ESSAYS ON DECISION MAKING

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DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

楊光普

YANG GUANGPU

28 March 2016

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Contents

Summary

This thesis consists of three chapters on decision making. The first two chapters, co-authored with Professor Chew Soo Hong and Professor Richard. P. Ebstein, investigate the genetic roots for people's attitudes towards time and uncertainty, and the third chapter, co-authored with Professor Chew Soo Hong, studies the interaction between people's attitudes towards time and attitudes towards uncertainty.

Focusing on people's attitudes towards time, which play an important role when making a decision regarding future, Chapter 1 explores the genetic root for the variations in time discounting and the near-term bias across individuals. We firstly elicited the degree of impatience in the remote future and near-term bias based on a series of incentivized decision tasks. Then, we selected retinoic acid receptor-α (RARA) as a novel candidate gene for explaining individual differences in time discounting based on the emerging new role for retinoic acid (RA) as a regulator of biological rhythms within the suprachiasmatic nucleus (SCN) of the hypothalamus. Our main finding is that the expression level of the gene RARA in peripheral blood is positively correlated with the degree of impatience in the remote future but negatively correlated with the degree of near-term bias. The significance of these correlations is robust with demographic characteristics including genders, ages and cognitive ability controlled. Of notable interest is the biological plausible finding that for the first time a gene known to be involved as mediators of rhythm in the brain has been implicated in temporal decision making elicited in terms of impatience in the remote future and near-term bias.

In Chapter 2, we elicited people's attitudes towards uncertainty based on four decision tasks involving different types of uncertainty, and we selected 10 candidate genes for explaining individual differences in uncertainty preferences based on findings in the literature about genes which have been shown related with behaviors involving rewards, impulsivity, risk, stress, and so on. We find that people' attitudes towards different types of uncertainty are associated with the expression level of different genes, and the expression of some individual gene can account for 2% variations in the degree of uncertainty aversion, which is plausibly strong from the perspective of genetic analysis. What's more, from the cognition perspective of view, it is worth noting that the cognitive ability dominates the candidate genes in explaining the variation of people's attitudes towards uncertainty. Our results, properly interpreted, may enhance our understanding of the explanation power of cognitive ability for uncertainty aversion. Beyond their purely descriptive value, our results also shed light on the use of models with heterogeneity in macro- and financial economics, and challenge the common assumption that people are born with identical preferences and identical uncertainty attitudes and that the main source of heterogeneity lies in the idiosyncratic shocks to individual incomes.

Last but not least, these two studies are conceivably among the first to bring in measures of gene expression to investigate choice behavior elicited from incentivized decision making tasks. And these open a novel strategy ("blood genomics") for economic modelling time preferences and uncertainty preferences in decision theory.

In Chapter 3, we focus on the interaction of people's attitudes towards uncertainty and time, and propose three main hypotheses based on a thorough review of the conceptual background. These hypotheses are (1.A) the more risk averse a decision maker is in risky situations, the more impatient he/she is in intertemporal settings; (1.B) the more risk averse a decision maker is in risky situations, the greater near-term bias he/she would exhibit; (2) the stronger common ratio effect a decision maker exhibits, the greater near-term bias he/she would exhibit; and (3) the more ambiguity averse a decision maker is, the greater near-term bias he/she would exhibit. On one hand, Hypothesis 1.A is supported in the near future, but gets rejected in the remote future; on the other hand, Hypothesis 1.B is supported from three of the four risky situations in our experiment, suggesting that people's risk aversion degree moderate risky situations is significantly positively associated with the degree of near-term bias people may exhibit when faced with decision situations involving different time delays. Furthermore, when we come to the Hypothesis 2, the experiment result in skewed risky decision situations turns out to provide significant support to the hypothesis, but the result in moderate risky decision situations does not. Besides, Hypothesis 3 cannot get any significant support from our experiment. In addition, it is also found that people's IQ value is significantly negatively associated with the degree of impatience both in the near future and in the remote future as well as the degree of near-term bias. These findings are robust to various econometric analysis approaches, as well as various measures of the two kinds of attitudes.

List of Tables

List of Figures

Chapter 1 Genetics of Intertemporal Decision Making

1.1 Introduction

Most choices in economics and daily life require decision-makers to trade off costs and benefits at different time points, which are referred to as intertemporal settings. As such, people's attitudes towards time play an important role when making a decision regarding the future. Beyond psychology, where addictive behaviours, temptation and self-control, and personality traits such as impulsivity have been widely studied from different perspectives, the degree of impatience is an essential dimension to be included when people study intertemporal decision making in economics. For instance, a person offered a check that can be paid in one week would be tempted perhaps 'on the spot' to accept a somewhat discounted amount of money. If the check could be cashed in one month a person might be willing to accept a greater discounting of the initial sum. This phenomenon is known as delay or time discounting (Laibson, 1997; Wittmann and Paulus, 2008).

The most widely used time discounting model assumes that total utility can be decomposed into a weighted sum – or weighted integral – of utility flows in each period of time (Frederick *et al.*, 2002; Ramsey, 1928; Read, 2004; Samuelson, 1937):

$$U_t = \sum_{k=0}^{n} D(k) \cdot u_{t+k}$$

where t denotes the time of evaluation, say, the current period; U_t is the total utility from the perspective of the current period; k refers to the number of periods of delay; n is the last period of evaluation; u_{t+k} is the instantaneous utility in period $t+k$; and $D(k)$ is the *discount function*, with $F(0)$ normalized to be 1.

Typically, $D(k)$ is a declining function of delay. A decision maker with such a declining discount function is said to be *impatient*, and the degree of impatience is summarized by the discount rate, the rate at which $D(k)$ declines; that is, for $k \geq 1$,

$$d(k) = -\frac{D(k) - D(k-1)}{D(k-1)}$$

Besides, another commonly used term to characterize people's degree of impatience is the discount factor, $\delta(k)$, which is defined as follows:

$$\delta(k) = \frac{D(k)}{D(k-1)} = 1 - d(k).$$

Thus, the higher the discount rate is – the lower the discount factor is, the more impatient the decision maker is – the greater the preference for immediate rewards over delayed rewards.

In the literature, the most frequently used discount function is the exponential discount function:

$$D(k) = \delta^k,$$

with $0 < \delta < 1$. One important property of this exponential discount function is that the discount rate and the discount factor are independent of the horizon, k. Specifically, the discount rate is $d(k) = 1 - \delta$ and the discount factor is $\delta(k) = \delta$. However, this fails to match several empirical regularities. Most importantly, a voluminous body of research has found that measured discount functions decline at a higher rate in the near future than in the remote future (Frederick *et al.*, 2002; Loewenstein and Prelec, 1992; Loewenstein and Thaler, 1989). In other words, people appear to be more impatient when making short-term trade-offs – today vs. tomorrow – than when making long-term trade-offs – 100 days later vs. 101 days later. This phenomenon is known as the near-term bias, which has led psychologists and economists to adopt discount functions in the family of generalized hyperbolas, including the quasi-hyperbolic discount function (Ainslie, 1975; Ainslie and Herrnstein, 1981; Harvey, 1994; Herrnstein, 1961; Laibson, 1997; Loewenstein and Prelec, 1992; Mazur, 1984; Strotz, 1955).

Table 1.1 Five Discount Functions and Their Discount Rates and Discount Factors

	Exponential Discounting	Hyperbolic Discounting			Quasi-Hyperbolic Discounting (Laibson, 1997)
		One-Parameter (Mazur, 1984)	Generalized (Loewenstein & Prelec, 1992)	Proportional Discounting (Harvey, 1994)	
$D(k)$	δ^k	$\frac{1}{1+\alpha k}$	$(1+\alpha k)^{-\beta/\alpha}$	$\frac{h}{h+k}$	$\begin{cases} 1, & if\ k=0 \\ \beta\cdot\delta^k, & if\ k=1,2,3,\ldots \end{cases}$
$d(k)$	$1-\delta$	$\frac{\alpha}{1+\alpha k}$	$\frac{\beta}{1+\alpha k}$	$\frac{1}{h+k}$	$\begin{cases} 1-\beta\delta, & if\ k=1 \\ 1-\delta, & if\ k=2,3,.. \end{cases}$
$\delta(k)$	δ	$\frac{1+\alpha(k-1)}{1+\alpha k}$	$\left(\frac{1+\alpha(k-1)}{1+\alpha k}\right)^{-\beta/\alpha}$	$\frac{h+k-1}{h+k}$	$\begin{cases} \beta\delta, & if\ k=1 \\ \delta, & if\ k=2,3,\ldots \end{cases}$

Table 1.1 summarizes five widely used discount functions $D(k)$ in the literature, together with their corresponding discount rates $d(k)$ and discount factors $\delta(k)$. As one may find, different assumptions about individual discounting behaviour generate significant differences in the understanding of behaviour in a wide range of settings. For a systematic investigation of these different functions, one may refer to Andersen *et al.* (2014).

From the behavioural point of view, vast variations in people's attitudes towards time across individuals have been documented in the literature (see Frederick *et al.* (2002); Harrison *et al.* (2002)), yet the determinants of these individual differences are not fully understood. Explaining decision makers' heterogeneity in time discounting is relevant to a number of prominent topics in economics, like the consumption-saving theory, the asset pricing theory, the wealth distribution theory, and so on. More importantly, a better understanding of the determinants of cross-sectional variance leads to facts that theories involving intertemporal choices have to be consistent. While the variation can be explained to some extent by demographics (Barsky *et al.*, 1997b), and there have been a few recent advances in identifying neurological and biological predictors of preferences like brain activation (Kim *et al.*, 2008; Weber and Huettel, 2008) or cognitive ability (Burks *et al.*, 2009; Dohmen *et al.*, 2010) or even genetic polymorphisms (Carpenter *et al.*, 2011), economists have yet to identify robust exogenous sources or hard wiring of these variations in time discounting. Fortunately, the increasing availability of genetic information now allows us to test hypotheses about candidate genes and their effects. One place to start the search for such genes is among those that have already been shown to account for variations in the observable traits and behaviours of interest.

In this study, we selected RARA (retinoic acid receptor-α) as a novel candidate gene to explain individual differences in time discounting based on the emerging new role for retinoic acid (RA) as a regulator of biological rhythms within the suprachiasmatic nucleus (SCN) of the hypothalamus (Ransom *et al.*, 2014). Vitamin A (all trans RA) is an essential component of the mammalian diet that circulates in the blood in the form of retinol. Interestingly, there is a reduction in maximum pineal melatonin synthesis under vitamin A-deficient conditions. Several components of the RA signalling pathway oscillate according to photoperiodic changes in light conditions. For example, increased day length leads to enhanced retinoid signalling within the hypothalamus. Hence, it makes ‘biological sense’ that there is a relationship between RARA & retinoids and time discounting. Such intertemporal preferences have been attributed to impulsivity to differences in cognitive representations between near and remote future events or to differences in time orientation.

Moreover, unlike the conventional gene association studies in the literature (see Beauchamp *et al.* (2011) for a quick review), we explore the association between time discounting and genetic variants based on behavioural measures of the degree of impatience elicited from incentivized decision making tasks and the expression data of the candidate gene RARA. One advantage of employing genetic expression data is that gene expression studies capture both environmental as well as hard wired gene variation and hence are complementary and perhaps even more informative than simple gene association studies. Moreover, to our knowledge, there are no studies comparing time discounting and gene expression in peripheral blood (‘blood genomics’ strategy), and there are few if any studies linking time discounting to an individual’s overall conceptualization or perception of time.

Our main finding is that the expression level of the gene RARA in peripheral blood is positively correlated with the degree of impatience in the remote future (ρ = 0.162, p=0.014, N=229) but negatively correlated with the degree of near-term bias (ρ =-0.151, p=0.022, N=229). The significance of these correlations is robust with demographic characteristics, including genders and ages, as well as cognitive ability controlled. Of notable interest is the biological plausible finding that for the first time a gene known to be involved as mediators of rhythm in the brain has been implicated in temporal decision making elicited in terms of impatience in the remote future and near-term bias. Finally, this is conceivably the first study to bring in measures of gene expression to investigate choice behaviour elicited from incentivized decision making tasks.

Following this introduction section, the rest of the paper is structured as follows. Section 2 provides some background information of elementary concepts about genes and gene expression. Section 3 describes the design of our experiment as well as the implementation. Section 4 presents the methodology of our analysis and reports the results, together with a series of robustness checks. In Section 5, we discuss the implications of our results, limitations of this study and directions for future research, followed by a conclusion in Section 6.

1.2 Elementary Concepts: Genes and Gene Expression

Before proceeding to introduce the experiment design and the results, we would like to give a very brief introduction to some elementary concepts about genes and gene expression.

1.2.1 DNA and Genes

Deoxyribonucleic acid (DNA) is a molecule whose sequence codes the genetic instructions used in the growth, development, functioning and reproduction of all known living organisms and indeed all living organisms on this planet. DNA consists of two biopolymer strands coiled around each other in anti-parallel fashion to form a double helix structure. The two DNA strands are known as polynucleotides since they are composed of simpler units called nucleotides. Each nucleotide is composed of a sugar called deoxyribose, a phosphate group, and a nitrogen-containing nucleobase – either cytosine (C), guanine (G), adenine (A), or thymine (T) – resulting in four distinct nucleotides. The sequence of the four bases or ‘letters’ of DNA – AGCT – constitutes of the genetic code.

Due to a property of DNA called complementarity that is based on the physical space occupied by each base in the strand, a nucleotide with the base A must always be paired (opposite to) with a nucleotide with the base T and a nucleotide with the base C is always paired with a nucleotide with the base G, forming so-called base pairs and holding the two strands of DNA together. This physical constraint of A paired with T and G with C explains the replication of the DNA molecule. When the two strands separate each strand acts as a template for the newly build strand and hence replicates exactly the sequence of letters in the DNA and the fidelity of the code.

Genes are sequences of nucleotide base pairs (AGCT) that is initially transcribed into RNA (an intermediary molecule that reflects the exact order of ‘letters’ in the DNA) and then is translated in the cell cytoplasm to protein products. Proteins are composed of 21 amino acids and each amino acid is coded for by three DNA letters e.g. ATG codes for methionine. Proteins compose enzymes and structural elements in cells which begin cascades of interactions that regulate bodily structures and functions. The human genome consists of approximately three billion such DNA letters (AGCT) arranged into the 23 (pairs of) chromosomes, but only a small portion of the genome consists of genes and most of the DNA does not actually code for proteins.

1.2.2 Gene Expression

In all organisms, two steps are required to read the information encoded in a gene's DNA and produce the protein it specifies. First, the gene's DNA is transcribed to messenger RNA (mRNA – which is complementary to the DNA i.e. the sequence of letters is the same as in DNA). Second, that mRNA is translated to protein. The process of producing a biologically functional molecule of either RNA or protein is called gene expression, and the resulting molecule is called a gene product.

The information flow from DNA to RNA to protein can be controlled at several points helping the cell to adjust the quality and quantity of resulting proteins and thus self-regulate its functions. Thus, regulation of gene expression is vital to allow a cell to produce the gene products where and when it needs them; in turn, this gives cells the flexibility to appropriately respond to a variety of signals such as hormones which are internal signals and external environmental signals. Crucially important is the quantitative regulation of the amount of protein produced which is determined the amount of mRNA transcribed and other factors that determine the level at which a particular gene is expressed within a cell, tissue or organism.

1.2.3 Genetic Variation

Humans share most, but not all, of their genetic material: approximately 99.6 percent of common genetic variants are the same when comparing any two unrelated individuals (Kidd et al., 2008). However, there are not two exactly identical individuals in the world except for identical twins.

Genetic variation comes in many forms, but most can be traced to one of two types of mutation events. The simplest mutation event is a base substitution, in which the base pair of a nucleotide pair is substituted for another, viz., A G. Whenever a nucleotide varies at a specific locus across individuals in the population, it is said to be a single nucleotide polymorphism, or SNP, with the different genetic variants of a SNP called "alleles." Other forms of genetic variation are due to repeated segments of DNA. In variable number of tandem repeat (VNTR) polymorphisms, there are differences across individuals in the number of times that particular short segments of DNA are repeated (AGGGATTA). In copy number variation (CNV) polymorphisms, there are differences in the number of repetitions or deletions of a long segment of DNA—of at least 1,000 base pairs and often many more. There are also whole chromosome deletions or additions. For example, Down's syndrome represents a duplication of chromosome 21.

The first level of genetic analysis is to analyze the sequence of DNA – the arrangement of the four letters – AGCT among individuals. For example, the sequence of a particular locus of DNA might be AGGGCCTAAG… in normal subjects and AGGTCCTAAG… in a subject afflicted with some disease e.g. hemophilia or sickle cell anemia. However, it is possible to also measure the expression of genes which is most easily done by measuring the levels of mRNA produced in a particular tissue e.g. white blood cells that are easily obtainable in humans. Measurement of mRNA levels in some sense captures the most inclusive genetic information since it is the level of mRNA which actually determines the level of proteins and enzymes in the cell. Ultimately, virtually all genetic variations and modifications will be reflected in differential mRNA expression between individuals. In humans, measurement of mRNA obtained from blood can often be used, with important caveats, as an index of gene expression in other tissues (for example, brain).

1.3 Experimental Design and Implementation

1.3.1 Experimental Design

1.3.1.1 Individual Discount Rates

Participants' discount rates were elicited from their choices in a menu related to the proximate future. The multiple price list design for this task in our experiment, which was proposed by Coller and Williams (1999) and widely used in experimental economics, is illustrated as below in Figure 1.1.

DECISION: For **each of the 20 rows** in the table below, please indicate your decision in the final column with a tick (√).

	Tomorrow	31 days later	Decision
1	$100	$101	A □ B □
2	$100	$104	A □ B □
3	$100	$107	A □ B □
4	$100	$110	A □ B □
5	$100	$113	A □ B □
6	$100	$116	A □ B □
7	$100	$119	A □ B □
8	$100	$122	A □ B □
9	$100	$125	A □ B □
10	$100	$128	A □ B □
	351 days later	**381 days later**	**Decision**
11	$100	$101	A □ B □
12	$100	$104	A □ B □
13	$100	$107	A □ B □
14	$100	$110	A □ B □
15	$100	$113	A □ B □
16	$100	$116	A □ B □
17	$100	$119	A □ B □
18	$100	$122	A □ B □
19	$100	$125	A □ B □
20	$100	$128	A □ B □

Figure 1.1 The Multiple Price List Design for Discounting Rate Elicitation

The multiple price list above includes two sections, referred to as Near Future (Row 1-10) and Remote Future (Row 11-20). In each section, which consists of 10 pairs of choices, participants were asked to indicate their preferences between Choice A and Choice B. For instance, in the Near Future section, Choice A refers to receiving Singapore $100 ($\approx$ US $77 in 2010) the next day, while Choice B refers to receiving a larger amount, ranging from $101 to $128 in an ascending order, 31 days later. Given that the payment in Choice A is fixed at $100 whereas the amount for Choice B is monotonically increasing on the menu, if they choose Choice B rather than Choice A at some point, for instance in the section of Near Future, then they are expected to choose Choice B for all afterwards questions in this section.

We recorded the point at which each subject switches from A to B. The earlier a participant's choice switches from A to B, the more patient he/she is. Numerically, a number *n* was assigned to the case when the switching occurs after *n* A's. In particular, 0 was assigned to those who chose B across all questions in a section, and 10 was assigned to those who chose A across all questions in a section. Hence, a higher score represents higher degree of impatience.

In the subsequent analysis, we mainly focus on participants' switching points in their responses to the intertemporal decision tasks, and alternative measures for participants' attitudes towards time will be constructed and employed for robustness tests in the next section. Actually, this strategy does not rely on the utility function, which helps avoid quite a lot of potential estimation bias resulting from misspecification of utility functions (Andersen *et al.*, 2008; 2014).

Moreover, according to the discussion in Section 1, the near-term bias refers to the scenario when the discounting rate for the same length of time, like one week or one month, tends to be smaller in the remote future than in the near future. Given the same pattern of payoffs for the Near Future and the Remote Future in our experiment design, a participant could be said to exhibit near-term bias if his/her choice switches earlier in the Remote Future than in the Near Future, and the difference naturally serves as a measure for the degree of near-term bias.

1.3.1.2 Expression Level of the RARA Gene

We selected the retinoic acid receptor-alpha (RARA) gene as a novel candidate gene to explain individual differences in delay discounting as well as near-term bias based on the emerging new role for retinoic acid (RA) as a regulator of biological rhythms within the SCN. Focusing on this candidate gene, we measured the expression levels of RARA, based on the level of mRNA, from a random pick of 230 of the 1158 participants.

1.3.1.3 Demographics and Cognitive Ability

In addition, we also collected demographic information of the participants, including their genders and their ages as of the date of our experiment. Their proxy IQ test scores were obtained based on the Raven’s Progressive Matrices.

1.3.2 Experimental Implementation

As a matter of fact, the experiment data employed in this paper is only a part of an experimental project on decision making, which aims to explore the biological foundation for economic and social decision making[1]. In November 2010, 1158 Han Chinese undergraduate students were recruited from National University of Singapore in Singapore to participate in decision-making experiments, in the forms of pencil-and-paper answer sheets as well as online questionnaires. Participants donated 10 to 20 cc of blood for extracting DNA after the economic decision making tasks and lifestyle & personality questionnaires. The study was approved by the university's Institutional Review Board and participants were given written informed consent prior to participation. Participants were reimbursed for participation in the project (S$25 per hour on average).

1.4 Results

To investigate the potential explanation power of the variation in the expression level of the RARA gene for the variation in people's attitudes towards time, we followed three steps to analyse the data of our experiment and present the analysis results in this section. Firstly, we examined and summarized the participants' responses to the intertemporal decision tasks as well as the expression data of the RARA gene, with the standard Pearson correlation coefficients calculated among the key variables; Secondly, more detailed multivariate regression analysis was conducted, with demographic characteristics and cognitive ability controlled; Thirdly, a series of robustness checks were implemented.

[1] For further details about this project, one could visit the web site of the lab for Behavioral Biological Economics and Social Sciences (B2ESS), http://b2ess.nus.edu.sg.

1.4.1 Behavioral Results and Genetic Data

1.4.1.1 Behavioral Results

As discussed in the previous section, participants' switching points in their responses to the intertemporal decision tasks have been taken as the measure for the degree of impatience -- a higher score represents a higher degree of impatience. In the experiment, we observe the following with regards to time discounting, as shown in Figure 1.2. Specifically, choices in Figure 1.2(a) reveal that more than one third of participants exhibit their willingness to accept SG$1 as a compensation for waiting for 30 days in the Near Future task and more than one half in the Remote Future task.

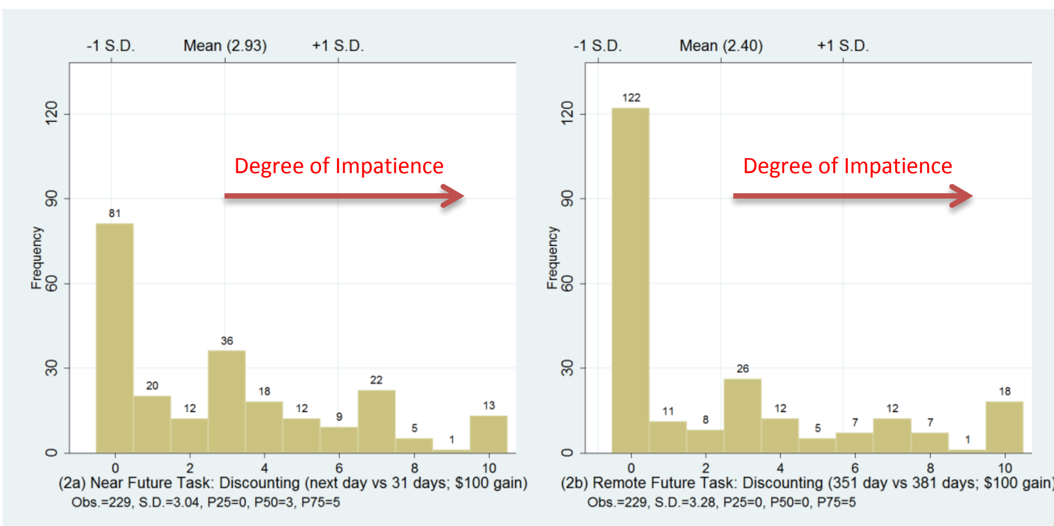

Figure 1.2 Graphic Illustration of Behavioral Results: Near Future vs Remote Future

Moreover, a visual inspection reveals that the switching points seem to come earlier in the Remote Future task than in the Near Future task. As shown in Figure 1.3, the red bar indicates those who show no difference in discounting the near future or the remote future, while the blue bars indicate a considerable fraction of participants who exhibit some near-term bias.

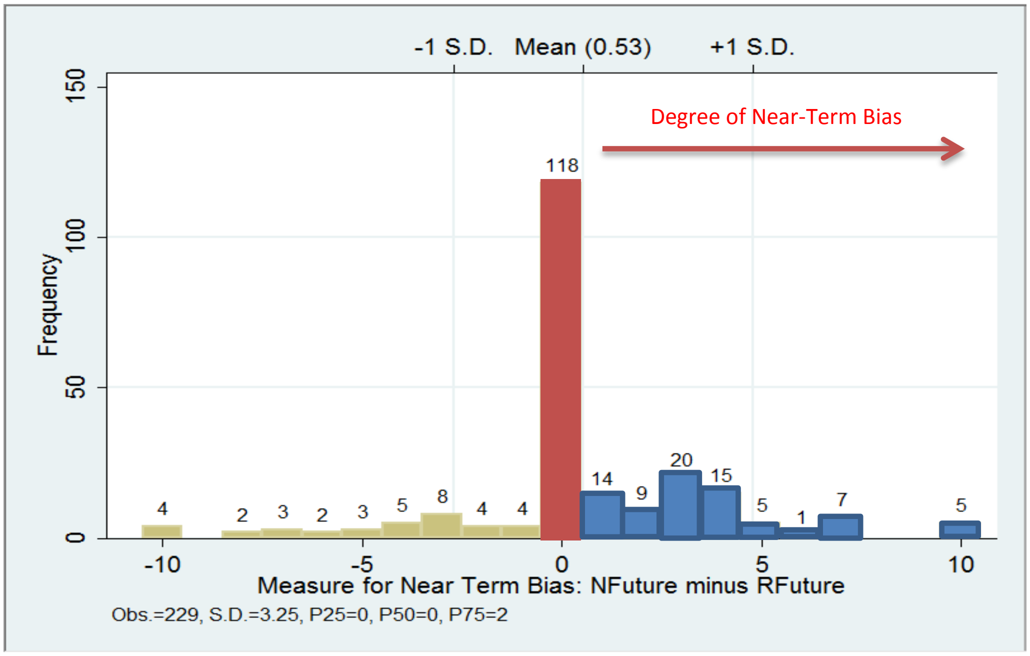

Figure 1.3 Graphic Illustration of Behavioral Results: Near-Term Bias

1.4.1.2 Genetic Data

Next, let us turn to the genetic data. The data of the normalized expression level of the RARA gene shows a wide range, from a minimal level of 3532 to the maximal level of 20799, and hence we take the natural logarithm of the variable, which is usually done in gene expression studies. Distributions of the genetic expression data are shown in Figure 1.4.

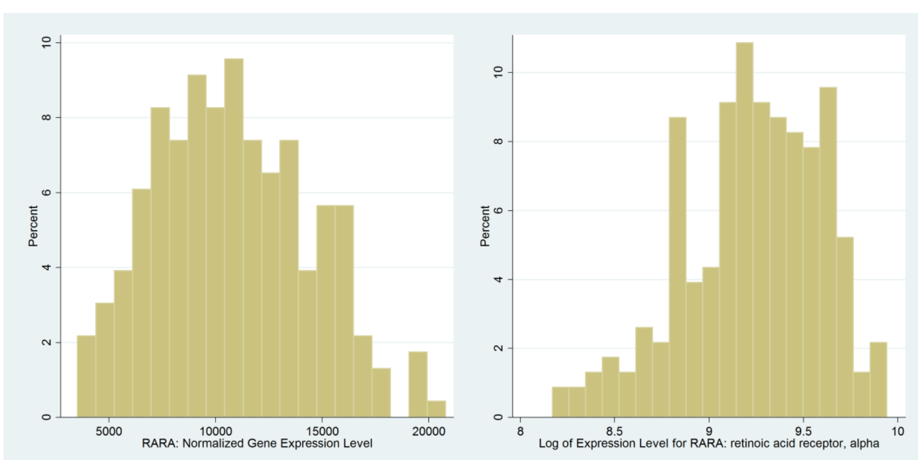

Figure 1.4 Statistical Distribution of the Expression Level of RARA

1.4.1.3 Summary Statistics

To sum up, the definition of variables and detailed descriptive statistics of the sample used in our following analysis are reported in Table 1.2.

In addition, further investigation shows that (1) there is no significant gender difference in the degree of impatience either in the near future or in the remote future; (2) there is no significant gender difference in the expression level of the RARA gene; but that (3) there is a significant gender difference in the degree of near-term bias – male participants tend to exhibit higher degrees of near-term bias than females at 10% significance level.

1.4.1.4 Correlation among Key Variables

Before proceeding to the regression analysis, we choose to investigate the correlation between the expression level of the RARA gene and people's attitudes towards time. The standard Pearson correlation coefficients with significance are calculated and reported in Table 1.3. Notably, the expression level of the RARA gene in peripheral blood is positively correlated with the degree of impatience in the remote future ($\rho = 0.162$, $p=0.014$, $N=229$) but not significantly correlated with the degree of impatience in the near future. Regarding Near-Term Bias, the expression level of the RARA gene is naturally negatively correlated with the degree of near-term bias ($\rho =-0.151$, $p=0.022$, $N=229$).

Table 1.2 Descriptive Statistics of Key Variables

Variable	Obs	Mean	Std. Dev.	Min	Max	Note
Gender (1=M)	230	0.53	0.500	0	1	A dummy variable for genders: Male=1, Female=0
IQ	230	56	3.367	32	59	IQ test score based on Raven's Progressive Matrices
Age	230	21.27	1.532	19	28	The age of participant as of the date of the experiment
NFuture	229	2.93	3.047	0	10	The switching point in the section of Near Future
RFuture	229	2.40	3.276	0	10	The switching point in the section of Remote Future
Near-Term Bias	229	0.53	3.246	-10	10	NFuture minus RFuture
RARA	230	10806.22	3633.469	3532.452	20799.02	The normalized expression level of the RARA gene
RARA_LN	230	9.23	0.361	8.170	9.94	The natural logarithm of RARA

Table 1.3 Standard Pearson Correlation Coefficients with Significance

	Near Future	**Remote Future**	**Near-Term Bias**	**RARA_LN**
Near Future	1.0000			
	(-)			
Remote Future	0.4747*	1.0000		
	(0.0000)	(-)		
Near-Term Bias	0.4596*	-0.5635*	1.0000	
	(0.0000)	(0.0000)	(-)	
RARA_LN	0.0126	0.1615*	-0.1511*	1.0000
	(0.8497)	(0.0144)	(0.0222)	(-)

Note: p-values are reported in the parentheses.

1.4.2 Econometric Analysis

Beyond the correlation analysis, we would like to conduct detailed investigation into the association between the expression level of the RARA gene and people's attitudes towards time based on econometric analysis.

1.4.2.1 Near Future Impatience and Expression of RARA

We firstly regress the degree of impatience in the near future (NFuture) on the logarithm of the RARA gene's expression level (RARA_LN), and the insignificant coefficient, as reported in column (1) in Table 1.4, is consistent with the insignificant result of the correlation analysis above. As a matter of fact, one might find that the adjusted R^2 is 0, which indicates zero explanation power of RARA_LN for the variation of NFuture.

Considering that there are many unobserved factors that might determine the degree of impatience both in the near future and in the remote future, we use the degree of impatience in the remote future (RFuture) to control these factors. However, the coefficient before RARA_LN is still insignificant. Moreover, after controlling for the demographic characteristics, including Gender and Age, we still have no significance in the coefficient of our interest.

Furthermore, we include the measure of cognitive ability, IQ, in the model, and it is found that the significance of RARA_LN does not get improved. But the coefficient before IQ itself is significantly negative; that is, decision makers with higher IQ test scores tend to be more patient in the near future, which is consistent with the results of Burks et al. (2009) and Dohmen et al. (2010).

Table 1.4 OLS Regression Results for the Near Future

	The Degree of Impatience in the Near Future (NFuture)				
	(1)	(2)	(3)	(4)	(5)
RARA_LN	0.106	-0.555	-0.545	-0.458	-0.351
	(0.18)	(1.05)	(1.03)	(0.91)	(0.70)
RFuture		0.451***	0.457***	0.435***	0.435***
		(6.85)	(7.12)	(6.61)	(6.71)
Gender (1=M)			0.432	0.443	0.126
			(1.24)	(1.28)	(0.32)
IQ				-0.123**	-0.120**
				(2.15)	(2.08)
Age					0.208*
					(1.87)
Constant	1.951	6.965	6.638	12.771**	7.339
	(0.37)	(1.43)	(1.35)	(2.17)	(1.17)
Adjusted R^2	-0.00	0.22	0.22	0.24	0.24
Observations	229	229	229	229	229

(1) Student t-statistics are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

1.4.2.2 Remote Future Impatience and Expression of RARA

Similarly to the analysis for the degree of impatience in the near future, we regress on the degree of impatience in the remote future (RFuture) on the logarithm of the RARA gene's expression level (RARA_LN), with NFuture, Gender, Age and IQ controlled step by step and report the results in Table 1.5.

One interesting finding is that the coefficient before RARA_LN is statistically significant (at 1% significance level) across all models, from Column (1) to Column (5), which is strikingly different from the case for the near future. In other words, decision makers with higher expression level of the RARA gene tend to be more impatient in the remote future. More importantly, RARA_LN can explain 2% of the variation in RFuture, which is quite strong for a single gene.

Another point worth noting is that the degree of impatience in the remote future is not significantly correlated with the IQ test score. Additionally, there is no significant gender difference either in the near future or in the remote future.

Table 1.5 OLS Regression Results for the Remote Future

	The Degree of Impatience in the Remote Future (RFuture)				
	(1)	(2)	(3)	(4)	(5)
RARA_LN	1.464***	1.410***	1.384***	1.416***	1.358***
	(2.73)	(2.85)	(2.78)	(2.80)	(2.68)
NFuture		0.508***	0.511***	0.495***	0.500***
		(6.89)	(6.99)	(6.55)	(6.65)
Gender (1=M)			-0.636*	-0.620	-0.454
			(1.69)	(1.64)	(1.04)
IQ				-0.067	-0.068
				(0.79)	(0.80)
Age					-0.110
					(0.80)
Constant	-11.107**	-12.099***	-11.533**	-8.035	-5.213
	(2.27)	(2.69)	(2.55)	(1.31)	(0.72)
Adjusted R^2	0.02	0.24	0.25	0.25	0.25
Observations	229	229	229	229	229

(1) Student t-statistics are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

1.4.2.3 Near-Term Bias and Expression of RARA

Given the fact that the degree of impatience is not significantly correlated to the RARA gene's expression level in the near future but significantly positively correlated to it in the remote future, we expect that the degree of near-term bias, which has been defined as NFuture minus RFuture, might be negatively correlated with the expression level of RARA. The regression results, as reported in Table 1.6, confirm the significance of the negative correlation. In words, decision makers with lower expression level of the RARA gene tend to exhibit greater degree of near-term bias.

However, the effect of the IQ test score on the degree of near-term bias is not significant, even though it is significant in the near future. In other words, people's cognitive ability is not significantly correlated with the difference in the degree of impatience between near future and remote future.

Table 1.6 OLS Regression Results for the Near-Term Bias

	The Degree of Near-Term Bias (NFuture minus RFuture)			
	(1)	(2)	(3)	(4)
RARA_LN	-1.358**	-1.328**	-1.314**	-1.204**
	(2.25)	(2.19)	(2.18)	(2.02)
Gender (1=M)		0.726*	0.732*	0.408
		(1.70)	(1.71)	(0.84)
IQ			-0.031	-0.027
			(0.36)	(0.31)
Age				0.212
				(1.45)
Constant	13.058**	12.405**	14.000*	8.454
	(2.36)	(2.22)	(1.92)	(1.04)
Adjusted R^2	0.02	0.03	0.02	0.03
Observations	229	229	229	229

(1) Student t-statistics are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

1.4.3 Robustness Checks

Finally, a series of robustness checks are conducted. For instance, we try different measures for the delay discounting rate through assuming utility function forms and not simply taking the switching points. One can refer to Appendix I for an approach to calculate the discounting rates for different switching points in the two intertemporal decision tasks.

We also try different econometric specifications like probit models and (two-limit) Tobit models to control for the ordering property and the censoring property of the data. For instance, estimation results for the two-limit Tobit model are reported in Table A.2 - Table A.4 in Appendix I. Notably, our results are robust to all of these checks.

1.5 Discussion

In this paper, we demonstrate the association between people's attitude towards time and the expression level of a candidate gene, RARA. Specifically, we find that decision makers with lower expression level of RARA gene tend to be more impatient in the remote future and in turn tend to exhibit greater near-term bias. These results, interpreted properly, may enhance our understanding of people's attitudes towards time.

The very first point we would like to highlight is that our results make biological sense from several aspects that there is a relationship between people's attitudes towards time and the expression of the RARA (retinoic acid receptor-α) gene. Firstly, people's attitudes towards time can be viewed as a result of their perception or sense of time, and it has recently been documented that both the neural system and the visual system account for human time perception (Eagleman, 2008; Ivry and Schlerf, 2008; Wittmann and Paulus, 2008). More specifically, researchers began to look at time perception around eye movement. For instance, Morrone *et al.* (2005) discovered that duration judgements were compressed during saccadic eye movements, and Morrone *et al.* (2005) suggested a possible explanation for the saccade results, showing more generally that stimuli with reduced visibility (as stimuli are during a saccade) lead to the same sort of duration compressions. Secondly, recent studies have determined that genes that control circadian rhythms are keenly involved in regulating the dopaminergic reward circuitry and that this regulation may be the cause of the increase in vulnerability and the plasticity that contributes to impulsivity and addictive behaviours, like alcoholic addiction or drug abuse (Kreek *et al.*, 2005; Parekh *et al.*, 2015; Partonen, 2015; Rosenwasser, 2010), which have been well established to be related with people's attitude towards time (Chabris *et al.*, 2006). Thirdly, circadian rhythms in mammals are regulated by the master circadian clock located in the suprachiasmatic nucleus (SCN) of the hypothalamus (Ko and Takahashi, 2006). A critical feature of circadian timing is the ability of the clockwork to be reset by environmental light to the 24-h day, with the retino-hypothalamic tract being the principal pathway through which entrainment information reaches the SCN. Vitamin A is a vital component of the mammalian diet that is delivered to tissues in the form of circulating retinol, and it is particularly crucial during development of the central nervous system. Recently, a novel homeostatic role is emerging for RA as a regulator of biological rhythms within the SCN (Ransom *et al.*, 2014). Several components of the RA signalling pathway oscillate according to photoperiodic changes in light conditions. For example, increased day length leads to enhanced retinoid signalling within the hypothalamus. And the RARA gene has been implicated in regulation of development, differentiation, apoptosis, granulopoeisis, and transcription of clock genes[1].

Another point we would like to emphasize is that the 2% explanation power of the RARA gene's expression for the variation in the degree of impatience in the remote future as well as the near-term bias is plausibly strong from the perspective of genetic analysis. On the one hand, given the vast genetic variation, some specific genetic variation usually only accounts for a very small amount of the variance in complex human behaviours (Beauchamp *et al.*, 2011; Benjamin *et al.*, 2012; De Neve *et al.*, 2012); on the other hand, the molecular clock consists of a number of genes that form transcriptional and post-transcriptional feedback loops, which function together to generate circadian oscillations that give rise to circadian rhythms of our behavioural and physiological processes, and hence the RARA gene is just one of them. One may refer to Ko and Takahashi (2006) and Zhang *et al.* (2013) for a detailed review about the

[1] Refer to http://www.genecards.org/cgi-bin/carddisp.pl?gene=RARA for more information.

diversity of human clock genotypes. Besides, there is likely to be a set of genes, whose expression, in combination with environmental factors, influences people's attitudes towards time.

What's more, from the cognition perspective of view, it is worth noting that the cognitive ability dominates the RARA gene in explaining the variation of people's impatience degree in the near future but that the RARA gene dominates the cognitive ability in the remote future. Our results, properly interpreted, may enhance our understanding of the explanation power of cognitive ability for time discounting. For instance, Burks *et al.* (2009) and Dohmen *et al.* (2010) report that people with lower cognitive ability are significantly more impatient, with which our result for the near future shares consistence. However, in those experiments, they did not distinguish the near future from the remote future. Furthermore, in the huge body of literature about the neural foundation for time discounting (Bechara, 2005; Weber and Huettel, 2008), there are few studies if any that distinguish the near future and the remote future, either. Besides, our results tend to suggest that whether a decision maker exhibits near-term bias does not significantly depend on their cognitive abilities.

Beyond their purely descriptive value, our results also shed light on the use of models with heterogeneity in macro- and financial economics (Aiyagari, 1993; Freeman, 1996; Mankiw, 1986; Telmer, 1993) and challenge the common assumption that people are born with identical preferences and identical discount rates and that the main source of heterogeneity lies in the idiosyncratic shocks to individual incomes. But, as we have documented, people's attitudes towards time could be very different, which has a solid biological foundation, and these differences could and should be taken into consideration to specify the preference heterogeneity to explain economic and financial outcomes.

Besides, our study has several potential limitations that should be addressed by future research. Firstly, in genetic analysis, it is very important to replicate the results for some specific genetic variation in independent samples. Such efforts to replicate a significant association result, as well as increasing the sample sizes, are critical to exclude the possibility that the original association would be spurious (De Neve *et al.*, 2012). However, due to budget constraints, we have no replication sample in this study. Secondly, to measure the degree of decision makers' impatience, we mainly focus on their switching points in the responses to the intertemporal decision tasks presented by multiple price lists, although there are some other seemingly plausible approaches proposed in the recent literature (Andersen *et al.*, 2008; 2014; Andreoni and Sprenger, 2012a). More importantly, our primary objective in this study is to establish the association between the expression level of the RARA gene and people's attitudes towards time, but not to explore the quantitative effect. In other words, it is not our primary interest to investigate whether a decision maker with an expression level of RARA 1% higher than the average level would be more impatient than the average by 1.5% or 5%. Thirdly, people might be concerned about the extent to which laboratory behaviour generalizes to the field (Harrison and List, 2004; Levitt and List, 2007). As a matter of fact, robust results have been reported to show that individual laboratory-measured discount rates predict field behaviour in a very broad sense, including smoking, drinking, exercise, nutrition, saving, borrowing, wealth, and gambling (Chabris *et al.*, 2008). Again, related to the second point, our primary aim is at the direction of the association but not the quantitative effects. Lastly, one might care about the representativeness of our sample. On the one hand, the 230 participants whose RARA gene's expression levels were measured are expected to be representative of the whole sample, since they were randomly picked out from the 1130 participants. Actually, distributions of the behavioral data are also compared over the whole sample and the subsample, but no significant difference is found. On the other hand, it might be true that the whole sample may not be representative of the Chinese population or even the Singaporean Chinese population, because all of our 1130 participants are geographically concentrated in Singapore and relatively more educated than the Singapore population. With these caveats in mind, we consider our results to be only suggestive. However, we believe that these methodological problems have primarily reduced the statistical clarity of our findings rather than biasing our results towards the conclusion that we have reported.

Most importantly, to our knowledge, the current report is the first showing a gene known to be involved as mediators of rhythm in the brain has been implicated in temporal decision making elicited as impatience in the remote future as well as near-term bias. And this is apparently the first study to bring in measures of gene expression to investigate choice behaviour elicited from incentivized decision making tasks. These open a novel strategy ("blood genomics") for economic modelling time preference in decision theory.

1.6 Conclusion

Time is a very important factor in decision making in the sense that the degree of impatience is an essential dimension to be included when people study dynamic decision making in economics. Focusing on the variation in the degree of impatience, this paper investigates the explanatory power by the expression level of the candidate gene, RARA (retinoic acid receptor-α), which has recently been implicated in regulation of development, differentiation, apoptosis, granulopoeisis, and transcription of clock genes. One of the main findings is that the expression level of the RARA gene in peripheral blood is positively correlated with the degree of impatience in the remote future; in words, decision makers with lower expression level of RARA gene tend to be more impatient in the remote future. But there is no such significance in the near future. Another finding is that the expression level of the RARA gene is negatively correlated with the degree of near-term bias. These plausible findings are robust with cognitive ability and demographic characteristics, including genders and ages, controlled.

To our knowledge, it is for the first time that a gene known to be involved as mediators of rhythm in the brain has been implicated in temporal decision making elicited in terms of impatience in the remote future and near-term bias. And this is conceivably the first study to bring in measures of gene expression to investigate choice behaviour elicited from incentivized decision making tasks.

Chapter 2 Genetics of People's Attitudes towards Uncertainty

2.1 Introduction

One of the most fundamental problems of modern decision theory is the analysis of decisions under uncertainty. From the behavioural point of view, vast variations in people's attitudes towards uncertainty across individuals have been documented in the literature (see Machina (1987); Starmer (2000)), yet the determinants of these individual differences are not fully understood. Explaining the heterogeneity in decision makers' attitudes towards uncertainty is relevant to a number of prominent topics in economics, like the asset pricing theory, the wealth distribution theory, and so on. More importantly, a better understanding of the determinants of cross-sectional variance leads to facts that theories involving uncertain choices have to be consistent. While the variation can be explained to some extent by demographics (Barsky *et al.*, 1997b), and there have been a few recent advances in identifying neurological and biological predictors of preferences like brain activation (Kim *et al.*, 2008; Weber and Huettel, 2008) or cognitive ability (Burks *et al.*, 2009; Dohmen *et al.*, 2010) or even genetic polymorphisms (Carpenter *et al.*, 2011), economists have yet to identify robust exogenous sources or hard wiring of these variations in uncertainty preferences. Fortunately, the increasing availability of genetic information now allows us to test hypotheses about candidate genes and their impacts on decision making. One place to start the search for such genes is among those that have already been shown to account for variation in the observable traits and behaviours of interest.

In this study, we selected ten candidate genes based on findings in the literature about genes which have been shown related to behaviors involving rewards, impulsivity, risk, stress, and so on. These genes are ADRB1, AR, AVPR1A, COMT, ERBB3, ESR1, ESR2, HTR2A, MAOA, and NRG1. For instance, previous studies suggest that a single nucleotide polymorphism in the catechol-O-methyltransferase (COMT) gene (val158met) may modulate reward-guided decision making in healthy individuals. The polymorphism affects dopamine catabolism and thus modulates prefrontal dopamine levels, which may lead to variation in individual responses to risk and reward (Lancaster *et al.*, 2015; Lancaster *et al.*, 2012). In the first result to link attitude towards longshot risks to a specific gene, Zhong *et al.* (2009) observe a significant association between subjects' preference for the longshot lottery and a widely studied, promoter-region repeat functional polymorphism in monoamine oxidase A gene (MAOA). In another study, Chew *et al.* (2012) report some significant association between the estrogen receptor beta (ESR2) gene with ambiguity aversion among female subjects.

Moreover, unlike the conventional gene association studies in the literature (see Beauchamp *et al.* (2011) for a quick review), we explore the association between people's attitudes towards uncertainty and genetic variants based on behavioural measures of the degree of uncertainty aversion elicited from incentivized decision making tasks and the expression data of the candidate genes. One advantage of employing genetic expression data is that gene expression studies capture both environmental as well as hard wired gene variation and hence are complementary and perhaps even more informative than simple gene association studies. Another advantage is that genetic expression data provides more variations than SNP data, in the sense that people with the same SNP in the same gene may still exhibit vast variation in the expression level. More importantly, to our knowledge, there are no studies comparing uncertainty aversion and gene expression in peripheral blood ('blood genomics' strategy).

Following this introduction section, the rest of the paper is structured as follows. Section 2 describes the design of our experiment as well as the implementation. Section 3 presents the methodology of our analysis and reports the results, together with a series of robustness checks. In Section 4, we conclude with a brief discussion about the implications of our results, limitations of this study and directions for future research.

2.2 Experimental Design and Implementation

2.2.1 Experimental Design

2.2.1.1 Elicitation of People's Attitudes towards Uncertainty

To elicit people's attitudes towards uncertainty in different contexts, we asked the subjects to respond to decision tasks in four types of uncertain decision situations, including two risky situations with explicit probabilities and another two ambiguous situations without explicit probabilities given. In particular, the two risky situations are the Moderate Prospect Task (MP) and the Moderate Hazard Task (MH), and the two ambiguous situations are the Ambiguous Prospect Task (AP), and the Ambiguous Hazard Task (AH).

The decision tasks are all presented in the form of multiple price lists (MPLs) with monetary payments (Holt and Laury, 2002). More specifically, we list ten pairs of options in each decision sheet for a specific decision situation, and each pair includes a fixed Option A and a varying Option B, with the 10 different Option

B's arranged in an ascending manner in terms of value, the amount of money. Given a price list, a decision maker with consistent preferences in a specific setting is expected to have a "switching" point between preferring Option A or Option B, and this switching point is believed to carry interval information about his/her preference.

For the sake of illustration, let's take the Moderate Prospect Task (MP) as an example. In this task, the expected value of the fixed Option A is $30, which corresponds to the seventh pair on the risk price list. Hence, if one chooses Option A initially and switches to Option B later but before or exactly at the seventh pair, we will say that this decision maker is risk-averse; and in an extreme case, if one does not choose Option A at all, he/she is risk-averse, of course, and his/her degree of risk aversion is viewed higher than those choosing at least one Option A on the list. On the other hand, if one chooses Option A initially and switches to Option B later than the seventh pair, we will say that this decision maker is risk-seeking; and, again, in an extreme case, if one does not choose Option B at all, he/she will be viewed as risk-seeking, with a higher degree of risk seeking than those choosing at least one Option B on the list. Correspondingly, the number of subjects' choices of Option A would be recorded, and we call this number the switching point in a task with specific situations, which could be viewed as a measure of the degree of risk aversion given the context. Therefore, subjects indicated by a number less than or equal to 7 are risk-averse, while those indicated by a number greater than 7 are risk-seeking. Moreover, the earlier the switching point is on the risk price list, the more risk-averse the decision maker is. In particular, those indicated "0" are the most risk-averse subjects in our sample, while those indicated "10" are the most risk-seeking.

Besides, there are several minor points about the differences among the four tasks. The first point is that tasks MP and AP are in the gain domain while tasks MH and AH in the loss domain; the second point is about the interpretation of the switching points in the task MH - subjects indicated by a number less than or equal to 4 are risk-averse, while those indicated by a number greater than 4 are risk-seeking; and the third point is about the difference between task MP (MH) and task AP (AH) – there are no explicit probabilities given in AP or AH, which cases are referred to as ambiguous situations. In the Ambiguous Prospect case, we follow the literature and take the expected payoff of the Option A as $30. Subsequently, we refer to those who switch from Option A to Option B before or exactly at the seventh pair on the ambiguity price list as uncertainty-averse decision makers in ambiguous situations. Similarly, in task AH, subjects indicated by a number less than or equal to 4 are uncertainty-averse, while those indicated by a number greater than 4 are uncertainty-seeking. Since the four tasks are designed in the same form, it's not necessary to discuss them one by one, and one can refer to Appendix III for the exact format of decision sheets presented to the subjects.

Moreover, we can also compare a subject’s switching points in task MP and AP, and the difference between them, say, AP minus MP, could be viewed as a measure for the degree of ambiguity aversion in the gain domain. And similarly, the difference between the switching points in task MH and AH, AH minus MH, could be taken as a measure for the degree of ambiguity aversion in the loss domain.

In the subsequent analysis, we mainly focus on participants' switching points in their responses to the decision tasks, and alternative measures for participants' attitudes towards uncertainty will be constructed and employed for robustness tests. In effect, this strategy does not rely on the utility function, which helps avoid quite a lot of potential estimation bias resulting from misspecification of utility functions (Chen and Pu, 2004; Reynaud and Couture, 2012).

2.2.1.2 Expression Level of Candidate Genes

In the present study, we selected 10 candidate genes based on findings in the literature about genes which have been shown related to behaviors involving rewards, impulsivity, risk, stress, and so on. These genes are ADRB1, AR, AVPR1A, COMT, ERBB3, ESR1, ESR2, HTR2A, MAOA, and NRG1. For instance, previous studies suggest that a single nucleotide polymorphism in the catechol-O-methyltransferase (COMT) gene (val158met) may modulate reward-guided decision making in healthy individuals. The polymorphism affects dopamine catabolism and thus modulates prefrontal dopamine levels, which may lead to variation in individual responses to risk and reward (Lancaster *et al.*, 2015; Lancaster *et al.*, 2012). In the first result to link attitude towards longshot risks to a specific gene, Zhong *et al.* (2009) observe the significant association between subjects' preference for the longshot lottery and a widely studied, promoter-region repeat functional polymorphism in monoamine oxidase A gene (MAOA). One may refer to Appendix IV for more detailed discussion about the rationales for the candidate gene selection. Focusing on these candidate genes, we measured the expression levels of them from a random pick of 230 of the 1158 participants.

2.2.1.3 *Demographics and Cognitive Ability*

In addition, we also collected demographic information of the participants, including their genders and their ages as of the date of our experiment. Their proxy IQ test scores were obtained based on the Raven's Progressive Matrices.

2.2.2 Experimental Implementation

As a matter of fact, the experiment data employed in this paper is only a part of an experimental project on decision making, which aims to explore the biological foundation for economic and social decision making[1]. In November, 2010, 1158 Han Chinese undergraduate students were recruited from National University of Singapore in Singapore to participate in decision-making experiments, in the forms of pencil-and-paper answer sheets as well as online questionnaires. Participants donated 10 to 20 cc of blood for extracting DNA after the economic decision making tasks and lifestyle & personality questionnaires. The study was approved by the university's Institutional Review Board and participants were given written informed consent prior to participation. Participants were reimbursed for participation in the project (S$25 per hour on average).

2.3 Results

To investigate the potential explanation power of the variation in the expression level of candidate genes for the variation in people's attitudes towards uncertainty, we followed three steps to analyse the data of our experiment and present the analysis results in this section. Firstly, we examined and summarized the participants' responses to the four decision tasks as well as the expression

[1] For further details about this project, one could visit the web site of the lab for Behavioral Biological Economics and Social Sciences (B2ESS), http://b2ess.nus.edu.sg.

data of the candidate genes, with the standard Pearson correlation coefficients calculated among the key variables. Secondly, detailed multivariate regression analyses were conducted, with demographic characteristics and cognitive ability controlled. Thirdly, a series of robustness checks were implemented.

2.3.1 Behavioral Results and Genetic Data

2.3.1.1 Behavior in Risky Situations

As we have discussed in the section of experimental design, to capture people's attitudes towards risk in different situations, we asked the subjects to respond to two tasks involving the gain case and the loss case, which are the Moderate Prospect Task (MP) and the Moderate Hazard Task (MH). Now, let us take a look at the subjects' behavioural patterns in different situations one by one, before investigating the potential interrelation between attitudes towards uncertainty and time.

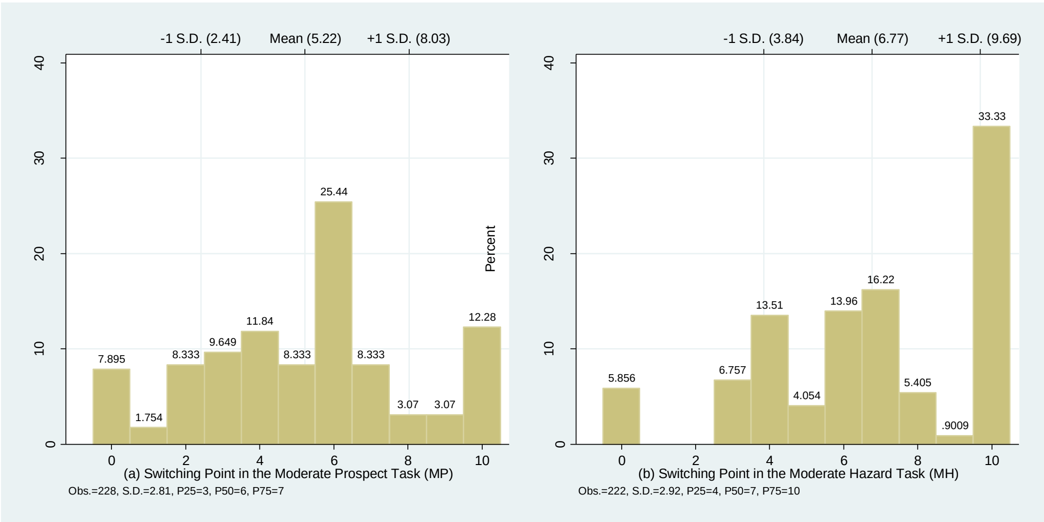

Figure 2.1 Distribution of Switching Points in Task MP and Task MH

In the Moderate Prospect Task (MP), as shown in Figure 2.1(a), 81.58% of subjects are indicated by a number less than or equal to 7, which means they chose the first Option B before or exactly at the seventh pair, corresponding to the expected value of the fixed Option A, \$30, and hence should be viewed as risk-averse decision makers; while the other 18.42% of the subjects switched after the seventh pair or even did not choose Option B at all and hence are risk-seeking. This pattern together with more detailed distributional characteristics indicates that in the moderate risky situations with potential gains, risk-averse subjects account for the majority. This observation is consistent with the result of the student-*t* test.

However, in the Moderate Hazard Task (MH), as shown in Figure 2.1(b), only 12.61% of subjects switched before the fourth pair, corresponding to the expected value of the fixed Option A, \$7.5, while the other 87.39% of them switched at or after the fourth pair, suggesting that in the moderate risky situations with potential losses, the majority of subjects exhibit risk seeking attitudes. This finding is supported by the result of the student-*t* test.

2.3.1.2 Behavior in Ambiguous Situations

Besides the two tasks with probabilities of the uncertain situations explicitly given, we also have another two tasks without explicit probabilities given in the uncertain decision-making situations, which we refer to as the Ambiguous Prospect Task (AP), and the Ambiguous Hazard Task (AH). Now, let us turn to examine the subjects' responses to the decision tasks in the two ambiguous situations.

In the Ambiguous Prospect Task (AP), as shown in Figure 2.2 (a), more than 90% of subjects are indicated by a number less than or equal to 7, which means they chose the first Option B before or exactly at the seventh pair, with the fixed

Option A and "Receiving $30 for sure" as Option B, and hence should be viewed as uncertainty-averse decision makers. In particular, more than 40% of subjects are extremely uncertainty-averse in the sense that they might choose Option B if an even smaller amount of money than $15 is offered in that option.

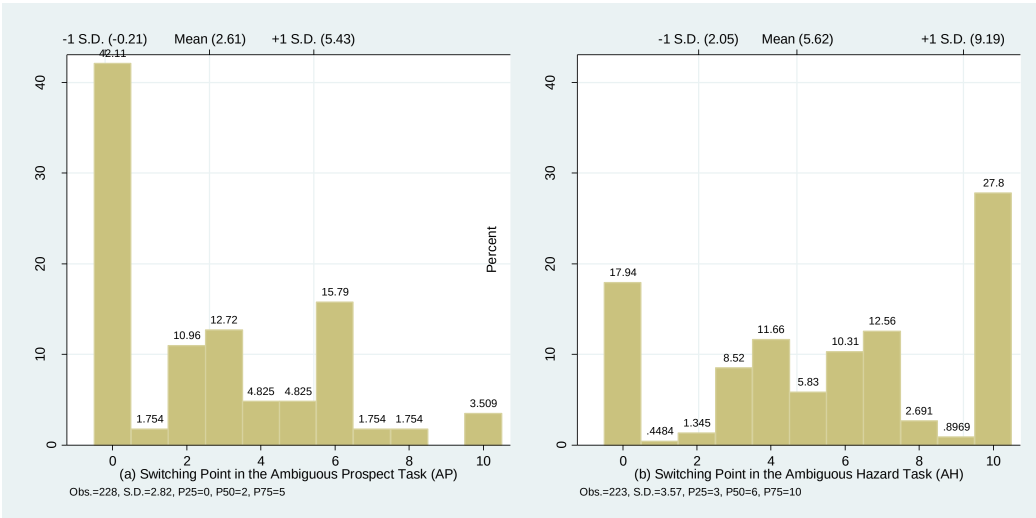

Figure 2.2 Distribution of Switching Points in Task AP and Task AH

But when coming to the Ambiguous Hazard Task (AH), as shown in Figure 2.2(b), one can find that more than 70% of subjects are risk-loving in the sense that they switched at or after the fourth pair from Option A to Option B.

Moreover, as one might have noticed, the reversal from being risk averse in Task AP to being risk loving in Task AH is parallel to that from Task MP to Task MH.

2.3.1.3 Comparison between Risky and Ambiguous Situations

Furthermore, comparing the subjects' behaviour patterns in Task MP and Task AP, one may note that the distributions are quite different, although the uncertainty-aversion patterns in both cases are significant. In particular, almost 42% of subjects chose the most conservative Option B, and more than 50% of subjects chose Option B when "Receiving $23 for sure" was available in Task AP, while in Task MP, only 40% chose Option B even when "Receiving $29 for sure" was available. In addition, the statistical tests suggest that the switching point locations in the two tasks, MP and AP, are significantly different from each other, and that the switching point in Task AP is significantly earlier than that in Task MP. Actually, this behaviour pattern has been well documented in the literature, which can be traced back to Ellsberg (1961), and the difference of the degrees of uncertainty aversion in the two situations is referred to as ambiguity aversion.

Since we have taken the switching point as a measure of the degree of uncertainty aversion, we can take the difference of the switching point locations in the two tasks, and view it as a measure of ambiguity aversion. From Figure 2.3(a), one can find the pattern of ambiguity aversion exhibited in the subjects' behaviour is significant, which is also consistent with the tests upon the difference between the behaviour patterns in Task MP and Task AP. A similar comparison between Task MH and Task AH is also illustrated in Figure 2.3(b).

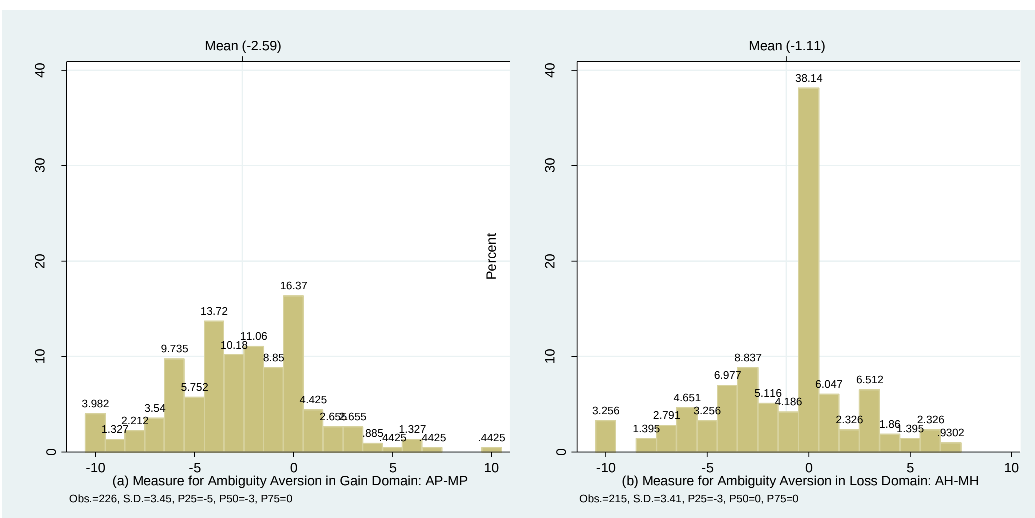

Figure 2.3 Difference in Switching Points of MP and AP and those of Task MH and AH

2.3.1.4 Genetic and Demographic Data

Next, let us turn to the genetic data. Focusing on ten candidate gene, we collect the normalized level of their expression, which shows a very broad range, and hence we take the natural logarithm of these variables, which is usually done in gene expression studies. Table 2.1 summarizes some detailed descriptive statistics of the genetic expression data, together with the demographic data.

Table 2.1 Descriptive Statistics of Key Variables

Variable	Obs	Mean	Std. Dev.	Min	Max	Note
ADRB1	210	2.79	0.84	-1.00	5.04	The natural logarithm of expression level of the ADRB1 gene
AR	227	5.04	0.58	1.19	6.32	The natural logarithm of expression level of the AR gene
AVPR1A	228	6.13	0.53	4.50	7.59	The natural logarithm of expression level of the AVPR1A gene
COMT	229	8.14	0.32	7.11	9.10	The natural logarithm of expression level of the COMT gene
ERBB3	227	4.07	0.62	2.22	8.24	The natural logarithm of expression level of the ERBB3 gene
ESR1	228	5.27	0.44	3.75	7.87	The natural logarithm of expression level of the ESR1 gene
ESR2	224	4.01	0.53	1.68	5.26	The natural logarithm of expression level of the ESR2 gene
HTR2A	207	2.79	0.83	-0.89	4.86	The natural logarithm of expression level of the HTR2A gene
MAOA	222	4.53	1.19	-0.74	7.76	The natural logarithm of expression level of the MAOA gene
NRG	230	7.23	0.60	4.34	10.20	The natural logarithm of expression level of the NRG gene
Gender	230	0.53	0.500	0	1	A dummy variable for genders: Male=1, Female=0
RPM IQ	230	56	3.367	32	59	IQ test score based on Raven's Progressive Matrices
Age	230	21.27	1.532	19	28	The age of participant as of the date of the experiment

2.3.1.5 Correlation among Key Variables

Before proceeding to the regression analysis, we choose to investigate the correlation between the expression level of the candidate genes and people's attitudes towards uncertainty. The standard Pearson correlation coefficients with significance are calculated and reported in Table 2.2.

Notably, the degree of uncertainty (risk) aversion in the Moderate Prospect Task (MP) is significantly positively correlated with the degree of uncertainty aversion across all other three tasks, which suggests that people's attitudes towards different types of uncertainty share some common factors. However, should one closely investigate the correlation among the other three tasks, he/she may find 1) people's attitudes towards loss in different kinds of uncertain situations (MH and AH) also share some common factors, but 2) people's attitudes towards loss in risky situation (MH) is not significantly correlated their attitudes towards gain in ambiguous situation (AP). Moreover, it seems that people's attitudes towards ambiguity in the gain domain share no common factors with the loss domain.

Moreover, according to the correlation between attitudes towards uncertainty and the expression level of candidate genes, it seems attitudes towards different types of uncertainty are correlated with the expression of different genes. For example, the degree of uncertainty (risk) aversion in the Moderate Prospect Task (MP) is associated with the expression level of ERBB3, ERS1 and HTR2A, while the degree of uncertainty aversion in the Ambiguous Hazard Task (AH) is associated with the expression level of AR, AVPR1A, HTR2A, MAOA and NRG1.

Table 2.2 Standard Pearson Correlation Coefficients with Significance

	MP	MH	AP	AH	AP-MP	AH-MH	ADRB1	AR	AVPR1A	COMT	ERBB3	ESR1	ESR2	HTR2A	MAOA	NRG1
MP	1															
	(-)															
MH	0.157*	1														
	0.020	(-)														
AP	0.247*	-0.031	1													
	0.000	0.644	(-)													
AH	0.124*	0.469*	-0.001	1												
	0.065	0.000	0.990	(-)												
AP-MP	-0.612*	-0.140*	0.616**	-0.095	1											
	0.000	0.039	0.000	0.160	(-)											
AH-MH	0.013	-0.366*	0.019	0.651*	0.006	1										
	0.856	0.000	0.779	0.000	0.926	(-)										
ADRB1	-0.002	0.087	0.139*	-0.004	0.116*	-0.076	1									
	0.980	0.213	0.046	0.952	0.097	0.285	(-)									
AR	0.024	0.045	-0.027	0.124*	-0.045	0.080	0.000	1								
	0.724	0.512	0.690	0.067	0.506	0.248	0.999	(-)								
AVPR1A	0.064	0.032	-0.113*	0.158*	-0.136*	0.132*	-0.088	0.273*	1							
	0.341	0.633	0.091	0.019	0.042	0.055	0.203	0.000	(-)							
COMT	-0.005	0.044	0.092	0.046	0.086	0.005	0.165*	0.001	0.257*	1						
	0.938	0.512	0.166	0.492	0.197	0.937	0.017	0.987	0.000	(-)						
ERBB3	0.124*	0.110	0.055	-0.007	-0.046	-0.117*	0.208*	0.040	0.091	0.297*	1					
	0.064	0.105	0.408	0.919	0.499	0.088	0.003	0.552	0.174	0.000	(-)					
ESR1	0.151*	-0.002	0.118*	0.104	-0.035	0.097	0.086	0.140*	0.178*	0.116*	0.232*	1				
	0.023	0.977	0.078	0.125	0.606	0.157	0.214	0.036	0.007	0.081	0.000	(-)				
ESR2	-0.003	0.004	0.030	0.050	0.037	0.070	0.071	-0.081	-0.015	0.263*	0.160*	0.124*	1			
	0.962	0.949	0.654	0.466	0.585	0.313	0.308	0.225	0.827	0.000	0.017	0.064	(-)			
HTR2A	0.135*	0.120*	-0.040	0.213*	-0.132*	0.104	-0.080	0.218*	0.260*	0.195*	-0.011	0.071	-0.011	1		
	0.055	0.090	0.570	0.003	0.060	0.149	0.268	0.002	0.000	0.005	0.877	0.308	0.871	(-)		
MAOA	0.053	-0.071	-0.031	-0.161*	-0.077	-0.129*	0.037	0.075	0.083	0.177*	0.091	0.058	-0.030	0.097	1	
	0.433	0.303	0.647	0.018	0.260	0.065	0.595	0.269	0.218	0.008	0.179	0.394	0.658	0.168	(-)	
NRG1	0.108	0.095	-0.032	0.117*	-0.105	0.030	-0.045	0.201*	0.175*	-0.068	0.076	0.117*	-0.082	0.115	0.010	1
	0.105	0.156	0.628	0.082	0.117	0.658	0.516	0.002	0.008	0.305	0.256	0.078	0.223	0.100	0.884	(-)

Note: (1) The first line is the Pearson correlation coefficient and the second line is the p-value;
(2) * denotes the correlation coefficients significant at the 10% level or lower.

2.3.2 Econometric Analysis

Beyond the correlation analysis, we would like to conduct an investigation into the association between the expression level of the ten candidate genes and people's attitudes towards uncertainty based on econometric analysis.

2.3.2.1 Uncertainty Aversion in Risky Situation (MP) and Gene Expression

Guided by the results of the correlation test above, we firstly regress the degree of uncertainty aversion in the Moderate Prospect Task (MP) on the log of the expression level of ERBB3, ERS1 and HTR2A, respectively. And the significant coefficients, as reported in columns (1-3) in Table 2.3, are consistent with the significant results of the correlation analysis above.

As a matter of fact, one might find that the adjusted R^2 indicates 2% explanation power of ESR1 and 1% explanation power of ERBB3 and HTR2A for the variation in the degree of uncertainty aversion in the Moderate Prospect Task. From the perspective of genetic study, this is quite plausible given that there are a huge number of genes.

Moreover, after controlling for the demographic characteristics, including Gender and Age, as well as the measure of cognitive ability, IQ, in the model, there is no significant change in the coefficients, as reported in columns (4-6). And even when all of the three genes are included in the model, it's found that the significance of HTR2A does not change.

Table 2.3 Robust OLS Regression Results for the Moderate Prospect Task (MP)

	Switching Point in the Moderate Prospect Task (MP)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ERBB3	0.557*			0.627**			0.562
	(1.81)			(2.05)			(1.58)
ESR1		0.970**			0.962**		0.541
		(2.38)			(2.36)		(1.12)
HTR2A			0.452**			0.474**	0.458**
			(2.06)			(2.17)	(2.04)
Gender (1=M)				0.464	0.450	0.658	0.540
				(1.13)	(1.13)	(1.54)	(1.24)
IQ				-0.128**	-0.119**	-0.132***	-0.146***
				(2.47)	(2.44)	(2.61)	(2.67)
Age				0.062	0.068	0.051	0.079
				(0.53)	(0.59)	(0.44)	(0.67)
Constant	2.978**	0.133	3.906***	8.315**	5.169	9.801**	5.003
	(2.30)	(0.06)	(6.20)	(2.21)	(1.20)	(2.57)	(1.01)
Adjusted R^2	0.01	0.02	0.01	0.03	0.04	0.04	0.05
Observations	225	226	205	225	226	205	204

(1) Student t-statistics based on robust standard errors are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

Besides, the coefficient before IQ itself is significantly negative; that is, decision makers with higher IQ test scores tend to be more patient in the near future, which is consistent with the results of Burks *et al.* (2009) and Dohmen *et al.* (2010).

2.3.2.2 Uncertainty Aversion in Risky Situation (MH) and Gene Expression

Using the same strategy, we regress the degree of uncertainty aversion in the Moderate Hazard Task (MH) on the log of the expression level of HTR2A. Again, the significant coefficient, as reported in column (1) in Table 2.4, is consistent with the significant results of the correlation analysis above.

Table 2.4 Robust OLS Regression Results for the Moderate Hazard Task (MH)

	Switching Point in the Moderate Hazard Task (MH)		
	(1)	(2)	(3)
HTR2A	0.437*	0.370	0.230
	(1.84)	(1.55)	(0.94)
Gender (1=M)		-0.827*	-0.970**
		(1.68)	(2.04)
IQ		-0.007	0.006
		(0.14)	(0.13)
Age		-0.186	-0.204
		(1.33)	(1.50)
A1			0.195**
			(2.16)
Constant	5.376***	10.380**	9.475**
	(7.72)	(2.45)	(2.41)
Adjusted R^2	0.01	0.04	0.06
Observations	200	200	198

(1) Student t-statistics based on robust standard errors are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

However, after controlling for the demographic characteristics, including Gender and Age, as well as the measure of cognitive ability, IQ, in the model, the coefficient before HTR2A is no longer significant. Another interesting finding is that the coefficient before IQ is no longer significant but that there seems to be significant difference between genders, which confirms the findings by Borghans et al. (2009). Moreover, controlling for A1, as shown in column (3), does not change the results much.

2.3.2.3 Uncertainty Aversion in Ambiguous Situation (AP) and Gene Expression

Now, let us turn to the Ambiguous Prospect Task (AP). Table 2.5 reports the robust regression results of the degree of uncertainty aversion in Task AP on the log of the expression level of ADRB1, AVPR1A and ESR1, respectively. As predicted by the correlation analysis above, the coefficients of major interest, as reported in columns (1-3) in Table 2.5, are significantly different from 0, which does not show any significant change with Gender, Age and IQ controlled in columns (4-6) in Table 2.5. When all of the three genes are included in the model, the significance of coefficients before HTR2A and ESR1 does not change, with that of AVPR1A dropping slightly.

Besides, another point worth mentioning is that the degree of uncertainty aversion in Task AP seems not to be significantly correlated with the three demographic characteristics.

Table 2.5 Robust OLS Regression Results for the Ambiguous Prospect Task (AP)

	Switching Point in the Ambiguous Prospect Task (AP)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ADRB1	0.466**			0.504**			0.454**
	(2.12)			(2.26)			(2.01)
AVPR1A		-0.599*			-0.588*		-0.541
		(1.80)			(1.77)		(1.54)
ESR1			0.762*			0.736*	1.044**
			(1.92)			(1.81)	(2.22)
Gender (1=M)				0.566	0.501	0.473	0.495
				(1.29)	(1.18)	(1.09)	(1.14)
IQ				0.000	-0.005	-0.007	0.009
				(0.01)	(0.08)	(0.12)	(0.15)
Age				-0.181	-0.206	-0.199	-0.171
				(1.37)	(1.56)	(1.51)	(1.32)
Constant	1.316**	6.274***	-1.387	4.756	10.583**	3.088	2.012
	(2.17)	(3.05)	(0.66)	(1.07)	(2.20)	(0.66)	(0.37)
Adjusted R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.03
Observations	208	226	226	208	226	226	207

(1) Student t-statistics based on robust standard errors are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

2.3.2.4 Uncertainty Aversion in Ambiguous Situation (AH) and Gene Expression

Taking a similar strategy to the previous three tasks, we report the robust regression results of the degree of uncertainty aversion in the Ambiguous Hazard Task (AH) on the log of the expression level of AR, AVPR1A, AHTR2A, MAOA and NRG1 in Table 2.6, with Gender, Age and IQ controlled step by step.

One interesting finding is that degree of uncertainty aversion in the Task AH is significantly positively associated with the expression level of AHTR2A, but significantly negatively associated with the expression level of MAOA. These results are robust to different sets of controls.

Again, the degree of uncertainty aversion in Task AH shares no significant correlation with the three demographic characteristics.

Table 2.6 Robust OLS Regression Results for the Ambiguous Hazard Task (AH)

	Switching Point in the Ambiguous Hazard Task (AH)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
AR	0.755*					0.768*					0.522
	(1.70)					(1.71)					(1.04)
AVPR1A		1.059**					1.012**				0.769
		(2.38)					(2.25)				(1.43)
HTR2A			0.944***					0.952***			0.733***
			(3.65)					(3.73)			(2.80)
MAOA				-0.481**					-0.430**		-0.576***
				(2.46)					(2.16)		(3.02)
NRG1					0.714*					0.673*	0.810*
					(1.92)					(1.76)	(1.73)
Gender (1=M)						-0.154	-0.113	-0.147	-0.082	-0.160	0.072
						(0.26)	(0.20)	(0.25)	(0.14)	(0.28)	(0.12)
IQ						0.138	0.128	0.119	0.110	0.132	0.071
						(1.59)	(1.61)	(1.52)	(1.26)	(1.62)	(0.88)
Age						0.121	0.048	0.111	0.020	0.090	0.053
						(0.63)	(0.25)	(0.57)	(0.11)	(0.47)	(0.28)
Constant	1.800	-0.879	2.866***	7.807***	0.446	-8.493	-8.706	-6.117	1.006	-8.490	-12.340*
	(0.79)	(0.32)	(3.77)	(8.60)	(0.16)	(1.22)	(1.35)	(1.04)	(0.15)	(1.29)	(1.68)
Adjusted R^2	0.01	0.02	0.04	0.02	0.01	0.01	0.02	0.04	0.02	0.01	0.09
Observations	220	221	200	215	223	220	221	200	215	223	195

(1) Student t-statistics based on robust standard errors are reported in the parentheses;

(2) * p<0.1; ** p<0.05; *** p<0.01.

2.3.2.5 Ambiguity Aversion and Gene Expression

Lastly, let’s turn to the measure of ambiguity aversion both in the gain domain and in the loss domain. As one might have noticed in the correlation test in Table 2.2, MP has no significant correlation with the expression level of ADRB1, while AP has significantly positive correlation with this gene, and naturally, the measure of ambiguity aversion in the gain domain, AP-MP, is significantly positively correlated with the expression level of ADRB1. Following the same logic, we have the significantly negative correlation between AP-MP and the expression level of AVPR1A and HTR2A. However, with regards to the gene of ESR1, whose expression level has been found significantly correlated with both MP and AP, we do not find any significant correlation between it and the degree of ambiguity aversion in the gain domain, AP-MP. These results are confirmed by the robust OLS regression results in Table 2.7, with no significant changes when the demographic characteristics are controlled.

Similar reasoning also applies to the measure of ambiguity aversion in the loss domain, AH-MH, and similar results are found in the significant association between AH-MH and the expression level of AVPR1A, ERBB3, and MAOA, as reported in Table 2.8. Again, both AH and MH are significantly positively associated with the expression of HTR2A, but it seems that AH-MH has no significant association with this gene.

Table 2.7 Robust OLS Regression Results for Ambiguity Aversion over Gains (AP-MP)

	Ambiguity Aversion over Gains (AP-MP)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ADRB1	0.465*				0.552*				0.360
	(1.66)				(1.96)				(1.25)
AVPR1A		-0.886*				-0.911*			-0.503
		(1.75)				(1.76)			(0.97)
HTR2A			-0.533*				-0.533*		-0.403
			(1.66)				(1.77)		(1.24)
ESR1				-0.274				-0.293	0.290
				(0.60)				(0.64)	(0.47)
Gender (1=M)					0.006	-0.012	-0.131	-0.003	-0.212
					(0.01)	(0.03)	(0.26)	(0.01)	(0.40)
IQ					0.122	0.127	0.163*	0.121	0.166*
					(1.50)	(1.61)	(1.91)	(1.56)	(1.83)
Age					-0.253*	-0.264*	-0.285*	-0.288*	-0.224
					(1.72)	(1.76)	(1.88)	(1.85)	(1.49)
Constant	-3.807***	2.825	-1.072	-1.149	-5.485	1.509	-4.083	-1.718	-5.238
	(4.90)	(0.90)	(1.13)	(0.48)	(0.97)	(0.23)	(0.67)	(0.27)	(0.66)
Adjusted R^2	0.01	0.01	0.01	-0.00	0.02	0.03	0.05	0.01	0.03
Observations	206	224	203	224	206	224	203	224	188

(1) Student t-statistics based on robust standard errors are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

Table 2.8 Robust OLS Regression Results for Ambiguity Aversion over Loss (AH-MH)

	Ambiguity Aversion over Gains (AH-MH)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AVPR1A	0.846*				0.806*				0.547
	(1.83)				(1.76)				(1.00)
ERBB3		-0.647*				-0.826**			-0.941**
		(1.87)				(2.58)			(2.15)
MAOA			-0.377*				-0.388*		-0.316
			(1.83)				(1.93)		(1.50)
HTR2A				0.439				0.519**	0.459*
				(1.62)				(2.02)	(1.69)
Gender (1=M)					0.897	0.871	0.936	0.976	1.166*
					(1.51)	(1.47)	(1.60)	(1.61)	(1.83)
IQ					0.107	0.129*	0.083	0.088	0.088
					(1.50)	(1.77)	(1.10)	(1.31)	(1.27)
Age					0.212	0.244	0.200	0.254	0.187
					(0.95)	(1.11)	(0.92)	(1.14)	(0.82)
Constant	-6.265**	1.527	0.659	-2.245***	-17.010**	-10.635	-8.666	-13.360**	-9.950
	(2.18)	(1.07)	(0.70)	(2.84)	(2.44)	(1.56)	(1.30)	(2.13)	(1.40)
Adjusted R^2	0.01	0.01	0.01	0.01	0.05	0.05	0.04	0.05	0.07
Observations	213	213	207	193	213	213	207	193	188

(1) Student t-statistics based on robust standard errors are reported in the parentheses;

(2) * p<0.1; ** p<0.05; *** p<0.01.

2.3.3 Robustness Checks

Finally, a series of robustness checks are conducted. Firstly, we try different econometric specifications, like Probit and (two-limit) Tobit models, to control for the ordering property and the censoring property of the data. As reported in Appendix V, little difference is found in the signs and the significance of coefficients of our major interest when we compare the robust OLS regression results and the Tobit regression results. Moreover, we also try different measures for people's attitudes towards uncertainty through assuming utility function forms but not simply taking the switching points. More specifically, we calculate the constant relative risk aversion (CRRA) in each uncertain situation for each subject based on the switching point from Option A to Option B on the uncertainty price list. The switching point could be regarded as the certainty equivalence of the subject with respect to the risky option. The calculation method for CRRA is described in Appendix VI. Notably, our results are robust to all of these checks.

2.4 Discussion and Conclusion

In this paper, we demonstrate the association between people's attitude towards uncertainty and the expression level of 10 candidate genes, which are ADRB1, AR, AVPR1A, COMT, ERBB3, ESR1, ESR2, HTR2A, MAOA, and NRG1.

The very first point we would like to highlight is that the 2% explanation power of one individual gene's expression for the variation in the degree of uncertainty aversion is plausibly strong from the perspective of genetic analysis. On the one hand, given the vast genetic variation, some specific genetic variation usually only accounts for a very small amount of the variance in complex human behaviours (Beauchamp *et al.*, 2011; Benjamin *et al.*, 2012; De Neve *et al.*, 2012); on the other hand, there is likely to be a set of genes, whose expression, in combination with environmental factors, influencing people's attitudes towards uncertainty.

What's more, from the cognition perspective of view, it is worth noting that the cognitive ability dominates the candidate genes in explaining the variation of people's attitudes towards uncertainty. Our results, properly interpreted, may enhance our understanding of the explanation power of cognitive ability for uncertainty aversion. For instance, Burks *et al.* (2009) and Dohmen *et al.* (2010) report that people with lower cognitive ability are significantly more risk-seeking, which is consistent with our results for risky situations. However, our results tend to suggest that whether a decision maker exhibits ambiguity aversion does not significantly depend on their cognitive abilities.

Beyond their purely descriptive value, our results also shed light on the use of models with heterogeneity in macro- and financial economics (Aiyagari, 1993; Freeman, 1996; Mankiw, 1986; Telmer, 1993) and challenge the common assumption that people are born with identical preferences and identical uncertainty attitudes and that the main source of heterogeneity lies in the idiosyncratic shocks to individual incomes. But, as we have documented, people's attitudes towards uncertainty could be very different, which has a solid biological foundation, and these differences could and should be taken into consideration when we specify the preference heterogeneity to explain economic and financial outcomes.

Besides, our study has several potential limitations that should be addressed by future research. Firstly, in genetic analysis, it is very important to replicate the results for some specific genetic variation in independent samples. Such efforts to replicate a significant association result, as well as increasing the sample sizes, are critical to exclude the possibility that the original association would be spurious (De Neve *et al.*, 2012). However, due to budget constraints, we have no replication sample in this study. Secondly, to measure the degree of decision makers' uncertainty aversion, we mainly focus on their switching points in the responses to the uncertain decision tasks presented by multiple price lists, although there are some other seemingly plausible approaches proposed in the recent literature. More importantly, our primary objective of this study is to establish the association between the expression level of the candidate genes and people's attitudes towards uncertainty, but not to explore the quantitative effect. Thirdly, people might be concerned about the extent to which laboratory behaviour generalizes to the field (Harrison and List, 2004; Levitt and List, 2007). As a matter of fact, robust results have been reported to show that individual laboratory-measured risk preferences predict filed behaviour in a very broad sense, including smoking, drinking, exercise, nutrition, saving, borrowing, wealth accumulation, and gambling (Chabris *et al.*, 2008). Again, related to the second point, our primary aim is at the direction of the association but not the quantitative effects. Lastly, one might care about the representativeness of our sample. On the one hand, the 230 participants whose candidate genes' expression levels were measured are expected to be representative of the whole sample, since they were randomly picked out of the 1158 participants. Actually, distributions of the behavioral data are also compared with the whole sample and the subsample, but no significant difference is found. On the other hand, it might be true that the whole sample may not be representative of the Chinese population or even the Singaporean Chinese population, because all of our 1158 participants are geographically concentrated in Singapore and relatively more educated than the entire Singapore population. With these caveats in mind, we consider our results to be only suggestive. However, we believe that these methodological problems have primarily reduced the statistical clarity of our findings rather than biasing our results towards the conclusion that we have reported.

Most importantly, this is apparently the first study to bring in measures of gene expression to investigate choice behaviour elicited from incentivized decision making tasks. It opens a novel strategy ("blood genomics") for economic modelling uncertainty preference in decision theory.

Chapter 3 Interacting Time and Uncertainty: Theory and Evidence

3.1 Introduction

Uncertainty and time are two most fundamental attributes in a typical decision situation, and hence people's attitudes towards uncertainty and time are naturally vital dimensions to consider when we model how people make decisions. In the huge body of literature about decision making, enormous amounts of efforts have been devoted, along two distinguished branches, towards developing alternatives to the expected utility theory (EUT) and alternatives to the discounted utility (DU) theory, with a typical focus on one of the two attitudes. Even in the discounted expected utility theory, which takes both attitudes into consideration, these two dimensions are still treated separately.

Although time and uncertainty initially appear different, there are closely related in a number of ways. Both are attributes that pertain to the delivery of choice objects – the time of delivery or the likelihood of occurring – rather than to characteristics of the objects themselves. Furthermore, time and uncertainty are typically correlated with one another in the real world. Specifically, anything that is delayed is inherently uncertain, and since it always takes time for uncertainty to resolve, uncertain outcomes are typically delayed. As in Prelec and Loewenstein (1991), these connections raise the possibility that the observed parallelism of choice behaviour is unique to these two dimension. Furthermore, they propose that discounting of delays and probabilities is due to a common internal aversive state (subtracting from reward value) generated by the delay period (with delayed rewards) and by losses (with probabilistic rewards).

However, what has to be admitted is that the nature of the mechanism underlying the interaction between uncertainty and time has been a matter of debate for some time. For instance, one natural question is which of the two is more fundamental. According to Rotter (1954), who first proposed the idea that people behave similarly in face of uncertainty and time, people choose a smaller more immediate reward over a larger but delayed reward because, in the local culture, promises of delayed rewards are rarely given or, if given, broken. In other words, delays of gratification act like less-than-unity probabilities, and longer delays means lower probabilities. In this sense, Rotter (1954) argues that probability discounting is more fundamental, and similar arguments can also be found in Keren and Roelofsma (1995), Weber and Chapman (2005) as well as Dasgupta and Maskin (2005). While some others argue that the decision making processes used uncertain choices might be a subset of those used by intertemporal choices because for repeated trials, the smaller the probability of receiving an outcome, the longer the time to receive the outcome (Rachlin *et al.*, 1986; Rachlin *et al.*, 1991; Rachlin and Siegel, 1994).

Rather than speculating about possible answers to that question, some others prefer to be guided by data to study the correlation between preferences over risk and preferences over time, and the results remain mixed. Barsky *et al.* (1997a) find no correlation between risk attitude and the elasticity of intertemporal substitution. Eckel *et al.* (2005) conduct a field study of time and risk, and find that subjects who choose the less risky lotteries have significantly higher individual discount rates, but they do not estimate the relationship between risk and time preferences. More recently, Andersen *et al.* (2008) use the information on risk attitudes to infer the discount rate defined over utility, predict risk attitudes and discount rates for each of their subjects using structural estimation approaches, and report evidence of a positive correlation between risk aversion and impatience. However, this result fails to be replicated by Sutter *et al.* (2013), who report that higher individual levels of risk aversion predict more patience.

Besides these studies based on separate decision tasks aiming to elicit preferences over risk and time, there are several studies based on decision tasks involving both time and risk. Anderhub *et al.* (2001) use the Becker-Degroot-Marschak (BDM) procedure to elicit certainty equivalents for lotteries with varied payoff dates, and directly investigate the interaction between risk attitudes and time preferences. In particular, in their study, 61 subjects are asked to price a simple lottery in three different scenarios: at the first, the lottery premium is paid "now"; at the second, it is paid "later"; and at the third, it is paid "even later", and the main result is a statistically negative correlation between subjects' degree of risk aversion and their (implicit) discount factors. Besides, Ahlbrecht and Weber (1997) use a similar design, albeit with hypothetical rewards, and find no significant relationship between risk aversion and individual discount rates in the gain domain.

As one may note, most studies just focus on people's attitudes towards time and risk, but the potential correlation between attitudes towards ambiguity and time seems to have seldom been studied. Moreover, the potential interrelation between anomalies to the expected utility theory (EUT), for instance, the Allais behaviour (Machina, 1987; Starmer, 2000), and anomalies to the discounted utility (DU) theory, like the diminishing impatience (Frederick *et al.*, 2002; Laibson, 1997; Loewenstein and Prelec, 1992), has received little attention (Andreoni and Sprenger, 2012b; Halevy, 2008; Saito, 2011). In the present paper, we would propose three testable hypotheses based on a thorough review of the literature on the interrelation between attitudes towards time and uncertainty: (1.A) the more risk averse a decision maker is in risky situations, the more impatient he/she is in intertemporal settings; (1.B) the more risk averse a decision maker is in risky situations, the greater near-term bias he/she would exhibit; (2) the stronger common ratio effect a decision maker exhibits, the greater near-term bias he/she would exhibit; and (3) the more ambiguity averse a decision maker is, the greater near-term bias he/she would exhibit.

Beyond these, we also test these three hypotheses based on a large-sample experiment. On one hand, Hypothesis 1.A is supported in the near future, but gets rejected in the remote future; on the other hand, Hypothesis 1.B is supported from three of the four risky situations in our experiment, suggesting that the degree of people's risk aversion in moderate risky situations is significantly positively associated with the degree of near-term bias people may exhibit when faced with decision situations involving different time delays. Furthermore, when we come to the Hypothesis 2, the experiment result in skewed risky decision situations (CRL) turns out to provide significant support to the hypothesis, but the result in moderate risky decision situations (CRH) does not. Besides, Hypothesis 3 cannot get any significant support from our experiment. In addition, it is also found that people's IQ value is significantly negatively associated with the degree of impatience both in the near future and in the remote future as well as the degree of near-term bias. These findings are robust to various econometric analysis approaches, various measures of the two kinds of attitudes as well as a replication study.

Following this introduction section, the rest of the paper is structured as follows. Section 2 thoroughly reviews the conceptual background, with the three hypotheses proposed. Section 3 describes the design of our experiment as well as its implementation. Section 4 presents the methodology of our analysis and reports the results for testing the three hypotheses. In Section 5, we conduct a series of robustness checks. This is followed by Section 6, which concludes and discusses the implications of our results, limitations of this study and directions for future research.

3.2 Conceptual Background and Hypotheses

Consider such a continuous intertemporal decision making situation, where the decision maker (DM) is evaluating such a prospect, $P = ((M, p), T)$, at the time point t, based on a discounted expected utility (DEU) function:

$$U_t(P) = D(T - t)V(M, p) \tag{1}$$

where (M, p) denotes a binary lottery of receiving an amount of money M at a probability of p and 0 at a probability of $1 - p$; T ($> t$) is the time point of delivery of the lottery; $V(\cdot)$ denotes the DM's periodic valuation function of the lottery, and $D(T - t)$ is the *discount function*, with $D(0)$ normalized to be 1. In particular, when $t = 0$, we have

$$U_0(P) = D(T)V(M, p) \tag{2}$$

Typically, $D(T-t)$ is a deceasing function of the time interval, $T-t$. That is, given a fixed $T(>t)$, $D(T-t)$ is increasing in t. A decision maker with such a discount function is said to be *impatient*, and the degree of impatience is summarized by the discount rate, the rate at which $D(T-t)$ changes as time moves onwards; that is, for $0 \leq t \leq T$,

$$d(t) = \frac{\dot{D}(T-t)}{D(T-t)}$$

where $\dot{D}(T-t) = \frac{\partial D(T-t)}{\partial t}$. Thus, the higher the discount rate is, the more impatient the DM is – the greater the preference for immediate rewards over delayed rewards.

In the literature, the most frequently used discount function is the exponential discount function:

$$D(T-t) = e^{-\delta(T-t)}, with\ 0 < \delta < 1$$

One important property[1] of this exponential discount function is that the discount rate, which is δ, is independent of the horizon, t. And this property has an immediate prediction about the consistency property of people's behaviour over time, as summarized in **Proposition 1**.

Proposition 1: *Given two prospects,* $\mathrm{P} = ((\mathrm{M}, \mathrm{p}), \mathrm{T})$ *and* $\mathrm{P}' = ((\mathrm{M}', \mathrm{p}'), \mathrm{T}')$, *with* $T < T'$*, the evaluation of the DM taking such a valuation function as follows*

$$\mathrm{U_t}(\mathrm{P}) = e^{-\delta(T-t)} V(M, p)$$

satisfies

$$U_0(P) > U_0(P') \Leftrightarrow U_t(P) > U_t(P') \ \textit{at all}\ 0 \leq t \leq T.$$

[1] For more detailed discussion about the properties of the exponential discount function, one may refer to Frederick, Loewenstein, and O'Donoghue (2002).

(PROOF: It follows immediately from the fact that $U_0(P) = e^{-\delta t} U_t(P)$.)

Furthermore, one widely used functional form for the DM's periodic valuation function $V(\cdot)$ is an expected utility form; that is,

$$V(M, p) = pu(M) + (1 - p)u(0).$$

where $u(\cdot)$ denotes the DM's instant utility function of monetary payoffs Thus, the DM's valuation function would take the following form, which is referred to as the Discounted Expected Utility (DEU) Model.

$$U_t(P) = e^{-\delta(T-t)} pu(M) \tag{3}$$

Given this specification, the model predicts a link between the degree of risk aversion and the degree of impatience through the curvature of the utility function $u(\cdot)$, summarized in **Hypothesis 1.A**.

Hypothesis 1.A *The more concave the DM's utility function, the more risk averse a decision maker is in risky situations, and the more impatient he/she is in intertemporal settings.*

However, the DEU fails to match several empirical regularities. One failure of this model is that it cannot account for the phenomenon of diminishing impatience, as defined below, which means that measured discount functions decline at a higher rate in the near future than in the remote future (Frederick *et al.*, 2002; Loewenstein and Prelec, 1992; Loewenstein and Thaler, 1989). Another failure of the DEU model is that it cannot account for Allais behaviour, like the common ratio effect and the coeternity effect (Machina, 1987; Starmer, 2000).

Definition 1: Diminishing Impatience
The DM exhibits diminishing impatience if $\frac{\partial d(t)}{\partial t} < 0$ *at all* $0 \leq t \leq T$.

As a matter of fact, it is well known that the exponential discounting model does not allow for diminishing impatience, and that the expected utility model does not allow for Allais behaviour. In other words, to account for diminishing impatience and Allais behaviour, one has to modify the DEU model. One way that the DEU model has been generalized in order to allow for diminishing impatience is by allowing for non-exponential discount functions, $D(T-t)$. For instance, psychologists and economists have tried to adopt discount functions in the family of generalized hyperbolas, including the hyperbolic discount function and quasi-hyperbolic discount function (Ainslie, 1975; Ainslie and Herrnstein, 1981; Harvey, 1994; Herrnstein, 1961; Laibson, 1997; Loewenstein and Prelec, 1992; Mazur, 1984; Strotz, 1955). In these generalized models, the prediction in **Hypothesis 1.A** still holds. In addition, these models also predict an relationship between the curvature of the utility function and the pattern of diminishing impatience, as summarized in **Hypothesis 1.B**. However, there is no predicted link between violations of EUT and the pattern of discounting rates.

Hypothesis 1.B *The more risk averse a decision maker is in risky situations, the greater near-term bias he/she would exhibit.*

Another generalization of the DEU model is to replace the expected utility in the model by non-expected utility to evaluate lotteries like (M, p) so that Allais behaviour could be accounted for. As Machina (1989) figures out, a DM who has non-expected utility preferences over state-contingent outcomes, and who treats borne risk in the manner of continuing to take it into account ex post, will be immune to the dynamic inconsistent behaviour. In other words, the pattern of diminishing impatience would not be allowed when the resolution of uncertainty is not an issue to the DM.

Therefore, it seems a feasible direction to include the timing of uncertainty resolution, which was first figured out by Kreps and Porteus (1978) as a choice variable, to account for Allais behaviour and diminishing impatience in a discounted non-expected utility model. In this line, Chew and Epstein (1989) are the first to axiomatize timing preference using a within-period non-expected utility function based on the idea of betweenness (Chew, 1983; Chew, 1989). And another recent try is Halevy (2008), who incorporates the resolution of the uncertainty that is inherently involved in time.

Basically, Halevy (2008) tries to explain diminishing impatience through treating the future as inherently risky. With a constant stopping probability (hazard) of λ introduced to capture the intuitive idea of implicit risk value, Halevy (2008) modifies the DEU as follows[1]:

$$U_t(P) = e^{-\delta(T-t)} g\left(e^{-\lambda(T-t)}\right) pu(M) \tag{4}$$

where δ is referred to as the constant "pure" time preference, and $g(\cdot)$ is a rank-dependent probability-weighting function, satisfying $g(0) = 0$, and $g(1) = 1$.

Thus, the *discount function* of this DM is $D(T-t) = e^{-\delta(T-t)} g\left(e^{-\lambda(T-t)}\right)$. It follows that the discounting rate

$$d(t) = \frac{\dot{D}(T-t)}{D(T-t)} = \lambda \frac{q\, \dot{g}(q)}{g(q)} + \delta \text{ with } q \triangleq e^{-\lambda(T-t)}.$$

[1] In the original model of Halevy (2008), the setting is based a discrete time structure. Moreover, in his set-up, the future payoff is a sure amount of monetary payoff but not a lottery.

As Halevy (2008) and Saito (2011) show, in this set up, there is a tight link between probability weighting (i.e. the property of function $g(\cdot)$) and diminishing impatience. More specifically, a DM who exhibits no probability weighting will exhibit no diminishing impatience; however, a DM exhibits diminishing impatience if he/she weights probabilities exactly in the way required for the common ratio effect. Following the CLAIM (3) in Saito (2011), we propose Hypothesis 2 naturally.

Hypothesis 2 *The stronger common ratio effect a decision maker exhibits, the greater near-term bias he/she would exhibit.*

From the theoretical point of view, as one might have noticed, the critical reason why Halevy (2008) can account for both Allais behaviour (common ratio effect) and diminishing impatience is that the introduction of the stopping probability has changed the resolution structure in the sense that the non-expected utility DM' immunisation conditions for dynamic inconsistency (Machina, 1989) no longer hold.

Furthermore, as Halevy (2008) as well as Andreoni and Sprenger (2012b) argue, the present is known while the future is inherently risky, and the asymmetry between the present and the future in the sense of uncertainty underpins the present-biased behaviour. In this sense, we can view time as a source of uncertainty, especially the kind of uncertainty that could be perceived but not be measured. Hence, people's attitudes towards time may interact with people's attitudes towards ambiguity. More specifically, this intuition is summarized in **Hypothesis 3** as follows.

Hypothesis 3 *The more ambiguity averse a decision maker is, the greater near-term bias he/she would exhibit.*

3.3 Experimental Design and Implementation

3.3.1 Experimental Design

3.3.1.1 Elicitation of People's Attitudes towards Uncertainty

Firstly, to elicit people's attitudes towards uncertainty in different contexts, we asked the subjects to respond to decision tasks in five types of uncertain decision situations, including four risky situations with explicit probabilities and one ambiguous situation without explicit probabilities given. In particular, the four risky situations include two Moderate Prospect Tasks (MP and MP'), one High Prospect Task (HP) as well as one Low Prospect Task (LP), and the ambiguous situation is the Ambiguous Prospect Task (AP).

The decision tasks were all presented in the form of multiple price lists (MPLs) with monetary payments (Holt and Laury, 2002). More specifically, we listed ten pairs of options in each decision sheet for a specific decision situation, and each pair includes a fixed Option A and a varying Option B, with the 10 different Option B's arranged in an ascending manner in terms of value (MP and AP) or probability (MP', HP and LP). Given a price list, a decision maker with consistent preferences in a specific setting is expected to have a "switching" point from preferring Option A to preferring Option B, if any, and this switching point is believed to carry interval information about his/her preference.

For the sake of illustration, let's take the Moderate Prospect Task (MP) as an example. In this task, the expected value of the fixed Option A is $30, which corresponds to the seventh pair on the risk price list. Hence, if one chooses Option A initially and switches to Option B later but before or exactly at the seventh pair, we will say that this decision maker is risk-averse; and in an extreme case, if one does not choose Option A at all, he/she is risk-averse, of course, and his/her degree of risk aversion is viewed higher than those choosing at least one Option A on the list. On the other hand, if one chooses Option A initially and switches to Option B later than the seventh pair, we will say that this decision maker is risk-seeking. In addition, in an extreme case, if one does not choose Option B at all, he/she will be viewed as risk-seeking, with a higher degree of risk seeking than those choosing at least one Option B on the list. Correspondingly, the number of subjects' choices of Option A, ranging from 0 to 10, would be recorded, and this number is referred to as the switching point in a task with specific situations, which could be viewed as a measure of the degree of risk aversion given the context. In particular, the earlier the switching point is on the risk price list, the more risk-averse the decision maker is.

Given that the seventh pair on the price list of Task MP corresponds to a benchmark for risk neutrality, we take the difference between 7 and the switching point of a subject as the risk premium requested by the subject, which could be viewed as an equivalent measure for the degree of risk aversion of the subject. And it follows that the risk premium for Task MP ranges from -3 to 7, that subjects with positive (negative) values are risk averse (seeking), and that a higher value means a higher degree of risk aversion, with 0 corresponding to risk neutrality.

Besides, there are several important points about the differences among the seven tasks. Firstly, the only difference between in Task MP and Task AP is that there are no explicit probabilities given in AP, which case is referred to as an ambiguous situation, and we follow the literature, taking the expected payoff of the Option A in Task AP as $30 and taking the difference between 7 and the switching point of a subject in Task AP as the uncertainty premium requested by the subject. Secondly, Task MP and Task MP' are different in the way that the fixed Option A is a lottery in Task MP but a certain amount of money ($30) in Task MP', while the varying Option B is a varying amount of money with the amount displayed in an ascending manner on the list of Task MP but a varying lottery with the probability of receiving a fixed amount of money ($60) displayed in an ascending manner on the list of Task MP'. Thirdly, similarly to Task MP', the varying Option B in both Task HP and Task LP is a varying lottery with the probability of receiving a fixed amount of money ($60) displayed in an ascending manner on the list, but the fixed Option A in these two tasks is a lottery.

Since the five tasks are designed in the same form, it's not necessary to discuss them one by one, and one can refer to Appendix VII for the exact format of decision sheets presented to the subjects.

Moreover, we can also compare a subject's risk premium in Task MP and his/her uncertainty premium in Task AP, and the difference between them, say, AP minus MP, could be viewed as the ambiguity premium requested by the subject, a measure for the degree of ambiguity aversion. Similarly, we take the difference between the switching points in Task MP' and Task HP, MP' minus HP, as a measure of the common ratio effect for the High Prospect Task, and take the difference between the switching points in Task MP' and Task LP, MP' minus LP, as a measure of the common ratio effect for the Low Prospect Task.

3.3.1.2 Elicitation of People's Attitudes towards Time

Secondly, we also asked the subjects to give their responses to decision tasks in two kinds of intertemporal settings so that we can capture their attitudes towards time. The multiple price list design for this task in our experiment, which was proposed by Coller and Williams (1999) and widely used in experimental economics, is illustrated as below in Figure 3.1.

DECISION: For **each of the 20 rows** in the table below, please indicate your decision in the final column with a tick (√).

	Tomorrow	31 days later	Decision
1	$100	$101	A ☐ B ☐
2	$100	$104	A ☐ B ☐
3	$100	$107	A ☐ B ☐
4	$100	$110	A ☐ B ☐
5	$100	$113	A ☐ B ☐
6	$100	$116	A ☐ B ☐
7	$100	$119	A ☐ B ☐
8	$100	$122	A ☐ B ☐
9	$100	$125	A ☐ B ☐
10	$100	$128	A ☐ B ☐
	351 days later	**381 days later**	**Decision**
11	$100	$101	A ☐ B ☐
12	$100	$104	A ☐ B ☐
13	$100	$107	A ☐ B ☐
14	$100	$110	A ☐ B ☐
15	$100	$113	A ☐ B ☐
16	$100	$116	A ☐ B ☐
17	$100	$119	A ☐ B ☐
18	$100	$122	A ☐ B ☐
19	$100	$125	A ☐ B ☐
20	$100	$128	A ☐ B ☐

Figure 3.1 The Multiple Price List Design for Discounting Rate Elicitation

The multiple price list above includes two sections, referred to as Near Future (Row 1-10) and Remote Future (Row 11-20). In each section, which consists of 10 pairs of choices, participants were asked to indicate their preferences between Choice A and Choice B. For instance, in the Near Future section, Choice A refers to receiving Singapore $100 ($\approx$ US $77 in 2010) next day, while Choice B refers to receiving a larger amount, ranging from $101 to $128 in an ascending order, 31 days later. Given that the payment in Choice A is fixed at $100 whereas the amount for Choice B is monotonically increasing on the menu, if they choose Choice B rather than Choice A at some point, for instance in the section of Near Future, then they are expected to choose Choice B for all afterwards questions in this section.

Similarly to the five decision tasks in uncertain situations, we also recorded the point at which each subject switches from A to B in the two intertemporal decision tasks. Numerically, a number *n* was assigned to the case when the switching occurs after *n* A's. In particular, 0 was assigned to those who chose B across all questions in a section, and 10 was assigned to those who chose A across all questions in a section. So, the earlier a participant's choice switches from A to B, the more patient he/she is. Alternatively speaking, a higher score represents higher degree of impatience.

Moreover, according to the discussion in Section 1, the near-term bias refers to the scenario when people are less impatient in the remote future than in the near future. Based on our experiment design above, a participant could be said to exhibit near-term bias if his/her choice switches earlier in the Remote Future than in the Near Future, and the difference naturally serves as a measure for the degree of near-term bias.

3.3.1.3 Demographics and Cognitive Ability

In addition, we also collected demographic information of the participants, including their genders and their ages as of the date of our experiment. Their proxy IQ test scores were obtained based on the Raven's Progressive Matrices.

3.3.2 Experimental Implementation

As a matter of fact, the experimental data employed in this paper is only a part of a sizable experimental project on decision making, which lasted from November 2010 to December 2015, aiming to explore the biological foundation for economic and social decision making[1].

From November 2010 to January 2011, 1158 Han Chinese undergraduate students from National University of Singapore and 669 Chinese Han students from universities within Haidian District in Beijing, China, were recruited to participate in decision-making experiments, in the forms of pencil-and-paper answer sheets as well as online lifestyle & personality questionnaires. In October 2012, we recruited another 1069 Han Chinese undergraduate students from National University of Singapore and another 614 Han Chinese undergraduate students from universities in Beijing, and all of the subjects completed the same set of decision tasks. Hence, in total, we have 3510 subjects.

Moreover, almost all participants in the two rounds donated 10 to 20 cc of blood for extracting DNA after these tasks. Participants were reimbursed for participation in the project (S$25 per hour in Singapore and CNY100 per hour on average).

3.4 Results

In this section, we would follow three steps to analyse the behaviour of our subjects in various situations and proceed to investigate the potential interrelation between attitudes towards uncertainty and time. Firstly, we examined and

[1] For further details about this project, one could visit the web site of the lab for Behavioral Biological Economics and Social Sciences (B2ESS), http://b2ess.nus.edu.sg.

summarized the subjects' behaviour in both uncertain situations and intertemporal situations; secondly, we reported the correlation between subjects' attitudes towards uncertainty and time based on the Spearman correlation test; thirdly, we tested the three hypotheses based on econometric analysis. All of the analyses in this section were based on subjects' switching points in their responses to various tasks (MP', HP, LP, NFuture, and RFuture) or risk/uncertainty premium defined based on the switching points (MP and AP). This strategy, which does not rely on the utility function, helps avoid quite a lot of potential estimation bias resulting from misspecification of utility functions.[1] Alternative measures for subjects' attitudes towards uncertainty and time would be constructed and employed for robustness tests in the next section.

3.4.1 Behavioral Results

3.4.1.1 Behavioral in Uncertain Situations

As we have discussed in the experimental design, to capture people's attitudes towards risk in different situations, we asked the subjects to respond to five tasks involving risk, which are Task MP, Task AP, Task MP', Task HP, and Task LP. Now, let's take a look at the subjects' behavioural patterns in different situations one by one, before investigating the potential interrelation between attitudes towards uncertainty and time.

[1] For such kind of potential bias, one may refer to *Andersen et al*. (2008), *Andreoni and Sprenger* (2012), as well as *Cheung* (2012).

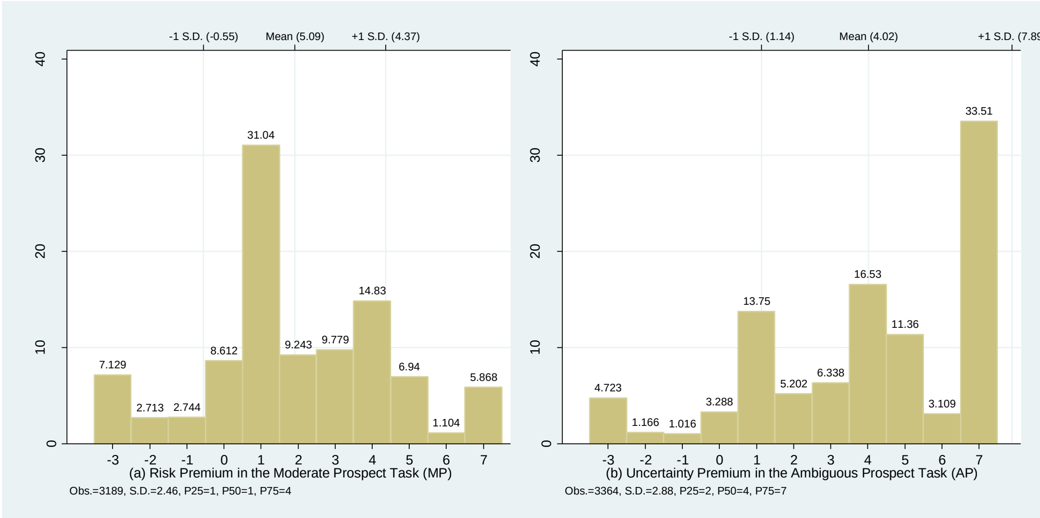

Figure 3.2 Distribution of Risk/Uncertainty Premium in Task MP and Task AP

In the Task MP, as shown in Figure 3.2(a), 78.8% of subjects are indicated by a number greater than 0, which means they chose the first Option B before at the seventh pair, corresponding to the expected value of the fixed Option A, \$30, and hence should be viewed as risk-averse decision makers, while the other 12.6% of the subjects indicated by a negative number switched after the seventh pair or even did not choose Option B at all and hence are risk-seeking. This pattern together with more detailed distributional characteristics indicates that in the moderate risky situations with potential gains, risk-averse subjects account for the majority, which is consistent with the result of student-*t* test.

However, In the Task AP, as shown in Figure 3.2(b), about 90% of subjects are indicated by a number greater than 0, and hence should be viewed as uncertainty-averse decision makers. In particular, more than 30% of subjects are extremely uncertainty-averse in the sense that they might choose Option B if an even smaller amount of money than \$15 is offered in that option.

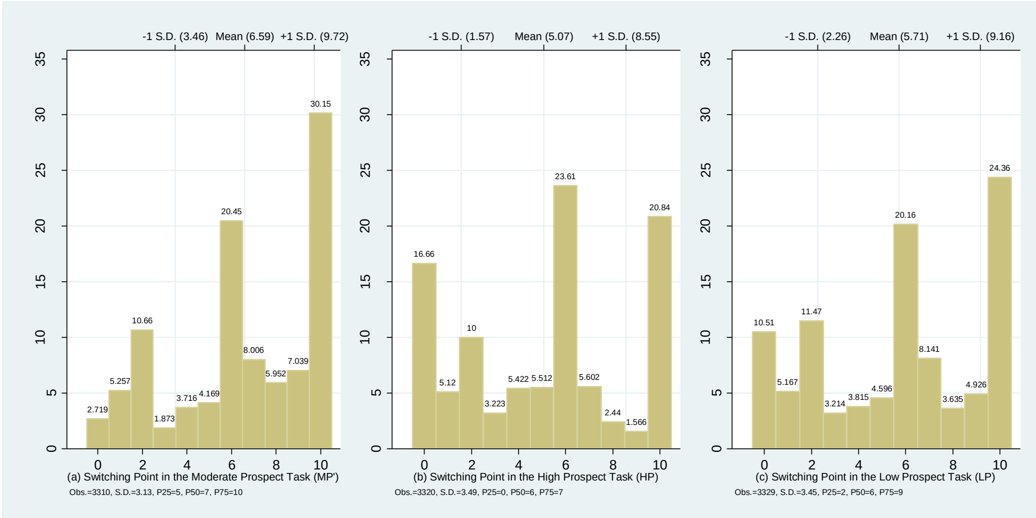

Figure 3.3 Distribution of Switching Points in Task MP', Task HP and Task LP

Similarly, we have the distribution of switching points in the other three risk decision tasks (Task MP', Task HP, and Task LP) shown in Figure 3.2. According to the design of these three tasks, a higher score of the switching point means a higher degree of risk aversion. As one may have observed, given the second point as the benchmark point for risk neutrality, most of subjects are risk averse in these three tasks, although the patterns are different.

3.4.1.2 Evidence for Allais Behavior and Ambiguity Attitudes

Furthermore, comparing Task AP and Task MP, we can take the difference between the uncertainty premium in Task AP and the risk premium in Task MP, and view it as a measure of ambiguity aversion (Ellsberg, 1961). From Figure 3.4, one can find the pattern of ambiguity aversion exhibited in the subjects' behaviour is significant, with 22.59% of subjects being ambiguity neutral and 64.41% being ambiguity averse.

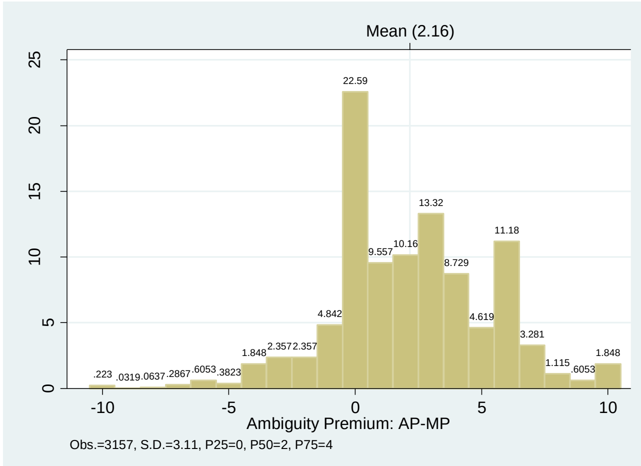

Figure 3.4 Distribution of Ambiguity Premium: AP minus MP

Moreover, taking the difference of switching points in Task MP' and Task HP, one can find that a considerable fraction of subjects exhibit significant common ratio effects (Kahneman and Tversky, 1979); that is, they are more risk averse in Task MP' than in Task HP, as shown in Figure 3.5(a). A similar examination is also conducted on Task MP' and Task LP, with the common ration effect reported by the positive values in Figure 3.5(b).

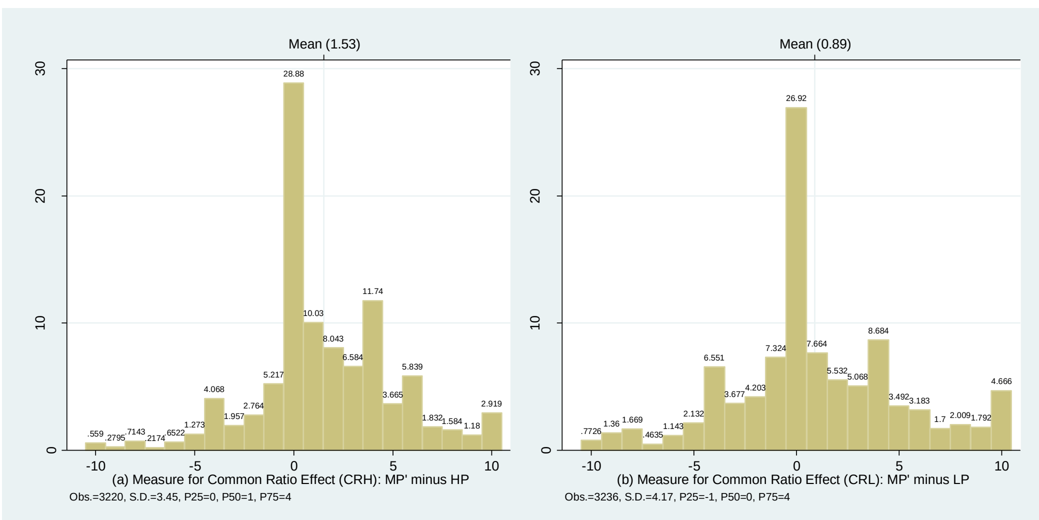

Figure 3.5 Distribution of Common Ratio Effect: CRH and CRL

3.4.1.3 Behavior in Intertemporal Settings

Finally, let's turn to examine the subjects' responses to the decision tasks in the intertemporal settings, including the Near Future Task and the Remote Future Task. As discussed in the previous section, participants' switching points in their responses to the intertemporal decision tasks have been taken as the measure for the degree of impatience – a higher score represents higher degree of impatience. From Figure 3.6, one can find that in the near future, from tomorrow to 31 days later, over 60% of the subjects required $7 as their least compensation for delayed payment, which means a switching point at or after Choice 3, while in the remote future, from 351 days later to 381 days later, 48.42% of the subjects could accept $1 as compensation for delayed payment. Furthermore, statistical tests suggest that the switching point in Remote Future Task is significantly earlier than in the Near Future Task. In other words, there are significantly more subjects who are more patient in the remote future than in the near future.

Actually, this behaviour pattern, the tendency for people to increasingly choose a smaller-sooner reward over a larger-later reward as the delay occurs sooner rather than later in time, has also been well documented in the literature, and the difference between the least compensations required for near future and remote future is referred to as the near-term bias.

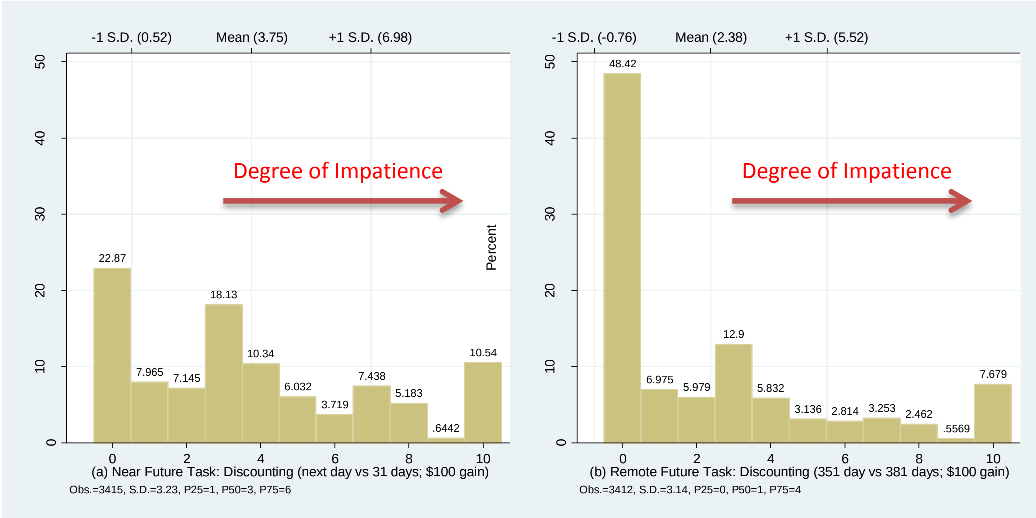

Figure 3.6 Graphic Illustration of Behavioral Results: Near Future vs Remote Future

Similarly to the case of ambiguity aversion, we can take the difference of the switching point locations in the two tasks, and view it as a measure for near-term bias. As shown in Figure 3.7, the red bar indicates those who show no difference in discounting the near future or the remote future, while the blue bars indicate a considerable fraction of participants who exhibit some near-term bias.

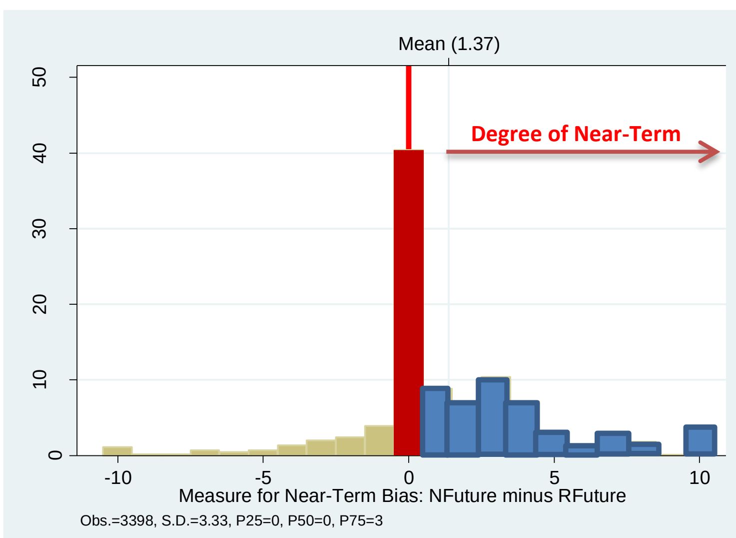

Figure 3.7 Graphic Illustration of Behavioral Results: Near-Term Bias

3.4.1.4 Summary Statistics

To sum up, the definition of variables and detailed descriptive statistics of the sample used in our following analysis are reported in Table 3.1.

3.4.2 Correlation among Key Variables

Beyond the descriptive statistics summarized above, we can proceed to examine the potential correlation among subjects' attitudes towards uncertainty and time through running the Spearman's rank correlation test, with the rest results reported in Table 3.2.

Notable findings include 1) that the degree of near term bias shares no significant correlation with the degree of risk aversion in Task MP or the degree of uncertainty aversion in Task AP, although both of them are significantly negatively correlated with the degree of impatience both in the near future and in the remote future; 2) that the degree of near term bias is significantly positively correlated with the degree of risk aversion in Task MP' and Task HP, but negatively with that in Task AP, with the degree of risk aversion in MP', HP, and LP positively correlated with the degree of impatience in the near future at 10% significance level; 3) that the degree of near-term bias shares no significant correlation with the degree of ambiguity premium (AP-MP); 4) that the common ratio effect in both cases (CRH and CRL), which is not significantly correlated with the degree of impatience in the near future, is significantly correlated with the degree of impatience in the remote future, but with different signs; 5) that the degree of near-term bias is only significantly correlated with the degree of common ratio effect in the High Prospect Task (CRH), but not significantly in the Low Prospect Task (CRL).

Table 3.1 Descriptive Statistics of Key Variables

Variable	Obs	Mean	Std. Dev.	Min	Max	Note
Gender (1=M; 0=F)	3388	0.486	0.500	0	1	A dummy variable for genders: Male=1, Female=0
City (1=SG; 0=BJ)	3458	0.635	0.481	0	1	A dummy variable for cities: Singapore=1, Beijing=0
Round (1=R1; 0=R2)	3441	0.522	0.500	0	1	A dummy variable for rounds: Round 1=1, Round 2=0
RPM IQ	3441	55.193	4.922	5	60	IQ test score based on Raven's Progressive Matrices
Age	3382	21.463	1.825	16	33	Age of participant as of the date of the experiment
MP	3170	1.910	2.464	-3	7	Risk premium in the Moderate Prospect Task (MP)
AP	3345	4.018	2.877	-3	7	Uncertainty premium in the Ambiguous Prospect Task
AP-MP	3139	2.162	3.108	-10	10	Ambiguity premium over gains: AP minus MP
MP’	3290	6.595	3.126	0	10	The switching point in the Task MP’
HP	3300	5.067	3.494	0	10	The switching point in the High Prospect Task
LP	3309	5.716	3.447	0	10	The switching point in the Low Prospect Task
CRH=MP’-HP	3200	1.537	3.496	-10	10	Common ration effect (CRH): MP’ minus HP
CRL=MP’-LP	3216	0.887	4.163	-10	10	Common ration effect (CRL): MP’ minus LP
NFuture	3395	3.751	3.233	0	10	The switching point in the section of Near Future
RFuture	3392	2.381	3.141	0	10	The switching point in the section of Remote Future
Near-Term Bias	3378	1.367	3.335	-10	10	NFuture minus RFuture

Note: In total, we have 3510 subjects, but in the table above, we excluded 32 subjects whose Raven’s Progressive Matrices IQ scores are 0 and 20 subjects who reported to be not older than 15.

Table 3.2 Spearman Rank Correlation Coefficients among Key Variables

	MP	AP	AP-MP	MP’	HP	LP	CRH=MP’-HP	CRL=MP’-LP	NFuture	RFuture	Near-Term Bias
MP	1 3170 (-)										
AP	0.2999* 3139 0.000	1 3345 (-)									
AP-MP	-0.4483* 3139 0.000	0.6605* 3139 0.000	1 3139 (-)								
MP’	0.3163* 3088 0.000	0.2629* 3231 0.000	0.0046 3064 0.800	1 3290 (-)							
HP	0.1918* 3091 0.000	0.1457* 3244 0.000	-0.012 3067 0.524	0.4542* 3200 0.000	1.000 3300 (-)						
LP	0.1080* 3099 0.000	0.0719* 3250 0.000	-0.0155 3072 0.390	0.1666* 3216 0.000	-0.0061 3216 0.731	1 3309 (-)					
CRH=MP’-HP	0.0676* 3025 0.000	0.0714* 3157 0.000	0.023 3004 0.208	0.3769* 3200 0.000	-0.5945* 3200 0.000	0.1902* 3139 0.000	1 3200 (-)				
CRL=MP’-LP	0.1361* 3034 0.000	0.1273* 3164 0.000	0.023 3010 0.208	0.5692* 3216 0.000	0.3468* 3139 0.000	-0.6698* 3216 0.000	0.1131* 3139 0.000	1 3216 (-)			
NFuture	-0.0371* 3143 0.038	-0.0981* 3308 0.000	-0.0476* 3113 0.008	0.0307 3259 0.079	0.0293 3268 0.094	0.0328 3279 0.060	0.0168 3174 0.343	-0.0011 3190 0.951	1 3395 (-)		
RFuture	-0.0491* 3140 0.006	-0.0715* 3304 0.000	-0.0131 3109 0.464	-0.018 3254 0.306	-0.0433* 3265 0.013	0.0941* 3274 0.000	0.0365* 3169 0.040	-0.0837* 3185 0.000	0.4541* 3378 0.000	1 3392 (-)	
Near-Term Bias	0.0201 3134 0.261	-0.0218 3293 0.211	-0.0271 3104 0.131	0.0547* 3248 0.002	0.0660* 3257 0.000	-0.0538* 3267 0.002	-0.0041 3164 0.818	0.0885* 3180 0.000	0.4996* 3378 0.000	-0.4424* 3378 0.000	1 3378 (-)

Note: (1) The first line is the Spearman's ρ, or, the Spearman rank correlation coefficient;
(2) The second line is the number of observations; and
(3) The third line is the significance level.
(4) * denotes the correlation coefficients significant at the 5% level or lower.

3.4.3 Econometric Analysis

Beyond the correlation analysis, we would like to conduct detailed investigation into the association between attitudes towards uncertainty and time, and directly test the three hypotheses proposed in Section 2 based on econometric analysis.

3.4.3.1 Test for Hypothesis 1.A

To test ***Hypothesis 1.A***, we can establish an equivalent test on our measures of these two kinds of attitudes, with the classical linear regression model specified as follows.

$$SP_i = \alpha_0 + \alpha_1 RP_i + \theta X_i + \varepsilon_i,\ \ \varepsilon | RP, X \sim N(0, \sigma^2) \tag{5}$$

where SP_i denotes the ***S***witching ***P***oint of subject i in the two intertemporal decision tasks (NFuture and RFuture), RP_i denotes the ***R***isk ***P***remium of subject i in the four risky decision tasks (MP, MP', HP, and LP), and X_i denotes a set of control variables, including the dummy for cities, the dummy for genders, the dummy for experiment rounds, ages and RPM IQ scores of subjects, as well as some others. Besides, to control potential unobserved factors which are common to the near future and the remote future, we would include the switching point in the remote future (RFuture) in X_i when estimating the model for the near future, and include NFuture when estimating the model for the rear future.

As ***Hypothesis 1.A*** says, decision makers who exhibit a relatively higher degree of risk aversion tend to request more compensation for delayed payment than those who are less risk averse. Hence, if ***Hypothesis 1.A*** is true, in the linear regression model with the degree of impatience being the dependent variable, we expect the coefficient before risk premium to be positive; that is, α_1 is expected to be positive.

Firstly, we estimate the model using OLS regression without controlling for other variables, X_i, and it is found that α_1 is significantly negative in MP, but significantly positive in MP', HP and LP for the near future, while for the remote future, we only have a significantly positive α_1 in LP, with all else negative. These findings are consistent with the Spearman's tests in Section 4.2. Detailed results could be found in Table A.12 in **Appendix VIII.**

Then, we estimate the model (5) again with the set of control variables added into the regression equation, and the OLS regression results for both the near future and the remote future are reported in Table 3.3. As one may note, in the near future, the coefficients before MP', and HP are significantly positive, and this is consistent with the Spearman's rank test; while we only have one significantly positive coefficient of interest in the remote future, which is the one before LP, with coefficients before MP, MP', and HP all significantly negative. Again, however, no significance is found in MP.

Moreover, the significantly negative coefficients before the city dummy across columns (1-4) of Table 3.3 indicate that our subjects in Singapore exhibit significantly lower degrees of impatience in the near future on average than subjects in China; but in the remote future as shown in columns (5-8) of Table 3.3, subjects in Singapore exhibit significantly higher degrees of impatience on average than those in China. Similarly, the positive coefficients before the gender dummy in columns (1-4) of Table 3.3 indicate that our male subjects exhibit significantly higher degrees of impatience than female subjects in the near future, but this is not significant in the remote future.

Besides, the coefficients before IQ are significantly negative both in the near future and in the remote, which suggests that people with higher cognitive ability, as measured by higher IQ scores, might be more likely to persuade themselves to be more patient to wait a delayed payment. These findings partially confirm those by Burks *et al.* (2009) and Dohmen *et al.* (2010), who did not distinguish the near future and the remote future.

In addition, as we expected above, as a control variable, the degree of impatience in the remote future is significantly powerful in explaining the degree of impatience in the near future, and it's similar to that in the near future to explain the remote future.

To sum up, let's come back to the ***Hypothesis 1.A***. In the moderate risky situation (MP), ***Hypothesis 1.A*** would be rejected, at least for the remote future case. In other words, the degree of people's risk aversion is significantly negatively correlated with people's impatience degree. Similarly, in the Task MP' and HP, ***Hypothesis 1.A*** would be rejected for the remote future. Moreover, the coefficients in Task MP' and HP support the ***Hypothesis 1.A*** at least for the near future case.

Table 3.3 OLS Regression Results for Test of Hypothesis 1.A

	Switching Point in the Near Future Task (NFuture)				Switching Point in the Remote Future Task (RFuture)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk Premium in the Moderate Prospect Task (MP)	-0.024				-0.042*			
	[0.022]				[0.021]			
Switching Point in the Moderate Prospect Task (MP')		0.063**				-0.036*		
		[0.017]				[0.016]		
Switching Point in the High Prospect Task (HP)			0.041**				-0.031*	
			[0.015]				[0.015]	
Switching Point in the Low Prospect Task (LP)				0.008				0.050**
				[0.016]				[0.015]
Switching Point in the Remote Future Task (RFuture)	0.488**	0.475**	0.478**	0.484**				
	[0.019]	[0.019]	[0.019]	[0.019]				
Switching Point in the Near Future Task (NFuture)					0.445**	0.442**	0.443**	0.450**
					[0.019]	[0.019]	[0.019]	[0.019]
Gender Dummy: 1=Male; 0=Female	0.262*	0.321**	0.308**	0.316**	-0.076	-0.043	-0.050	-0.030
	[0.110]	[0.108]	[0.108]	[0.108]	[0.104]	[0.105]	[0.105]	[0.104]
City Dummy: 1=SG; 0=BJ	-0.721**	-0.692**	-0.645**	-0.669**	0.868**	0.904**	0.854**	0.795**
	[0.108]	[0.105]	[0.106]	[0.106]	[0.100]	[0.099]	[0.100]	[0.099]
Ages of Subjects as of the Experiment	0.006	0.009	0.013	0.018	0.023	0.022	0.031	0.023
	[0.030]	[0.029]	[0.029]	[0.029]	[0.028]	[0.029]	[0.029]	[0.029]
Round Dummy: 1=Round 1, 0=Round 2	-0.091	-0.062	-0.076	-0.113	0.282**	0.250*	0.251*	0.282**
	[0.104]	[0.102]	[0.102]	[0.102]	[0.099]	[0.098]	[0.098]	[0.098]
RPM IQ Score	-0.037**	-0.040**	-0.039**	-0.043**	-0.025*	-0.029*	-0.027*	-0.024*
	[0.012]	[0.012]	[0.011]	[0.012]	[0.012]	[0.012]	[0.011]	[0.012]
Constant	4.942**	4.559**	4.565**	4.845**	0.943	1.424	1.036	0.600
	[0.902]	[0.889]	[0.864]	[0.896]	[0.879]	[0.891]	[0.855]	[0.895]
R^2	0.23	0.22	0.23	0.23	0.24	0.23	0.23	0.24
Observations	3,051	3,162	3,171	3,181	3,051	3,162	3,171	3,181

Note: (1) Standard errors are reported in the squared brackets below the estimated coefficients;

(2) * $p<0.05$; ** $p<0.01$.

3.4.3.2 Test for Hypothesis 1.B

Then, let's turn to test ***Hypothesis 1.B***. Similarly to test ***Hypothesis 1.A***, we can test it based on the following linear regression model.

$$NTB_i = \beta_0 + \beta_1 RP_i + \rho X_i + \mu_i,\ \ \mu|RP, X \sim N(0, \sigma^2) \tag{6}$$

where NTB_i denotes the measure of ***N**ear-**T**erm **B**ias*, which is the difference between the switching points of subject i in the near future decision task and the remote future task (NFuture minus RFuture), RP_i denotes the ***R**isk **P**remium* of subject i in the four risky decision tasks (MP, MP', HP, and LP), and X_i denotes a same set of control variables as in model (5). Since higher (positive) values of NTB_i means higher degrees of near-term bias and higher values of RP_i means higher degree of risk aversion, thus, the coefficient β_1 is expected to be positive if ***Hypothesis 1.B*** is true.

As reported in Table 3.4, the coefficients before MP, MP' and HP are all significantly positive while that before LP is significantly negative. Moreover, when we add the subjects' attitudes towards risk in all of the four situations into the regression equation, and the negative coefficient before LP is still significant and the other three positive coefficients are no longer significant. In other words, it seems that the degree of near-term bias is most likely to be associated with the degree of risk aversion in various situations. More specifically, the significantly positive sign of β_1 in column (1-3) indicates that ***Hypothesis 1.B*** is supported.

Table 3.4 OLS Regression Results for Test of Hypothesis 1.B

	Near-Term Bias: NFuture minus RFuture				
	(1)	(2)	(3)	(4)	(5)
Risk Premium in the Moderate Prospect Task (MP)	0.042*				0.033
	[0.021]				[0.023]
Switching Point in the Moderate Prospect Task (MP')		0.036*			0.026
		[0.016]			[0.020]
Switching Point in the High Prospect Task (HP)			0.031*		0.011
			[0.015]		[0.017]
Switching Point in the Low Prospect Task (LP)				-0.050**	-0.055**
				[0.015]	[0.015]
Switching Point in the Near Future Task (NFuture)	0.555**	0.558**	0.557**	0.550**	0.561**
	[0.019]	[0.019]	[0.019]	[0.019]	[0.020]
Gender Dummy: 1=Male; 0=Female	0.076	0.043	0.050	0.030	0.036
	[0.104]	[0.105]	[0.105]	[0.104]	[0.108]
City Dummy: 1=SG; 0=BJ	-0.868**	-0.904**	-0.854**	-0.795**	-0.777**
	[0.100]	[0.099]	[0.100]	[0.099]	[0.105]
Ages of Subjects as of the Experiment	-0.023	-0.022	-0.031	-0.023	-0.024
	[0.028]	[0.029]	[0.029]	[0.029]	[0.029]
Round Dummy: 1=Round 1, 0=Round 2	-0.282**	-0.250*	-0.251*	-0.282**	-0.287**
	[0.099]	[0.098]	[0.098]	[0.098]	[0.102]
RPM IQ Score	0.025*	0.029*	0.027*	0.024*	0.021
	[0.012]	[0.012]	[0.011]	[0.012]	[0.013]
Constant	-0.943	-1.424	-1.036	-0.600	-0.677
	[0.879]	[0.891]	[0.855]	[0.895]	[0.958]
R^2	0.32	0.32	0.32	0.31	0.33
Observations	3,051	3,162	3,171	3,181	2,864

Note: (1) Standard errors are reported in the squared brackets below the estimated coefficients;

(2) * p<0.05; ** p<0.01.

Besides, the results in Table 3.4 also indicate that 1) the degree of near-term bias is positively associated with the degree of impatience in the near future; 2) the subjects in Singapore seem to exhibit lower degree of near-term bias than those in Beijing on average, from the significantly negative coefficients before the city dummy across columns (1-5), which is consistent with the earlier observation that the Singapore subjects exhibit significantly lower degrees of impatience in the near future but significantly higher degrees of impatience in the remote future; and 3) the correlation between the IQ score and the degree of near-term bias people is still significantly positive.

3.4.3.3 Test for Hypothesis 2

Next, we will move onwards to test ***Hypothesis 2***.using a similar strategy, for which a linear regression model is specified as follows.

$$NTB_i = \gamma_0 + \gamma_1 CR_i + \varphi X_i + \mu_i,\ \ \mu|CR, X \sim N(0, \sigma^2) \tag{7}$$

where NTB_i denotes the measure of ***N***ear-***T***erm ***B***ias, which is defined the same as above in model (6), CR_i denotes the degree of ***C***ommon ***R***atio effect, which is defined as the difference between the switching point of subject i in Task MP' and the switching point in Task HP or LP, and X_i denotes a set of control variables, including the dummy for cities, the dummy for genders, the dummy for experiment rounds, ages and RPM IQ scores of subjects, as well as all kinds of risky decision situations.

If ***Hypothesis 2*** is true, the coefficient γ_1 is expected to be positive. As shown in Table 3.5, the coefficient γ_1 is significantly positive in the Low Prospect Task (LP), but not significant in the Task HP.

Table 3.5 OLS Regression Results for Test of Hypothesis 2

	Near-Term Bias: NFuture minus RFuture							
	Common Ratio Effect (CRH): MP' minus HP				Common Ratio Effect (CRL): MP' minus LP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Common Ratio Effect (CRH): MP' minus HP	0.007	-0.002	0.025	0.021				
	[0.018]	[0.015]	[0.018]	[0.020]				
Common Ratio Effect (CRL): MP' minus LP					0.057**	0.052**	0.045**	0.021
					[0.015]	[0.012]	[0.016]	[0.020]
Switching Point in the Near Future Task (NFuture)		0.563**	0.561**	0.566**		0.553**	0.554**	0.566**
		[0.019]	[0.019]	[0.020]		[0.019]	[0.019]	[0.020]
Switching Point in the High Prospect Task (HP)			0.045*	0.034				0.013
			[0.018]	[0.020]				[0.017]
Risk Premium in the Moderate Prospect Task (MP)				0.023				0.023
				[0.024]				[0.024]
Uncertainty Premium in the Ambiguous Prospect Task (AP)				0.025				0.025
				[0.020]				[0.020]
Switching Point in the Low Prospect Task (LP)				-0.056**			-0.012	-0.035
				[0.016]			[0.020]	[0.023]
Gender Dummy: 1=Male; 0=Female	0.250	0.041	0.052	0.051	0.242	0.037	0.032	0.051
	[0.128]	[0.106]	[0.107]	[0.108]	[0.127]	[0.105]	[0.106]	[0.108]
City Dummy: 1=SG; 0=BJ	-1.067**	-0.887**	-0.882**	-0.783**	-0.981**	-0.815**	-0.807**	-0.783**
	[0.125]	[0.101]	[0.101]	[0.105]	[0.122]	[0.100]	[0.100]	[0.105]
Ages of Subjects as of the Experiment	-0.020	-0.033	-0.032	-0.027	-0.005	-0.020	-0.021	-0.027
	[0.035]	[0.029]	[0.029]	[0.030]	[0.035]	[0.029]	[0.029]	[0.030]
Round Dummy: 1=Round 1, 0=Round 2	-0.201	-0.243*	-0.246*	-0.282**	-0.249*	-0.283**	-0.283**	-0.282**
	[0.119]	[0.100]	[0.099]	[0.102]	[0.118]	[0.099]	[0.099]	[0.102]
RPM IQ Score	-0.010	0.028*	0.027*	0.021	-0.015	0.025*	0.024	0.021
	[0.014]	[0.012]	[0.012]	[0.013]	[0.015]	[0.012]	[0.012]	[0.013]
Constant	2.987**	-0.890	-1.136	-0.667	2.893**	-1.008	-0.928	-0.667
	[1.036]	[0.885]	[0.892]	[0.964]	[1.062]	[0.910]	[0.923]	[0.964]
R^2	0.03	0.32	0.32	0.33	0.03	0.32	0.32	0.33
Observations	3,079	3,079	3,079	2,843	3,095	3,095	3,095	2,843

Note: (1) Standard errors are reported in the squared brackets below the estimated coefficients;

(2) * $p<0.05$; ** $p<0.01$.

3.4.3.4 Test for Hypothesis 3

Lastly, we test ***Hypothesis 3***.using a similar strategy, with a linear regression model specified as follows.

$$NTB_i = \delta_0 + \delta_1 AMB_i + \chi X_i + \mu_i,\ \mu | AMB, X \sim N(0, \sigma^2) \tag{8}$$

where NTB_i denotes the measure of ***N***ear-***T***erm ***B***ias, which is defined the same as above in model (6), AMB_i denotes the degree of ***AMB***iguity aversion, which is defined as the difference between the uncertainty premium of subject i in the Ambiguous Prospect Task (AP) and the risk premium in the Moderate Prospect Task (MP), and X_i denotes the same set of control variables.

If ***Hypothesis 3*** is true, the coefficient $\boldsymbol{\delta_1}$ is expected to be positive. However, the estimated coefficients are not significantly different from 0, as shown in Table 3.6, which means that ***Hypothesis 3*** cannot get any significant support from our experiment.

Table 3.6 OLS Regression Results for Test of Hypothesis 3

	Near-Term Bias: NFuture minus RFuture		
	(1)	(2)	(3)
Ambiguity Premium: AP-MP	-0.011	0.008	0.031
	[0.019]	[0.017]	[0.019]
Risk Premium in the Moderate Prospect Task (MP)			0.060*
			[0.024]
Switching Point in the Near Future Task (NFuture)		0.556**	0.559**
		[0.019]	[0.019]
Gender Dummy: 1=Male; 0=Female	0.243	0.075	0.099
	[0.127]	[0.105]	[0.105]
City Dummy: 1=SG; 0=BJ	-1.082**	-0.889**	-0.878**
	[0.124]	[0.101]	[0.101]
Ages of Subjects as of the Experiment	-0.013	-0.028	-0.028
	[0.035]	[0.029]	[0.029]
Round Dummy: 1=Round 1, 0=Round 2	-0.242*	-0.282**	-0.282**
	[0.119]	[0.099]	[0.099]
RPM IQ Score	-0.010	0.025*	0.025*
	[0.014]	[0.012]	[0.012]
Constant	2.930**	-0.795	-0.957
	[1.039]	[0.882]	[0.887]
R^2	0.03	0.32	0.32
Observations	3,021	3,021	3,021

Note: (1) Standard errors are reported in the squared brackets below the estimated coefficients;

(2) * p<0.05; ** p<0.01.

3.5 Robustness Checks

3.5.1 Alternative Econometric Analysis Approach

The econometric analysis part is only based on OLS regression approach. To test the robustness of the OLS regression results, we can also try the two-limit Tobit modelling approach, whose latent form specification is expected to help control for the two-limit censoring property of the experimental data.

Taking model (5) as an example, we can modify the linear specification to the latent form specification as follows.

$$SI_i^* = \alpha_0 + \alpha_1 RP_i + \theta X_i + \varepsilon_i,\ \varepsilon|RP, X \sim N(0, \sigma^2) \tag{9}$$

where

$$SI_i = \begin{cases} a_1, & if\ SI_i^* \leq a_1 \\ SI_i^*, & if\ a_1 < SI_i^* < a_2\,, \\ a_2, & if\ SI_i^* \geq a_2 \end{cases} \qquad a_1 = 0\ and\ a_2 = 10 \text{ in our data.}$$

The estimation results for the two-limit Tobit model are reported in Table A.13. As one may notice, there is only one slight changes in the estimation results; that is, the coefficient before MP is not significantly different from zero any more in the model for the remote future, column (5) in Table A.13.

Given the similar censoring property in the data for near-term bias, models (6-8) can also be modified to this two-limit Tobit model, with the estimation results reported in Table A.14, Table A.15, and Table A.16. Comparing results of the linear model and the Tobit model, we do not see any obvious change in the signs as well as significance of the parameters in the Tobit model.

Moreover, we can introduce a dummy variable for the near-term bias, denoted by $\boldsymbol{D\_NTB_i}$, so that we can also test the potential correlation between people's attitudes towards ambiguity and the likelihood to exhibit near-term bias, based on a Probit model in the following latent form. The estimation results for model (6) and model (7) are reported in Table A.17 and Table A.16.

$$NTB_i^* = \beta_0 + \beta_1 RP_i + \rho X_i + \mu_i,\ \ \mu|SU, X \sim N(0, \sigma^2) \tag{10}$$

where

$$D\_NTB_i = \begin{cases} 1, & if\ NTB_i^* > 0 \\ 0, & if\ NTB_i^* \leq 0 \end{cases}$$

Again, comparing the estimation results of the linear model and the Probit model for the likelihood to exhibit near-term bias, we do not find obvious difference.

Alternatively, we can also try other discrete ordered response modelling approaches, including the ordered Probit model, as well as the quantile regression models, and again, no obvious changes in the significance of the signs of interest are observed in the estimation results, except that some insignificant coefficients or significant coefficients but with the opposite signs are found in some relatively low quantiles, like 10% or 20% quantiles. Overall, we can still argue that the pervious findings are robust to various econometric analysis approaches we have tried.

3.5.2 Alternative Measures for Preferences

Although we may avoid potential estimation bias resulting from misspecification of utility functions by taking the strategy of using the switching points on the multiple price lists as measures of people's attitudes towards uncertainty and time, which does not rely on the utility function, we can still make use of other alternative measures for the attitudes to test the robustness of our results.

One alternative measure for the subjects' attitudes towards uncertainty is the so-called uncertainty premium, which is the difference between the expected payoff of the fixed uncertain option and the certainty equivalence of the subject with respect to the risky option, which is the switching point from Option A to Option B on the uncertainty price list. Moreover, for the intertemporal situations, either in NFuture or RFuture, as we have discussed in Section 3, we can take the differences in the amounts of money between Option A and Option B at the switching point on the time price list as the least compensation required by subjects for delayed payment, which is an alternative measure of the subjects' impatience degree. Then, we replace the switching point measures in previous analysis by the uncertainty premium and the least compensation and the results do not undermine the validity of previous results, but seem to provide stronger support to the previous results.

Besides, we also try another bundle of alternative measures for our subjects' attitudes towards uncertainty and time. More specifically, we calculate the constant relative risk aversion (*CRRA*) in each uncertain situation for each subject based on the switching point from Option A to Option B on the uncertainty price list, which point could be regarded as the certainty equivalence of the subject with respect to the risky option, and their discounting rates for both the near future and the remote future based on the switching point from Option A to Option B on the time price lists. The calculation methods for *CRRA* and discounting rates are described in Appendix VI and Appendix I. Again, by replacing the switching point measures in the previous analysis by *CRRA* and discounting rates, we find no significant change in the sign of coefficients in the new results, comparing with those obtained based on the other two bunches of measures.

3.6 Discussion with Concluding Remarks

Focusing on people's attitudes towards uncertainty and time, we examine the interrelation between them in this paper. In particular, based on a thorough review of the conceptual background, we propose and test three main hypotheses based on a large-sample experiment: (1.A) the more risk averse a decision maker is in risky situations, the more impatient he/she is in intertemporal settings; (1.B) the more risk averse a decision maker is in risky situations, the greater near-term bias he/she would exhibit; (2) the stronger common ratio effect a decision maker exhibits, the greater near-term bias he/she would exhibit; and (3) the more ambiguity averse a decision maker is, the greater near-term bias he/she would exhibit. On one hand, Hypothesis 1.A is supported in the near future, but gets rejected in the remote future; on the other hand, Hypothesis 1.B is supported from three of the four risky situations in our experiment, suggesting that people's risk aversion degree moderate risky situations is significantly positively associated with the degree of near-term bias people may exhibit when faced with decision situations involving different time delays. Furthermore, when we come to the Hypothesis 2, the experiment result in skewed risky decision situations (CRL) turns out to provide significant support to the hypothesis, but the result in moderate risky decision situations (CRH) does not. Besides, Hypothesis 3 cannot get any significant support from our experiment. In addition, it is also found that people's IQ value is significantly negatively associated with the degree of impatience both in the near future and in the remote future as well as the degree of near-term bias. These findings are robust to various econometric analysis approaches, various measures of the two kinds of attitudes as well as a replication study.

From the perspective of literature, we are contributing to the growing literature on the correlations between preferences over uncertainty and preferences over time in the several ways. Firstly, we are adding new evidence on the correlation between preferences over risk and preferences over time. In particular, the signs of our results in the remote future are in line with Anderhub *et al.* (2001) and Sutter *et al.* (2013), but contradict with Andersen *et al.* (2008), while in the near future, we have the reversal signs. Secondly, and more importantly, we are among the first few studies focusing on the interaction between people's attitudes towards ambiguity and time. It seems that we do not have any significant support to the intuition that time is a source of uncertainty, especially ambiguity. Therefore, it might be necessary to reconsider whether it is appropriate to view time as a source of ambiguity and to figure out the source of near-term bias. Moreover, the findings in the significant association between RPM IQ scores and the degree of impatience as well as the degree of near-term bias enrich the growing literature upon the relationship between time preferences and cognitive skills as well as personalities (See Burks *et al.* (2009); Dohmen *et al.* (2010)).

But there are still several points related with attitudes towards uncertainty and time that we have not touched in this paper, including loss aversion, preferences over resolution of uncertainty, and so on. Moreover, we have not answered the questions, like, is it possible that people who are more uncertainty averse would show more impatience in situations with uncertainty and time involved simultaneously? Is there any attitude dominating others when people make decisions in some situations? Is it possible that one kind of attitude is endogenous in another? Should the different kinds of attitudes be treated separately or jointly?

Besides, although we have obtained the significant association between people's attitudes towards uncertainty and time, this finding is based on measures of these attitudes elicited from separate decision tasks, which suggests that the test of the association is indirect. Hence, including a rigorous treatment of implicit uncertainty in the decision tasks seems necessary and natural to directly test the interaction between these two kinds of attitudes. Moreover, a measure of uncertainty, or ambiguity, perceived from the length of time is also desirable. This extension work is also expected to be done in the future.

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Appendices

Appendix I Calculation of Discounting Rates

Given our experiment design, to calculate the discounting rate, we can assume that the future value of the payment in Option A equals to the payment in Option B at the switching point from Option A to Option B on the time price list. That is,

$$\boldsymbol{x_1 = e^{-\delta} x_2}$$

where $\boldsymbol{x_1}$ is the payment in Option A, $\boldsymbol{x_1}$ is the payoff at the switching point in Option B, and $\boldsymbol{\delta}$ is the discounting rate for one month in our tasks, NFuture and RFuture. And subjects' discounting rates corresponding to different switching points in each of the two tasks are summarized in Table A.1.

Table A.1 Discounting Rates for One Month in Tasks NFuture and RFuture

	Location of the Switching Point									
	1	2	3	4	5	6	7	8	9	10
Option A	100	100	100	100	100	100	100	100	100	100
Option B	101	104	107	110	113	116	119	122	125	128
Discounting Rate	0.995%	3.922%	6.766%	9.531%	12.222%	14.842%	17.395%	19.885%	22.314%	24.686%

Appendix II Two-Limit Tobit Regression Results for Chapter 1

Table A.2 Tobit Regression Results for the Near Future

		The Degree of Impatience in the Near Future (NFuture)				
		(1)	(2)	(3)	(4)	(5)
Modell	RARA_LN	0.443	-0.667	-0.670	-0.562	-0.375
		(0.47)	(0.81)	(0.81)	(0.69)	(0.46)
	RFuture		0.681***	0.687***	0.654***	0.653***
			(7.47)	(7.53)	(7.19)	(7.22)
	Gender (1=M)			0.538	0.552	0.036
				(0.93)	(0.96)	(0.06)
	IQ				-0.178**	-0.173**
					(2.14)	(2.09)
	Age					0.341
						(1.60)
	Constant	-2.168	6.495	6.226	15.280*	6.251
		(0.25)	(0.86)	(0.82)	(1.78)	(0.61)
Sigma	Constant	4.752***	4.104***	4.090***	4.035***	4.009***
		(14.68)	(14.83)	(14.83)	(14.84)	(14.84)
Observation Summary						
	Left-censored observations at MP<=0	81	81	81	81	81
	Uncensored observations	135	135	135	135	135
	Right-censored observations at MP>=10	13	13	13	13	13

(1) Student t-statistics are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

Table A.3 Tobit Regression Results for the Remote Future

		The Degree of Impatience in the Remote Future (RFuture)				
		(1)	(2)	(3)	(4)	(5)
*Model*l	RARA_LN	3.962**	3.901***	3.832***	3.901***	3.848***
		(2.56)	(2.89)	(2.87)	(2.93)	(2.86)
	RFuture		1.171***	1.177***	1.141***	1.144***
			(7.17)	(7.24)	(6.98)	(6.99)
	Gender (1=M)			-1.495	-1.453	-1.315
				(1.64)	(1.60)	(1.28)
	IQ				-0.156	-0.157
					(1.20)	(1.22)
	Age					-0.094
						(0.28)
	Constant	-37.075**	-39.880***	-38.468***	-30.307**	-27.816*
		(2.58)	(3.16)	(3.08)	(2.16)	(1.68)
Sigma	Constant	7.075***	5.922***	5.867***	5.841***	5.836***
		(11.29)	(11.51)	(11.51)	(11.52)	(11.52)
Observation Summary						
	Left-censored observations at MP<=0	122	122	122	122	122
	Uncensored observations	89	89	89	89	89
	Right-censored observations at MP>=10	18	18	18	18	18

(1) Student t-statistics are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

Table A.4 Tobit Regression Results for the Near-Term Bias

		The Degree of Near-Term Bias (NFuture minus RFuture)				
		(1)	(2)	(3)	(4)	(5)
*Model*l	RARA_LN	-1.413	-1.381	-1.368	-1.249	-1.412
		(2.31)**	(2.28)**	(2.25)**	(2.04)**	(2.61)***
	Gender (1=M)		0.767	0.772	0.422	0.469
			(1.75)*	(1.76)*	(0.84)	(1.05)
	IQ			-0.032	-0.028	0.072
				(0.48)	(0.43)	(1.23)
	Age				0.230	0.122
					(1.38)	(0.83)
	NFuture					0.524
						(8.00)***
	Constant	13.571	12.878	14.516	8.514	5.156
		(2.41)**	(2.29)**	(2.22)**	(1.09)	(0.74)
Sigma	Constant	3.325	3.303	3.302	3.289	2.906
		(20.66)***	(20.66)***	(20.66)***	(20.66)***	(20.69)***
Observation Summary						
	Left-censored observations at MP<=-10	4	4	4	4	4
	Uncensored observations	220	220	220	220	220
	Right-censored observations at MP>=10	5	5	5	5	5

(1) Student t-statistics are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

Appendix III Experimental Design for Chapter 2

Figure A.1 Exhibit of the Moderate Prospect Task

This situation involves your guessing the color – red or black – of a card drawn randomly from a deck of 20 cards, comprising **10 black** cards and **10 red** cards.

Option A: You guess the color – black or red – and then draw a card from the deck of 20 cards. If you make a correct guess, you receive $60; otherwise, you receive nothing. That is: **50% chance of receiving $60 and 50% chance of receiving $0.**

The **Option B** column lists **10 amounts** (*displayed in an ascending manner*) each corresponding to what you will receive for sure if you choose this option.

DECISION: For each of the 10 rows, please indicate your decision in the final column with a tick (√).

	Option A	Option B	Decision
1	50% of receiving $60, 50% of receiving $0	Receiving $15 for sure	A□ B□
2	50% of receiving $60, 50% of receiving $0	Receiving $19 for sure	A□ B□
3	50% of receiving $60, 50% of receiving $0	Receiving $23 for sure	A□ B□
4	50% of receiving $60, 50% of receiving $0	Receiving $25 for sure	A□ B□
5	50% of receiving $60, 50% of receiving $0	Receiving $27 for sure	A□ B□
6	50% of receiving $60, 50% of receiving $0	Receiving $29 for sure	A□ B□
7	50% of receiving $60, 50% of receiving $0	Receiving $30 for sure	A□ B□
8	50% of receiving $60, 50% of receiving $0	Receiving $31 for sure	A□ B□
9	50% of receiving $60, 50% of receiving $0	Receiving $33 for sure	A□ B□
10	50% of receiving $60, 50% of receiving $0	Receiving $35 for sure	A□ B□

Figure A.2 Exhibit of the Moderate Hazard Task

This situation involves your guessing the color – red or black – of a card drawn randomly from a deck of 20 cards, comprising **10 black** cards and **10 red** cards.

Option A: You guess the color – black or red – and then draw a card from the deck of 20 cards. If you make a correct guess, you lose $0; otherwise, you lose $15. That is: **50% chance of losing $15 and 50% chance of losing $0.**

The **Option B** column lists **10 loss amounts** each corresponding to what you will lose for sure if you choose this option. (*Notice that the loss amounts are displayed in a descending manner.*)

DECISION: For each of the 10 rows, please indicate your decision in the final column with a tick (√).

	Option A	Option B	Decision
1	50% of losing $15, 50% of losing $0	Losing $8.00 for sure	A ▯ B ▯
2	50% of losing $15, 50% of losing $0	Losing $7.80 for sure	A ▯ B ▯
3	50% of losing $15, 50% of losing $0	Losing $7.60 for sure	A ▯ B ▯
4	50% of losing $15, 50% of losing $0	Losing $7.50 for sure	A ▯ B ▯
5	50% of losing $15, 50% of losing $0	Losing $7.40 for sure	A ▯ B ▯
6	50% of losing $15, 50% of losing $0	Losing $7.20 for sure	A ▯ B ▯
7	50% of losing $15, 50% of losing $0	Losing $7.00 for sure	A ▯ B ▯
8	50% of losing $15, 50% of losing $0	Losing $6.80 for sure	A ▯ B ▯
9	50% of losing $15, 50% of losing $0	Losing $6.60 for sure	A ▯ B ▯
10	50% of losing $15, 50% of losing $0	Losing $6.40 for sure	A ▯ B ▯

Figure A.3 Exhibit of the Ambiguous Prospect Task

This situation involves your drawing randomly one card from a **deck of 20 cards** **with unknown proportions of red and black cards**.

Option A: Guess the color of a card to be drawn randomly by you from a deck of 20 cards with unknown proportions of red and black cards. You will **receive $60 if your guess is correct**; and **receive $0 otherwise**.

The **Option B** column lists **10 amounts** (*displayed in an ascending manner*) each corresponding to what you will receive for sure if you choose this option.

DECISION: For each of the 10 rows, please indicate your decision in the final column with a tick (√).

	Option A	Option B	Decision
1	Betting on the color of a card drawn	Receiving $15 for sure	A▯ B▯
2	Betting on the color of a card drawn	Receiving $19 for sure	A▯ B▯
3	Betting on the color of a card drawn	Receiving $23 for sure	A▯ B▯
4	Betting on the color of a card drawn	Receiving $25 for sure	A▯ B▯
5	Betting on the color of a card drawn	Receiving $27 for sure	A▯ B▯
6	Betting on the color of a card drawn	Receiving $29 for sure	A▯ B▯
7	Betting on the color of a card drawn	Receiving $30 for sure	A▯ B▯
8	Betting on the color of a card drawn	Receiving $31 for sure	A▯ B▯
9	Betting on the color of a card drawn	Receiving $33 for sure	A▯ B▯
10	Betting on the color of a card drawn	Receiving $35 for sure	A▯ B▯

Figure A.4 Exhibit of the Ambiguous Hazard Task

This situation involves your guessing the color of a card drawn randomly from a deck of 20 cards with **unknown proportions of black cards and red cards**.

Option A: Guess the color of a card to be drawn randomly by you from a deck of 20 cards with unknown proportions of red and black cards. You will **receive $0 if your guess is correct; otherwise, you will lose $15**.

The **Option B** column lists **10 loss amounts** each corresponding to what you will receive for sure if you choose this option. (*Notice that the loss amounts are displayed in a descending manner.*)

DECISION: For each of the 10 rows, please indicate your decision in the final column with a tick (√).

	Option A	Option B	Decision
1	Betting on the color of a card drawn	Losing $8.00 for sure	A▯ B▯
2	Betting on the color of a card drawn	Losing $7.80 for sure	A▯ B▯
3	Betting on the color of a card drawn	Losing $7.60 for sure	A▯ B▯
4	Betting on the color of a card drawn	Losing $7.50 for sure	A▯ B▯
5	Betting on the color of a card drawn	Losing $7.40 for sure	A▯ B▯
6	Betting on the color of a card drawn	Losing $7.20 for sure	A▯ B▯
7	Betting on the color of a card drawn	Losing $7.00 for sure	A▯ B▯
8	Betting on the color of a card drawn	Losing $6.80 for sure	A▯ B▯
9	Betting on the color of a card drawn	Losing $6.60 for sure	A▯ B▯
10	Betting on the color of a card drawn	Losing $6.40 for sure	A▯ B▯

Appendix IV About the Candidate Genes

Table A.5 The List of Candidate Genes in the Present Study

Short Name	Full Name	Gene ID	Location	URL
ADRB1	Adrenoceptor beta 1 [Homo sapiens (human)]	153	Chromosome 10, NC_000010.11 (114044047..114046908)	http://www.ncbi.nlm.nih.gov/gene/153
AR	Androgen receptor [Homo sapiens (human)]	367	Chromosome X, NC_000023.11 (67544032..67730619)	http://www.ncbi.nlm.nih.gov/gene/367
AVPR1A	Arginine vasopressin receptor 1A [Homo sapiens (human)]	552	Chromosome 12, NC_000012.12 (63142287..63153860, complement)	http://www.ncbi.nlm.nih.gov/gene/552
COMT	Catechol-O-methyltransferase [Homo sapiens (human)]	1312	Chromosome 22, NC_000022.11 (19941740..19969975)	http://www.ncbi.nlm.nih.gov/gene/1312
ERBB3	ERB-b2 receptor tyrosine kinase 3 [Homo sapiens (human)]	2065	Chromosome 12, NC_000012.12 (56080025..56103507)	http://www.ncbi.nlm.nih.gov/gene/2065
ESR1	Estrogen receptor 1 [Homo sapiens (human)]	2099	Chromosome 6, NC_000006.12 (151690496..152103274)	http://www.ncbi.nlm.nih.gov/gene/2099
ESR2	Estrogen receptor 2 (ER beta) [Homo sapiens (human)]	2100	Chromosome 14, NC_000014.9 (64172925..64338550, complement)	http://www.ncbi.nlm.nih.gov/gene/2100
HTR2A	5-Hydroxytryptamine (serotonin) receptor 2A, G protein-coupled [Homo sapiens (human)]	3356	Chromosome 13, NC_000013.11 (46831542..46897076, complement)	http://www.ncbi.nlm.nih.gov/gene/3356
MAOA	Monoamine Oxidase A [Homo sapiens (human)]	4128	Chromosome X, NC_000023.11 (43654907..43746824)	http://www.ncbi.nlm.nih.gov/gene/4128
NRG1	Nuclear receptor subfamily 3, group C, member 1 (glucocorticoid receptor) [Homo sapiens (human)]	2908	Chromosome 5, NC_000005.10 (143277931..143435512, complement)	http://www.ncbi.nlm.nih.gov/gene/2908

Appendix V Robustness Checks for Chapter 2

Table A.6 Tobit Regression Results for the Moderate Prospect Task (MP)

		Switching Point in the Moderate Prospect Task (MP)						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model								
	ERBB3	0.714*			0.786**			0.655
		(1.88)			(2.09)			(1.58)
	ESR1		1.276**			1.252**		0.666
			(2.38)			(2.37)		(1.11)
	HTR2A			0.524*			0.546*	0.526*
				(1.84)			(1.96)	(1.87)
	Gender (1=M)				0.626	0.600	0.834	0.696
					(1.20)	(1.16)	(1.57)	(1.31)
	IQ				-0.152**	-0.141**	-0.161**	-0.175**
					(2.23)	(2.09)	(2.34)	(2.55)
	Age				0.064	0.073	0.055	0.086
					(0.38)	(0.43)	(0.33)	(0.52)
	Constant	2.424	-1.393	3.765***	8.939*	4.783	11.096**	5.235
		(1.55)	(0.49)	(4.57)	(1.66)	(0.81)	(2.11)	(0.83)
Sigma	Constant	3.395***	3.372***	3.315***	3.334***	3.316***	3.235***	3.212***
		(17.79)	(17.85)	(17.13)	(17.81)	(17.86)	(17.15)	(17.10)
Observation Summary								
	Left-censored observations at MP<=0	17	17	16	17	17	16	16
	Uncensored observations	180	181	166	180	181	166	165
	Right-censored observations at MP>=10	28	28	23	28	28	23	23

(1) Student t-statistics based on robust standard errors are reported in the parentheses;
(2) * *p*<0.1; ** *p*<0.05; *** *p*<0.01.

Table A.7 Tobit Regression Results for the Moderate Hazard Task (MH)

		Switching Point in the Moderate Hazard Task (MH)		
		(1)	(2)	(3)
Model				
	HTR2A	0.626	0.540	0.325
		(1.57)	(1.38)	(0.83)
	Gender (1=M)		-1.307*	-1.483**
			(1.74)	(2.00)
	IQ		0.005	0.026
			(0.06)	(0.28)
	Age		-0.295	-0.318
			(1.26)	(1.39)
	A1			0.304**
				(2.51)
	Constant	5.604***	12.517*	10.990
		(4.86)	(1.73)	(1.52)
Sigma	Constant	4.473***	4.363***	4.269***
		(14.04)	(14.07)	(14.03)
Observation Summary				
	Left-censored observations at MH<=0	13	13	13
	Uncensored observations	124	123	123
	Right-censored observations at MH>=10	63	63	62

(1) Student t-statistics based on robust standard errors are reported in the parentheses;

(2) * p<0.1; ** p<0.05; *** p<0.01.

Table A.8 Tobit Regression Results for the Ambiguous Prospect Task (AP)

		Switching Point in the Ambiguous Prospect Task (AP)						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model								
	ADRB1	0.832*			0.912**			0.792*
		(1.97)			(2.14)			(1.83)
	AVPR1A		-1.231*			-1.212*		-1.248*
			(1.92)			(1.90)		(1.81)
	ESR1			1.438*			1.388*	2.307**
				(1.87)			(1.82)	(2.45)
	Gender (1=M)				1.068	0.813	0.776	0.959
					(1.33)	(1.06)	(1.00)	(1.20)
	IQ				0.017	0.003	-0.002	0.037
					(0.17)	(0.03)	(0.02)	(0.37)
	Age				-0.310	-0.347	-0.327	-0.274
					(1.20)	(1.40)	(1.31)	(1.06)
	Constant	-1.025	8.803**	-6.291	3.835	15.484*	0.643	-2.243
		(0.82))	(2.25)	(1.54)	(0.49)	(1.86)	(0.07)	(0.23)
Sigma	Constant	4.678***	4.665***	4.679***	4.648***	4.635***	4.652***	4.592***
		(13.26)	(13.84)	(13.84)	(13.27)	(13.85)	(13.84)	(13.23)
Observation Summary								
	Left-censored observations at AP<=0	87	95	95	87	95	95	87
	Uncensored observations	113	123	123	113	123	123	112
	Right-censored observations at AP>=10	8	8	8	8	8	8	8

(1) Student t-statistics based on robust standard errors are reported in the parentheses;
(2) * p<0.1; ** p<0.05; *** p<0.01.

Table A.9 Tobit Regression Results for the Ambiguous Hazard Task (AH)

		Switching Point in the Ambiguous Hazard Task (AH)										
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Model												
	AR	1.271*					1.268*					0.796
		(1.69)					(1.68)					(0.88)
	AVPR1A		1.965**					1.893**				1.517
			(2.37)					(2.29)				(1.57)
	HTR2A			1.434***					1.444***			1.035*
				(2.63)					(2.66)			(1.88)
	MAOA				-0.790**					-0.699*		-0.927**
					(2.17)					(1.89)		(2.54)
	NRG1					1.181					1.092	1.345
						(1.61)					(1.50)	(1.54)
	Gender (1=M)						-0.209	-0.061	-0.236	-0.006	-0.200	0.223
							(0.20)	(0.06)	(0.22)	(0.01)	(0.19)	(0.21)
	IQ						0.254*	0.239*	0.212	0.207	0.242*	0.131
							(1.91)	(1.82)	(1.59)	(1.55)	(1.86)	(1.01)
	Age						0.157	0.011	0.135	-0.036	0.090	-0.001
							(0.43)	(0.03)	(0.38)	(0.10)	(0.26)	(0.00)
	Constant	-0.343	-5.972	1.882	9.688***	-2.477	-17.770	-19.116*	-12.761	-1.579	-17.208	-23.339*
		(0.09)	(1.17)	(1.19)	(5.65)	(0.47)	(1.52)	(1.68)	(1.19)	(0.14)	(1.49)	(1.80)
Sigma	Constant	6.190***	6.121***	5.989***	6.096***	6.099***	6.131***	6.072***	5.943***	6.061***	6.046***	5.640***
		(13.28)	(13.35)	(12.80)	(13.18)	(13.47)	(13.29)	(13.36)	(12.80)	(13.19)	(13.48)	(12.73)
Observation Summary												
	Left-censored observations at AP<=0	40	40	37	38	40	40	40	37	38	40	35
	Uncensored observations	118	119	109	116	121	118	119	109	116	121	107
	Right-censored observations at AP>=10	62	62	54	61	62	62	62	54	61	62	53

(1) Student t-statistics based on robust standard errors are reported in the parentheses;
(2) * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Appendix VI Calculation of CRRA

As an alternative measure for our subjects' attitudes towards uncertainty, the relative risk aversion (*RRA*) for each subject could be calculated based on the switching point from Option A to Option B on the uncertainty price list, which point could be regarded as the certainty equivalence of the subject with respect to the risky option. More specifically, we can assume the utility function $\boldsymbol{u}(\cdot)$ takes the following form

$$u(x) = \begin{cases} \frac{x^{1-\gamma}}{1-\gamma}, & for\ x > 0 \\ -\frac{(-x)^{1-\delta}}{1-\delta}, & for\ x < 0 \end{cases}$$

Thus, according to the definition of relative risk aversion, $RRA_u = \frac{-xu''(x)}{u'(x)}$, in the gain domain ($x > 0$), we have $RRA_u = \gamma$, which is a constant. Moreover, decision makers with positive γ are risk averse, those with negative γ are risk loving, and zero γ means risk neutrality. Moreover, for positive γ, the higher the value it is, the more risk averse the decision maker is.

Similarly, we also have a constant $RRA_u = \delta$ in the loss domain ($x < 0$), but decision makers with positive $\boldsymbol{\delta}$ are risk loving, those with negative $\boldsymbol{\delta}$ are risk averse, and zero $\boldsymbol{\delta}$ means risk neutrality. And for positive $\boldsymbol{\delta}$ means, the higher the value it is, the more risk loving the decision maker is.

And hence the subject's constant relative risk aversion (*CRRA)* could be given by the following equation:

$$P_1 u(x_1) + P_2 u(x_2) = u(CE)$$

where P_1 is the probability of the first outcome with payoff of $\boldsymbol{x_1}$ in Option A, P_2 is the probability of the second outcome with payoff of $\boldsymbol{x_2}$ in Option A, $\boldsymbol{CE}$ denotes the payoff of the switching point from Option A to Option B in the series of choices.

For example, one subject's response to the task MP is as shown in Table A.10, and his/her *CRRA* could be given by the following equation

$$0.5\left(\frac{60^{1-\gamma}}{1-\gamma}\right) + 0 = \frac{25^{1-\gamma}}{1-\gamma}$$

It follows that $\gamma = 0.2083$.

Table A.10 An Example for Subjects' Response to the Moderate Prospect Task (MP)

	Option A	Option B	Decision
1	50% of receiving \$60, 50% of receiving \$0	Receiving \$15 for sure	A ■ B □
2	50% of receiving \$60, 50% of receiving \$0	Receiving \$19 for sure	A ■ B □
3	50% of receiving \$60, 50% of receiving \$0	Receiving \$23 for sure	A ■ B □
4	50% of receiving \$60, 50% of receiving \$0	Receiving \$25 for sure	A □ B ■
5	50% of receiving \$60, 50% of receiving \$0	Receiving \$27 for sure	A □ B ■
6	50% of receiving \$60, 50% of receiving \$0	Receiving \$29 for sure	A □ B ■
7	50% of receiving \$60, 50% of receiving \$0	Receiving \$30 for sure	A □ B ■
8	50% of receiving \$60, 50% of receiving \$0	Receiving \$31 for sure	A □ B ■
9	50% of receiving \$60, 50% of receiving \$0	Receiving \$33 for sure	A □ B ■
10	50% of receiving \$60, 50% of receiving \$0	Receiving \$35 for sure	A □ B ■

Similarly, we can calculate subjects CRRAs with different switching points in each of the four decision tasks in uncertain situations, which are summarized in Table A 11.

Table A 11 *CRRAs* for Tasks MP, MH, AP, and AH

	Location of the Switching Point (Certainty Equivalence)										
	0	1	2	3	4	5	6	7	8	9	10
Task MP	>0.5	0.5000	0.3972	0.2771	0.2083	0.1319	0.0466	0.0000	-0.0497	-0.1594	<-0.1594
Task MH	<-0.1027	-0.1027	-0.0600	-0.0195	0.0000	0.0190	0.0556	0.0905	0.1238	0.1557	>1.557
Task AP	>0.5	0.5000	0.3972	0.2771	0.2083	0.1319	0.0466	0.0000	-0.0497	-0.1594	<-0.1594
Task AH	<-0.1027	0.5000	0.3972	0.2771	0.2083	0.1319	0.0466	0.0000	-0.0497	-0.1594	>1.557

Note: (1) In Task MP and Task AP, decision makers with positive *CRRA* are risks averse, those with negative CRRA are risk loving, and zero *CRRA* means risk neutrality. And for positive *CRRA*, the higher the value it is, the more risk averse the decision maker is.

(2) In Task MH and Task AH, decision makers with positive *CRRA* are risks loving, those with negative CRRA are risk averse, and zero *CRRA* means risk neutrality. And for negative *CRRA*, the lower the value it is, the more risk averse the decision maker is.

Appendix VII Experimental Design for Chapter 3

Figure A.5 Exhibit of the Moderate Prospect Task (MP)

This situation involves your guessing the color – red or black – of a card drawn randomly from a deck of 20 cards, comprising **10 black** cards and **10 red** cards.

Option A: You guess the color – black or red – and then draw a card from the deck of 20 cards. If you make a correct guess, you receive $60; otherwise, you receive nothing. That is: **50% chance of receiving $60 and 50% chance of receiving $0.**

The **Option B** column lists **10 amounts** (*displayed in an ascending manner*) each corresponding to what you will receive for sure if you choose this option.

DECISION: For each of the 10 rows, please indicate your decision in the final column with a tick (√).

	Option A	Option B	Decision
1	50% of receiving $60, 50% of receiving $0	Receiving $15 for sure	A ▯ B ▯
2	50% of receiving $60, 50% of receiving $0	Receiving $19 for sure	A ▯ B ▯
3	50% of receiving $60, 50% of receiving $0	Receiving $23 for sure	A ▯ B ▯
4	50% of receiving $60, 50% of receiving $0	Receiving $25 for sure	A ▯ B ▯
5	50% of receiving $60, 50% of receiving $0	Receiving $27 for sure	A ▯ B ▯
6	50% of receiving $60, 50% of receiving $0	Receiving $29 for sure	A ▯ B ▯
7	50% of receiving $60, 50% of receiving $0	Receiving $30 for sure	A ▯ B ▯
8	50% of receiving $60, 50% of receiving $0	Receiving $31 for sure	A ▯ B ▯
9	50% of receiving $60, 50% of receiving $0	Receiving $33 for sure	A ▯ B ▯
10	50% of receiving $60, 50% of receiving $0	Receiving $35 for sure	A ▯ B ▯

Figure A.6 Exhibit of the Ambiguous Prospect Task (AP)

This situation involves your drawing randomly one card from a **deck of 20 cards** **with unknown proportions of red and black cards**.

Option A: Guess the color of a card to be drawn randomly by you from a deck of 20 cards with unknown proportions of red and black cards. You will **receive $60 if your guess is correct**; and **receive $0 otherwise**.

The **Option B** column lists **10 amounts** (*displayed in an ascending manner*) each corresponding to what you will receive for sure if you choose this option.

DECISION: For each of the 10 rows, please indicate your decision in the final column with a tick (√).

	Option A	Option B	Decision
1	Betting on the color of a card drawn	Receiving $15 for sure	A▯ B▯
2	Betting on the color of a card drawn	Receiving $19 for sure	A▯ B▯
3	Betting on the color of a card drawn	Receiving $23 for sure	A▯ B▯
4	Betting on the color of a card drawn	Receiving $25 for sure	A▯ B▯
5	Betting on the color of a card drawn	Receiving $27 for sure	A▯ B▯
6	Betting on the color of a card drawn	Receiving $29 for sure	A▯ B▯
7	Betting on the color of a card drawn	Receiving $30 for sure	A▯ B▯
8	Betting on the color of a card drawn	Receiving $31 for sure	A▯ B▯
9	Betting on the color of a card drawn	Receiving $33 for sure	A▯ B▯
10	Betting on the color of a card drawn	Receiving $35 for sure	A▯ B▯

Figure A.7 Exhibit of the Moderate Prospect Task (MP')

Option A: Receiving **$30 for sure**

The **Option B** column lists **<u>different chances of receiving $60 and receiving $0 otherwise</u>**. (*Notice the chances of receiving $60 are displayed in an ascending manner.*)

DECISION: For each of the 10 rows in the table below, please indicate your decision in the final column with a tick (√).

	Option A	Option B	Decision
1	Receiving $30 for sure	48% of receiving $60, 52% of receiving $0	A☐ B☐
2	Receiving $30 for sure	50% of receiving $60, 50% of receiving $0	A☐ B☐
3	Receiving $30 for sure	52% of receiving $60, 48% of receiving $0	A☐ B☐
4	Receiving $30 for sure	54% of receiving $60, 46% of receiving $0	A☐ B☐
5	Receiving $30 for sure	56% of receiving $60, 44% of receiving $0	A☐ B☐
6	Receiving $30 for sure	58% of receiving $60, 42% of receiving $0	A☐ B☐
7	Receiving $30 for sure	60% of receiving $60, 40% of receiving $0	A☐ B☐
8	Receiving $30 for sure	62% of receiving $60, 38% of receiving $0	A☐ B☐
9	Receiving $30 for sure	64% of receiving $60, 36% of receiving $0	A☐ B☐
10	Receiving $30 for sure	66% of receiving $60, 34% of receiving $0	A☐ B☐

Figure A.8 Exhibit of the High Prospect Task (HP)

Option A: 50% of receiving \$60, 50% of receiving \$30

The **Option B** column lists **<u>different chances of receiving \$60 and receiving \$0 otherwise</u>**. (*Notice the chances of receiving \$60 are displayed in an ascending manner.*)

DECISION: For each of the 10 rows in the table below, please indicate your decision in the final column with a tick (√).

	Option A	Option B	Decision
1	50% of receiving \$60, 50% of receiving \$30	74% of receiving \$60, 26% of receiving \$0	A□ B□
2	50% of receiving \$60, 50% of receiving \$30	75% of receiving \$60, 25% of receiving \$0	A□ B□
3	50% of receiving \$60, 50% of receiving \$30	76% of receiving \$60, 24% of receiving \$0	A□ B□
4	50% of receiving \$60, 50% of receiving \$30	77% of receiving \$60, 23% of receiving \$0	A□ B□
5	50% of receiving \$60, 50% of receiving \$30	78% of receiving \$60, 22% of receiving \$0	A□ B□
6	50% of receiving \$60, 50% of receiving \$30	79% of receiving \$60, 21% of receiving \$0	A□ B□
7	50% of receiving \$60, 50% of receiving \$30	80% of receiving \$60, 20% of receiving \$0	A□ B□
8	50% of receiving \$60, 50% of receiving \$30	81% of receiving \$60, 19% of receiving \$0	A□ B□
9	50% of receiving \$60, 50% of receiving \$30	82% of receiving \$60, 18% of receiving \$0	A□ B□
10	50% of receiving \$60, 50% of receiving \$30	83% of receiving \$60, 17% of receiving \$0	A□ B□

Figure A.9 Exhibit of the Low Prospect Task (LP)

Option A: 50% chance of receiving $30 and 50% chance of receiving $0

The **Option B** column lists **different chances of receiving $60 and receiving $0 otherwise**. (*Notice the chances of receiving $60 are displayed in an ascending manner.*)

DECISION: For each of the 10 rows in the table below, please indicate your decision in the final column with a tick (√).

	Option A	Option B	Decision
1	50% of receiving $30, 50% of receiving $0	24% of receiving $60, 76% of receiving $0	A ▯ B ▯
2	50% of receiving $30, 50% of receiving $0	25% of receiving $60, 75% of receiving $0	A ▯ B ▯
3	50% of receiving $30, 50% of receiving $0	26% of receiving $60, 74% of receiving $0	A ▯ B ▯
4	50% of receiving $30, 50% of receiving $0	27% of receiving $60, 73% of receiving $0	A ▯ B ▯
5	50% of receiving $30, 50% of receiving $0	28% of receiving $60, 72% of receiving $0	A ▯ B ▯
6	50% of receiving $30, 50% of receiving $0	29% of receiving $60, 71% of receiving $0	A ▯ B ▯
7	50% of receiving $30, 50% of receiving $0	30% of receiving $60, 70% of receiving $0	A ▯ B ▯
8	50% of receiving $30, 50% of receiving $0	31% of receiving $60, 69% of receiving $0	A ▯ B ▯
9	50% of receiving $30, 50% of receiving $0	32% of receiving $60, 68% of receiving $0	A ▯ B ▯
10	50% of receiving $30, 50% of receiving $0	33% of receiving $60, 67% of receiving $0	A ▯ B ▯

Appendix VIII Supplementary Analysis Results for Chapter 3

Table A.12 Regression Results for Test of Hypothesis 1.A (No Control)

	Switching Point in the Near Future Task (NFuture)				Switching Point in the Remote Future Task (RFuture)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk Premium in the Moderate Prospect Task (MP)	-0.063*				-0.076**			
	[0.025]				[0.024]			
Switching Point in the Moderate Prospect Task (MP')		0.047*				-0.004		
		[0.019]				[0.018]		
Switching Point in the High Prospect Task (HP)			0.033*				-0.024	
			[0.017]				[0.016]	
Switching Point in the Low Prospect Task (LP)				0.030				0.090**
				[0.017]				[0.016]
Constant	3.816**	3.424**	3.544**	3.556**	2.451**	2.390**	2.465**	1.846**
	[0.077]	[0.134]	[0.101]	[0.115]	[0.075]	[0.131]	[0.099]	[0.103]
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Observations	3,143	3,259	3,268	3,279	3,140	3,254	3,265	3,274

Note: (1) Standard errors are reported in the squared brackets below the estimated coefficients;

(2) * p<0.05; ** p<0.01.

Table A.13 Tobit Regression Results for Test of Hypothesis 1.A

		Switching Point in the Near Future Task (NFuture)				Switching Point in the Remote Future Task (RFuture)			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	Risk Premium in the Moderate Prospect Task (MP)	-0.040				-0.077			
		[0.032]				[0.044]			
	Switching Point in the Moderate Prospect Task (MP')		0.107**				-0.074*		
			[0.024]				[0.034]		
	Switching Point in the High Prospect Task (HP)			0.064**				-0.075*	
				[0.022]				[0.031]	
	Switching Point in the Low Prospect Task (LP)				0.023				0.110**
					[0.022]				[0.032]
	Switching Point in the Remote Future Task (RFuture)	0.703**	0.681**	0.687**	0.693**				
		[0.026]	[0.025]	[0.025]	[0.025]				
	Switching Point in the Near Future Task (NFuture)					0.898**	0.884**	0.891**	0.899**
						[0.036]	[0.035]	[0.035]	[0.035]
	Gender Dummy: 1=Male; 0=Female	0.277	0.370*	0.356*	0.370*	-0.327	-0.250	-0.276	-0.227
		[0.163]	[0.159]	[0.159]	[0.159]	[0.229]	[0.225]	[0.225]	[0.224]
	City Dummy: 1=SG; 0=BJ	-1.271**	-1.217**	-1.152**	-1.204**	1.527**	1.602**	1.495**	1.333**
		[0.162]	[0.157]	[0.157]	[0.159]	[0.228]	[0.222]	[0.222]	[0.225]
	Ages of Subjects as of the Experiment	0.009	0.013	0.019	0.025	0.081	0.082	0.101	0.082
		[0.045]	[0.043]	[0.044]	[0.044]	[0.063]	[0.061]	[0.062]	[0.061]
	Round Dummy: 1=Round 1, 0=Round 2	-0.153	-0.105	-0.118	-0.179	0.739**	0.651**	0.678**	0.717**
		[0.154]	[0.151]	[0.151]	[0.150]	[0.216]	[0.212]	[0.213]	[0.212]
	RPM IQ Score	-0.057**	-0.060**	-0.057**	-0.062**	-0.069**	-0.075**	-0.072**	-0.066**
		[0.017]	[0.016]	[0.016]	[0.016]	[0.023]	[0.022]	[0.021]	[0.023]
	Constant	5.494**	4.725**	4.732**	5.140**	-2.117	-1.327	-2.016	-2.929
		[1.326]	[1.285]	[1.278]	[1.300]	[1.848]	[1.797]	[1.784]	[1.820]
Sigma	Constant	4.041**	4.027**	4.039**	4.022**	5.241**	5.260**	5.263**	5.246**
		[0.070]	[0.068]	[0.068]	[0.068]	[0.117]	[0.114]	[0.115]	[0.114]
Observation Summary									
	Left-censored observations at NFuture (RFuture) <=0	725	732	745	745	1502	1526	1545	1545
	Uncensored observations	2004	2093	2090	2098	1320	1391	1386	1391
	Right-censored observations at NFuture (RFuture) >=10	322	337	336	338	229	229	240	245

Note: (1) Standard errors are reported in the squared brackets below the estimated coefficients;

(2) * *p*<0.05; ** *p*<0.01.

Table A.14 Tobit Regression Results for Test of Hypothesis 1.B

		Near-Term Bias (NTB): NFuture minus RFuture			
		(1)	(2)	(3)	(4)
Model	Risk Premium in the Moderate Prospect Task (MP)	0.047*			
		[0.021]			
	Switching Point in the Moderate Prospect Task (MP')		0.039*		
			[0.017]		
	Switching Point in the High Prospect Task (HP)			0.035*	
				[0.015]	
	Switching Point in the Low Prospect Task (LP)				-0.054**
					[0.015]
	Switching Point in the Near Future Task (NFuture)	0.587**	0.590**	0.588**	0.581**
		[0.016]	[0.016]	[0.016]	[0.016]
	Gender Dummy: 1=Male; 0=Female	0.088	0.054	0.060	0.039
		[0.110]	[0.110]	[0.109]	[0.109]
	City Dummy: 1=SG; 0=BJ	-0.891**	-0.932**	-0.876**	-0.814**
		[0.109]	[0.107]	[0.107]	[0.108]
	Ages of Subjects as of the Experiment	-0.025	-0.024	-0.033	-0.026
		[0.031]	[0.030]	[0.030]	[0.030]
	Round Dummy: 1=Round 1, 0=Round 2	-0.303**	-0.267**	-0.267**	-0.300**
		[0.104]	[0.103]	[0.103]	[0.102]
	RPM IQ Score	0.025*	0.030**	0.028*	0.024*
		[0.011]	[0.011]	[0.011]	[0.011]
	Constant	-1.000	-1.489	-1.111	-0.597
		[0.906]	[0.896]	[0.885]	[0.900]
Sigma	Constant	2.841**	2.884**	2.873**	2.864**
		[0.038]	[0.038]	[0.038]	[0.037]
Observation Summary					
	Left-censored observations at NFuture<=-10	32	36	35	32
	Uncensored observations	2898	2999	3010	3023
	Right-censored observations at NFuture >=10	121	127	126	126

Note: (1) Standard errors are reported in the squared brackets below the estimated coefficients;

(2) * p<0.1; ** p<0.05; *** p<0.01.

Table A.15 Tobit Regression Results for Test of Hypothesis 2

		Near-Term Bias: NFuture minus RFuture							
		Common Ratio Effect (CRH): MP' minus HP				Common Ratio Effect (CRL): MP' minus LP			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	Common Ratio Effect (CRH): MP' minus HP	0.006	-0.004	0.026	0.020				
		[0.018]	[0.015]	[0.019]	[0.021]				
	Common Ratio Effect (CRL): MP' minus LP					0.060**	0.056**	0.048**	0.020
						[0.015]	[0.013]	[0.017]	[0.021]
	Switching Point in the Near Future Task (NFuture)		0.595**	0.593**	0.598**		0.585**	0.585**	0.598**
			[0.016]	[0.016]	[0.017]		[0.016]	[0.016]	[0.017]
	Switching Point in the High Prospect Task (HP)			0.050**	0.038				0.018
				[0.019]	[0.020]				[0.017]
	Risk Premium in the Moderate Prospect Task (MP)				0.027				0.027
					[0.024]				[0.024]
	Uncertainty Premium in the Ambiguous Prospect Task (AP)				0.027				0.027
					[0.020]				[0.020]
	Switching Point in the Low Prospect Task (LP)				-0.061**			-0.014	-0.041
					[0.016]			[0.021]	[0.024]
	Gender Dummy: 1=Male; 0=Female	0.269*	0.048	0.061	0.060	0.264*	0.047	0.042	0.060
		[0.133]	[0.111]	[0.111]	[0.114]	[0.131]	[0.110]	[0.110]	[0.114]
	City Dummy: 1=SG; 0=BJ	-1.101**	-0.911**	-0.906**	-0.797**	-1.011**	-0.836**	-0.826**	-0.797**
		[0.131]	[0.109]	[0.109]	[0.115]	[0.130]	[0.109]	[0.110]	[0.115]
	Ages of Subjects as of the Experiment	-0.021	-0.035	-0.034	-0.029	-0.006	-0.022	-0.023	-0.029
		[0.037]	[0.031]	[0.031]	[0.032]	[0.036]	[0.030]	[0.030]	[0.032]
	Round Dummy: 1=Round 1, 0=Round 2	-0.212	-0.258*	-0.262*	-0.302**	-0.264*	-0.302**	-0.301**	-0.302**
		[0.125]	[0.105]	[0.104]	[0.107]	[0.124]	[0.104]	[0.104]	[0.107]
	RPM IQ Score	-0.012	0.029*	0.028*	0.021	-0.018	0.025*	0.024*	0.021
		[0.013]	[0.011]	[0.011]	[0.012]	[0.014]	[0.011]	[0.011]	[0.012]
	Constant	3.173**	-0.937	-1.209	-0.696	3.107**	-1.028	-0.937	-0.696
		[1.074]	[0.902]	[0.907]	[0.961]	[1.073]	[0.906]	[0.917]	[0.961]
Sigma	Constant	3.454**	2.878**	2.874**	2.824**	3.423**	2.865**	2.865**	2.824**
		[0.046]	[0.038]	[0.038]	[0.039]	[0.046]	[0.038]	[0.038]	[0.039]
Observation Summary									
	Left-censored observations at NFuture<=-10	35	35	35	29	32	32	32	29
	Uncensored observations	2919	2919	2919	2698	2938	2938	2938	2698
	Right-censored observations at NFuture >=10	125	125	125	116	125	125	125	116

Note: (1) Standard errors are reported in the squared brackets below the estimated coefficients;

(2) * p<0.05; ** p<0.01.

Table A.16 Tobit and Probit Regression Results for Test of Hypothesis 3

	Near-Term Bias: NFuture minus RFuture		
	OLS	Tobit	Probit
Ambiguity Premium: AP-MP	0.031	0.033	0.021*
	[0.019]	[0.019]	[0.009]
Risk Premium in the Moderate Prospect Task (MP)	0.060*	0.066**	0.028*
	[0.024]	[0.024]	[0.012]
Switching Point in the Near Future Task (NFuture)	0.559**	0.591**	0.174**
	[0.019]	[0.016]	[0.008]
Gender Dummy: 1=Male; 0=Female	0.099	0.111	-0.028
	[0.105]	[0.111]	[0.053]
City Dummy: 1=SG; 0=BJ	-0.878**	-0.902**	-0.634**
	[0.101]	[0.109]	[0.052]
Ages of Subjects as of the Experiment	-0.028	-0.030	-0.020
	[0.029]	[0.031]	[0.014]
Round Dummy: 1=Round 1, 0=Round 2	-0.282**	-0.303**	-0.146**
	[0.099]	[0.104]	[0.049]
RPM IQ Score	0.025*	0.025*	0.009
	[0.012]	[0.011]	[0.005]
Constant	-0.957	2.836**	-0.401
	[0.887]	[0.038]	[0.425]
R^2	0.32		
Observations	3,021	3,021	3,021

Note: (1) In the Probit model, the dependent variable is a dummy variable for near-term bias: D_NTB=1 if NTB>0; otherwise, D_NTB=0;

(2) Standard errors are reported in the squared brackets below the estimated coefficients;

(3) * p<0.05; ** p<0.001.

Table A.17 Probit Regression Results for Test of Hypothesis 1.B

	Near-Term Bias Dummy: 1 if NTB>0; 0 otherwise				
	(1)	(2)	(3)	(4)	(5)
Risk Premium in the Moderate Prospect Task (MP)	0.015				0.005
	[0.010]				[0.011]
Switching Point in the Moderate Prospect Task (MP')		0.027***			0.022**
		[0.008]			[0.010]
Switching Point in the High Prospect Task (HP)			0.018***		0.005
			[0.007]		[0.008]
Switching Point in the Low Prospect Task (LP)				-0.002	-0.005
				[0.007]	[0.008]
Switching Point in the Near Future Task (NFuture)	0.172***	0.173***	0.174***	0.171***	0.173***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
Gender Dummy: 1=Male; 0=Female	-0.042	-0.057	-0.037	-0.048	-0.040
	[0.052]	[0.051]	[0.051]	[0.051]	[0.054]
City Dummy: 1=SG; 0=BJ	-0.627***	-0.657***	-0.633***	-0.634***	-0.632***
	[0.051]	[0.050]	[0.050]	[0.051]	[0.054]
Ages of Subjects as of the Experiment	-0.017	-0.017	-0.020	-0.014	-0.014
	[0.014]	[0.014]	[0.014]	[0.014]	[0.015]
Round Dummy: 1=Round 1, 0=Round 2	-0.149***	-0.148***	-0.160***	-0.162***	-0.170***
	[0.049]	[0.048]	[0.048]	[0.048]	[0.051]
RPM IQ Score	0.009*	0.009*	0.007	0.007	0.007
	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]
Constant	-0.394	-0.536	-0.317	-0.328	-0.502
	[0.424]	[0.412]	[0.410]	[0.418]	[0.451]
Observations	3,051	3,162	3,171	3,181	2,864

Note: (1) Standard errors are reported in the squared brackets below the estimated coefficients;

(2) * p<0.05; ** p<0.01.