et al. (2005), the probability of perceived effectiveness is *p* and Bt cotton is perceived as ineffective with probability (1 - *p*). When Bt cotton is effective, farmers do not need to spray any pesticide, but when it is ineffective, farmers need to spray as much pesticide as they use on the traditional cotton. Therefore, we can express Bt cotton's yield as the following lottery:

$$L^{BT} = \begin{cases} \Pr(1-C^{BT}) = p \\ \Pr(1-b-C^{BT}) = (1-p)q \\ \Pr(1-2b-C^{BT}) = (1-p)(1-q). \end{cases}$$

To simplify the notation, if we rescale and set $(1 - b - C^{BT})$ as the reference point, we can then write the lottery as follows:

$$L^T = \begin{cases} \Pr(M) = q \\ \Pr(M-b) = 1-q \end{cases} \qquad L^{BT} = \begin{cases} \Pr(b) = p \\ \Pr(0) = (1-p)q \\ \Pr(-b) = (1-p)(1-q) \end{cases}$$

$$1 > b > 0;\ \ b > M > 0 > M-b > -b;\ \ 1 \geq p \geq 0;\ \ 1 \geq q \geq 0.$$

Let us take a probit approach in which a farmer has to choose either Bt cotton or traditional cotton seeds at the beginning of planting season. A farmer could infer from past experience the size of q, the probability of bollworm pest infestation. A farmer would select Bt cotton if $U(L^{BT}) - U(L^T) > 0$ where U(·) takes the same form as the TCN design in Equation 1. The probability of choosing Bt cotton over traditional cotton is described by the density function: $\Pr(L^{BT}) = F(U(L^{BT}) - U(L^T) > 0).$

From the existing literature on Bt cotton performance in China, we can infer the relative size of *M*, *b*, and *q* (see the work by Huang, et al. (2002a) and Huang, et al. (2002b) on Bt cotton in China). The difference in cost of seeds, *M*, is small relative to the difference in the cost of pesticides, *b*. (1-*q*), the probability of severe bollworm infestation, is also a small probability. We would analyze the adoption decision based on the perceived efficacy of Bt cotton (the size of *p*). For the farmer with risk preference of an average person(σ=0.48, λ = 3.47, and α = 0.69), if he perceives Bt cotton to be ineffective (lim $p \to 0^+$), the model would predict those farmers who are more risk averse, along with farmers who are more loss averse, would be less likely to adopt Bt cotton. It is intuitive that if Bt cotton is ineffective, Bt cotton would have higher yield variance and more likely to lead to losses, therefore, farmers who are more loss averse or more risk averse should not adopt. On the other hand, if the farmer perceives Bt cotton to be effective (lim $p \to 1^-$), Bt cotton would have higher yield and lower variance compared to traditional cotton, therefore, farmers who are more risk averse or more loss averse would be more likely to adopt Bt cotton. The model prediction is ambiguous for the sign of α (see Online Appendix for mathematical derivation).

6. Econometric Framework and Empirical Results

6.1 Econometric Framework

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 & 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:

$$h_i(t \mid X(t), \beta) = h_o(t) \exp\{X_i'(t)\beta\}, \qquad (6.1)$$

where $h_o(t)$ is the baseline hazard. To test whether hazard is time dependent, I use a Weibull baseline hazard specification.

6.2 Basic Specification

The estimates of the parameters of the duration model for Bt cotton adoption and associated standard errors are reported in Table 4. Time of exposure to Bt cotton is defined as the year (1993) before the first subject in the sample adopted Bt cotton. Village fixed-effects are controlled for in all specifications.

[Insert Table 4 About Here]

The main characteristic of interest is individual risk preference. In the existing literature, most studies do not have any control for individual risk preference; therefore, the regression result in Column 1 excludes the risk preferences parameter as a comparison. To interpret the coefficients, I exponentiate coefficients reported in the table obtaining hazard ratios. For example, to interpret the coefficient of σ in Column 2, we need to exponentiate (-0.361) = 0.69. This implies that the risk-averse individual with $\sigma = 1$ in the sample is 31% less likely to adopt Bt cotton than the risk-neutral individual ($\sigma = 0$) at any given time. In Column 3, the result suggests that being one standard deviation (3.92) more loss averse than the average person in the sample would lower the probability of adoption by 12% at any given time. The sample size is smaller than the sample size in Table 3 because the households that were formed after the year of exposure (1993) were dropped.[27]

One caveat about my dataset is that it contains cross-sectional data and the survey was conducted after the adoption of Bt cotton had 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 and are therefore endogenous. However, some demographic variables are less likely to suffer from endogeneity because they are fixed over time. As mentioned earlier, land is assigned to each household and is rather constant over time.[28] Therefore, I can use the size of land reported in my survey as a proxy of land holdings in the past. In the earlier literature on technology adoption, size of land is usually treated as a proxy for wealth (Feder, 1980; Just & Zilberman, 1983). Given China's land assignment policy, farm size may not be a good indicator of wealth. Therefore, it is not surprising that the coefficient on farm size is insignificant.[29]

As previously mentioned, detailed social network information such as the one in Conley and Udry (2010) is missing from the existing survey. It can be a concern that size of social networks may be correlated with risk preferences, and social network is also correlated with technology adoption. I can investigate this extent of this problem in two ways. First, by examining whether risk preferences are correlated with contemporaneous measures of social networks. If it is not correlated with contemporaneous social network proxies, it is less likely that risk preferences would be correlated with social networks prior to adoption. Second, I can include various social network proxies as a regressor in the duration analysis for Bt cotton adoption. I have a few proxies to measure how wide one's social network is. These social network proxies are:

- Whether one is a village official.
- Time to walk to 20 neighbors (this was used in the previous version of the paper).

- Number of weddings attended last year.
- Number of people invited to your family's last festive celebration (e.g. wedding, house warming, baby shower, major birthday, etc.) prior to Bt cotton adoption. This could potentially be a noisy proxy for social network and wealth/credit constraint before Bt cotton adoption.
- A dummy variable indicating whether the interviewee's last name is among the most popular last name in the village.

None of the contemporaneous social network proxies is correlated with the risk aversion coefficient.[30] It suggests that among Chinese cotton farmers sample, risk preferences and various social network measures are uncorrelated.

Moreover, in Table 4, once I control for risk preference, the social network proxy (Time_20 Neighbors) is not statistically significant across all specifications. Potentially, the village official is most likely to have a large social network. I create a dummy variable indicates whether an individual is a village leader or official. Throughout the analysis, the coefficient of the village leader dummy is insignificant and the inclusion of this measure does not affect the magnitude or significance level of the coefficient for risk preferences. I also tried other social network proxies listed above. The coefficients on risk preferences are stable across various measures of social network proxy. The regression results including these additional proxies are available upon request.

As expected, the coefficient on education is positive and significant, indicating that the more educated farmers adopt Bt cotton earlier. However, compared to either of the risk preference parameters, the impact of education is quantitatively small. Having one more year of education would imply a 4.3 percentage point increase in the probability of adopting Bt at any given time. Bt cotton was expected to be less labor intensive than traditional cotton since it does not require as much pesticide. Therefore, we should expect the families which had less available workforce to be more likely to adopt Bt cotton, thus implying a negative coefficient. The number of adults older than 28 years of age is a proxy for the families' labor force participation a decade ago. As predicted, the coefficient on this proxy is negative and significant at the 10% level.

In Columns 5 and 6 of Table 4, 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 for Column 6, in which a dummy variable equal to 1 indicates an individual who puts excessive decision weight on small probabilities ($\alpha < 1$) and a dummy variable equal to z0 indicates an individual who does not overweight small probabilities ($\alpha \geq 1$). Results from Columns 5 and 6 suggest that individuals who overweight small probabilities are more likely to adopt Bt cotton at any given time than individuals who do not overweight. It suggests that the farmers who overweight the probability of a severe pest infestation would be those farmers who are more likely to adopt the Bt cotton.

6.3 Wealth Measure

One variable I would like to include in the specification, but which is not available in this dataset, is a measure of wealth prior to Bt cotton adoption. Existing studies suggest that wealth affects technology adoption because it is associated with credit constraints (which we did not ask about in this dataset) and greater access to resources. To deal with this possible concern, I present two robustness checks in this section.

First, ideally I would like to include a measure of baseline wealth. The only proxy I have is information about each household's ownership of DG in 2001.[31] However, the interpretation of this coefficient on *ex post* wealth measure requires caution. In Columns 1 and 2 of Table 5, I present results with the number of DG owned in 2001 as a proxy for baseline wealth. Using this proxy for wealth, I implicitly give the same weight to each DG when I measure household wealth. Certainly, there are some DG 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 principal components analysis. I use these wealth indices 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 risk preferences parameters are robust to including this measure of wealth in the specification.

[Insert Table 5 About Here]

Second, if one supposes that credit constraints are correlated with risk preferences and negatively correlated with technology adoption, then this leads to a bias in the estimates. Credit constraints for adoption decisions are less likely to play a role in wealthier farm households, and as a result the estimate bias should be minimal among the wealthier households. Therefore, in the following analysis, I restrict the sample to the wealthier households in 2001. The results with only the top 33rd percentile of wealthy householdsare presented in Column 5 and the results with only the top 25th percentile of wealthy households are presented in Column 6. While the smaller sample sizes increase standard errors, the sign across all risk attitudes parameters are consistent. More importantly, risk aversion, which is most susceptible to being a biased estimate, remains significant at a 5% level.

In addition, 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-nothing decision. As stated above, if the farmers were to plant only Bt cotton in the earlier year, it would cost him about five to ten days worth of wages. If the farmers were truly credit constrained, but would like to try Bt cotton seeds, they could still purchase a small amount, in lieu of traditional cotton, with which to experiment. In my study, given that I only measure time to adoption, these farmers would have been recorded as switching to Bt cotton. Therefore, credit constraint is not a sufficient explanation for why Chinese cotton farmers delayed their decision to adopt Bt cotton. I test several measures of wealth as a proxy for baseline wealth and find that the results for risk preferences to be robust. I also have tried leaving out wealth in the regression and the regression results were robust. Given the lack of a compelling reason to incorporate an endogenous wealth measure, I leave out the wealth measure from the remainder of the study.[32]

6.4 Robustness Check-Other Concerns

In this sample, twenty farmers adopted Bt cotton before it was commercialized. One could suspect that these farmers who were able to obtain the seeds prior to official commercialization could possibly have behaved differently from the rest of the sample. As a robustness check, I exclude these individuals from the sample and redefine the time of exposure as 1996 for everyone in the sample; the results are presented in Column 1 of Table 6. The interpretations of the coefficients do not vary too much from regression results with the full sample.

[Insert Table 6 About Here]

Whether these farmers understand how the game works 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 do not understand the game, they add noise to the estimates. As long as their choices during the experiment are not systematically correlated with their adoption decisions, coefficients are not biased.[33] In Column 2, I exclude those 7.6% of individuals from the full sample. The impacts of risk aversion and loss aversion coefficients on technology adoption are even more prominent compared to the similar specification with the full sample in Table 5. In Column 3 of Table 6, I cluster the standard errors at the village level and all the coefficients remain robust.

The specification above, without the individuals who seem to have trouble understanding the game, could be preferable. In the following regressions, I exclude those individuals again. Up until this point, time of exposure to Bt cotton is defined as the year (1993) before the first person in the sample adopted it. It is possible that Bt cotton may not have been available to all farmers at that time, especially considering that this survey covers four provinces. Therefore, I redefine the exposure date as the year before the first person adopted Bt cotton in each province. Results are shown in Column 4 of Table 6. In Column 5, the exposure date is defined as the year before the first person adopted Bt cotton in that county.[34]

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 toward risk and Bt cotton adoption decision making.

6.5 Robustness Check-Specification

In this section, I estimate these relationships by using different specifications. So far, my parametric estimates of the hazard model assume that $h_o(t)$ in Equation 6.1 follows a Weibull distribution. I relax this assumption by estimating the Cox proportional hazard model (Cox, 1972). Column 6 in Table 6 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 remains negative but insignificant. The coefficients on λ and α both remain robust.[35] In Section 6.2, when I assume a Weibull hazard model, I find that hazard of adoption is time dependent and increases over time. The results from σ, λ, and α are not particularly sensitive to the functional form of the baseline hazard I use.

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 any predictions for the adoption decision without having to assume a specific utility functional form. Therefore, as a robustness check without using any function form, I divide the subjects into 18 groups based on the sets of switching points across the three elicitation tasks (see Figure 3). Individuals who choose to switch to the riskier lottery option during the first iteration for all three series would belong to group 1 (the most risk-seeking group); individuals who choose to never switch in all three series would belong to group 18 (the most risk-averse group). The advantage of this simple division of the subjects into 18 groups is that we can capture nonparametric representation of risk preferences from the experiment instead of using labels such as risk aversion, loss aversion, and nonlinear probability weighting. In the duration model, instead of using three risk preference parameters, I replace them with 17 dummy variables. The estimated coefficients on the dummy variables are reported in Table 7, and the number of observations in each group is reported in brackets. It is less meaningful and intuitive to interpret the coefficients in Table 7. More important, an *F*-test rejects the null hypothesis that the 17 dummy variables are jointly equal to zero at a 99.9% confidence level. It is solid evidence that the design of this field experiment plays some role in farmers' adoption decision even after controlling for village fixed effect and farmers' individual characteristics.

[Insert Figure 3 About Here]

[Insert Table 7 About Here]

Now that I have demonstrated the connection between the TCN field experiment and technology adoption, the next step is to confirm if the risk preference parameters under the taxonomy of PT can capture the essence of the game and provide us with a more meaningful interpretation than the group dummy variables Therefore, I perform a horse race between the full specification model (including the 17 dummy variables and the 3 risk preference parameters as regressors) and the nested specification model (which includes only 3 risk preference parameters). Since the latter model is the nested model of the full specification, I can test these two competing specifications.[36] The result from the likelihood ratio test indicates that adding the 17 dummy variables does not improve the fit of the model at the 5% level, compared with a model containing only 3 risk preference parameters.

Using the result from the *F*-test, I can conclude that the nonparametric results from this experiment (represented by simply dividing them into groups) still provide some predictions for the timing of adoption. Furthermore, with the result from the likelihood ratio test, I can conclude that these 3 risk preference parameters derived from the structured value function have already captured the essence of this game without using the non-structured, group dummy variables.

6.6 Further Discussion

One concern regarding this study is that I only have *ex post* measures of attitudes toward risk. This situation might be problematic if risk preferences have changed because of farmers' adoption decisions. While it is probable, in the context of this study, has all of the farmers had adopted Bt cotton by the time the risk experiments were conducted. Therefore, unless the timing of Bt cotton adoption has a differential impact on risk preferences, it is less of a concern.[37] 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 beyond the scope of this paper.

The lack of a baseline wealth measure may seem to pose a 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 suffer from upward bias. On the other hand, it is also possible that farmers can save money from lesser pesticide costs after adopting Bt cotton seeds, resulting in the more credit-constrained farmers possibly having greater incentives to use Bt cotton seeds, and thus adopting Bt cotton earlier. In this case, the coefficients would suffer from a downward bias. Overall, it is difficult to determine the direction of this omitted-variable bias. However, as explained earlier (Section 6.3), farmers could sow a portion of their farmland with Bt cotton seeds according to what their budget constraints allow. 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 instead of risk aversion, uncertainty aversion (ambiguity aversion) might be at play in this context. A commonly used definition that distinguishes risk versus (Knightian) uncertainty is that "risk is imperfect knowledge where the probabilities of the possible outcomes are known, and (Knightian) uncertainty exists when these probabilities are unknown" (Hardaker et al., 1997).[38] When farmers need to make the adoption decision, they do not have perfect information on the distribution of cotton yields, and therefore, uncertainty aversion (ambiguity aversion) should be the key factor in their technology adoption decisions. Even if one believes that uncertainty aversion ought to play a more prominent role, we find that the results are significant across various specifications, and this could suggest that the risk aversion measures from the experiment are a good proxy for uncertainty aversion.

Lastly, the model suggests that the subjective view of yield risk of Bt cotton could be different from the objective risk of Bt cotton. One factor that can drive farmers to have biased subjective view could be due to the lack of trust of extension agents, whose salaries are tied to the sales of farming inputs (Huang et al., 2002a). One's attitude of trust could potentially play an important role in farmers' adoption decision. However, with the current dataset, I cannot further test this hypothesis.[39]

7. Conclusion

In this paper, I find that farmers with higher risk aversion or higher loss aversion adopt Bt cotton later, while farmers who overweight small probabilities adopt Bt cotton earlier. In other words, the less risk-averse or less loss-averse farmers would be able to accumulate more wealth from this technological innovation by adopting it earlier. Given that Bt cotton is no riskier than traditional cotton, the findings suggest that the farmers' perceived risk and potential loss influence their technology adoption decisions.

The above findings have important policy implications. 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. 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 levels of education to understand.[40] From a business point of view, as suggested in Sunding and Zilberman (2001), seeds with money-back guarantees can be a means to persuade farmers to try the new seeds. In terms of reducing the perceived risk associated with the new technology, the government can set up demonstration plots in each village. Demonstration plots would help farmers understand the characteristics of the new technology within a growing condition that is similar to their own. Standards of living across different continents were quite similar up until the rate of technological progress increased dramatically in the nineteenth century. Many economists have sought to uncover the underlying reasons for this disparity in wealth accumulation and economic growth in the past two centuries. Some economists have alluded to cross-country differences in technology adoption (Comin & Hobijn, 2004). The findings in the current paper suggest that less risk-averse or less loss-averse farmers could accumulate more wealth be more quickly embracing technological innovations. If risk attitudes are transmitted across generations from parents to children as suggested by Dohmen et al. (2008) and Cesarini et al. (2009), we would see persistence in intergenerational poverty or widening inequality over time. Therefore, understanding the role of risk preference in technology adoption could help us understand developing countries' persistent poverty.

REFERENCES

Aldana, Ursula, Bradford Barham, Jeremy Foltz and Pilar Useche (2009): "The Dynamics of GM Corn Adoption in Minnesota and Wisconsin: Stacked Varieties, Sequential Adoption, and Learning." *University of Wisconsin*.

Antle, John M. (1987): "Econometric Estimation of Producers' Risk Attitudes," *Am.J.Agric.Econ.*, 69(3), 509-522.

Appleton, Simon, Lina Song and Qingjie Xia (2005): "Has China crossed the river? The evolution of wage structure in urban China during reform and retrenchment,"*Journal of Comparative Economics*, 33(4), 644-663.

Barrett, Christopher B. and Christine. M. Moser (2003): "Better Technology, Better Plots or Better Farmers? Identifying Changes in Productivity and Risk Among Malagasy Rice Farmers," American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association).

Battalio, Raymond C., John H. Kagel and Komain Jiranyakul (1990): "Testing between alternative models of choice under uncertainty: Some initial results," *Journal of Risk and Uncertainty*, 3(1), 25-50.

Bellemare, Marc F. (2009): "When Perception is Reality: Subjective Expectations and Contracting," *American Journal of Agricultural Economics, Forthcoming*.

Bellemare, Marc F. and Zachary S. Brown (2009): "On the (Mis)Use of Wealth as a Proxy for Risk Aversion," *American Journal of Agricultural Economics, Forthcoming*.

Benjamin, Daniel J., Sebastian. Brown and Jess Shapiro (2006): "Who is ‘Behavioral’? Cognitive Ability and Anomalous Preferences," Harvard University mimeo.

Bennett, Richard, Yousouf Ismael and Stephen Morse (2005): "Explaining contradictory evidence regarding impacts of genetically modified crops in developing countries. Varietal performance of transgenic cotton in India," *The Journal of Agricultural Science*, 143(01), 35-41.

Besley, Timothy and Anne Case (1993): "Modeling Technology Adoption in Developing Countries," *Am.Econ.Rev.*, 83(2), 396-402.

Binswanger, Hans P. (1980): "Attitudes toward Risk: Experimental Measurement in Rural India," *Am.J.Agric.Econ.*, 62(3), 395-407.

Brandt, Loren, Jikun Huang, Guo Li and Scott Rozelle (2002): "Land Rights in China: Fact, Fiction, and Issues," *China Journal*, 18, 67-97.

Camerer, Colin F. (1989): "An experimental test of several generalized utility theories," *J.Risk Uncertainty*, 2(1), 61-104.

Camerer, Colin, Linda Babcock, George Loewenstein and Richard Thaler (1997): "Labor Supply of New York City Cabdrivers: One Day At A Time*," *Quarterly Journal of Economics*, 112(2), 407-441.

Camerer, Colin F. and Robin M. Hogarth (1999): "The Effects of Financial Incentives in Experiments: A Review and Capital-Labor-Production Framework," *Journal of Risk and Uncertainty*, 19(1), 7-42.

Camerer, Colin and Martin Weber (1992): “Recent developments in modeling preferences: Uncertainty and ambiguity”. *Journal of Risk and Uncertainty, 5*(4), 325-370.

Cardenas, Juan C. and Jeffrey Carpenter (2008): Behavioural development economics: Lessons from field labs in the developing world. *Journal of Development Studies, 44*(3), 311-338.

Cesarini, David, Christopher T. Dawes, Magnus Johannesson, Paul Lichtenstein and Bjorn Wallace (2009): "Genetic Variation in Preferences for Giving and Risk Taking*," *Quarterly Journal of Economics*, 124(2), 809-842.

Cole, Shawn A., Xavier Gine, Jeremy Tobacman, Petia Topalova, Robert Townsend and James Vickery (2009): "Barriers to Household Risk Management: Evidence from India." *Harvard Business School Working Paper, No. 09-116*.

Comin, Diego, and Hobijn, Bart (2004): Cross-country technology adoption: Making the theories face the facts. *Journal of Monetary Economics, 51*(1), 39-83.

Conley, Timothy and Christopher Udry (2010): "Learning about a new technology: Pineapple in Ghana," *American Economic Review,* 100(1), 35-69(35).

Cox, David R. (1972): "Regression Models and Life-Tables," *Journal of the Royal Statistical Society B*, 34, 187-200.

Croppenstedt, Andre, Mulat Demeke and Meloria M. Meschi (2003): "Technology Adoption in the Presence of Constraints: the Case of Fertilizer Demand in Ethiopia," *Review of Development Economics*, 7(1), 58-70.

Crost, Benjamin and Bhavani Shankar (2008): "Bt-cotton and production risk: panel data estimates," *International Journal of Biotechnology*, 10, 122-131(10).

Crost, Benjamin, Bhavani Shankar, Richard Bennett and Stephen Morse (2007): "Bias from Farmer Self-Selection in Genetically Modified Crop Productivity Estimates: Evidence from Indian Data," *Journal of Agricultural Economics*, 58(1), 24-36.

De Janvry, Aain, Gregory Graff, Elisabeth Sadoulet and David Zilberman (2000): "Technological Change in Agriculture and Poverty Reduction," Concept paper for the World Development Report on Poverty and Development, 2000/2001, University of California at Berkeley/World Bank.

Deck, Cary A. and Harris Schlesinger (2010): "Exploring Higher-Order Risk Effects," *Review of Economic Study*, 77(4), 1403-1420.

Dercon, Stefan, Jan W. Gunning, and Andrew Zeitlin (2011). *The demand for insurance under limited credibility: Evidence from kenya.* Unpublished manuscript.

Dohmen, Thomas, Armin Falk, David Huffman and Uwe Sunde (2008): "The Intergenerational Transmission of Risk and Trust Attitudes," CESifo Group Munich.

Duflo, Esther, Michael Kremer and Jonathan Robinson (2008): "How High Are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya," *American Economic Review*, 98(2), 482-488.

Ebert, Sebastian and Daniel Wiesen (2009): "An experimental methodology testing for prudence and third-order preferences," University of Bonn, Germany.

Engle-Warnick Jim, Javier Escobal and Laszlo Sonia (2006): "Ambiguity Aversion as a Predictor of Technology Choice: Experimental Evidence From Peru," Departmental Working Paper, McGill University, Department of Economics.

Epstein, Larry G. (1999): "A Definition of Uncertainty Aversion," *The Review of Economic Studies*, 66(3), 579-608.

Farber, Henry S. (2008): "Reference-Dependent Preferences and Labor Supply: The Case of New York City Taxi Drivers," *The American Economic Review*, 98, 1069-1082(14).

Feder, Gershon. (1980): "Farm Size, Risk Aversion and the Adoption of New Technology Under Uncertainty," *Oxford Economic Papers*, 32(2), 263-283.

Feder, Gershon, Richard E. Just and David Zilberman (1985): "Adoption of Agricultural Innovations in Developing Countries: A Survey," *Economic Development & Cultural Change*, 33(2), 255.

Fehr, Ernst and Lorenz Goette (2007): "Do Workers Work More if Wages Are High? Evidence from a Randomized Field Experiment," *American Economic Review, 97*(1), 298-317.

Filmer, Deon and Lant H. Pritchett (2001): "Estimating Wealth Effects without Expenditure Data-or Tears: An Application to Educational Enrollments in States of India," *Demography*, 38(1), 115-132.

Food and Agriculture Organization of the United Nations (2004): "The State of Food and Agriculture 2003-2004. Agricultural biotechnology: Meeting the needs of the poor?" FAO.

Foster, Andrew D. and Mark R. Rosenzweig (1996): "Technical Change and Human-Capital Returns and Investments: Evidence from the Green Revolution,"*Am.Econ.Rev.*, 86(4), 931-953.

Foster, Anrew D. and Mark R. Rosenzweig (1995): "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture," *The Journal of Political Economy*, 103(6), 1176-1209.

Gandhi, Vasant P. and N. V. Namboodiri (2006): "The Adoption and Economics of Bt Cotton in India: Preliminary Results from a Study," Indian Institute of Management Ahmedabad, Research and Publication Department.

Gonzalez, Richard and George Wu (1999): "On the Shape of the Probability Weighting Function," *Cognitive Psychology*, 38(1), 129-166.

Griliches, Zvi (1957): "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica*, 25(4), 501-522.

Hannan, Timothy H. and John M. McDowell (1984): "The Determinants of Technology Adoption: The Case of the Banking Firm," *Rand J.Econ.*, 15(3), 328-335.

Hardaker, Brian J., Ruud B.M. Huirne, Jock R.Anderson and Gudbrand Lien(1997): "Coping with Risk in Agriculture," CAB International.

Harrison, Glenn W., Eic Johnson, Melayne M. McInnes and E. Elisabet Rutström (2005): "Risk Aversion and Incentive Effects: Comment," *Am.Econ.Rev.*, 95(3), 897-901.

Harrison, Glenn W. and John A. List (2004): "Field Experiments," *Journal of Economic Literature*, 42(4), 1009-1055.

Harrison, Glenn and Elisabet Rutström (2009): "Expected utility theory and prospect theory: one wedding and a decent funeral," *Experimental Economics*, 12(2), 133-158.

Hershey, John C. and Paul J. H. Schoemaker (1980): "Risk Taking and Problem Context in the Domain of Losses: An Expected Utility Analysis," *J.Risk Insur.*, 47(1), 111-132.

Holt, Charles. A. and Susan K. Laury (2002): "Risk Aversion and Incentive Effects," *American Economic Review, 92*(5), 1644-1655.

Horowitz, John K. and Erik Lichtenberg (1993): "Insurance, Moral Hazard, and Chemical Use in Agriculture," *Am.J.Agric.Econ.*, 75(4), 926-935.

Huang, Jikun, Scott. Rozelle, Carl E. Pray,and Qinfang Wang, (2002a): "Plant biotechnology in China," *Science*, 295(25), 674-677.

Huang, Jikun, Ruifa. Hu, Scott. Rozelle, Fangbin Qiao and Carl E. Pray (2002b): "Transgenic varieties and productivity of smallholder cotton farmers in China," *Australian Journal of Agricultural & Resource Economics*, 46(3), 367-387.

Huffman, Wallace. E. (2001): "Human capital: Education and agriculture," in *Handbook of Agricultural Economics; Handbook of Agricultural Economics*, ed. by B. L. Gardner and G. C. Rausser: Elsevier.

Jaeger, David A, Thomas. Dohmen, Armin Falk, David Huffman Uwe Sunde and Holger Bonin (2010): "Direct Evidence on Risk Attitudes and Migration," *Review of Economics and Statistics*. 92(3), 684-689.

Just, Richard E. and David Zilberman (1983): "Stochastic Structure, Farm Size and Technology Adoption in Developing Agriculture," *Oxford Economic Papers*, 35(2), 307-328.

Kahneman, Daniel, Jack L. Knetsch and Richard H. Thaler (1990): "Experimental Tests of the Endowment Effect and the Coase Theorem," *The Journal of Political Economy*, 98(6), 1325-1348.

Kahneman, Daniel and Amos Tversky (1979): "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47(2), 263-291.

Kalaitzandonakes, Nicholas G. (2003): "The economic and environmental impacts of agbiotech: An introduction," in The Economic and environmental impacts of agbiotech, ed. by N.G. Kalaitzandonakes: Kluwer Academic.

Karplus, Valerie J. and Xing Wang Deng (2008): "Agricultural biotechnology in China : origins and prospects." Springer.

Knight, Frank (1921): *Risk, uncertainty and profit*. Boston, MA: Schaffner & Marx.

Knight, John, Sharada Weir and Tassew Woldehanna (2003): "The Role of Education in Facilitating Risk-Taking and Innovation in Agriculture," *Journal of Development Studies*, 39(6), 1-22.

Krishna, Vijesh V., David Zilberman and Matin Qaim (2009): "GM Technology Adoption, Production Risk and On-farm Varietal Diversity," Agricultural and Applied Economics Association.

Liu, Elaine and Jikun Huang (Forthcoming): “Risk preferences and pesticide use by cotton farmers in China”, Journal of Development Economics

Lybbert, Travs J. and David R. Just (2007): "Is Risk Aversion "Really" Correlated with Wealth? How Estimated Probabilities Introduce Spurious Correlation," *American Journal of Agricultural Economics*, 89(4), 964-979.

McInish, Thomas H., Sridhar N. Ramaswami and Rajendra K. Srivastava (1993): "Do More Risk-Averse Investors Have Lower Net Worth and Income?" *The Financial Review*, 28(1), 91-106.

Moscardi, Edgardo and Alain de Janvry (1977): "Attitudes toward Risk among Peasants: An Econometric Approach," *Am. J. Agric. Econ.*, 59(4), 710-716.

Mosley, Paul and Arjan Verschoor (2005): “*The Development of Trust and Social Capital in Rural Uganda: An Experimental Approach.”* The University of Sheffield, Department of Economics.

Mullainathan, Sendhil (2004): "Psychology and Development Economics," Unpublished Manuscript.

Munshi, Kaivan (2004): "Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution," *Journal of Development Economics*, 73(1), 185-213.

Narayanamoorthy, A. and S. S. Kalamar (2006): "Is Bt cotton cultivation economically viable for Indian farmers? An empirical analysis," *Economic and Political Weekly*, 41, 2719-2774.

Novemsky, Nathan and Daniel Kahneman (2005): "The Boundaries of Loss Aversion," *Journal of Marketing Research (JMR)*, 42(2), 119-128.

Pemsl, Diemuth (2006): "Economics of Agricultural biotechnology in Crop Protection in Developing Countries- The Case of Bt Cotton in Shandong Province, China," Publication Series, Special Issue No. 11, Hannover, Pesticide Policy Project.

Pray, Carl, Danmeng. Ma, Jikun Huang and Fangbin Qiao (2001): "Impact of Bt Cotton in China," *World Development*, 29(5), 813-825.

Prelec, Drazen (1998): "The Probability Weighting Function," *Econometrica*, 66(3), 497-527.

Qaim, Matin, Arjunan Subramanian, Gopal Naik and David Zilberman (2006): "Adoption of Bt Cotton and Impact Variability: Insights from India," *Review of Agricultural Economics*, 28(1), 48-58.

Rabin, Mattthew (2000): "Risk Aversion and Expected-utility Theory: A Calibration Theorem," *Econometrica*, 68(5), 1281-1292.

Rizzo, John A. and Richard J. Zeckhauser (2003): "Reference Incomes, Loss Aversion, and Physician Behavior," *Review of Economics and Statistics*, 85(4), 909-922.

Rosenzweig, Mark R. and Hans P. Binswanger (1993): "Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments," *Economic Journal*, 103(416), 56-78.

Rozelle, Scott., J. Edward Taylor .,and Alan.deBrauw (1999): "Migration, Remittances and Agricultural Productivity in China," *American Economics Review Papers and Proceeding*, 89(2), 287-292.

Saha, Atanu (1993): "Expo-Power Utility: A ‘Flexible’ Form for Absolute and Relative Risk Aversion," *American Journal of Agricultural Economics*, 75(4), 905-913.

Samuelson, William and Richard Zeckhauser (1988): “Status quo bias in decision making,” *Journal of Risk & Uncertainty, 1*(1), 7.

Shaw, Kathryn L. (1996): "An Empirical Analysis of Risk Aversion and Income Growth," *Journal of Labor Economics*, 14(4), 626-653.

Sunding, David and David Zilberman (2001): "The Agricultural Innovation Process: Research and Technology Adoption in a changing agricultural sector," in Handbook of Agricultural Economics, edition 1, volume 1, ed. by B.L. Gardner and G.C. Rausser, Elsevier.

Suri, T. (2011). Selection and comparative advantage in technology adoption. Econometrica, 79(1), 159-209.

Tanaka, Tomomi, Colin Camerer and Quang Nguyen (2009): "Poverty, politics, and preferences: Field experiments and survey data from Vietnam," *The American Economic Review*.

Telser, Lester G. (1955): "Safety First and Hedging," *The Review of Economic Studies*, 23(1), 1-16.

Tversky, Amos. and Daniel Kahneman (1992): "Advances in Prospect Theory: Cumulative Representation of Uncertainty," *Journal of Risk & Uncertainty*, 5(4), 297-323.

Yang, Dennis T. (1997): "Education and Off-Farm Work," *Economic Development and Cultural Change*, 45(3), 613-632.

Yang, Puyun, Malcolm Iles, Su Yan and Flavia Jolliffe (2005): "Farmers' knowledge, perceptions and practices in transgenic Bt cotton in small producer systems in Northern China," *Crop Protection*, 24(3), 229-239.

.

[1] Starting with Griliches (1957); for more papers, see Conley and Udry (forthcoming), Besley and Case (1993), Munshi (2004), Suri (2011), and Duflo, Kremer, and Robinson (2008).

[2] Methods of eliciting the farmers' risk attitudes usually fall into two categories. The first approach imposes assumptions and imputes risk preferences from the standard household survey (Antle, 1987; Moscardi & de Janvry, 1977). However, this method suffers from serious drawbacks (see discussion in Lybbert & Just, 2007; Bellemare & Brown, 2009). The second approach follows Binswanger's (1980) method of using risky choices with different expected payoffs and variance. I decided to pursue the experimental elicitation method in the current study.

[3] With a back-of-the-envelope calculation, I estimated that to use Bt cotton seeds in a farmer's entire plot would cost about 118 yuan (equivalent to 5-10 days worth of wages in 1995) more than the traditional cotton seed. Calculations follow below:

The average farmer in the sample plants 0.54 ha of cotton.

Upfront cost:

Bt cotton seeds cost – Traditional cotton seeds cost:

0.54 ha * (547 yuan/Ha - 327 yuan/Ha) = 118 yuan (~5 to 10 days of wages)

Saving (Bt cotton kills bollworm pest and thus requires less pesticide):

Bt cotton pesticide cost - Traditional cotton pesticide cost:

0.54 ha * (244 yuan/Ha – 1996 yuan/Ha) = -946 yuan

The seed and pesticide costs are from Pray et al.'s (2001) article which was imputed using survey data from China in 1999 and represents one of the earliest dataset available on Bt cotton in China. One hundred and eighteen yuan is valued at about 10 days worth of wages in 1990 using Yang's (1997) rural income measure for Chinese households or 5 days worth of wages in 1995 using Appleton, Song, and Xia's (2005) income measure.

[4] By Harrison and List's (2004) proposed taxonomy of field experiment, the more formal way of describing the experiment I use should be an arte-factual field experiment since it is essentially a lab experiment, but it is done with a nonstandard subject pool. In the remainder of the paper, I will simply refer to it as a field experiment.

[5] Several studies such as Benjamin, Brown, and Shapiro (2006), Harrison and Rutström (2009), and List (2003) have shown that some subjects would behave more in line with EU theory than PT. In particular, Benjamin et al (2006) and List (2003) have shown that the more sophisticated subjects would behave more in line with EU theory.

[6] Ambiguity (also known as Knightian uncertainty) aversion refers to the aversion to outcomes with unknown distribution, whereas, risk aversion refers to the aversion to risky outcomes with known distribution. Interested readers can refer to Frank Knight's seminal work in 1921 and Camerer and Weber's (1992) provide a survey of the more recent and innovative work on ambiguity and risk.

[7] Approximately 16% of households had adopted Bt cotton prior to governmental approval. My communications with farmers suggested that they were not aware of the illegality of Bt cotton seeds before 1997. Pemsl (2006) conducted her field study in Shandong and encountered similar findings.

[8] See Online Appendix for a map of China with cotton production regions and the location of

survey sites.

[9] One concern that has been raised is the survey's representativeness. In any study involving intensive, lengthy surveys such as this, one is necessarily constrained to choose a location that will be cooperative. The villages and counties selected were places in which it was feasible to implement the survey. I was responsible for the administration and execution of the survey, eliminating the possibility that a local bureaucrat could manipulate the data within any particular village. Moreover, in terms of the survey's representativeness, I compared this dataset with the China Health and Nutrition Survey (CHNS) dataset. CHNS is a large-scale, multistage, random cluster sample that is representative at the provincial level. CHNS overlaps with my samples in Shandong and Henan provinces in 2006, allowing me to compare the variables that are available in both samples. When I restrict the CHNS sample to farm households and compare it with my sample in Shandong and Henan provinces, I fail to reject the null hypothesis that the samples from my survey and CHNS are the same in terms of education level and household size.

[10] 1USD ≈ 7.88 yuan (as of November 1, 2006).

[11] The sample is relatively old since migration of young men out of villages is common (Rozelle, Taylor & de Brauw, 1999).

[12] 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 EU under constant relative risk aversion (CRRA) in which $u(x) = x^{1-\sigma}/(1-\sigma)$, I rewrite the value function as $v(x) = x^{1-\sigma}$.

[13] This functional form, assuming that people are risk-loving for losses and risk-averse for gains, comes from PT and is referred to as the reflection effect. See Kahneman and Tversky (1979) for a more detailed discussion. See Hershey and Schoemaker (1980), Battalio, Kagel, and Jiranyakul

(1990), and Camerer (1989) for further empirical evidences of reflection effect. With $\lambda = 1$ and $\alpha = 1$, it reduces to a particular utility functional form.

[14] It is also known as monotonic switching. There are debates in the literature as to whether to force monotonic switching. I decided to enforce monotonic switching because it is the first time the TCN experiment has been used (other than to their Vietnam subjects). Supposing I had not used monotonic switching, and the results are dramatically different from TCN's Vietnam results, then it would not be clear whether it is due to an incorrect execution of the experiments, the individuals not understanding the experiment, or innate differences between the preferences of Chinese versus Vietnamese. Having known that the TCN experiment was run smoothly in Vietnam with subjects that are comparable in education level to those in this study is one of the main reasons why I chose this experiment design. Therefore, I decided to adhere to their protocol.

[15] As Camerer (1989) points out, losses that are in fact net gains, such as in Series 3, may be treated differently from real losses. This is a typical problem with any experiment involving monetary losses. Farmers are told the 10 yuan was given to compensate for their time spent with the experimenters in the hopes that the farmers would not treat as a windfall gain. If farmers still treat the 10 yuan payment as a windfall gain, it is more difficult to find the existence of a kink around zero.

[16] Holt and Laury (2002) find evidence that individuals exhibit more risk aversion in high-stakes games. Since I wish to relate the game results to their farming decisions, I 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. Using high monetary payoff is better than asking risk preference questions on the survey with

hypothetical payoff since the survey questions are not incentive compatible and there are many reasons why the actual payoff could generate a less noisy risk preference measure compared to the hypothetical payoff (Camerer & Hogarth, 1999).

[17] A dummy variable that is equal to one when the subject chose only lottery A or only lottery B throughout all three series is constructed. I find that individuals with higher education are less likely to choose only lottery A or only lottery B throughout all three series.

[18] In the case of "never switch" or "switching at row 1," I have one inequality. Thus, I arbitrarily determine the lower/upper bound of the parameters, which is also TCN's approach. This arbitrariness could create noise in the data, thus in the robustness check in Table 6, I report regression results leaving out these individuals.

[19] I follow TCN convention using the income from the game, rather than income plus existing wealth level to estimate one's utility functional form. While it is a standard approach in the experimental economics literature (Holt & Laury, 2002). In particular, in studies related to loss aversion, Rabin (2000) points out that individual utility is determined by change of wealth rather than the absolute wealth level. In the empirical analysis, I also did various specifications controlling for the initial wealth.

[20] More details about estimation method can be found in Tanaka et al. (2009).

[21] Our estimates is higher than the conventional loss aversion coefficients ($\lambda \sim 2$) from studies performed in developed countries (Novemsky & Kahneman, 2005).

[22] The TCN Vietnam sample consists of people in all professions. In their farmer subsample, the estimate of (1-σ), which is comparable to σ in this paper, is 0.40; their estimate of α is 0.75 and their estimate of λ is 3.00.

[23] The ongoing debate between PT and EU is not this paper's focus. The above results could

only reject one specific standard EU functional form. However, there are many other forms of utility functions, including those presented in Saha (1993), random utility model, and EU with prudence measure. One can probably construct a theoretical EU model involving prudence that would cause farmers to adopt the technology later without invoking the use of PT. Empirically, it would be difficult to test the model since there are few experiments which are designed to elicit the measure of prudence (Deck & Schlesinger, 2010) and none of the papers have gone through a peer-review process. It is far beyond the scope of this paper to take a stand on whether EU or PT is better. I can only cautiously conclude that in this particular sample with the TCN utility function and setup, PT describes farmers' decisions better than EU.

[24] While Binswanger (1980) and Mosley and Verschoor (2005) find no correlation between wealth and risk aversion, Rosenzweig and Binswanger (1993) suggest that wealthier households invest in riskier activities. See the survey by Cardenas and Carpenter (2008) for further discussion.

[25] Various empirical studies such as Bellemare (2009), Cole et al (2009), Lybbert & Just (2007) have shown the importance of subjective expectation when farmers make farming decisions.

[26] Cotton market buyers do not differentiate between Bt and traditional cotton. Therefore, the price of Bt and traditional cotton are the same. The sensitivity to soil condition, water, and fertilizer inputs for both Bt cotton seeds and traditional cotton seeds are the same. Therefore, the yield of Bt cotton and traditional cotton without pests present would have been the same.

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

[28] Although there were some incidents of land redistribution over time, unfortunately, the dataset does not have information on land redistribution that may have taken place in the village. In the CHNS dataset afore mentioned in footnote 10, the question regarding land redistribution was

asked only in 1993 and 1997 (the exact question read "the year of last land redistribution"). CHNS dataset indicates that less than 1/3 of farmers have experienced land redistribution between 1993 to 1997, which is also the relevant period for my study. To the extent that this size of land measure in 2006 is a noisy proxy for size of land prior to adoption, this could create more noise, thus coefficients on risk preferences could be muted.

[29] Ideally, I would like to include a set of farming characteristics from prior to Bt cotton adoption. In particular, one might imagine that farmers could self insure by changing the composition of activities. If hedging is possible, then a more risk-averse individual could hedge his or her Bt cotton adoption with less risky projects. Therefore, those individuals who are more risk averse would be able to adopt sooner than in the counterfactual scenario when there is no hedging capacity. In this case, the coefficients on risk preferences could be muted, which suggests that my finding on risk preferences could be a lower bound.

[30] For brevity, the table can be found in online appendix.

[31] In the previous draft of this paper, I included a noisy measure of 1999 DG ownership. We had asked farmers about a list of DG they had owned in 2006 and 2001. If they reported that they had owned a particular DG, we then inquired in what year they bought this particular DG. Using the year reported, we can estimate the number of DG owned in 1999. A very noisy measure results from using this method since in 1999 more than half of the farmers only owned one DG on the list.

[32] It is debatable as to which problem is more serious—omitted variable bias or including an endogenous variable. I have performed the regression analysis for both with and without wealth. Given that the results are similar, it is less of a concern. The replication of Table 6 with wealth

variable is available upon request.

[33] One could argue that farmers with extremely low cognitive ability may be the ones who choose all risky options (all lottery B selections) in the game as well as adopt Bt cotton the latest. Therefore, the estimate on risk preference could be biased upward. On the other hand, it is as likely that those with low cognitive ability could choose all safe options in the game (all lottery A selections) but they adopt Bt cotton later, then it would be downward bias. *A priori*, it is not clear in which direction the bias would occur. However, by excluding those individuals who seem to not understand the game should provide us with a better estimate.

[34] It is not sensible to define the time of exposure as the year before the first person adopted Bt cotton in the village because we only surveyed 20 households in each village. It is very likely that someone adopted Bt cotton earlier than the first person reported in village in the sample, but that this individual was not interviewed and therefore did not show up in the sample.

[35] As a specification check, I assume baseline hazard has a Gompertz specification, which is also monotonic. Regression results are not presented, but the coefficient and significance of risk preference parameters remain robust.

[36] In order to run a likelihood ratio tests, the standard errors from these regressions cannot be robust standard errors.

[37]Jaeger et al. (2010) investigates the relationship between risk attitudes and migration decisions while accommodating a similar problem (of having no baseline data). Taking advantage of the fact that risk preference parameters were collected in 2004 and migration occurred between 2000 and 2006, they find that individual risk attitude measures are both significant in *ex ante* and *ex post* migration decisions.

[38] For more discussion on the difference between ambiguity (uncertainty) aversion and risk

aversion see Epstein (1999).

[39] In a working paper by Dercon, Gunning and Zetlin (2011), they examine the relationship between trust, risk aversion and the take-up of crop insurance, they find evidence that individual trust measure elicited from the experiment is negatively associated with take-up of crop insurance.

[40] In a series of randomized field experiments conducted in rural India, Cole et al (2009) find higher insurance take-up rates among more risk-averse individuals. See Horowitz and Lichtenberg (1993) for the use of crop insurance in the United States.

Figure 1: Cumulative Distribution Function of Household Adoption of Bt Cotton

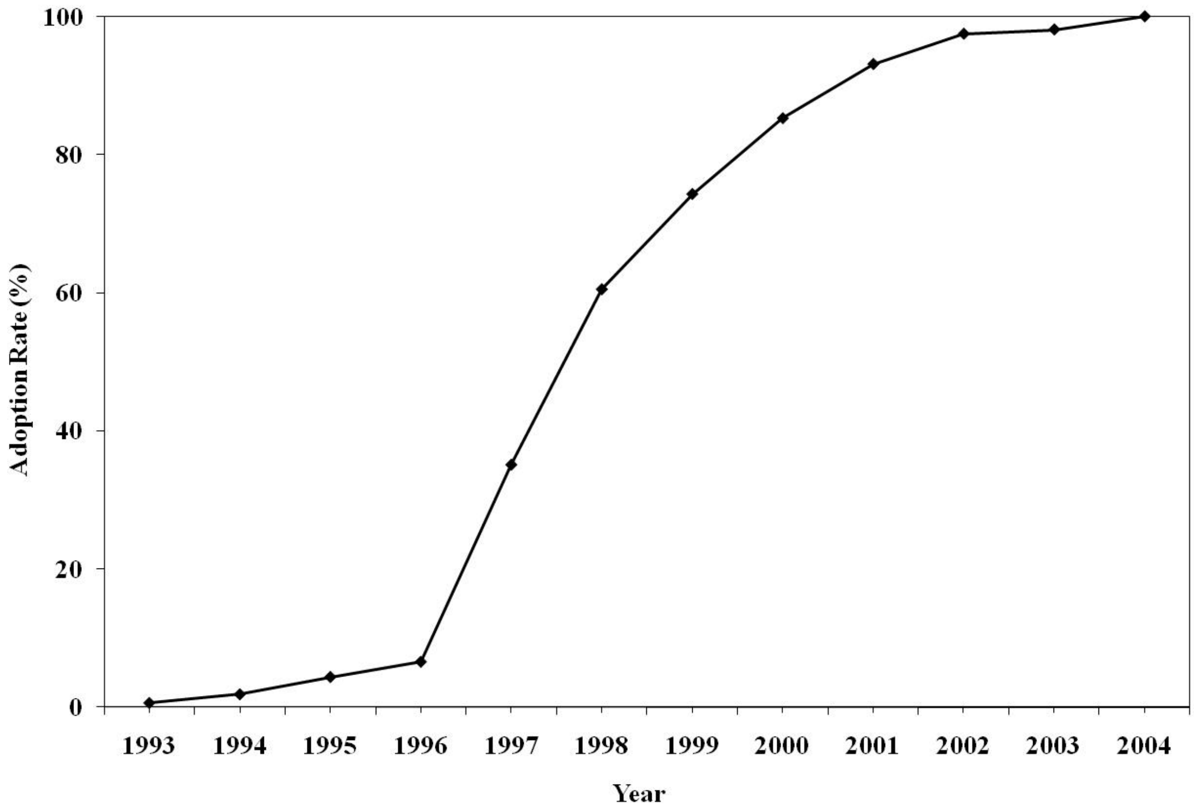


Figure 2: Distribution of Risk Preference Parameters

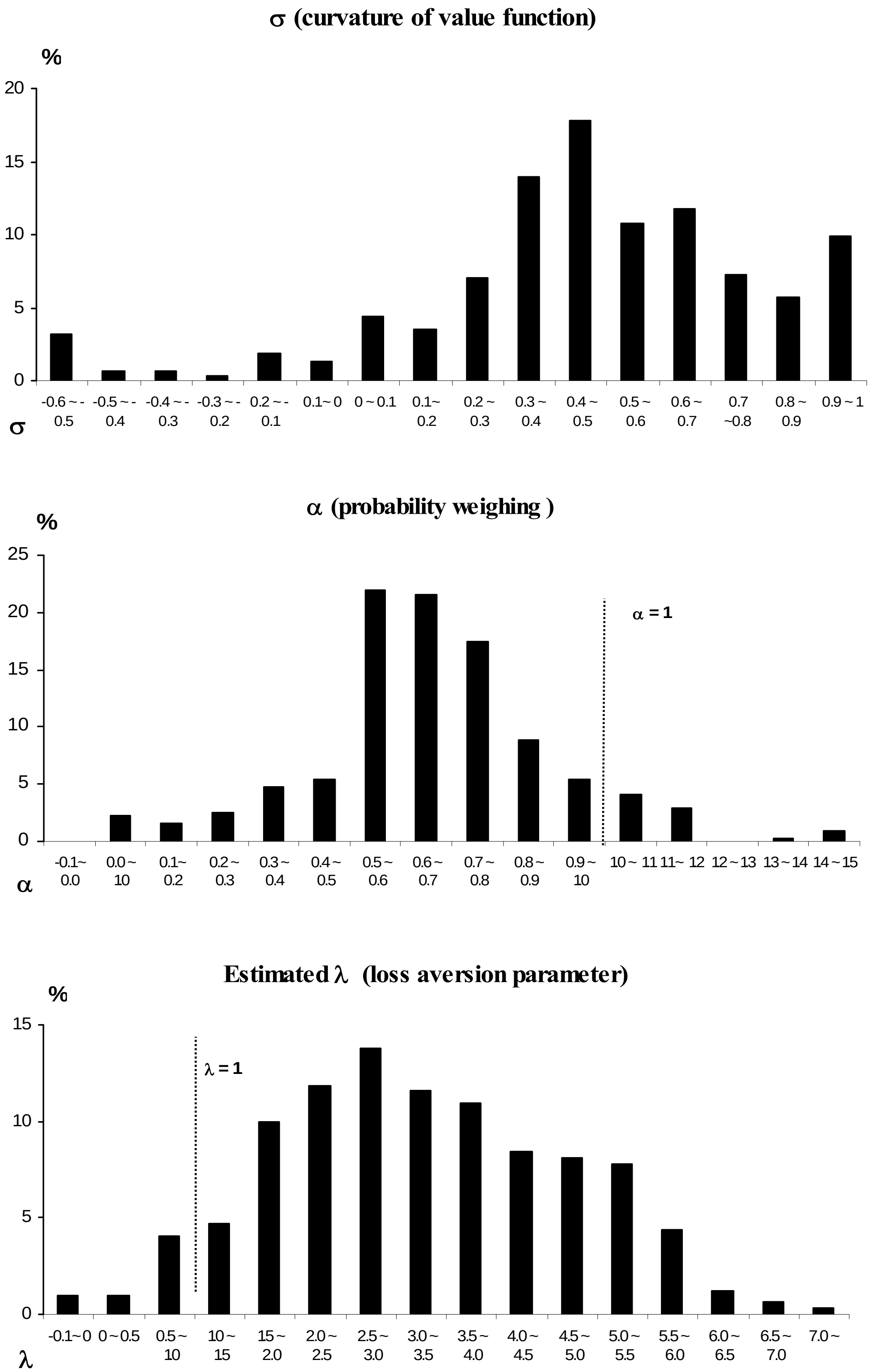


Figure 3a: Box Chart of σ

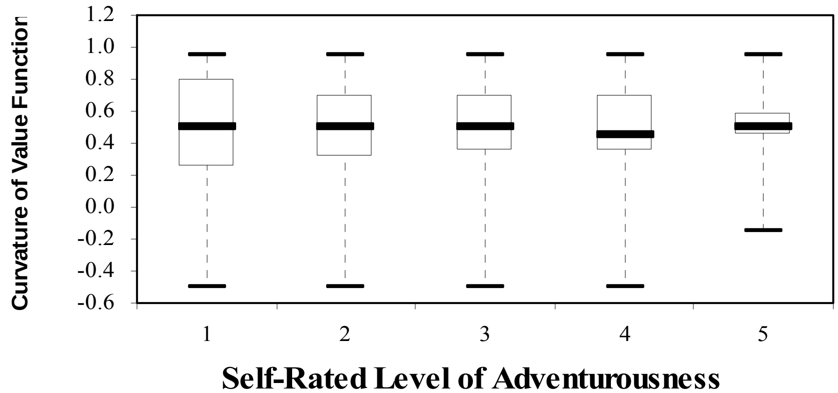
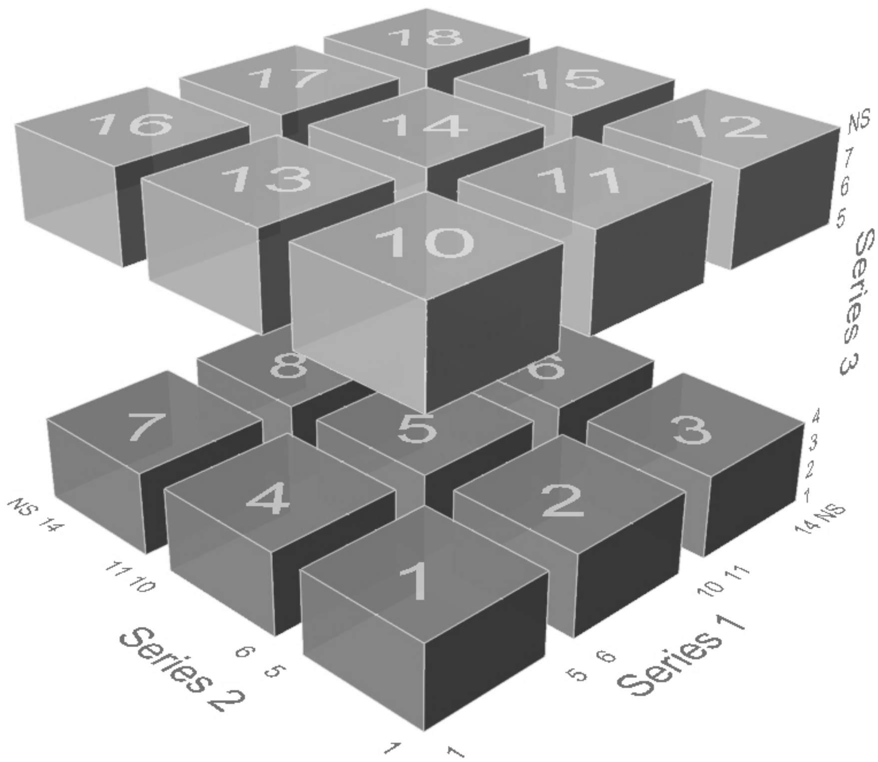


Figure 3b: Box Chart of λ

Note: For each level of adventurousness, the bottom bar corresponds to the minimum value of σ (Figure 3a) or λ (Figure 3b), 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 represented by the bold line bisecting the rectangle.

Figure 4: Division of Switching Points



Note: Each axis indicates the switching point for each series. The coordinate indicates the switching points of the three series. NS indicates that no switching occurred. For example, those who choose never switch in all three series (NS, NS, NS) would be in group 18. Those who choose always switch in row 1 in all three series (1, 1, 1) would be in group 1.

Table 1
Summary Characteristics

Age	49.52
	(8.89)
Education	7.10
	(2.96)
Female	0.14
	(0.35)
Household Size	4.49
	(1.45)
Time Spent Working On the Farm (months)	7.63
	(1.76)
Time Spent Working Off the Farm (months)	0.13
	(0.69)
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)
Time takes to walk to 20 neighbors (minutes)	15.50
	(10.8)
Total Cotton Sown Area (Ha)	0.54
	(0.33)
Total Land Owned (Ha)	0.59
	(0.29)
Average Year of Bt Cotton Adoption	1998
	(1.90)
Total Value of Durable Goods Per Capita in 2006 (Yuan)	588.40
	(9.37)
# of Durable Goods Owned in 2006	4.85
	(3.02)
# of Durable Goods Owned in 2001	3.21
	(5.51)
Observations	320

Note : Standard deviation are in parentheses.

Table 2: 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 3
OLS Regression of Individual Risk Preferences

	(1) σ (value function curvature)	(2) λ (loss aversion)	(3) α (probability weighting)
Age	-0.001	-0.044	0.000
	(0.002)	(0.033)	(0.002)
Education	0.002	-0.067	-0.008
	(0.009)	(0.089)	(0.005)
Female	0.107	0.920	0.044
	(0.047)**	(0.567)	(0.030)
Village Official (1 = Yes)	0.053	-0.445	0.016
	(0.043)	(0.639)	(0.045)
Wealth per capita (10000 Yuan)	-0.042	0.315	-0.003
	(0.018)**	(0.199)	(0.018)
Religious (1 = Yes)	-0.231	1.378	-0.012
	(0.071)***	(0.786)	(0.056)
% Time Spent Working On-Farm	0.162	3.163	-0.035
	(0.086)*	(1.003)***	(0.078)
Land owned (Ha)	-0.109	-0.957	-0.002
	(0.101)	(1.075)	(0.048)
Constant	0.582	4.947	0.741
	(0.199)**	(2.265)**	(0.111)***
Observations	314	314	314
R-squared	0.09	0.17	0.07

Note: Standard errors are clustered at the village level.
* significant at 10%; ** significant at 5%; *** significant at 1%.
All regressions include village fixed effects.

Table 4
Weibull Model for Duration of Time to Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
σ		-0.361		-0.328	-0.333	-0.366
(value function curvature)		(0.182)**		(0.185)*	(0.181)*	(0.181)**
λ			-0.030	-0.028	-0.033	-0.035
(loss aversion)			(0.017)*	(0.017)	(0.017)*	(0.017)**
α					-0.818	
(probability weighting)					(0.255)***	
α<1 dummy						0.689
(probability weighting)						(0.297)**
Age[a]	0.001	0.000	-0.001	-0.002	-0.003	-0.002
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
Female	0.194	0.189	0.208	0.210	0.221	0.228
	(0.150)	(0.150)	(0.150)	(0.149)	(0.164)	(0.155)
Land owned (ha)	-0.352	-0.344	-0.369	-0.364	-0.359	-0.419
	(0.315)	(0.316)	(0.319)	(0.318)	(0.329)	(0.317)
Education (years)	0.038	0.043	0.042	0.042	0.033	0.043
	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.020)*	(0.020)**
Village Official	-0.224	-0.245	-0.223	-0.224	-0.222	-0.219
	(0.168)	(0.169)	(0.157)	(0.158)	(0.160)	(0.162)
# of Adults Age > 28	-0.123	-0.109	-0.114	-0.111	-0.087	-0.079
	(0.069)*	(0.067)	(0.067)*	(0.066)*	(0.067)	(0.066)
Time_20 Neighbors	0.007	0.006	0.006	0.006	0.005	0.005
	(0.004)*	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
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 village fixed effects. Sample exclude all households that were formed after 1993.
a. Age at time of exposure

Table 5: Weibull Model for Duration of Time to Adoption
Robustness Check on Wealth Measures

	(1) # of DG in 2001	(2) # of DG in 2001	(3) Wealth Index 2001	(4) Wealth Index 2001	(5) Top 1/3 Wealth Bracket	(6) Top 25th Percentile in
σ	-0.337	-0.370	-0.334	-0.366	-0.571	-0.797
(value function curvature)	(0.182)*	(0.182)**	(0.181)*	(0.181)**	(0.284)**	(0.314)**
λ	-0.034	-0.036	-0.035	-0.037	-0.036	-0.052
(loss aversion)	(0.018)*	(0.018)**	(0.018)**	(0.018)**	(0.030)	(0.030)*
α	-0.811		-0.809		-0.026	-0.514
(probability weighting)	(0.257)***		(0.258)***		(0.507)	(0.634)
α<1		0.681		0.676		
(probability weighting)		(0.300)**		(0.303)**		
Age	-0.003	-0.002	-0.003	-0.002	0.015	0.042
	(0.009)	(0.009)	(0.009)	(0.009)	(0.021)	(0.025)*
Female	0.225	0.233	0.224	0.231	0.476	0.678
	(0.164)	(0.155)	(0.164)	(0.155)	(0.289)*	(0.394)*
Land owned (Ha)	-0.365	-0.427	-0.365	-0.426	-0.799	-0.148
	(0.332)	(0.320)	(0.331)	(0.319)	(0.641)	(0.708)
Education (years)	0.034	0.044	0.034	0.044	0.023	0.014
	(0.020)*	(0.020)**	(0.020)*	(0.020)**	(0.056)	(0.061)
Village official	-0.230	-0.227	-0.239	-0.235	0.082	-0.010
	(0.163)	(0.164)	(0.165)	(0.167)	(0.234)	(0.323)
# of Adults Age > 28	-0.086	-0.078	-0.086	-0.078	0.034	-0.149
	(0.067)	(0.066)	(0.067)	(0.066)	(0.151)	(0.143)
Time_20 Neighbors	0.005	0.005	0.005	0.005	-0.001	-0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.011)	(0.011)
Wealth Measure	0.006	0.006	0.015	0.014		
	(0.009)	(0.009)	(0.017)	(0.016)		
Observations	302	302	302	302	97	77

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

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

	(1) Drop Early Adopter	(2) Drop No-switching	(3) Cluster	(4) Province	(5) County	(6) Cox	Original (from Table 5)
σ	-0.426	-0.519	-0.519	-0.588	-0.616	-0.297	-0.333
(value function curvature)	(0.215)**	(0.199)***	(0.218)**	(0.197)***	(0.190)***	(0.157)*	(0.181)*
λ	-0.036	-0.063	-0.063	-0.042	-0.030	-0.050	-0.033
(loss aversion)	(0.021)*	(0.022)***	(0.029)**	(0.018)**	(0.016)*	(0.018)***	(0.017)*
α	-0.653	-0.780	-0.780	-0.756	-0.804	-0.477	-0.818
(probability weighting)	(0.270)**	(0.253)***	(0.340)**	(0.241)***	(0.235)***	(0.187)**	(0.255)***
Age	0.000	-0.005	-0.005	-0.010	-0.008	-0.003	-0.003
	(0.009)	(0.008)	(0.011)	(0.008)	(0.008)	(0.007)	(0.009)
Female	0.366	0.269	0.269	0.194	0.225	0.222	0.221
	(0.177)**	(0.167)	(0.185)	(0.174)	(0.163)	(0.126)*	(0.164)
Land owned (Ha)	-0.351	-0.256	-0.256	-0.188	0.009	-0.181	-0.359
	(0.365)	(0.342)	(0.491)	(0.317)	(0.307)	(0.270)	(0.329)
Education (years)	0.029	0.041	0.041	0.037	0.031	0.031	0.033
	(0.021)	(0.020)**	(0.023)*	(0.021)*	(0.020)	(0.015)**	(0.020)*
Village official	-0.102	-0.166	-0.166	-0.108	-0.116	-0.165	-0.222
	(0.167)	(0.157)	(0.224)	(0.154)	(0.155)	(0.123)	(0.160)
# of Adults Age > 28	-0.031	-0.091	-0.091	-0.071	-0.071	-0.064	-0.087
	(0.067)	(0.069)	(0.098)	(0.068)	(0.068)	(0.051)	(0.067)
Time to 20 Neighbors	0.001	0.003	0.003	0.004	0.003	0.002	0.005
	(0.007)	(0.005)	(0.007)	(0.004)	(0.004)	(0.006)	(0.005)
Observations	282	280	280	280	280	280	302

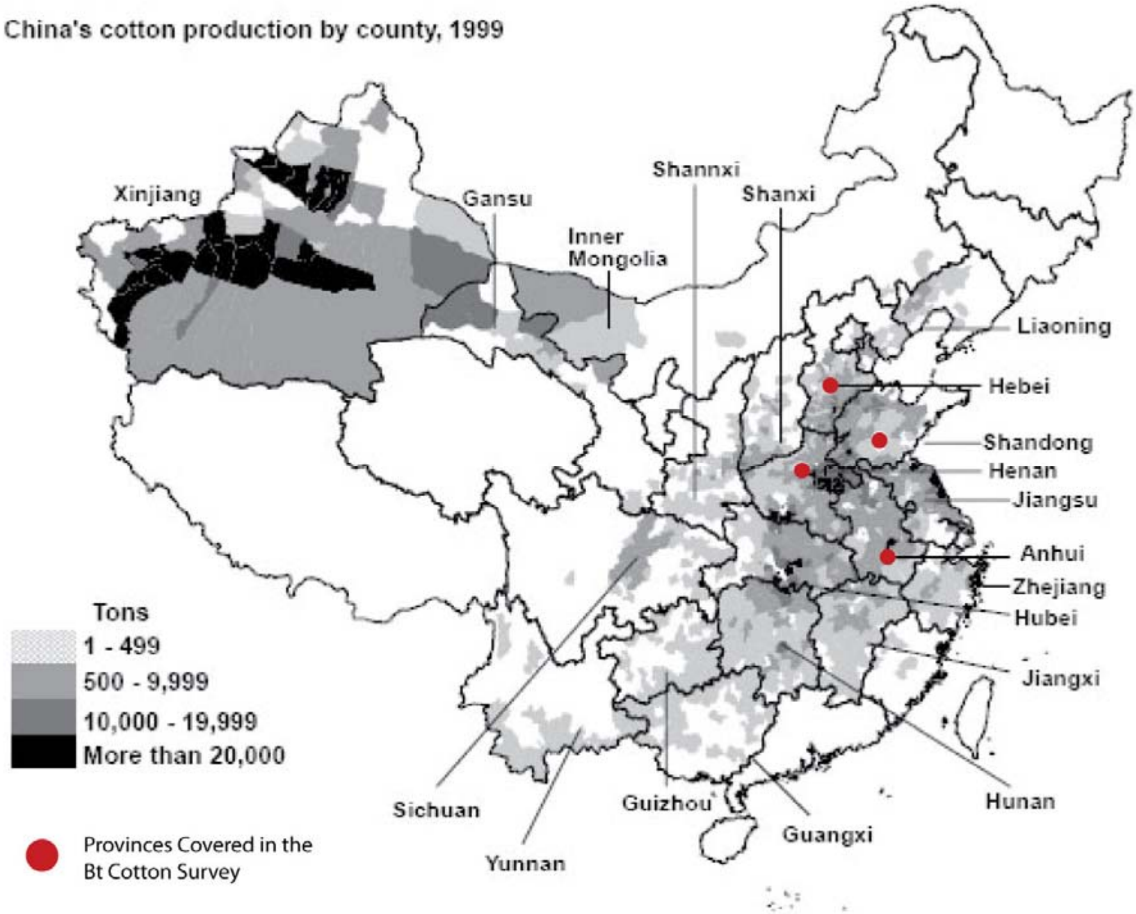
*Note: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include village fixed effects. Sample exclude all households that were formed after 1993. Columns 3, 4, 5 and 6 use the same sample as Column 2.*

Table 7: Duration of Time to Adoption
Coefficients on Group Dummies

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

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 Row 1 to _____.
I choose lottery B for Row _____ 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 Row 1 to _____.
I choose lottery B for Row _____ 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 Row 1 to _____.
I choose lottery B for Row _____ to 7.

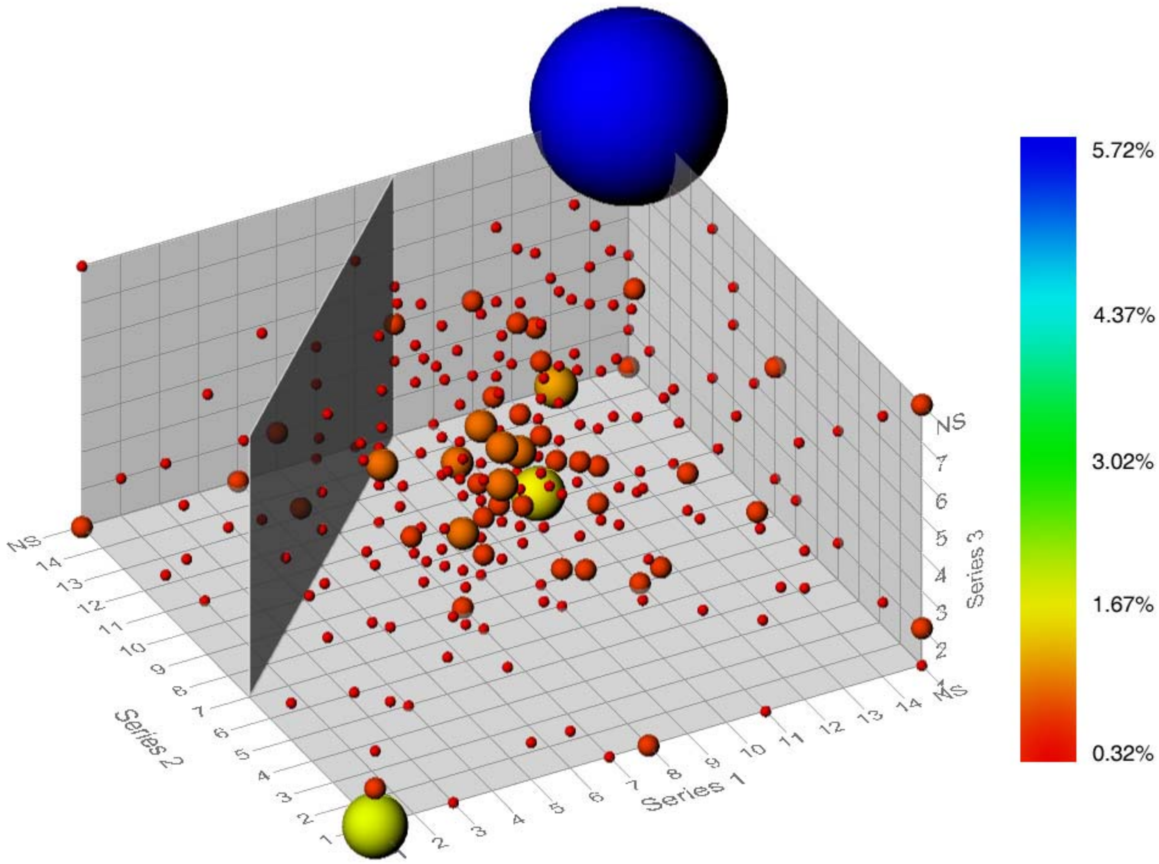
Appendix 3

Game Instruction

Twenty farmers from a single village gather in the village office at the end of the interview day. We also invite the village leaders to be present in the room to witness the game so that the farmers will trust us. The village leader first explains to the farmers that we are researchers from the Center for Chinese Agricultural Policy (CCAP) is a department in Chinese Academy of Science (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 that might have the chance to lose all 10 Yuan or they might have the chance to win up to 850 Yuan. The farmers who do not wish to participate are given the opportunity to leave the room at this point in 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 the 35 rows 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 will determine which line out of the 35 that they have answered will 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 will 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, asking the participants each time how much the payoff would be, in order to ensure that most of them understand how the game works. We instruct the participants not to communicate with each other during the game. A few of participants who cannot read have special assistants who read the instruction sheet and questions to them. A cover sheet is attached to the answer sheet; therefore, participants need not worry that others will see their answers. This whole process normally takes an hour to an hour and an half.

Appendix 4: Distribution of Switching Points



Note: Each axis indicates the switching point for each series. The coordinate indicates the switching points of the three series. NS indicates that no switching occurred. For example, the coordinate of blue ball (NS, NS, NS) consists of people who never switched from lottery A to lottery B and thereby always chose safest option in all three series. The size of a ball describes the frequency of people choosing that combination of coordinate. Again, the blue ball indicates the 5.72% of sample that chose to never switch during all three series.

Appendix 5

The two technology options are presented below. L^T shows the performance of traditional cotton and L^{BT} shows the performance of Bt cotton.

$$L^T = \begin{cases} \Pr(M) = q \\ \Pr(M-b) = 1-q \end{cases} \qquad L^{BT} = \begin{cases} \Pr(b) = p \\ \Pr(0) = (1-p)q \\ \Pr(-b) = (1-p)(1-q) \end{cases}$$

$$1 > b > 0;\ b > M > 0 > M-b > -b;\ \ 1 \geq p \geq 0;\ 1 \geq q \geq 0.$$

The TCN utility function has the following format:

$$U(x,p;y,q) = \begin{cases} v(y) + w(p)(v(x)-v(y)) & x > y > 0 \text{ or } x < y < 0 \\ w(p)v(x) + w(q)v(y) & x < 0 < y \end{cases} \quad ----(1)$$

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

$0 < w(p) < 1$ and $0 < p < 1$

Based on existing studies of Bt cotton in China such as Huang, Hu et al.(2002), we are able to infer the relative sizes of M and b compared to the profit. For simplicity, let us assuming M = 0.05 and b = 0.4. We then proceed with the analysis in a piecemeal fashion by considering the range of perceived effectiveness of Bt cotton as effective ($\lim p \to 1$), ineffective ($\lim p \to 0$), or uncertain $0 < p < 1$

$$U(L^{BT}) = w(p)\cdot v(b) + w((1-p)(1-q))\cdot v(-b)$$
$$U(L^{BT}) = w(p)\cdot v(0.4) - w((1-p)(1-q))\cdot \lambda \cdot v(0.4)$$

$$U(L^{T}) = w(q)\cdot v(M) + w(1-q)\cdot v(M-b)$$
$$U(L^{T}) = w(q)\cdot v(0.05) - w(1-q)\cdot \lambda \cdot v(0.35)$$

$$dU(L^{BT})/d\sigma = -w(p)\cdot(0.4)^{1-\sigma}\cdot\ln(0.4) + w((1-p)(1-q))\cdot\lambda\cdot(0.4)^{1-\sigma}\cdot\ln(0.4)$$
$$dU(L^{T})/d\sigma = -w(q)\cdot(0.05)^{1-\sigma}\cdot\ln(0.05) + w((1-q))\cdot\lambda\cdot(0.35)^{1-\sigma}\cdot\ln(0.35)$$

$$\begin{aligned}
&dF/d\sigma \\
&= dU(L^{Bt})/d\sigma - dU(L^{T})/d\sigma \\
&= (0.4)^{1-\sigma}\cdot\ln(0.4)\cdot[\lambda\cdot w((1-p)(1-q)) - w(p)] - w((1-q))\cdot\lambda\cdot(0.35)^{1-\sigma}\cdot\ln(0.35) + w(q)\cdot(0.05)^{1-\sigma}\cdot\ln(0.05)
\end{aligned}$$

$$\begin{aligned}
&dF/d\lambda \\
&= dU(L^{Bt})/d\lambda - dU(L^{T})/d\lambda \\
&= -w((1-p)(1-q))\cdot v(0.4) + w(1-q)\cdot v(0.35) \\
&= -w((1-p)(1-q))\cdot(0.4)^{1-\sigma} + w(1-q)\cdot(0.35)^{1-\sigma}
\end{aligned}$$

$$dw(x)/d\alpha = -e^{-(-\ln x)^{\alpha}}\cdot\ln(-\ln x)\cdot(-\ln x)^{\alpha}$$

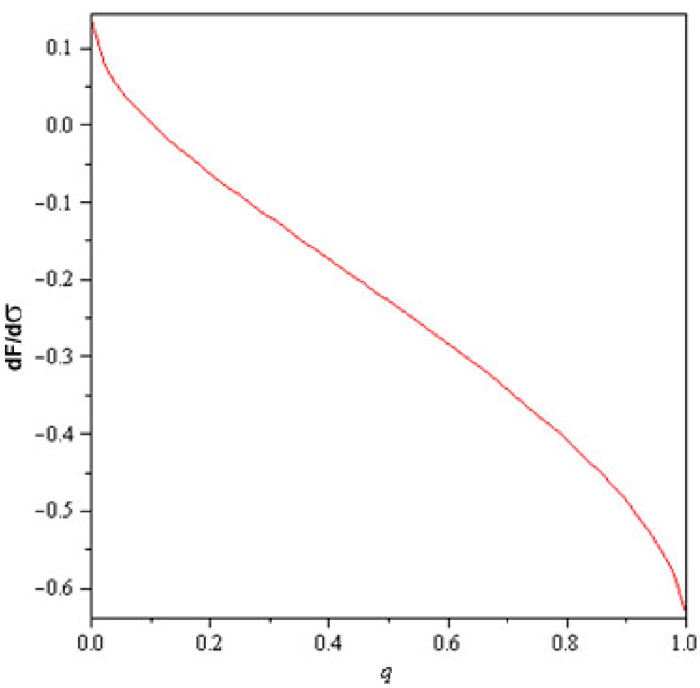
$$\begin{aligned}
&dF/d\alpha \\
&= dU(L^{Bt})/d\alpha - dU(L^{T})/d\alpha \\
&= dw(p)/d\alpha\cdot v(0.4) - dw((1-p)(1-q))/d\alpha\cdot\lambda\cdot v(0.4) - dw(q)/d\alpha\cdot v(0.05) + dw(1-q)/d\alpha\cdot\lambda\cdot v(0.35) \\
&= dw(p)/d\alpha\cdot v(0.4) + dw(1-q)/d\alpha\cdot\lambda\cdot v(0.35) - dw((1-p)(1-q))/d\alpha\cdot\lambda\cdot v(0.4) - dw(q)/d\alpha\cdot v(0.05) \\
&= -e^{-(-\ln p)^{\alpha}}\cdot\ln(-\ln p)\cdot(-\ln p)^{\alpha}\cdot v(0.4) - e^{-(-\ln(1-q))^{\alpha}}\cdot\ln(-\ln(1-q))\cdot(-\ln(1-q))^{\alpha}\cdot\lambda\cdot v(0.35) \\
&+ e^{-(-\ln((1-p)(1-q)))^{\alpha}}\cdot\ln(-\ln((1-p)(1-q)))\cdot(-\ln((1-p)(1-q)))^{\alpha}\cdot\lambda\cdot v(0.4) + e^{-(-\ln q)^{\alpha}}\cdot\ln(-\ln q)\cdot(-\ln q)^{\alpha}\cdot v(0.05)
\end{aligned}$$

1. **Bt cotton is perceived as ineffective (lim p->0^{+})**

$$\begin{aligned}
&dF/d\sigma \\
&= dU(L^{Bt})/d\sigma - dU(L^{T})/d\sigma \\
&= \lim_{p\to 0^{+}}(0.4)^{1-\sigma}\cdot\ln(0.4)\cdot[\lambda\cdot w((1-p)(1-q)) - w(p)] - w(1-q)\cdot\lambda\cdot(0.35)^{1-\sigma}\cdot\ln(0.35) + w(q)\cdot(0.05)^{1-\sigma}\cdot\ln(0.05) \\
&= (0.4)^{1-\sigma}\cdot\ln(0.4)\cdot\lambda\cdot w(1-q) - w(1-q)\cdot\lambda\cdot(0.35)^{1-\sigma}\cdot\ln(0.35) + w(q)\cdot(0.05)^{1-\sigma}\cdot\ln(0.05) \\
&= \lambda\cdot w(1-q)\cdot[(0.4)^{1-\sigma}\cdot\ln(0.4) - (0.35)^{1-\sigma}\cdot\ln(0.35)] + w(q)\cdot(0.05)^{1-\sigma}\cdot\ln(0.05) <> 0
\end{aligned}$$

Since $(1-\sigma)\geq 0,\ \lambda\cdot w(1-q)\geq 0,\ (0.35)^{1-\sigma}\cdot\ln(0.35)-(0.4)^{1-\sigma}\cdot\ln(0.4)>0$ and $w(q)\cdot(0.05)^{1-\sigma}\cdot\ln(0.05)\leq 0,$ the sign can't be determined.

If we assume that σ =0.48, λ = 3.47 and α = 0.69 (to be the mean of the population), then we can graph dF/dσ for a given range of q. dF/dσ is on the y-axis. As presented in the figure below, if Bt cotton is perceived as ineffective, except for the extremely low value of q, then more risk averse individuals would adopt it later.



$$
\begin{aligned}
dF/d\lambda &= dU(L^{Bt})/d\lambda - dU(L^{T})/d\lambda \\
&= \lim_{p\to 0^+} -w((1-p)(1-q))\cdot v(0.4) + w(1-q)\cdot v(0.35) \\
&= \lim_{p\to 0^+} w(1-q)\cdot(0.35)^{1-\sigma} - w((1-p)(1-q))\cdot(0.4)^{1-\sigma} \\
&= w(1-q)\cdot(0.35)^{1-\sigma} - w((1-q))\cdot(0.4)^{1-\sigma} \\
&= w(1-q)\cdot[(0.35)^{1-\sigma} - (0.4)^{1-\sigma}] \leq 0
\end{aligned}
$$

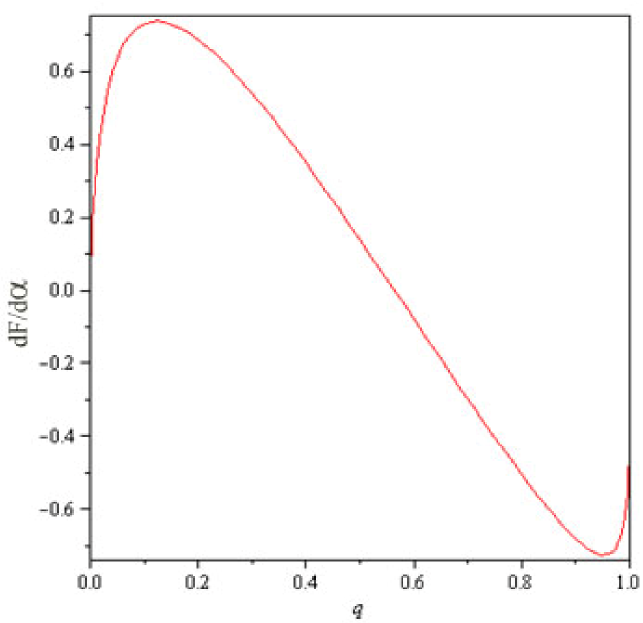
Since $1 > w(1-q) \geq 0$ and $[(-1)\cdot(0.4)^{1-\sigma} + (0.35)^{1-\sigma}] \leq 0$ if $0<\sigma<1$
It indicates that the more loss averse farmers would adopt Bt cotton later.

$$dF/d\alpha = dU(L^{Bt})/d\alpha - dU(L^{T})/d\alpha$$

$$\lim_{p\to 0^+} dF/d\alpha$$

$$\lim_{p\to 0^+} dF/d\alpha$$
$$= \lim_{p\to 0^+} dw(p)/d\alpha \cdot v(0.4) - dw((1-p)(1-q))/d\alpha \cdot \lambda \cdot v(0.4) - dw(q)/d\alpha \cdot v(0.05) + dw(1-q)/d\alpha \cdot \lambda \cdot v(0.35)$$
$$= \lim_{p\to 0^+} e^{-(-\ln(1-p)(1-q))^{\alpha}} \cdot \ln(-\ln((1-p)(1-q))) \cdot (-\ln(1-p)(1-q))^{\alpha} \cdot \lambda \cdot v(0.4) + e^{-(-\ln q)^{\alpha}} \cdot \ln(-\ln q) \cdot (-\ln q)^{\alpha} \cdot v(0.05)$$
$$- e^{-(-\ln p)^{\alpha}} \cdot \ln(-\ln p) \cdot (-\ln p)^{\alpha} \cdot v(0.4) - e^{-(-\ln(1-q))^{\alpha}} \cdot \ln(-\ln(1-q)) \cdot (-\ln(1-q))^{\alpha} \cdot \lambda \cdot v(0.35)$$

The sign of $dF/d\alpha$ depends on q, λ, α and σ. If we assume that λ = 3.47, σ=0.48, and α=0.69 , then we can graph $dF/d\alpha$ for a range of q. Suppose severe pest infestation is not frequent (large q), it indicates that when Bt cotton is perceived as ineffective, $dF/d\alpha$ would be negative. Thus, those with higher α, would adopt Bt cotton later.



2. **Bt is effective** $(\lim p \to 1^{-})$

$$\lim_{p \to 1^{-}} dF/d\sigma$$

$$= \lim_{p \to 1^{-}} (0.4)^{1-\sigma} \cdot \ln(0.4) \cdot [\lambda \cdot w((1-p)(1-q)) - w(p)] - w(1-q) \cdot \lambda \cdot (0.35)^{1-\sigma} \cdot \ln(0.35) + w(q) \cdot (0.05)^{1-\sigma} \cdot \ln(0.05)$$

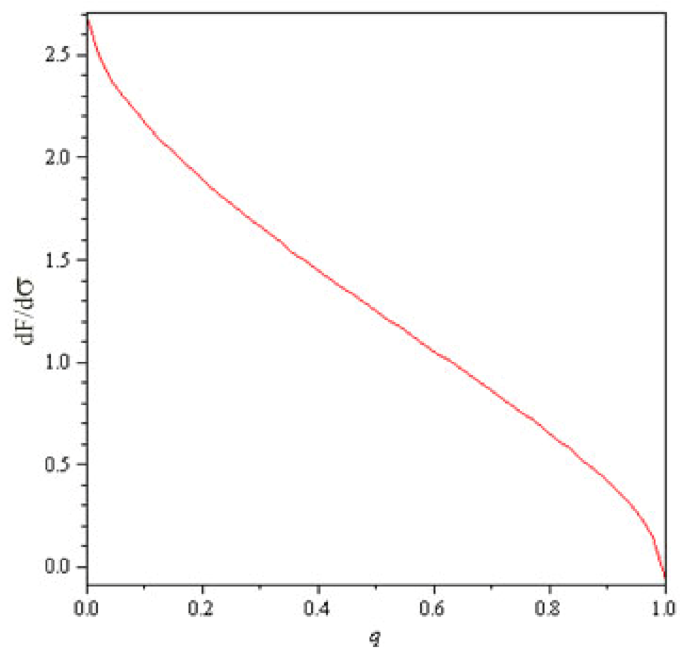
$$= (0.4)^{1-\sigma} \cdot \ln(0.4) \cdot [\lambda \cdot 0 - 1] - w(1-q) \cdot \lambda \cdot (0.35)^{1-\sigma} \cdot \ln(0.35) + w(q) \cdot (0.05)^{1-\sigma} \cdot \ln(0.05)$$

$$= -(0.4)^{1-\sigma} \cdot \ln(0.4) - w(1-q) \cdot \lambda \cdot (0.35)^{1-\sigma} \cdot \ln(0.35) + w(q) \cdot (0.05)^{1-\sigma} \cdot \ln(0.05)$$

$$= w(q) \cdot (0.05)^{1-\sigma} \cdot \ln(0.05) - w(1-q) \cdot \lambda \cdot (0.35)^{1-\sigma} \cdot \ln(0.35) - (0.4)^{1-\sigma} \cdot \ln(0.4) <> 0$$

Since $\ln(0.05) \cong -2.99$, $\ln(0.4) \cong -0.916$ and $\ln(0.35) \cong -1.049$, the sign of the derivative depends on q, λ, α and σ.

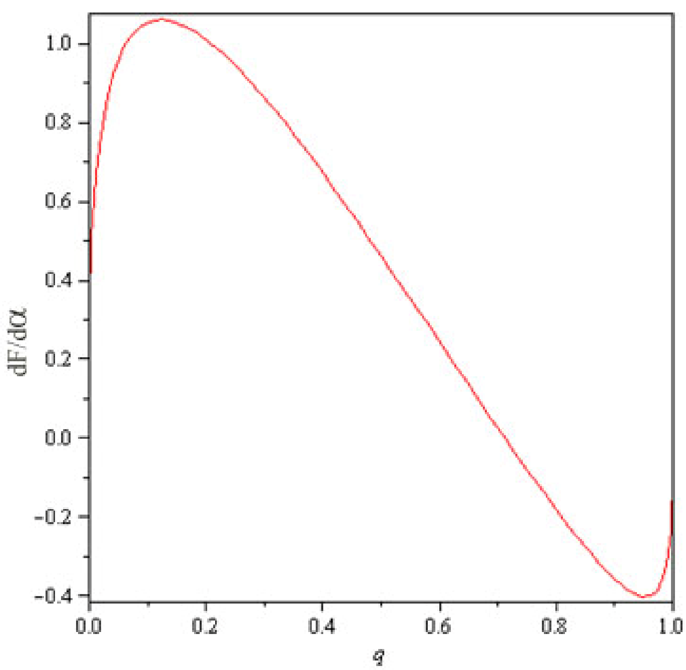
If we assume that σ =0.48, λ = 3.47 and α = 0.69 (to be the mean of population), then we can graph dF/dσ for a given range of q and σ. As presented below, if Bt cotton is perceived to be effective, then the more risk averse farmers would adopt it sooner.



$$\lim_{p\to 1^-} dF/d\lambda$$
$$= \lim_{p\to 1^-} - w((1-p)(1-q))\cdot v(0.4) + w(1-q)\cdot v(0.35)$$
$$= \lim_{p\to 1^-} w(1-q)\cdot(0.35)^{1-\sigma} - w((1-p)(1-q))\cdot(0.4)^{1-\sigma}$$
$$= w(1-q)\cdot(0.35)^{1-\sigma} > 0$$

$$\lim_{p\to 1^-} dF/d\alpha$$
$$= \lim_{p\to 1^-} dw(p)/d\alpha\cdot v(0.4) - dw((1-p)(1-q))/d\alpha\cdot\lambda\cdot v(0.4) - dw(q)/d\alpha\cdot v(0.05) + dw(1-q)/d\alpha\cdot\lambda\cdot v(0.35)$$
$$= \lim_{p\to 1^-} dw(p)/d\alpha\cdot v(0.4) + dw(1-q)/d\alpha\cdot\lambda\cdot v(0.35) - dw((1-p)(1-q))/d\alpha\cdot\lambda\cdot v(0.4) - dw(q)/d\alpha\cdot v(0.05)$$
$$= \lim_{p\to 1^-} e^{-((-\ln(1-p)(1-q))^{\alpha}}\cdot\ln(-\ln((1-p)(1-q)))\cdot(-\ln((1-p)(1-q)))^{\alpha}\cdot\lambda\cdot(0.4)^{1-\sigma} + e^{-(-\ln q)^{\alpha}}\cdot\ln(-\ln q)\cdot(-\ln q)^{\alpha}\cdot(0.05)^{1-\sigma}$$
$$- e^{-(-\ln p)^{\alpha}}\cdot\ln(-\ln p)\cdot(-\ln p)^{\alpha}\cdot(0.4)^{1-\sigma} - e^{-(-\ln(1-q))^{\alpha}}\cdot\ln(-\ln(1-q))\cdot(-\ln(1-q))^{\alpha}\cdot\lambda\cdot(0.35)^{1-\sigma} <> 0$$

The sign of $dF/d\alpha$ depends on q, λ, α and σ. If we assume α=0.69, λ = 3.47 and σ=0.48 and $\lim p \to 1^-$, then we can graph $dF/d\alpha$ for a range of q as presented in Figure below. $dF/d\alpha$ is on the y-axis.

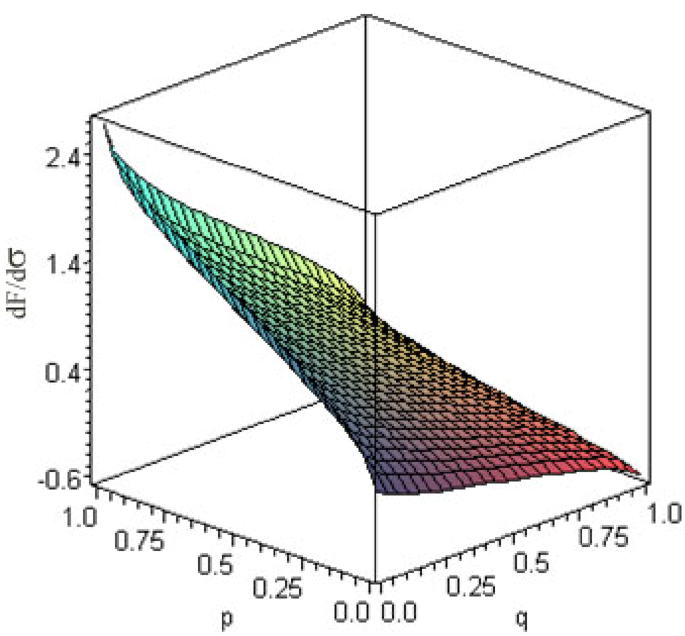


3. **Bt cotton is perceived as having mixed effectiveness (0<p<1)**

$$dF/d\sigma$$
$$= dU(L^{Bt})/d\sigma - dU(L^{T})/d\sigma$$
$$= (0.4)^{1-\sigma} \cdot \ln(0.4) \cdot [\lambda \cdot w((1-p)(1-q)) - w(p)] - w(1-q) \cdot \lambda \cdot (0.35)^{1-\sigma} \cdot \ln(0.35) + w(q) \cdot (0.05)^{1-\sigma} \cdot \ln(0.05)$$

The sign of $dF/d\sigma$ would depend on the size of σ, α, p, q and λ.

If we assume that σ =0.48, λ = 3.47 and α = 0.69 (to be the mean of population), then we can graph dF/dσ for a given range of p and q.

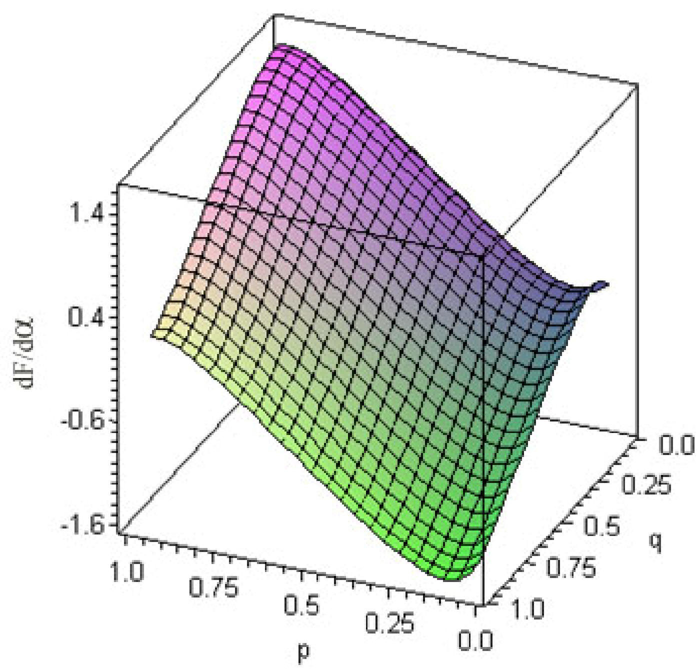


$$dF/d\lambda$$
$$= dU(L^{Bt})/d\lambda - dU(L^{T})/d\lambda$$
$$= -w((1-p)(1-q)) \cdot v(0.4) + w(1-q) \cdot v(0.35)$$
$$= -w((1-p)(1-q)) \cdot (0.4)^{1-\sigma} + w(1-q) \cdot (0.35)^{1-\sigma}$$

The sign of $dF/d\lambda$ depends on the size of p and q

$$
\begin{aligned}
& dF/d\alpha \\
&= dU(L^{Bt})/d\alpha - dU(L^{T})/d\alpha \\
&= dw(p)/d\alpha \cdot v(0.4) - dw((1-p)(1-q))/d\alpha \cdot \lambda \cdot v(0.4) - dw(q)/d\alpha \cdot v(0.05) + dw(1-q)/d\alpha \cdot \lambda \cdot v(0.35) \\
&= e^{-(-\ln(1-p)(1-q))^{\alpha}} \cdot \ln(-\ln((1-p)(1-q))) \cdot (-\ln(1-p)(1-q))^{\alpha} \cdot \lambda \cdot v(0.4) + e^{-(-\ln q)^{\alpha}} \cdot \ln(-\ln q) \cdot (-\ln q)^{\alpha} \cdot v(0.05) \\
& - e^{-(-\ln p)^{\alpha}} \cdot \ln(-\ln p) \cdot (-\ln p)^{\alpha} \cdot v(0.4) - e^{-(-\ln(1-q))^{\alpha}} \cdot \ln(-\ln(1-q)) \cdot (-\ln(1-q))^{\alpha} \cdot \lambda \cdot v(0.35)
\end{aligned}
$$

The sign of $dF/d\alpha$ depends on p, q, λ, α and σ. If we assume α =0.69, λ = 3.47 and σ=0.48, then we can graph $dF/d\alpha$ for a range of p and q.



Appendix 6: Replication of Table 6 including a Wealth Measure

Appendix 6: Weibull Model for Duration of Time to Adoption
Robustness Check

	(1) Drop Early Adopter	(2) Drop No-switching	(3) Cluster	(4) Province	(5) County	(6) Cox
σ	-0.426	-0.509	-0.509	-0.577	-0.605	-0.429
(value function curvature)	(0.214)**	(0.197)***	(0.215)**	(0.197)***	(0.190)***	(0.155)***
λ	-0.037	-0.064	-0.064	-0.045	-0.032	-0.023
(loss aversion)	(0.021)*	(0.022)***	(0.028)**	(0.018)**	(0.016)**	(0.013)*
α	-0.647	-0.765	-0.765	-0.742	-0.795	-0.594
(probability weighting)	(0.272)**	(0.259)***	(0.352)**	(0.246)***	(0.238)***	(0.199)***
Age	0.000	-0.005	-0.005	-0.01	-0.008	-0.006
	(0.009)	(0.009)	(0.010)	(0.008)	(0.008)	(0.006)
Female	0.369	0.274	0.274	0.199	0.228	0.189
	(0.176)**	(0.167)	(0.180)	(0.173)	(0.162)	(0.134)
Land owned (Ha)	-0.357	-0.223	-0.223	-0.172	0.014	-0.003
	(0.370)	(0.338)	(0.492)	(0.314)	(0.305)	(0.244)
Education (years)	0.03	0.046	0.046	0.042	0.035	0.028
	(0.021)	(0.021)**	(0.024)*	(0.021)**	(0.020)*	(0.016)*
Village official	-0.113	-0.206	-0.206	-0.149	-0.152	-0.044
	(0.172)	(0.162)	(0.245)	(0.159)	(0.158)	(0.115)
# of Adults Age > 28	-0.03	-0.087	-0.087	-0.068	-0.069	-0.053
	(0.067)	(0.068)	(0.093)	(0.068)	(0.067)	(0.052)
Time to 20 Neighbors	0.001	0.003	0.003	0.004	0.003	0.002
	(0.007)	(0.005)	(0.007)	(0.004)	(0.004)	(0.003)
Wealth Proxy (index01)	0.01	0.028	0.028	0.026	0.022	0.014
	(0.021)	(0.018)	(0.018)	(0.017)	(0.016)	(0.014)
Observations	282	280	280	280	280	280

*Note: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include village fixed effects. Sample exclude all households that were formed after 1993. Columns 3, 4, 5 and 6 use the same sample as Column 2.*