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Incentive Compatible Payoff Mechanisms for General Risk Theories

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ABSTRACT

INCENTIVE COMPATIBLE PAYOFF MECHANISMS

FOR GENERAL RISK THEORIES

BY

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This dissertation focuses on one methodological problem in experimental economics: how to pay subjects, or in other words, payoff mechanism issue. For example, one popular payoff mechanism is Random Lottery Incentive System (RLIS), that is, after subjects have made all their choices, one among all their decisions is randomly selected as their payment. Payoff mechanism is part of the incentive in economic experiments, and people respond to incentives. When economists think they observe subjects' responses to experimental tasks, the observed behavior is actually the joint effect of the decision tasks and the payoff mechanism used in the experiment. When the payoff mechanism is not incentive compatible, it may distort behavior. Cox et al.(2015) have shown that with the same decision tasks, when payoff mechanism changes, people make different choices.

When it comes to the experiments of decision making under risk, Holt(1986) firstly points out that RLIS is incentive compatible when Independence Axiom is assumed. Independence Axiom says that if one prefers Gamble A to Gamble B, when both gambles mix the same proportion with a third Gamble C, one would prefer the combination of A and C to B and C. Independence is one of the fundamental axioms of Expected Utility Theory (EUT).

Later decision models relax such axiom and allow violations of Independence, such as Rank Dependent Utility Theory (RDU) and Cumulative Prospect Theory (CPT). Therefore, when RDU or CPT is assumed, RLIS becomes incentive incompatible. It is well-known in the literature that one round task, where subjects make one decision and get paid by their choice, is incentive compatible with all the decision models. Harrison and Swarthout (2014) have shown that when RDU is assumed, the estimation from the data using RLIS is different from that using one round task. The gap in the literature is that under a multiple-round setting, it's still mysterious what incentive compatible payoff mechanisms are for the general risk theories.

In the dissertation, I discuss the incentive compatible payoff mechanisms for general risk models. The "general" refers to the models where well-behaved (complete and transitive) preference is assumed. In Chapter 1, I propose a new payoff mechanism, which I call "Accumulative Best Choice" (ABC) design and show that it is incentive compatible with general risk models. I also test the validity of ABC in the lab. The data from two experiments show that there is no significant difference for the choices or the estimates under ABC design and under one round task at 5% level. In Chapter 2, with the data from ABC design, I estimate the structural parameters for both EUT and RDU models, which is so far the first using an incentive compatible payoff mechanism for RDU model under a multiple-round setting. In Chapter 3, I apply ABC design on the most popular risk attitude elicitation method: Holt and Laury (HL) (2002) multiple price list. With estimations for EUT, Dual Theory of Expected Utility (DU) and RDU, I show that the HL list offers more information about the probability curvature than the utility curvature.

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BY

YI (LILY) LI

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Introduction

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When it comes to the experiments of decision making under risk, Holt(1986) firstly points out that RLIS is incentive compatible when Independence Axiom is assumed. Independence Axiom says that if one prefers Gamble A to Gamble B, when both gambles mix the same proportion with a third Gamble C, one would prefer the combination of A and C to B and C. Independence is one of the fundamental axioms of Expected Utility Theory (EUT). Later decision models relax such axiom and allow violations of Independence, such as Rank Dependent Utility Theory (RDU) and Cumulative Prospect Theory (CPT). Therefore, when RDU or CPT is assumed, RLIS becomes incentive incompatible. It is well-known in the literature that one round task, where subjects make one decision and get paid by their choice, is incentive compatible with all the decision models. Harrison and Swarthout (2014) have shown that when RDU is assumed, the estimation from the data using RLIS is different from that using one round task. The gap in the literature is that under a multiple round setting, it's still mysterious what incentive compatible payoff mechanisms are for the general risk theories.

In the dissertation, I discuss the incentive compatible payoff mechanisms for general risk models. The "general" refers to the models where well-behaved (complete and transitive) preference is assumed.

Chapter 1: I propose a new payoff mechanism, which I call "Accumulative Best Choice" (ABC) design and show that it is incentive compatible with general risk models. I test the validity of ABC in the lab for both a choice-pattern experiment and a preference estimation experiment. The data from two experiments show that there is no significant difference for the choices or the estimates under ABC design and under one round task at 5% level.

Chapter 2: In previous literature, when economists estimate RDU or CPT model, they use the data generated from the experiments with the incentive incompatible payoff mechanism. Now, with the ABC design I proposed in Chapter 1, which is incentive compatible with general risk theories, we can estimate the RDU or CPT models without the bias from the data generating process. In this chapter, I perform the analysis of the data from "replicating" Harrison and Swarthout (2014) with ABC design. The data shows that the ABC treatment generates data with no significant difference compared with one round task treatment for all six structural models; As long as RDU model is assumed, RLIS leads to different estimations compared with one round task design. The results from RDU estimation show that the CRRA parameter is 0.571, and the probability weighting function is inverse-S shaped. No gender effect has been found in this study.

Chapter 3: I apply the ABC design on the most popular risk attitude elicitation method: Holt and Laury (2002) (HL) multiple price list design. Such implementation would allow us to estimate models beyond EUT since ABC is incentive compatible with general risk theories. The first result is that there's no significant difference for the choices under the ABC design and under when subjects choose from one lottery pair only. Then, with data from the ABC treatment, I estimate the risk preferences with EUT, DU, and RDU models. I find out that for the HL list, EUT is not a better model than DU, and estimation with RDU model rejects the linearity in probability. It implies that the HL list offers more information about probability weighting function rather than the utility function since it only has four outcomes.

On the whole, these three chapters complete my exploration of discovering and applying the incentive compatible payoff mechanisms for general risk models. That's also the main contribution of this dissertation: offering a tool for risk elicitation experiments so that we can test risk theories or incorporate more risk models in the data analysis without worrying about the confounding issue of the decision task and the payoff mechanism in the data generating process.

Chapter 1

A New Incentive Compatible Payoff Mechanism for General Risk Theories: Theory and Experiments

1.1 Introduction

The ability to elicit risk preferences in an unbiased manner is crucial in general study of individual behavior. Risk attitude is involved in many economic fields and issues: preferences over time (Strotz (1955)), auctions (Cox et al. (1982)), tax behavior (Alm et al. (1992)), searching behavior (Pissarides (1974), Schunk and Winter (2009), Spivey (2010)), health outcomes (Gafni and Torrance (1984), Anderson and Mellor (2008)), climate change issues (Leiserowitz (2006)), and agricultural economics (Lusk and Coble (2005)). The most popular model to describe an individual's behavior under risk is Expected Utility Theory (EUT), initially proposed by Bernoulli, and axiomatized by von Neumann and Morgenstern (1944). One of the key axioms of EUT is the Independence Axiom. It states that if someone prefers Gamble A to Gamble B, he/she should also prefer the mixture of A and a third gamble C to the mixture of B and C. Yet many empirical facts have called into question the validity of Independence Axiom. As a result, many decision theories relax the Independence Axiom, such as Rank Dependent Utility Theory (RDU) (Quiggin (1982)) and Cumulative Prospect Theory (CPT) (Tversky and Kahneman (1992)).

When experimenters test the behavioral models, one of the most popular payoff mechanisms they use is called Random Lottery Incentive System (RLIS). Each individual is required to make choices among lotteries for a multiple-round task. RLIS mechanism states that at the end of an experiment, one and only one round out of all rounds will be randomly selected as the paying round. Then subjects get paid by the realized outcome of the lottery they chose in that round. However, RLIS is only valid when Independence is satisfied (Holt (1986), Cubitt et al. (1998), Azrieli et al. (2014)). What's more, evidences from experiments show that people do respond to variations of payoff mechanisms (Cox et al. (2015)), and lead to different estimations of risk attitudes (Harrison and Swarthout (2014)). So far, the only known incentive compatible payoff mechanism for general risk theories is the between-subject design: to give each individual one round risk task and pay him/her choice[1]. Economists expect more and would like to design an incentive compatible way to pay subjects under a multiple-round setting. Such a question is of fundamental importance since one individual making multiple choices allows us to do within-subject analysis and thus address a wider range of questions. For example, in the field of decision theory, taking Allais Paradox as an example, it is more desirable to see whether one individual makes inconsistent choices in two lottery pairs. Or, if we want to learn how people update their belief in Bayesian models, it must be through multiple choices by the same individual. Charness et al. (2012) argue that between-subject designs are more conservative but with limitations, while within designs are more attractive but may suffer from confounds.

In this case, the confound is that people may view a payoff mechanism as one part of the experiment. When experimenters intend to test the model solely, they actually test the joint effects of the decision tasks and the payoff mechanism. With such confound

[1] I'm using between-subject design and one round task interchangeably in the paper.

detected by previous literature, is it possible to resolve it? Is there a within-subject design for testing general risk theories? The "general" risk theories in this paper refer to those with the assumption of complete and transitive risk preferences, which includes the models mentioned earlier, such as EUT, RDU, Dual Expected Utility Theory (DU, Yaari (1987)) and CPT with fixed reference point. However, the risk theories that allows the violations of transitivity, such as CPT with endogenous reference point or reference-dependent utility theory (Kőszegi and Rabin (2006)), regret theory (Bell (1982), Loomes and Sugden (1982)) and disappointment aversion (Bell (1985), Gul (1991)), are beyond the discussion range of this paper. In this paper, I propose a new payoff mechanism *Accumulative Best Choice* (ABC) design and show that it is incentive compatible despite Independence Axiom or Reduction Axiom are assumed. The ABC design works as follows: In sequential choice situation, that is, individuals are not informed of all the lottery options beforehand, each individual's choice from the preceding round will be carried over to become one of the accessible lottery options in the following round, and eventually one gets paid by his or her chosen lottery in the last round (The formal definition will be given in the next section).

Theory tells one story, while behavior may tell a different one. The empirical validity of the ABC is tested in the paper, too. We should expect to see that it gives us the same results as the between-subject design. I apply the ABC design on two types of risk preference elicitation experiments: both a choice pattern experiment (from Cox et al. (2015)) with non-structural estimation and a preference estimation experiment (from Harrison and Swarthout (2014)) with structural estimation. The key null hypothesis is that individuals' choices or the estimates under the between-subject design are statistically the same as under the ABC design. Data from both experiments show that the null hypothesis cannot be rejected at the 5% significance level.

The contribution of this work is twofold. The first contribution is to show the ABC design is theoretical incentive compatible; the second is to illustrate its validity in the lab.

Beyond these, it offers broader implications for applied work. Take time preference as an example. Risk preference is embedded in time preference. Inconsistent behavior in elicitation of time preferences is found to be empirically associated with smoking (Burks et al. (2012)), BMI (Sutter et al. (2013), Courtemanche et al. (2015)), and credit card borrowing (Meier and Sprenger (2010)). When measuring the time preferences with monetary rewards, most studies with incentivized experiments use RLIS payoff mechanism (Tanaka et al. (2010), Andersen et al. (2008)) and its variations (such as randomly selected one round, and only partial participants that are randomly selected get paid by their choices of that round (Meier and Sprenger (2010), Burks et al. (2012)); or randomly selected one round first, and then whether sooner payment and later payment are paid are independently determined by two random devices (Andreoni and Sprenger (2012))). With RLIS, the underlying assumption is the Independence Axiom or Expected Utility Theory. On the other hand, theoretical literature show that time inconsistent behavior can be explained by non-Expected Utility models, too (Halevy (2008), Epper and Fehr-Duda (2015)). Adopting the ABC design in the elicitation procedure allows a richer set of risk decision models. Therefore it could benefit our understanding of people's preferences over time and the correlations between such preferences and the health or financial outcomes.

In the environmental and energy field, Shaw and Woodward (2008) point out why environmental economists should care about non-expected utility models; Riddel and Shaw (2006) find evidence with survey data to support non-expected utility models. In the taxation field, Dhami and Al-Nowaihi (2007) find evidence with simulation data to support Prospect Theory rather than Expected Utility Theory when explaining the tax evasion behavior. If economists or policy makers want to examine the issues with non-Expected Utility Theory and incentivized experimental data, RLIS may mislead since it's not incentive compatible with risk theories that violate Independence. They may consider the ABC design as one of the candidates.

The rest of the paper is arranged as follows: In Section 1.2, I will develop a theoretical framework. Section 1.3 reports the experimental procedures in detail and displays the results of data analysis. Section 1.4 concludes the paper with some further discussion.

1.2 Theoretical Framework and the Results

An n-round decision making task is defined as: $D = \{D_1, \cdots, D_n\}$, where $D_i(i = 1, \cdots, n)$ is a collection of some lotteries drawn from a lottery pool $\mathbb{L}$, and the lottery set $\mathbb{L}_0$ in D is finite and predetermined. Subjects are required to choose one lottery for each D_i and their choices are recorded as a choice lottery vector $c = (c_1, \cdots, c_n), c_i \in D_i$ for all $i = 1, \cdots, n$.

1.2.1 Payoff Rule and Payoff Mechanism

From each individual's choices c to what he or she eventually gets paid, it is the payoff rule. We define a payoff rule ϕ as mapping any $(c_1, \cdots, c_n)$ to a collection of lotteries and how they associate if more than one lottery is involved.

Suppose a lottery $l = (x_1, p_1; \cdots; x_m, p_m)$. Given the nature of the lottery, eventually one and only one out of $x_1, \cdots, x_m$ will be determined by a random device Ω as the outcome. Ω determines the realized state of the worlds. We use $\Omega(l)$ to represent the realized outcome of lottery l. Therefore, $\{\Omega(l)\} = \{x_1, \cdots, x_m\}$. A payoff rule ϕ is a mapping from $(c_1, \cdots, c_n)$ to $f_\phi(\Omega^1(c_1), \cdots, \Omega^n(c_n))$, where f_ϕ is a function of how to operate those random outcomes from all the choice lotteries given that payoff rule ϕ. For example, flat-pay, if experimenter informs subjects before they make any decision that they will get paid \$10 in total regardless what they choose (even though \$10 with 100% probability may not appear in the decision problems at all), then $f_\phi = \$10$. If experimenter pays subjects only their choice in the first round, then $f_\phi = \Omega(c_1)$. Without causing confusion, when paying individuals their choice lottery of one certain round, that is, $f_\phi = \Omega(c_i), i = 1, \cdots, n$, we just use the notation as $\phi(c) = f_\phi = c_i$.

Another example, $f_\phi = \Omega^1(c_1) + \cdots + \Omega^n(c_n)$, that is, subjects get paid by the sum of the outcomes of the choice lotteries of all rounds, and all the outcomes are independently determined by independent random devices. Another possible way of paying all rounds is proposed by Cox et al. (2015), what they call "Pay All Correlated". It is that: after subjects finish all their choices, first to array the outcomes of each chosen lottery comonotonically (either all from the worst outcome to the best outcome, or the opposite direction), then a random device will determine one same state for all the lotteries therefore realize the outcomes for all the chosen lotteries at the same time. We can use $f_\phi = \Omega(c_1) + \cdots + \Omega(c_n)$. There's no superscription for Ω now. All the outcomes are determined by one common random device.

f_ϕ also can be a lottery. For example, $f_\phi = (\Omega^1(c_1), 1/n; \cdots ; \Omega^n(c_n), 1/n)$. That is, only the realized outcome of one choice lottery from all rounds is as the payment. One example of a complicated payoff rule is randomly selected multiple rounds to pay (Charness and Rabin (2002)). It could be represented as a grand lottery of $f_\phi = (\Omega^i(c_i) + \Omega^j(c_j) + \Omega^k(c_k), 1/\binom{n}{3})$, where $i \neq j \neq k$ and $\binom{n}{3}$ is the 3-combinations from an n-element set.

We could also modify f_ϕ to add in the time attribute. Since there are n rounds, there are $(n + 1)$ time slots in the whole experiment. Extending f_ϕ from a function to an $1 \times (n + 1)$ vector can inform when the uncertainty is resolved. For example, compare $f_{\phi_1} = (0, \cdots, 0, \Omega^1(c_1) + \cdots + \Omega^n(c_n))$ with $f_{\phi_2} = (0, \Omega^1(c_1), \cdots, \Omega^n(c_n))$. The payoff mechanism ϕ_1 is that resolving all the choice lotteries at the end of the experiment and paying subjects the sum of the realized outcomes of all rounds. The payoff mechanism ϕ_2 is that after subject making each decision, the outcome of the choice lottery in that round is realized, and eventually subjects get paid by the sum of all the realized outcomes of all the choice lotteries.

In this framework, ϕ is a general symbol representing all possible payoff rules. It is the bridge to connect subjects' choices to their final payment. In essence, the payment consists of a collection of lotteries and the procedure of realizations of those lotteries. As long as the involved lotteries or the operation procedures of paying subjects are different in the experiment, we can treat them as different ϕ. Whether two payoff rules are equivalent under some assumptions or contexts is beyond the discussion of this article.

Notice that there is an implicit assumption made here. It is assumed the realization of the random events and the revelation of the results to subjects happen at the same time. It is not an issue for the experiments of decision tasks under risk, but matters for those under uncertainty (Baillon et al. (2014)).

We can define a payoff mechanism as (D, ϕ). If $D = \{D_1, \cdots, D_n\}$ are fixed and exogenously given by experimenters, then subjects' choice c are independent with D. In that case, ϕ, the payoff rule, can refer to the payoff mechanism which is the term well-known in the literature. If choices c and task D are not independent, the payoff mechanism, the whole package of (D, ϕ) tells us how c and D related as well as the payoff rule. We call such bundle (D, ϕ) as a payoff mechanism. In previous literature, usually all the lotteries in every D_i $(i = 1, \cdots, n)$ in D are treated as fixed and determined by experimenters, therefore, the only variable is ϕ in the discussion of the possible payoff mechanisms. In this setup, I only restrict the lottery set in D, $\mathbb{L}_0$ is predetermined. Therefore, when we discuss the payoff mechanism, we then have one more variable, D, the structure of the tasks, can be changed as well. Thus, we enlarge the scope of the discussion.

A general experiment can be identified by $(\mathbb{L}_0, D, \phi)$. For every individual, the set of all lotteries $\cup\{l | l \in \{D_i\}, \forall i \in \{1, \cdots, n\}\} = \mathbb{L}_0$ is fixed or predetermined. Compared with a very close work by Azrieli et al. (2014), the setup is different in this paper. Azrieli et al. (2014) denote (D, ϕ) as an experiment. In their settings, all the lotteries in every $D_i, i = 1, \cdots, n$ are fixed and determined completely exogenously by experimenters and are the same across individuals. Under such setting, the incentive compatibility requires that the payoff mechanism is either one round task only or RLIS when $n > 1$ with extra assumption about the preference satisfying compound independence axiom. In my setting, I include the task structure D as one more variable in the discussion of the payoff mechanism (D, ϕ) while allowing dependence between c and D (Only the lottery set of the decision problems $\mathbb{L}_0$ is predetermined before the decision making process. Two individuals may not see the same lotteries at the same round, or even not the same subset of $\mathbb{L}_0$ for the whole experiments. However, the sets of the lotteries they meet in the experiment are totally irrelevant of their choices. See more discussion in Section 1.2.3.). In this sense, the domain of the payoff mechanism in this paper is more general than that in the previous literature. Payoff mechanism (D, ϕ) is given exogenously by the experimenter. Subjects are also informed of the number of rounds n.

1.2.2 Preferences

After discussing the payoff rule ϕ and the payoff mechanism (D, ϕ), let's turn to the preferences. Suppose for each individual, one has a binary relation $\succeq$ over the general lottery pool $\mathbb{L}$, which is complete and transitive, $\succ$ is the corresponding asymmetric relation. Such preference $\succeq$ is also known as the "true preference" in previous literature. We use $c^* = (c_1^*, \cdots, c_n^*)$ to denote the observed choices we see from the experiments, which is assumed to be based on the optimization of the payment of the whole experiment $\phi(c)$. $C(D, \phi, \succeq) = \{c_1^*, \cdots, c_n^*\}$ to denote the optimal choice lottery set chosen by the subject with preference $\succeq$.

1.2.3 Accumulative Best Choice Design

Cox et al. (2015) categorizes an experiment into two protocols:

- with prior information: each individual is fully informed of all the lotteries in the whole experiment before they make any decisions, such as multiple price list (for example, see Holt and Laury (2002));
- with no prior information: each individual is only informed of the lotteries in the past and the current rounds, they don't know what lotteries are in the upcoming rounds (for example, see Hey and Orme (1994)).

Note that when the protocol is with no prior information, then uncertainty may kick in since the subjects don't know what the later lottery options are. Epstein and Halevy (2014) discuss that one's uncertainty attitude about how different tasks are related could affect his or her choices under risk. That's the reason we must keep $\mathbb{L}_0$ predetermined, to let the subjects know that their choices in earlier rounds have no effect on the lotteries they see in the whole experiment, even though the lottery order may be different. Thus, we only deal with risk preferences here.

We now introduce *Accumulative Best Choice* design formally:

Definition. [Accumulative Best Choice Design]: An payoff mechanism is called Accumulative Best Choice (ABC) design if it satisfies: (1) it's conducted with no prior information; (2) $\phi(c) = c_n$; and (3)$\forall i = 1, \cdots, n-1, c_i \in D_{i+1}$.

1.2.4 Incentive Compatibility

Definition. [Incentive Compatibility] An experiment is $(\mathbb{L}_0, D, \phi)$. For each round i, $c_i \in C(D, \phi, \succeq)$ if and only if $c_i \succeq x_i, \forall x_i \in D_i, i = 1, \cdots, n$ for all well-behaved preferences $\succeq$, then we say such payoff mechanism (D, ϕ) is *incentive compatible* (IC).[2]

In words, IC refers to that given a payoff mechanism, for each individual, the choice bundle of the experiment, where we assume one makes optimization for the whole experiment, consists of one's preferred option from their true preference in every round only. From the definition of IC, we directly derive that if $x_i, y_i \in D_i$ with the preference $x_i \succ y_i$, IC requires that $y_i \notin C(D, \phi, \succeq)$.

1.2.5 Propositions

(All the proofs of the propositions are in Appendix A.)

[2]Relate this definition with close works by Cox et al. (2015) and Azrieli et al. (2014), both of them use notations of another preference relation $\succeq^m$ or $\succeq^*$ to refer to subjects' preferences given the payoff mechanism. Here, I just adopt the notation of choice set to represent it. In essence, they all are equivalent. Cox et al. (2015) also distinguish strong and weak IC; while in this paper, all IC refers to their weak IC.

After constructing the framework, the question I would like to answer is that given preferences only restricted on completeness and transitivity, to ensure incentive compatibility, what conditions D, n, ϕ need to satisfy? One sufficient answer to this question is ABC design.

Proposition 1. *ABC design is IC for general risk theories.*

There are three features in ABC design: (1) only paying last round, (2) the choices being carried over; and (3) no prior information. Now, let's take a look at each feature closely. Are those three features all necessary for IC condition? What should a general IC payoff mechanism look like?

Proposition 2. *If a payoff mechanism (D, ϕ) is incentive compatible for general risk theories, it must have the following three features:*

1. *(D, ϕ) is incentive compatible for Round n if and only if $\phi(c_1, \cdots, c_n) = c_n$*

2. *If $n > 1$, to ensure IC for round $i < n$, $\forall i = 1, \cdots, n-1$, there exists some $k_i, i < k_i \leq n$ such that $c_i \in D_{k_i}$*

3. *If $n > 1$, with prior information, an IC payoff mechanism doesn't exist.*

This proposition states that all three features in ABC design are necessary. Part 1 says if we experimenters want subjects to reveal their true preference in Round n, considering all the general well-behaved preferences, we have to pay them for their choice in the last round for sure. The premise of this proposition is not the complete IC condition, but one necessary part of IC: If subjects reveal their true preference in every round for all n rounds, they must reveal their true preference in the last round as well.

Based on this part of proposition, we can directly get the following corollary:

Corollary 1. *When $n = 1$, an IC payoff mechanism (D, ϕ) is that: $\phi(c_1) = c_1, c_1 \in D_1$.*

The between-subject design is incentive compatible for general risk theories.

Part 2 of Proposition 2 implies that the whole experiment needs to be chained-up. The choices in previous rounds should be options in later rounds. That's how we incentivize subjects to treat unpaid rounds seriously: it is because the choices of unpaid rounds will affect the options in the paying round. From this condition, we can get the following corollary:

Corollary 2. *If a payoff mechanism (D, ϕ) is IC, then, with the strategy $s^* = (s_1^*, \cdots, s_n^*)$ where $s_i^* \succeq x_i, \forall x_i \in D_i, i = 1, \cdots, n$, then $\phi(s^*) \in d$ where $d = \{x : x \succeq y, \forall y \in D\}$.*

Corollary 2 says an IC payoff mechanism should allow subjects to choose the most preferred lottery of the whole experiment in the last round if they always reveal their true preference in every rounds. So far, Part 1, Part 2 and Corollary 2 identify the candidate of the IC payoff mechanisms family: it is some form of a "tournament", a tournament of the lotteries, and subjects get paid for the champion lottery. The intuition is clear: In order to get paid by the champion lottery in the last round, they have incentive to kick out the "loser" lotteries in every round. Such family of payoff mechanisms is also payoff equivalent to single round decision task in which experimenters display all the lotteries at once and let subjects pick one and pay them their choice lottery. With the single round task, all the information from observing one individual's choice is that he or she prefers the chosen lottery to all the remaining lotteries. When we apply the ABC design and break the procedure down to multiple rounds, we could get more information. For example, there are four lotteries in the pool $\{A, B, C, D\}$ and one's preference is $C \succ B \succ A \succ D$. With one round that showing four lotteries at one time, we'll observe C is picked. All we can infer is that $C \succeq A, C \succeq B, C \succeq D$. If we apply ABC with binary lottery comparison, with the lottery order of $\{A, B, C, D\}$, we can observe subject choosing B, C, C. In this case, compared to the one-round setting, we have an extra piece of information which is $B \succeq A$. Every time subject changes the carried-over lottery, we have some more information about his or her risk attitude.

The last part of Proposition 2 answers the following question: Will it work for n-round decision tasks if subjects are informed of all the lotteries beforehand? And the answer is no. If they are informed of all the lotteries beforehand, they have the knowledge or information power to "manipulate" the experiment. I haven't made any assumptions about the mental effort cost of making decisions. If such cost exists and one individual can easily identify the most preferred lottery, then the optimal strategy is to make random choices before the round in which the most preferred lottery appears and then choose his/her champion lottery and carry it to the end.

Remark 1. It's easy to check that ABC design satisfies all three parts of Proposition 2. However, notice that ABC design is not the sufficient and necessary condition for incentive compatibility since the way of chaining-up is not unique. The following example provides another IC payoff mechanism but not the ABC design.

Example 1. There is a 4-round experiment. Lotteries are $\{A_1, B_1, A_2, B_2, A_3, B_3\}$ and there's strict first order stochastic dominance relations between them: A_3, B_3 are strictly better than A_2, B_2, and A_2, B_2 are strictly better than A_1, B_1. Use $c_i, i = 1, 2, 3, 4$ to record subjects' choices. An IC payoff mechanism but not a ABC design can be as: (1) it's under with no prior information; (2) $\phi(c_1, \cdots, c_4) = c_4$; (3) $D_i = \{A_i, B_i\}$ for $i = 1, 2, 3$,and $D_4 = \{c_1, c_2, c_3\}$.

However, when the dominance relations break down, such payoff mechanism can be problematic. If A_1 is the most preferred lottery and appears in Round 1, then one individual can choose A_1 in Round 1, then randomly choose in Round 2 and 3, and choose A_1 in Round 4 again and get paid by A_1.

Besides no restriction on the domain on the theoretical side, ABC has another appealing feature on the empirical side is its easiness to explain. The intuition with the "tournament" metaphor is also easy for subjects to understand. In the following section, I conduct the experiments that apply the ABC design. The instruction is in the Appendix. In both experiments, only 1 subject seemed confused and carried over the Option A in his/her first round to the very end and violated first order stochastic dominance 6 times. All others violated first order stochastic dominance no greater than three times.

To briefly summarize this section, we have three necessary conditions for a potential IC payoff mechanism for general risk theories: (1) Experimenters only pay individual's choice of the last round; (2) The whole experiment needs to be chained-up; and (3) It must use the protocol with no prior information. Also, I propose one payoff mechanism, the ABC design and show it is sufficient for the incentive compatibility condition. In the next section, I will discuss the empirical test of ABC design.

1.3 Empirical Validity of the ABC Design

Harrison and Swarthout (2014) argue that studying choice patterns and the preference estimation approach are complementary to each other. In the two recent literature of discussing payoff mechanism issues, Cox et al. (2015) use the choice pattern design, preferred in testing for the violations of certain properties, such as Common Consequence Effect, Common Ratio Effect (violations of Independence Axiom), as they focus on choices behavior in *certain* lottery pairs. Harrison and Swarthout (2014) adopts Hey and Orme (1994)'s approach: There are no real "trip wire" pairwise lotteries, and economists mainly rely on econometric techniques (specifically conditional maximum likelihood) to infer the preferences. To thoroughly examine the ABC design, I adopt both methodologies and conduct both experiments from Cox et al. (2015) and Harrison and Swarthout (2014) (same lotteries, same ways of lottery representations, same show-up fees) with ABC design procedure. Both papers have the one round task data, which I will use to compare my ABC design data with. In both experiments, the null hypothesis is: The choices or the estimates under ABC design are the same as those under between-subject or one round task design. If ABC works, then such null hypothesis should not be rejected.

The applications of ABC design for these two types of experiments are a little different.

In Hey and Orme (1994) or Harrison and Swarthout (2014) type, there are no restrictions on that one lottery must have its own counterpart. Therefore, to apply ABC design, we can simply randomize the order of the lotteries beforehand, and carry subjects' most recent choice over to the next round. However, to apply ABC design in Cox et al. (2015) such choice pattern type of experiment is a little tricky. Each lottery has its own counterpart, and only comparisons within some certain lottery pairs are meaningful for detecting violations only. However, in ABC design, current round choice is carried over to the next round. So the question is, how can we get subjects' choices for *certain* pairs of lotteries if we don't know their preferences beforehand? For this, I will assume that a lottery that is first order stochastically dominated is not chosen. Details on how to use first order stochastic dominance relations as bridges in choice pattern experiment are provided below.

1.3.1 Experiment I: Choice Pattern Experiment (non-structural)

Lottery Pairs

Cox et al. (2015)'s five lottery pairs allow us to directly observe the Common Ratio Effect (CRE), Common Consequence Effect (CCE), Dual CRE and Dual CCE therefore the violations of Independence Axiom (or EUT) or Dual Independence Axiom (or DU). They use the same lottery pairs under different payoff mechanisms. One of their treatments uses between-subject design: each individual is randomly assigned one of the five pairs, makes one choice and gets paid for that choice. This treatment is their baseline, the gold standard among all payoff mechanisms.

Table 1.1: Lottery Pairs in Experiment I

Pair	Less Risky (S)	More Risky (R)
1	(\$0, 0.75; \$3, 0.25)	(\$0, 0.8; \$5, 0.2)
2	(\$6, 1)	(\$0, 0.2; \$10, 0.8)
3	(\$0, 0.75; \$6, 0.25)	(\$0, 0.8; \$10, 0.2)
4	(\$6, 0.25; \$12, 0.75)	(\$0, 0.05; \$10, 0.2; \$12, 0.75)
5	(\$18, 1)	(\$12, 0.2; \$22, 0.8)

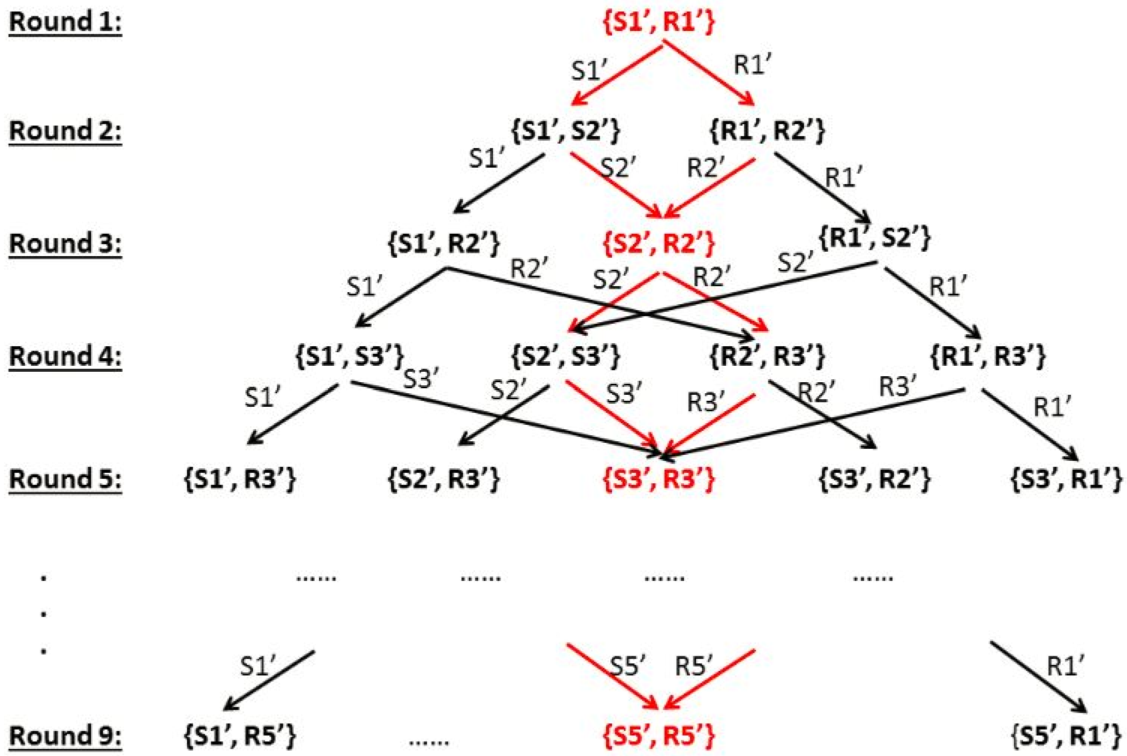
Another feature of their lottery pairs is that between S (Safer) lotteries and between R (Riskier) lotteries in different pairs, there are lotteries that are strictly first order stochastic dominance related ($S_5 \succ^{SD} S_4 \succ^{SD} S_2 \succ^{SD} S_3 \succ^{SD} S_1$, and $R_5 \succ^{SD} R_4 \succ^{SD} R_2 \succ^{SD} R_3 \succ^{SD} R_1$). Such first order stochastic dominance is the crucial feature to get the paired-up lottery choices (S_1 vs R_1,...,S_5 vs R_5) through ABC design procedure.

ABC Design Experiment Procedure

The desirable comparisons are between S_i and R_i as shown in Table 1.1. Recall that ABC design carries over only the chosen lottery in a given round to the following round, therefore we cannot ensure that S_i and R_i are feasible in the same round. The key to make it happen is the first order stochastic dominance. In my design, an individual who satisfies the first order stochastic dominance will face lotteries S_i and R_i $i = 1, \cdots, 5$ at some round. Since there are 5 S lotteries and 5 R lotteries, therefore 10 lotteries in total and the ABC design needs 9 rounds.

For easier description, let's switch the orders of lotteries in Pair 2 and Pair 3. That is, define $S'_2 = S_3, R'_2 = R_3, S'_3 = S_2, R'_3 = R_2$, and $S'_i = S_i, R'_i = R_i$ for $i = 1, 4, 5$. Then we have $S'_5 \succ^{SD} S'_4 \succ^{SD} S'_3 \succ^{SD} S'_2 \succ^{SD} S'_1$, and $R'_5 \succ^{SD} R'_4 \succ^{SD} R'_3 \succ^{SD} R'_2 \succ^{SD} R'_1$. The procedure goes like this:

Figure 1.1: Complete Path of Experiment I with ABC design



- **Step 1:** In Round 1, each individual faces $\{R_1', S_1'\}$, and makes their choice $c_1 \in \{R_1', S_1'\}$;

- **Step 2:** In Round 2, if a subject chooses R_1' in Round 1, then he/she will face $\{R_1', R_2'\}$ (R_1' is carried over from Round 1); if a subject chooses S_1' in Round 1, then he/she will face $\{S_1', S_2'\}$ (S_1' is carried over from Round 1). It is shown in Figure 1.1 as the procedures between Round 1 and Round 2.

  Since $R_2' \succ^{SD} R_1', S_2' \succ^{SD} S_1'$, if a subject follows first order stochastic dominance, then $c_2 = S_2'$ if one faces $\{S_1', S_2'\}$, and $c_2 = R_2'$ if one faces $\{R_1', R_2'\}$. It is shown in Figure 1.1 as the red arrows between Round 2 and Round 3.

- **Step 3:** In Round 3, if a subject chooses $c_2 = R_2'$, then he/she will face $\{R_2', S_2'\}$ (R_2' is carried over from Round 2 and S_2' is the new added option); if a subject chooses

$c_2 = S'_2$, then he/she will face $\{S'_2, R'_2\}$ (S'_2 is carried over from Round 2 and R'_2 is the new added option). So no matter what subjects choose in Round 1, S'_1 or R'_1, as long as they satisfy first order stochastic dominance, they face S'_2 and R'_2 in Round 3.

- **Step 4:** In Round 4, subjects are divided into two paths again based on their choices in Round 3, either S'_2 or R'_2. If $c_3 = S'_2$, then one will face $\{S'_2, S'_3\}$; if $c_3 = R'_2$, then one will face $\{R'_2, R'_3\}$, as shown in the procedures between Round 3 and Round 4 in Figure 1.1. And so on and so forth...

If individuals always follow first order stochastic dominance, their behavior can be represented by the red paths in Figure 1.1. In even rounds, they make choices between two lotteries that are ordered according to the first order stochastic dominance; in odd rounds, they make choices between S_i and R_i. If they don't follow first oder stochastic dominance, they still will meet the same all 10 lotteries through 9 rounds of the ABC design (see the black arrow paths in Figure 1.1, as well as the mathematical expressions in Appendix C).

The subjects were all undergraduates from Georgia State University. I recruited 49 subjects from the same population in June 2015, and conducted ABC design using the same lottery pairs. There were 10 lotteries, therefore in ABC design there were 9 rounds. Subjects were informed that the choice they made in previous round will be carried over to the next round, and they would be paid for their last choice. They were also informed why choosing their preferred lottery in every round is the dominant (best) strategy (see subject instruction in Appendix B for detail). I adopted the same strategy as Cox et al. (2015) did. No show-up fee was offered. Instead, after subjects finish all their choices, I announced that I would like to pay them \$5 (the same amount as in Cox et al. (2015)) for completing a demographic survey. The experiment was conducted with ZTREE software (Fischbacher (2007)).

Data Results

The byproduct of this design is that we can test whether first order stochastic dominance is violated. The data shows that only 3 (out of 49) subjects made choices that violate first order stochastic dominance. If subjects don't follow such dominance assumption, they will miss the paired-up lottery comparisons, therefore their choices are excluded in the following analysis.

The null hypothesis is:

Hypothesis 1. *The choices come from the same population under one round task design and under ABC design.*

If ABC design works, we expect that such null hypothesis is not rejected. The results are displayed in Table 1.2 and 1.3. (The data of One Round and RLIS are from Cox et al. (2015).)

Table 1.2: Proportions of Choosing Risker Lottery in Experiment I

	One Round (Baseline)	ABC	RLIS	
			no prior info.	with prior info.
All Pairs: $\frac{R}{R+S}\%$	71.43 (231 obs)	75.22 (230 obs)	55.50 (40 obs)	61.50 (40 obs)
Pair 1: $\frac{R}{R+S}\%$	60.53 (38 obs)	78.26 (46 obs)	62.50 (40 obs)	72.50 (40 obs)
Pair 2: $\frac{R}{R+S}\%$	84.48 (58 obs)	78.26 (46 obs)	55.00 (40 obs)	50.00 (40 obs)
Pair 3: $\frac{R}{R+S}\%$	72.41 (58 obs)	76.09 (46 obs)	52.50 (40 obs)	57.50 (40 obs)
Pair 4: $\frac{R}{R+S}\%$	71.05 (38 obs)	69.57 (46 obs)	67.50 (40 obs)	77.50 (40 obs)
Pair 5: $\frac{R}{R+S}\%$	61.54 (39 obs)	73.91 (46 obs)	40.00 (40 obs)	50.00 (40 obs)

In both tables, the key variable is the proportion of R Choices in all pairs (overall risk tolerance) or within each pair (violations). Table 1.2 shows that in the sense of being close to the baseline, except for Pair 1, the ABC design outperforms both versions of RLIS (with

Table 1.3: Test Results for Experiment I

	One Round	ABC	p-value	
			T-test	Pearson Test
All Pairs: R/(R+S)%	71.43 (231obs)	75.22 (230obs)	0.359	0.358
95% CI (T-test)	[65.56, 77.30]	[69.60, 80.84]		
Pair 1: R/(R+S)%	60.53 (38obs)	78.26 (46obs)	0.079*	0.077*
95% CI (T-test)	[44.24, 76.81]	[65.88, 90.65]		
Pair 2: R/(R+S)%	84.48 (58obs)	78.26 (46obs)	0.420	0.415
95% CI (T-test)	[74.88, 94.09]	[65.88, 90.65]		
Pair 3: R/(R+S)%	72.41 (58obs)	76.09 (46obs)	0.675	0.671
95% CI (T-test)	[60.56, 84.27]	[63.28, 88.89]		
Pair 4: R/(R+S)%	71.05 (38obs)	69.57(46obs)	0.884	0.882
95% CI (T-test)	[55.95, 86.16]	[55.75, 83.38]		
Pair 5: R/(R+S)%	61.54 (39obs)	73.91(46obs)	0.227	0.222
95% CI (T-test)	[45.56, 77.52]	[60.73, 87.10]		

T-test refers to the two-sided T-test. * $p < 0.1$; ** $p < 0.05$; ***$p < 0.01$

and without prior information). Table 1.3 shows the statistical test results of the choice differences between One Round and ABC treatments. We can see that for two-sided T test or Pearson test, the p-value of Pair 1 is significant at 10% level but not at 5% level, and all other p-values are not significant.[3] Therefore, the null hypothesis cannot be rejected at 5% significant level. In other words, ABC design works empirically for this choice pattern experiment.

1.3.2 Experiment II: Preference Estimation Experiment (structural)

Lotteries and ABC Design Experiment Procedure

In the setting of Harrison and Swarthout (2014), there are 69 lottery pairs. Those pairs consist of 38 different lotteries (see Appendix D for the lottery list). The ABC design with those 38 lotteries is conducted as the follows: the orders of lotteries are independently randomized for each subject beforehand. Subject's choice in the preceding round will be

[3]Proportion test gives qualitative the same result.

carried over to the following round, and eventually one gets paid for the realized outcome of the chosen lottery of the last round.

There were 20 rounds in the experiment. The experiment was conducted in July 2015 and April 2016. The subjects were all undergraduates from Georgia State University. 51 subjects participated in the experiment. So in total there were 1020 observations. To get better comparisons with Harrison and Swarthout (2014), I adopted their $7.50 show-up fee and used pie representations of lotteries as they did. The experiment was conducted with ZTREE software(Fischbacher (2007)).

Data Results

Among those 38 lotteries, some are first order stochastically dominated by others. Therefore, it is possible that subjects see such dominance pairings in some rounds. Even though first order stochastic dominance is not required when analyzing the data, it can be used to check whether subjects understand the ABC design procedure. For example, one subject kept the same option for all 20 rounds, and violated first order stochastic dominance 6 times. I treat this subject as not understanding the procedure. And each of the rest of 50 subjects violates first order stochastic dominance for no more than 3 times. Therefore, after excluding that individual, I have $50 \times 20 = 1000$ observations. Out of 1000 observations of binary lottery pairs, 762 pairs have dominance relations. In total, all 50 subjects violated first order stochastic dominance for 19 times.

The data set consists of the ABC design data (1000 observations) with one round task data (75 observations) from Harrison and Swarthout (2014). Following their non-parametric estimation approach (as well as Hey and Orme (1994) and Wilcox (2010)), in the EUT model, assume

$$U(\$5) = 0, U(\$10) = u_{10}, U(\$20) = u_{20}, U(\$35) = u_{35}, U(\$70) = 1$$

and in RDU model, assume more probability weighting parameters as:

$$\omega(0) = 0, \omega(1/4) = \varphi_{1/4}, \omega(1/2) = \varphi_{1/2}, \omega(3/4) = \varphi_{3/4}, \omega(1) = 1$$

(Please see Harrison and Rutström (2008) or Appendix F for details on the estimation methods).

The key parameter in testing whether ABC design works is the binary dummy variable "**pay1**" (to keep the same variable name with the original paper). The "pay1" dummies equal to 1 for the one round task treatment, and equal to 0 for the ABC design. So the key hypotheses is that:

Hypothesis 2. *The estimated coefficients for the variables "pay1" are not significantly different from 0.*

The full estimation result table is in Appendix G. The data show that there's no significant effect of "pay1" under both models. Overall, according to χ^2 test, in EUT model, there's no significant effect of treatment for utility weighting (The null hypothesis is that the dummy variables "pay1" equal to 0 for u_{10}, u_{20}, u_{35} and μ jointly, $\chi^2 = 2.06$, and Prob> $\chi^2 = 0.725$.) In RDU model, there's no significant effect of treatment for the utility weighting ($\chi^2 = 0.91$, and Prob> $\chi^2 = 0.823$), and for the probability weighting ($\chi^2 = 3.81$, and Prob> $\chi^2 = 0.282$). Across all coefficients including the noise μ $\chi^2 = 6.74$, and Prob> $\chi^2 = 0.456$.

In summary, all estimates of the "pay1" dummy variables are insignificant. Hypothesis 2 cannot be rejected.

1.4 Conclusion and Discussion

With this chapter, I ask the question that other than the between-subject design, whether it is possible to find an incentive compatible payoff mechanism for general risk theories. One answer is the Accumulative Best Choice design I proposed in the paper: Subjects are not informed of all the lotteries in the experiment beforehand, their choice from the preceding round will be carried over to the following round as one of the lottery options, and eventually they get paid for their choice in the last round. I defined incentive compatibility and assumed preferences only restricted on well-behaved-ness, I derive three necessary conditions for a "proper" payoff mechanism for testing general risk theories: (1) experimenters must only pay subject's last choice; (2) the whole experiment needs to be chained-up, and (3) the use of no prior information protocol.

The intuition behind these conditions rests on avoid wealth effect and/or portfolio effect, requiring that experimenters pay the choice of *one certain* round. However, it's impossible to incentivize subjects for the rounds after the paying round, so the paying round has to be the last round. On the other hand, we must find a way to incentivize subjects for the rounds before the last; choices from the previous rounds must have some forms of connections to the options of the last round. Thus, the whole experiment needs to be chained-up. Even though the current choice is not paid, since one's choice now affects the options one sees at the paying round, subjects have an incentive to treat the current round seriously. In other words, such incentive compatible payoff mechanisms require that the decision tasks cannot be totally exogenous even though the lottery set is exogenous and fixed.

The "chaining-up" idea is not new in preference elicitation experiment. The *Trade-off* (TO) method, first proposed by Wakker and Deneffe (1996) and used in many following experiments (for example, see Abdellaoui (2000)) is an alternative way of chaining up the experiment. TO method consists of several stages. At Stage i, each individual is asked to elicit the prize x_i to make lottery $(x_i, p; r, 1-p)$ and $(x_{i-1}, p; R, 1-p)$ indifferent for them, where p, r, R are fixed and given exogenously by experimenters, and x_{i-1} is elicited by subjects themselves in Stage $i-1$ (with $x_0 = 0$ for $i = 1$). Compared to certainty or probability equivalent methods, the advantage of TO method is to elicit utility values without assuming whether subjects weighting probability or not. However, such method is not incentive compatible. In Wakker and Deneffe (1996)'s experiment, all the questions are hypothetical, which cannot make sure subjects truthfully reveal their preferences. In Abdellaoui (2000)'s experiment, one of six elicitation values ($x_i(i = 1, \cdots, 6)$) in the gain domain is randomly selected to pay. Such payoff mechanism incentivizes subjects to overstate all $x_i(i = 1, \cdots, n)$ in order to gain higher monetary payment (Harrison and Rutström (2008)). In TO method, subjects can construct their own lotteries. With the ABC design, they do not state any numerical values. The lottery set is fixed and given by experimenters. In this regard, subjects cannot control the lottery options they meet in the experiment.

I show that the ABC design is theoretically incentive compatible and tested it empirically in the lab. The data from both one choice pattern experiment (Experiment I) (Cox et al. (2015)) and one preference estimation experiment (Experiment II) (Harrison and Swarthout (2014)) show that there are no significant differences between the choices under one round task design and under the ABC design.

In Experiment I, the implementation of the ABC design takes advantage of first order stochastic dominance relations. It is "path dependent" in the sense of that subjects may face different orders of the lotteries due to their choices. But at the end, the whole lottery set they see in the experiment is fixed. Each individual has encountered choices for every required lottery pair if their behavior follows first order stochastic dominance. The implementation is easier in risk preference elicitation exercises. In Experiment II, with adoption of econometric techniques, lotteries are not required to be paired-up in a certain way to make inference about risk preferences. In this scenario, to apply ABC design we can just predetermine a random order of the lottery set and subjects' current choice will not affect the order of the lotteries they see in the future.

How applicable the ABC design is for the decision tasks under risk? From Experiment I and II, we know that the ABC design can be applied to the experiments that test the paradoxes if there exists first order stochastic dominance between different lottery pairs, as well as those that estimate the risk preferences when it mainly relies on econometric techniques and no certain lottery pairs need to be paired-up.

Now that we have an incentive compatible payoff mechanism for general risk theories, then it can be linked immediately to the research questions: (1) Test of the ABC design with more evidence; (2) Unbiased estimation of people's risk attitude; (3) Can the ABC design be applied to other types of experiment under risk, such as the multiple price list? These three questions are answered in the later two chapters.

Some other open questions are: (4) Is the ABC design incentive compatible for general uncertainty models? (5) Are other incentive compatible payoff mechanisms for risk and uncertainty different from one round or ABC design? The second line of my research focuses on the empirical studies. I'd like to revisit using risk preferences elicited with the ABC design to understand behavior in other fields, such as health outcomes, tax compliance and credit card savings. These questions are on my current research agenda.

Chapter 2

Estimating Structural Risk Models with a New Incentive Compatible Payoff Mechanism

2.1 Introduction

Expected Utility Theory (EUT) has been the most popular model to explain behavior under risk since Bernoulli firstly used the transformations of prizes to solve the St. Petersburg Paradox in the 18th century. However, since the mid-1900s, more and more evidence have been found that people violate EUT sometimes, such as Allais (1953) Paradox. Alternative non-EUT models have popped up from then with introducing probability weighting function along with the utility function. Nowadays, some alternate popular non-EUT models are: Rank Dependent Utility Theory (RDU, Quiggin (1982)), Cumulative Prospect Theory (CPT, Tversky and Kahneman (1992)), Dual Expected Utility Theory (DU,Yaari (1987)).

However, almost all the estimations of non-EUT models suffer the bias from data generating process – the incentive incompatibility between the non-EUT model and Random Lottery Incentive System (RLIS) as the payoff mechanism in the experiments. RLIS refers to the payoff mechanism that when an individual finishes all the decisions, one of the decisions will be randomly selected as his or her payment. As firstly pointed out by Holt (1986), RLIS is incentive compatible with models having linear probability, the EUT model. Cox et al. (2015) show that people do respond to different payoff mechanisms. Further later, Harrison and Swarthout (2014) use structural models to estimate risk preferences. They find out that when RDU is assumed, the estimation from RLIS data is significantly different from the one round task data. One round task refers to the payoff mechanism that subjects are only given one round of decision task and get paid by their choices. It's incentive compatible with all the theories and therefore is the gold standard.

My contribution in this chapter is first to use an incentive compatible payoff mechanism to estimate the parametric RDU models when the decision task involves more than one round. In the last chapter, I proposed a new payoff mechanism, which I called *Accumulative Best Choice* (ABC) design. I have shown that it's incentive compatible with general risk theories that assume well-behaved risk preferences. ABC works in the following way: In the decision experiment under risk, each subject is not informed of all the options beforehand; one's choice from the previous round is carried over to the following round to become one of the options; eventually each subject gets paid by their choice in the last round. By applying ABC with the experiments in Cox et al. (2015) and Harrison and Swarthout (2014), I compare the choices under ABC with those under one round task in the original papers. The data from both experiments show that I cannot reject the null hypothesis that the choices under ABC and one round task are the same at 5% significance level. Now, the next question is: what can we tell now about risk preference? That's the theme of this chapter. Following the methodology of series papers by Glenn Harrison and his coauthors (Harrison and Rutström (2008, 2009), Harrison and Swarthout (2014), Andersen et al. (2008)), I will use the data under ABC design to estimate parametric models, both EUT and RDU.

The rest of this paper arranges as the following: Section 2.2 will review the models and methodology of structural estimation; Section 2.3 will show the results of multiple structural models; Section 2.4 is conclusion and discussion.

2.2 Structural Estimation Methodology

2.2.1 Models

This section reviews the models and the estimation methodology (see more details in Harrison and Rutström (2008)). I choose the two most popular models in the field of risk as my candidates for estimations: Expected Utility Theory (EUT, von Neumann and Morgenstern (1944)) and Rank Dependent Utility Theory (RDU, Quiggin (1982)).[1]

To avoid complication, all the lottery options in this paper are simple lotteries. Suppose a lottery l has series of prizes $(x_1, \cdots, x_m)(x_i \geq 0, \forall i = 1, \cdots, m, x_1 \leq x_2 \leq \cdots \leq x_m)$ over the probability distribution $(p_1, \cdots, p_m)(0 \leq p_i \leq 1, \sum p_i = 1, i = 1, \cdots, m)$. That is, the lottery has probability p_i to win the prize $x_i (i = 1, \cdots, m)$. Those m events are exclusive and exhaustive.

Expected Utility Theory tells us that the utility of the lottery l is calculated as:

$$EU(l) = p_1 u(x_1) + \cdots + p_m u(x_m)$$

If we want to calculate the utility of l according to Rank Dependent Utility Theory, first we need to find out the weighted accumulative probability: $w(p_m), w(p_m + p_{m-1}), \cdots, w(p_m + \cdots + p_1))(0 \leq w(.) \leq 1, w(0) = 0, w(1) = 1, w(a) \geq w(b)$ if $a \geq b)$. The next step is to calculate decision weight: $w_i = w(p_m + \cdots + p_i) - w(p_m + \cdots + p_{i+1}), \forall i = 1, \cdots, m$. Eventually, Rank Dependent Utility of the lottery l is calculated by:

$$RDU(l) = w_1 u(x_1) + \cdots + w_m u(x_m)$$

[1] Cumulative Prospect Theory (CPT,Tversky and Kahneman (1992)) under the gain domain is identical to RDU model.

In the non-parametric models, those $u(x)$ and $W(p)$ are the numbers we need to estimate; in the parametric models, $u(x)$ and $w(p)$ can be calculated from the assumed functions, such as power function, the parameters in the assumed functions are what we'll estimate then. This paper focuses on the parametric estimation.

2.2.2 Structural Functions

Utility Functions

I adopt two utility functions: the simple CRRA function and a more general function: Expo-Power(EP) function (Saha (1993)), which includes CRRA and CARA as its special case. To be specific,

$$\text{CRRA function: } u(x) = \frac{x^{1-r}}{1-r}$$

Following Holt and Laury (2002),

$$\text{EP function: } u(x) = \frac{1 - \exp(-\alpha x^{1-r})}{\alpha}$$

When α goes toward 0, Expo-Power reduces to CRRA.

Probability Weighting Functions

I also consider two probability weighting functions here: the single-parameter Tversky and Kahneman (1992)'s inverse-S function, and the two-parameter Prelec (1998) function.

$$\text{TK function: } w(p) = \frac{p^{\gamma}}{[p^{\gamma} + (1-p)^{\gamma}]^{1/\gamma}}$$

$$\text{Prelec function: } w(p) = e^{-\eta(-\ln p)^{\sigma}}$$

When $\sigma = 1$, it collapses to the power function $w(p) = p^{\eta}$.

So in total, to consider the single models, I have 2 EUT models (CRRA, EP) and 4 RDU models (CRRA&TK, CRRA&Prelec, EP&TK, EP&Prelec).

2.2.3 Structural Estimation Methodology

Same as Chapter 1, the estimation methodology follows Harrison and Rutström (2008). Please see detail in Appendix F.

2.3 Estimation Results

The lottery options are from Harrison and Swarthout (2014), which consists of 38 different lotteries (see Appendix for the whole list of lotteries). All the lotteries have 5 possible prizes ($5, $10, $20, $35, $70) and 5 possible probabilities (0, 0.25, 0.50, 0.75, 1).

There were 20 rounds in the ABC treatment. For each individual, 21 lotteries were randomly drawn from those 38 lottery pool before they make any choices (independently drawn for each subject). In each round, they chose one to keep between the two lotteries. The lotteries are displayed as the pie chart (same as the original paper).Their choice from preceding round was carried over to the following round to become one of the options, and they got paid for their choice in Round 20. One's payment was determined by rolling dices themselves plus $7.50 show-up fee (the same setting as the original paper). I conducted the experiment in the ExCEN lab at Georgia State University, with all the subjects Georgia State undergraduates. 51 subjects completed the task. One subject always chose the same option for 20 rounds, and eventually violated first order stochastic dominance 6 times during the 20 rounds, therefore I treat him/her as the confused subject and exclude him/her from the following analysis.

In Harrison and Swarthout (2014), they have the 1-in-1 treatment, that is, subjects only have 1-round decision task, and get paid for their choice, that is, one round task; and 1-in-30 treatment, which is, subjects have 30-round decision task, and get paid for one of their choices randomly selected from those 30 choices, that is, RLIS treatment. Combining my treatment ABC data with the one round data and RLIS data from Harrison and Swarthout (2014), I'm able to show more in-depth analysis about the payoff mechanisms as well as the risk attitudes.

Table 2.1: Data Summarization

Treatment	Subjects	Observations
One Round Task	75	75
RLIS	208	6240
ABC	50	1000

2.3.1 The comparisons between ABC, One Round Task and RLIS

One round task is the gold standard for testing all payoff mechanisms since it's always incentive compatible. To check the effects of different payoff mechanisms, we can add treatment dummies for each estimated coefficient to check whether it's significantly different from 0. Table 2.2 gives out the summarized results (see Appendix H for the full results.) There's no significant difference for all 6 structural models between ABC treatment and one round task treatment. ABC and RLIS are not significantly different under EUT with EP utility function and different for the rest models. RLIS and one round task are not significantly different for EUT models, but different for all RDU models.

The most important general result is that ABC passes further tests of parametric estimations besides the nonparametric estimations as shown in the first chapter. The one round task dummies are not significantly different from 0 in the second half of the table when EUT is assumed, which are consistent with the theoretical derivation that RLIS is incentive incompatible with EUT.

Table 2.2: Payoff Mechanism Effects

Treatment	Dummy	EUT		RDU			
		CRRA	EP	CRRA&TK	CRRA&Prelec	EP&TK	EP&Prelec
ABC	one round						
	RLIS	***		***	***	***	***
RLIS	one round			***	***	**	***
	ABC	***		***	***	***	***

Note: star refers to the significance of the p-value of the joint F-test for all the treatment dummies in each model.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.3.2 Risk Preference with Allowance for Heterogeneity

From previous section we can claim that at least we find no evidence to against the ABC when we apply EUT or RDU models. So the next question is, what's the risk attitude estimated with the ABC treatment? Table 3 shows the estimated parameters of the six structural models.

Table 2.3: Estimated Parameters for Single Models

	Expected Utility Models		Rank Dependent Utility Models			
	CRRA	EP	CRRA&TK	EP&TK	CRRA&Prelec	EP&Prelec
r	0.724***	0.865***	0.571***	0.793***	0.579***	0.787***
α		-0.679**		-0.559*		-0.542**
γ			0.832***	0.829***		
η					0.965***	0.979***
σ					0.809***	0.801***
μ	0.426**	0.105	0.675*	0.205*	0.659	0.212
$H_0 : \gamma = 1$ (p-value)			0.0183**	0.0190**		
$H_0 : \eta = 1, \sigma = 1$ (p-value)					0.0842*	0.0755*
Log lik.	-187.64651	-187.62716	-185.1809	-185.11597	-185.28842	-185.22123
N	1000	1000	1000	1000	1000	1000

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

From Table 2.3, we can see that the parameter r is greater than 0 for all models, which indicates people are risk averse. All the models show the concavity of the utility function. r in EUT(CRRA) is higher than that in RDU(CRRA&TK, CRRA&Prelec). When incorporating probability weighting, the degree of risk aversion on the utility side decreases. For the RDU models with both TK and Prelec probability weighting functions, we reject that the probability is linear (see H_0 hypothesis test results in Table 2.3). Akaike Information Criterion (AIC) value (Akaike (1974)) has been used to do the model selection for decision models (for example, Carbone and Hey (2000), Buschena and Zilberman (2000)). In this case, The CRRA&TK has the lowest AIC value, which indicates it's the most preferable model among these six models. $\gamma = 0.83$ shows that it's an inverse-S function: people over-weigh low probability and under-weigh high probability. Comparing the results with the data under RLIS, from Appendix H, we can see that both r and γ are significantly higher under RLIS.

Also, we can include some demographic dummy variables: **female** (=1, if female; =0, if male), **black** (=1, if black; =0 if non-black), **age21** (=1, if age>21; =0, if age≤21), **busiecon** (=1, if major in Business or Economics; =0, if major in other fields), **birthorder** (=1, if being the oldest child; =2, if being the middle child; =3, if being the youngest child; =4, if being the only child.) The full results are shown in the appendix.

One interesting finding is that the joint F-test (χ^2 test) for the female dummies in each model is not significant. Contradicting to most literature that find there's gender difference in risk preference, there's no gender difference detected in this study.

2.3.3 the Efficiency of the ABC Design

I would like to mention more about the efficiency of ABC design. In conventional risk experiments, all the lottery pairs are given exogenously by experimenters. Because of the feature of ABC design that subjects can carry over their choice to the next round, experimenters lose some control over the lottery pairs they would like subjects to compare. For example, in the original experiment I "replicate", Harrison and Swarthout (2014), for each of their 69 lottery pair, there's no first order stochastic dominance (FOSD) relations between the two lotteries. The "problem" of FOSD is that the data in FOSD pairs being "useless". Most decision models satisfy FOSD assumption (There are exceptions though, for example, Prospect Theory with variable reference point model). If we observe a subject choose the dominant lottery in the FOSD pair, then we don't have useful information to infer which model fits the data better since all of the models fit. If one has an experiment consisting of 10 binary lottery choices, with 9 of them being FOSD pairs, then such experiment is very inefficient.

In the ABC treatment in this experiment, out of 1000 observations, 762 pairs of lotteries exist first order stochastic dominance relations. Therefore, the inferences with the real "useful" data are from the rest 238 binary lottery pairs. This is the case where I assign the lotteries totally random from the lottery pool. Of course, one could partially control the lottery selection. For example, based on the rank of expected value (EV), we could categorize the lotteries into three subsets “low EV”, “mid EV” and “high EV”. We could randomize the lotteries within each subset, and start from “low EV”, then to “mid EV” and at last go to “high EV”. In that way, it will prevent some cases such as the high EV lotteries appear at the very beginning, and then most of the rest of the experiments are all FOSD pairs. Or, one could fully control the order of the lotteries. Another way is that one could select the lottery pool such that there are no two lotteries in the set having FOSD relations.

2.4 Conclusion and Discussion

Two main results can be drawn from this paper: First, the ABC design passes the tests of parametric structural models. There are no significant differences found between ABC and one round task. Second, RDU is unbiasedly estimated for the first time from the data generating process under a multiple-round decision task setting. The results show the concave utility curve and the inverse-S shaped probability weighting curve. No gender effect has been found.

From the estimation results, we do see that the estimations with RDU models are significantly different compared RLIS treatment with both One round task and ABC treatment. The impact of this payoff mechanism effect may spread beyond the decision theory studies. More and more studies introduce non-EUT model and probability weighting into empirical micro studies, such as Wakker and Stiggelbout (1995), Bleichrodt and Pinto (2000), Jones et al. (2006). The lesson from this paper is that we need to make sure what we measure is what we intend to measure. If the payoff mechanism, is not incentive compatible with our assumed model, then the data generating process itself may sabotage the validity of the data.

Chapter 3

When Multiple Price Lists Meet General Risk Theories

3.1 Introduction

Among various risk elicitation methods with economic experiments, Holt and Laury (2002) (henceforth HL) design is the most popular one.[1] The original HL design, proposed in Holt and Laury (2002), is shown in Table 3.1. Ten pairwise lotteries are arrayed and displayed in a table, known in the literature as "multiple price list". In each of the ten rows, the pair of lotteries, Option A and Option B, have the same probabilities for events with "good" and "bad" outcomes. All the Option As in the table share the same payoff amount of "good" and "bad" outcomes; similarly for Option Bs. Down the list, the probability of the "good" outcome increases, and therefore the probability of the "bad" outcome decreases. Subjects are required to make a choice between Option A and Option B for each row. Each subject gets paid for one decision randomly selected from all decisions, a payoff mechanism also well-known as Random Lottery Incentive System (RLIS).

[1]Up to Mar. 27 2016, citation of Holt and Laury (2002): 3474, Binswanger (1980, 1981) Eckel and Grossman (2002) and Eckel and Grossman (2008) in total: 3015, Gneezy and Potters (1997):580 (Data Source: Google Scholar Citation)

Table 3.1: Holt and Laury (2002) Design

Option A	Option B	Expected Payoff Difference
(\$2.00, 0.1; \$1.60, 0.9)	(\$3.85, 0.1; \$0.10, 0.9)	\$1.17
(\$2.00, 0.2; \$1.60, 0.8)	(\$3.85, 0.2; \$0.10, 0.8)	\$0.83
(\$2.00, 0.3; \$1.60, 0.7)	(\$3.85, 0.3; \$0.10, 0.7)	\$0.50
(\$2.00, 0.4; \$1.60, 0.6)	(\$3.85, 0.4; \$0.10, 0.6)	\$0.16
(\$2.00, 0.5; \$1.60, 0.5)	(\$3.85, 0.5; \$0.10, 0.5)	-\$0.18
(\$2.00, 0.6; \$1.60, 0.4)	(\$3.85, 0.6; \$0.10, 0.4)	-\$0.51
(\$2.00, 0.7; \$1.60, 0.3)	(\$3.85, 0.7; \$0.10, 0.3)	-\$0.85
(\$2.00, 0.8; \$1.60, 0.2)	(\$3.85, 0.8; \$0.10, 0.2)	-\$1.18
(\$2.00, 0.9; \$1.60, 0.1)	(\$3.85, 0.9; \$0.10, 0.1)	-\$1.52
(\$2.00, 1.0; \$1.60, 0.0)	(\$3.85, 1.0; \$0.10, 0.0)	-\$1.85

As discussed earlier in Chapter 1, Holt (1986) first points out that RLIS is incentive compatible when Independence Axiom is assumed. Therefore, theoretically, the institution of the original HL design should work when economists estimate risk preferences with Expected Utility Theory (EUT) model. Most literature adopting the HL design follow the analysis in Holt and Laury (2002) to estimate the parameters in EUT models with CRRA or Expo-Power (Saha (1993)) utility functions. There are a few studies that check non-EUT models with multiple price lists. They find the evidence of probability weighting under some structural models (Harrison and Rutström (2008), Drichoutis and Lusk (2012)). Given the payoff mechanism in those experiments are RLIS, further robustness check is needed with non-EUT estimations.

Meanwhile, some evidence shows the violations of separation or Independence with multiple price lists. Andersen et al. (2006) point out that people tend to choose the midpoint of the list. Bosch-Domènech and Silvestre (2013) show that with the removal of three bottom rows in the list, significantly fewer safe options are chosen. Freeman et al. (2015) use their price lists to compare subjects' choices in one specific row when they complete the whole lists and with RLIS payment protocol with those when subjects make one decision only about that certain lottery pair and get paid by their choices. The latter is the gold standard to compare the payoff mechanism effects since one task only is incentive compatible with all theories. They find out that significantly different proportions of the safer lottery are chosen under those two treatments. Such results reject separation effect, that is, subjects treat each decision separately from others; and Independence Axiom, which requires subjects' preference between two gambles do not change when they mix with a third one with the same proportion.

Now, the open question is: How can we infer non-EUT risk preferences via the data from the HL design? That is the research question I'm going to answer in this chapter. In the first chapter, I proposed a new payoff mechanism, Accumulative Best Choice (ABC) Design, and showed that it's incentive compatible for general risk theories. ABC works in the following way: subjects are not informed of all the lotteries beforehand; their choice in preceding round is carried over to the next round to become one of the options; eventually subjects get paid for their decisions in the last round. I'm going to apply the ABC design to the HL design and estimate both EUT and Rank Dependent Utility (RDU,Quiggin (1982)) structural models. To my knowledge, this is the first paper to use an incentive compatible payoff mechanism for general risk theories with the multiple price list to elicit risk preferences with EUT and RDU models.

The rest of the paper is arranged as the following: Section 3.2 shows my design; Section 3.3 analyzes the results; Section 3.4 is conclusion and discussion.

3.2 Experimental Design

3.2.1 HLabc treatments (N=64)

In this implementation, considering the time use in the experiment (in total about 45 minutes including experimenter explaining instructions, subjects making decisions, each subject drawing a ball to determine their payments) and the minimum wage of \$7.25/hour in Georgia, I use the 5X of the prizes on the original HL design to keep the saliency of the payment. The adjusted prizes for Option A are \$10 and \$8, and for Option B are \$19.25 and \$0.5. The following table shows the lottery pairs used in the experiment:

Table 3.2: HLabc Treatment Design

	Option A	Option B
Row 1	A_1 : 3/10 of \$10, 7/10 of \$8	B_1 : 3/10 of \$19.25, 7/10 of \$0.5
Row 2	A_2 : 4/10 of \$10, 6/10 of \$8	B_2 : 4/10 of \$19.25, 6/10 of \$0.5
Row 3	A_3 : 5/10 of \$10, 5/10 of \$8	B_3 : 5/10 of \$19.25, 5/10 of \$0.5
Row 4	A_4 : 6/10 of \$10, 4/10 of \$8	B_4 : 6/10 of \$19.25, 4/10 of \$0.5
Row 5	A_5 : 7/10 of \$10, 3/10 of \$8	B_5 : 7/10 of \$19.25, 3/10 of \$0.5
Row 6	A_6 : 8/10 of \$10, 2/10 of \$8	B_6 : 8/10 of \$19.25, 2/10 of \$0.5

In the ABC design, only one option is carried over from the preceding round to the following round. However, in the HL list, what we want to compare is the pairwise options, Option A and Option B *within* each row. To apply the ABC design, I use a procedure very similar to that of the choice-pattern experiment in Chapter 1, which takes advantage of ranking lotteries according to the first order stochastic dominance. A quick inspection of the HL list: An Option A in a lower row always first order stochastically dominates any Option A in its upper rows, similar for Option Bs. The feature of the design is that the increasing probability of the "good" outcome leads to the decreasing probability of the "bad" outcome as well as the expected payoff differences (the last column of Table 3.1). We expect to see that subjects start with Option A, then at some row switch to Option B and stick with it until the last row. Such dominance feature allows us to establish the bridge between rows when we apply ABC.

In the first round, subjects are given two options in Row 1, A_1 and B_1 in Table 3.2. If a subject chooses A_1, then in the second round, he or she will choose between the carried over choice, A_1, with the new option, A_2 in Row 2. Similarly, if a subject chooses B_1 in the first round, then he faces B_1 and B_2 in the second round. If individual's behavior satisfies first order stochastic dominance, then one should choose A_2 (or B_2) in the second round. Then, in the third round, the subject will compare between A_2 and B_2 (if his choice in the second round is A_2, then the new option in Round 3 is B_2; if his choice in the second round is B_2, then the new option is A_2). So on and so forth. The key to making the bridge from one row to another in the HL list is the dominance relations across rows. As long as subjects' behavior satisfy dominance, in the odd rounds, they make comparisons between the options within the same row; in the even rounds, they face dominant pairs across two adjacent rows.

One thing needs to be noted in ABC design is that individuals are not informed of all the options beforehand. The reason that ABC could work is that if one didn't truthfully reveal his or her preference in some round, *since he or she doesn't know what options are in the future,* it is possible that he or she would never see an option as least as good as the forgone option. In that case, one ends up with a less preferred option. However, if one always reveals own true preference in each round, he or she can get the "champion" option of all the options. Therefore, choosing preferred option in each round is the weakly dominant strategy for every individual. Such reasoning could be totally sabotaged if subjects are shown all the options beforehand. If a subject who identifies the most favorable option and carries that one over to the paying round. Before the first best option shows up, he or she could make random choices. Therefore, to apply ABC design, we must let subject make one choice at a time. Also, Lévy-Garboua et al. (2012) has shown that doing decisions without prior information can also reduce the bias of choosing the midpoint of the list, a critique of HL put forward by Andersen et al. (2006).

Failure of ABC could also happen if subjects have strong subjective belief or prediction about the pattern of the options. For example, in this case, after a few rounds, subjects may realize that in the even rounds the options are always easy to choose, and the options always get better and better. Given the whole list, subjects may learn the pattern through the procedure and make random choices until near the end of the experiment. That's the reason why I use only part of the HL list to reduce the chance of learning. Given the feature of the whole HL list where the top rows and the bottom rows have larger absolute values of expected payoff difference, we expect that most subjects choose Option A(safer option) at the top rows and Option B(riskier option) for the bottom rows. As predicted, most studies show that with the prize scales no greater than 20X, more than 90% subjects choose the safer option for the top two rows and more than 80% subjects choose the riskier option for the bottom two rows (Holt and Laury (2002, 2005), Bosch-Domènech and Silvestre (2013), Andersen et al. (2006), Dave et al. (2010), Deck et al. (2012)). Therefore since most people switching in the middle rows and given the concern of learning effect mentioned earlier, I chop off the top two rows and bottom two rows in the whole HL list and use the middle part, as shown in Table 3.2.

There were 65 subjects in this treatment. However, one subject violates first order stochastic dominance. That is, this subject didn't fully compare all six pairwise lotteries in the Table 3.2. Therefore, this subject's data is excluded from the following analysis.

3.2.2 HLrow3 Treatment (N=41)

In this treatment, subjects are given the lottery pair in Row 3 in Table 3.2 to choose from and get paid by their choice. This treatment is to take the suggestion by Freeman et al. (2015), use one pair lottery between-subject design as the control group to detect the systemic bias with the list. To the purpose of this dissertation, it allows us to test the ABC design with the choice list. In total, 41 subjects participated in this treatment.

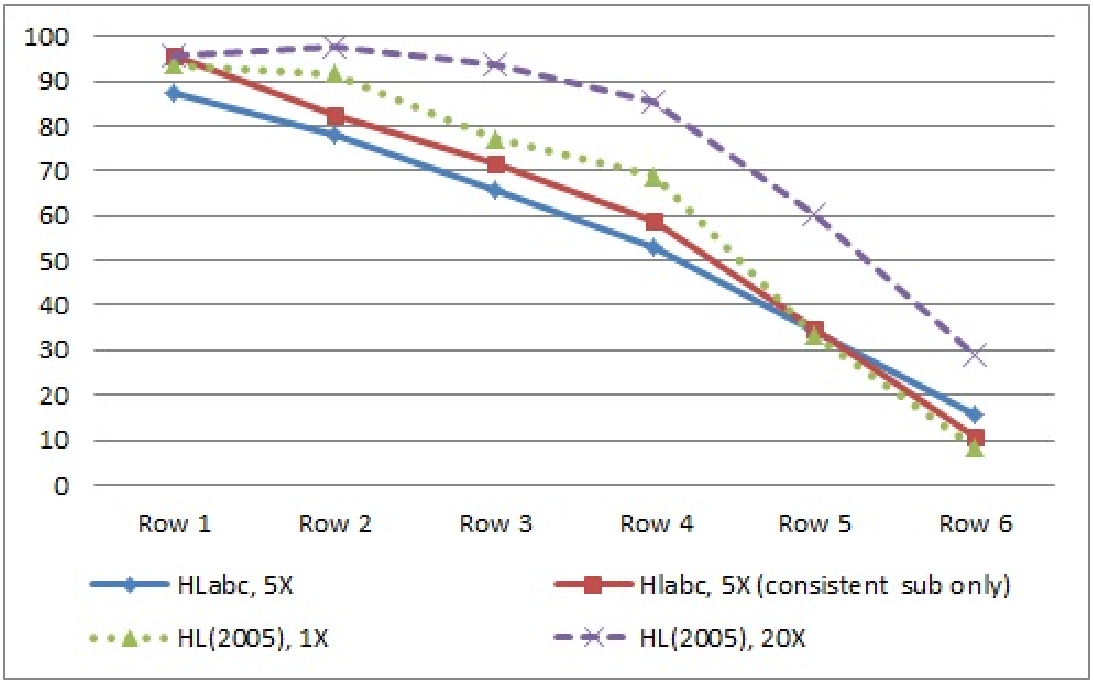
The experiments were conducted in Experimental Economics Center (ExCEN) at Georgia State University. All the subjects were undergraduates from Georgia State University. Subjects were informed that the choice they made in previous round would be carried over to the next round, and they would be paid for their last choice. They were also informed why choosing their preferred lottery in every round is the dominant (best) strategy (see subject instruction in Appendix B for detail). I adopted the same strategy as Cox et al. (2015) did: No show-up fee was offered. Instead, after subjects finish all their choices, I announced that I would like to pay them $5 (the same amount as in Cox et al. (2015)) for completing a demographic survey. The experiment was operated with ZTREE software (Fischbacher (2007)). See Appendix B for subject instruction (The only thing in instruction changed compared to Experiment I in Chapter 1 is total number of rounds. In HLabc Treatment, given there are 6 pairwise lotteries, there are 11 rounds.)

3.3 Data Analysis and Results

3.3.1 Choice Pattern

First, let's take a look at how many people choose Option A in each pair.

Figure 3.1: % of Safer Options Chosen in Each Pair



The dash lines are from Holt and Laury (2005). The prizes are one time and twenty times of those in the original HL design (Table 3.1). The data in the graph are from the treatments are with real payments, not hypothetical ones. The solid lines are from the current study. The blue line (diamond) consists of all 64 subjects in HLabc treatment. The red line (square) only include those who are "consistent". Based on previous studies, "consistent" behavior refers to one of the following: (1) choose Option A at the first few rows, and switch to Option B at some row and stick with Option B ever after. For example, if one is risk neutral, he or she should choose Option A for the first four rows, and Option B for the rest; (2) Always choose Option A; (3) Always choose Option B. Otherwise it is considered "inconsistent". The inconsistent rate in literature on average is between 10%-15% (Charness and Viceisza (2015), 14% is calculated from the HL meta-analysis by Filippin and Crosetto (2014)), and can be much higher in the fields (for example, 75% in Senegal (Charness and Viceisza (2015)) and 55% in Rwanda (Jacobson and Petrie (2009))). In this study, the inconsistent rate is 28.13%, in line with Lévy-Garboua et al. (2012)'s result that higher inconsistent rates are found when HL is conducted sequentially (average 37.5% inconsistent rate in their sequential treatments).

Now let's check whether there's a treatment effect for the choices in Row 3. For Row 3, 60.98% subjects choose Option A in HLrow3 treatment and 65.63% in HLabc treatment. The results from both T-test and Wilcox-Mann-Whitney test show that the choices for Row 3 under HLabc and HLrow3 are not significantly different (p-value for T-test: 0.6326; p-value for Wilcox-Mann-Whitney test: 0.6303).

So far, with all the results we have from all three chapters, we haven't found any significant difference between the ABC design and the one task design.

3.3.2 Risk Preference Estimation Methodology

Now, let's use the HLabc data to estimate risk preferences. The estimation methodology follows Harrison and Rutström (2008) (see Appendix F for detail).

In this analysis, I assume CRRA utility: $u(x) = x^{(1-r)}/(1-r)$ as the transformation of outcome and the one-parameter inverse-S function by Tversky and Kahneman (1992): $w(p) = p^{\gamma}/(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}$ as the transformation of probability.

Another exercise along with this is that we add the gender dummy on each parameter to check the gender effect.

3.3.3 Results

Table 3.3 shows the estimated results from EUT, DU, and RDU. One interesting finding: for RDU estimation, we can reject the linear probability assumption, but not the linearity in the prize. Comparing EUT and DU, we see that DU has slightly higher log likelihood. From the model selection perspective, both AIC and BIC prefer DU (EUT: AIC: 429.416; BIC: 437.3173; DU: AIC: 428.3337; BIC: 436.235). However, the result from the non-nested model Vuong (1989) test shows that neither EUT nor DU is significantly better than the other. The implication is that, when we do the estimation for the HL design, at least we may want to consider other models than EUT. Drichoutis and Lusk (2012) argue that in the HL list, there are only four outcomes, but with ten different probabilities. The HL list offers more information on probability weighting function than on utility function.

Table 3.3: Estimated Results for Different Models

	Current Study Data						HL(2005) with Real Payments Data			
	EUT		DU		RDU		EUT		RDU	
r	0.396***	(0.0678)			-0.0915	(0.516)	0.76***	(0.04)	0.85***	(0.08)
γ			0.565***	(0.0187)	0.524**	(0.213)			1.46	(0.35)
μ	1.147***	(0.186)	1.221***	(0.144)	1.307**	(0.544)	0.94***	(0.15)	0.89***	(0.14)
Log Lik.	-212.708		-212.167		-212.153		-330.93		-325.50	
N	384		384		384		960		960	

Standard errors in parentheses, clustered by individual. Null hypothesis for γ is $\gamma = 1$

HL(2005) data estimated by Harrison and Rutström (2008)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Compared with the estimations by Harrison and Rutström (2008) with the data from Holt and Laury (2005), we can see the results are quite different. First of all, one thing needs to be noted that HL(2005) data including two HL lists, 1X and 20X, while I use only one price list in this paper. For the EUT model, since HL(2005) data covers a wider range of the prizes, it may boost the tendency of risk aversion. $r = 0.396$ still rejects the risk neutrality assumption, and is in line with the estimation with 1X treatment in Holt and Laury (2002) and the meta-analysis of 62 studies using HL design by Filippin and Crosetto (2014)[2]. For the estimation of RDU model, the difference is even larger. My estimation cannot reject the linearity in the outcome, but can reject the linearity in probability, while Harrison and Rutström (2008)'s result shows the opposite. When we allow probability weighting, the disadvantage of single HL list is that it only has four outcomes. We need more variation on the prizes to get more accurate estimation when we allow the risk aversion from both the

[2]In Filippin and Crosetto (2014), they used the function of $u(x) = x^r$, and get the result of $r = 0.64$.

prize and the probability sides. That's one of the possible reasons to explain the insignificant r parameter in my estimation with RDU model.

The estimated noise μ is higher compared to most studies with HL list. It is in line with the higher inconsistent rate when HL list is conducted sequentially as in this paper.

Table 3.4: Gender Effect

		EUT		DU		RDU	
r	constant	0.323***	(0.102)			-0.167	(0.956)
	female	0.118	(0.136)			0.0842	(1.138)
γ	constant			0.587***	(0.0334)	0.509	(0.380)
	female			-0.0343	(0.0403)	0.00887	(0.452)
μ	constant	1.199***	(0.326)	1.183***	(0.239)	1.330	(1.032)
	female	-0.0896	(0.396)	0.0526	(0.298)	-0.0114	(1.233)
	Log Lik.	-211.83288		-211.26433		-211.2389	
	N	384		384		384	

Standard errors in parentheses, clustered by individual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4 shows the results of gender effect checking. From the table, we couldn't find any "female" dummy significantly different from 0. I also did the robustness test to check whether the joint "female" dummies are different from 0 in each model, and all the results are negative.

3.4 Conclusion and Discussion

In this chapter, I apply the ABC design on the multiple price list. Such implementation would allow us to estimate models beyond EUT since ABC is incentive compatible with general risk theories. The first result is that there's no significant difference for the choices of Row 3 under the ABC design and the gold standard – one decision only. Then, I estimate the risk preferences with data from HLabc treatment. I find out that for the HL list, EUT is not a better model than DU, and estimation with RDU model rejects linearity in probability. The immediate implication is that the HL list offers more information about probability weighting rather than the transformation of the outcome. The further implication is that if we want to get a more accurate estimation of risk preference, we may need more than one list so that they would cover more outcomes to help us infer utility function. For example, a dual list is adopted in Bruner (2009) and Drichoutis and Lusk (2012) where they vary the outcomes but hold the probability of the lotteries constant. Binswanger (1980,?) design, which later popularized by Eckel and Grossman (2002, 2008) (EG) matches such dual HL list idea. In EG design, they offer six lotteries to the subjects and let them choose one. All the lotteries have the probability of 50% for "good" outcome and 50% for "bad" outcome. This design is neat and simple for providing information about utility curvature. There is a battery of literature to compare the elicited risk preferences by different methods. An even further implication of this paper is that for different elicitation procedures, such as HL and EG, we might have to treat them as complementary methods rather than competing ones.

Conclusion

This dissertation aims at answering a methodological question: What are the incentive compatible payoff mechanisms for general theories under a multiple round setting? If we just assume people have well-behaved preferences, how should we pay them in the experiments of decision making under risk? The literature offers one answer: one round task design – people making one decision and getting paid by their choice. That is incentive compatible with all risk theories. However, it remains mysterious when we want one individual making multiple decisions.

In the first chapter of this dissertation, I propose a new payoff mechanism, *Accumulative Best Choice* (ABC) design. It has three features: (1) With no prior information. That is, subjects are not informed of all the lotteries beforehand; (2) The choice in the preceding round will be carried over to the following round to become one of the options; (3) eventually one is get paid by his or her choice in the last round. In the first chapter, I have shown that the ABC design is incentive compatible with risk models that assume well-behaved preferences. Also, all those three features are necessary for the family of incentive compatible payoff mechanisms for general risk theories. I apply ABC on both choice-pattern and preference estimation experiments to test its validity. Given that one round task is incentive compatible with all the theories, it's our gold standard. The key hypothesis is the choices or the estimates under the ABC design are not different from those under the one round task design. Data from both experiments show that such hypothesis cannot be rejected at 5% significant level.

With the first step paved (ABC is incentive compatible), the next step is to examine risk preferences with different models with ABC. In Chapter 2, I estimate six structural models of EUT and RDU and the payoff mechanism effects. The estimates under ABC design are not significantly different from those under one round task design for all models. However, the results under RLIS are significantly different from those under one round task design for all RDU models. That further confirms that the incentive incompatible payoff mechanism can lead to the biased estimation. The impact of this payoff mechanism effect may spread beyond the decision theory studies. More and more studies introduce non-EUT model and probability weighting into empirical micro studies, such as Wakker and Stiggelbout (1995), Bleichrodt and Pinto (2000), Jones et al. (2006). The Akaike Information Criterion prefers the RDU model with CRRA utility function and the TK probability weighting function. $r = 0.57$ indicates concave utility function and $\gamma = 0.83$ indicates inverse-S shaped probability weighting function, where people under-weigh low probability and over-weigh high probability.

The third chapter is to apply ABC on the most popular risk preference elicitation method: the multiple price list by Holt and Laury (2002). To apply ABC on the list, I use the first order stochastic dominance relations between lotteries across rows in the same column as the intermediate rounds to make people move from one row to the row below. Again, I compare the choices under ABC with one round task and find no significant difference. Now I can estimate the risk models with the data from HL list beyond EUT model. The results show that compared with DU, EUT is not a better model and DU is even preferred by AIC value. The estimation of RDU model rejected the linearity in probability but not that in utility, which is possibly due to the HL list only has four outcomes that couldn't offer enough information about utility function if we allow probability weighting. On the contrary, plenty of variations on the probability side offer more information about the curvature of probability weighting function. Therefore, we either need another list or another elicitation method to gain more information about utility function.

On the whole, the ABC design is a tool that makes us worry no more about the confounding of the payoff mechanism when we elicit risk preferences with general risk models. So far, we see that ABC passes all the tests in all chapters: It generates no significant different choices or estimations compared with one round task (with only one test significant at 10% level, but not 5% level; all the rest tests are not significant at 10% level). As discussed in Chapter 2, different ways of applying ABC may affect the efficiency of gathering information. For example, for the choice-pattern experiment in Chapter 1 or the multiple price list, deliberate use of the first order stochastic dominance would help to get the information if we have specific paired-up lotteries we would like subjects to compare. How to apply ABC properly is a case by case problem, and can be customized according to different research questions and tasks.

Appendix A

Theory Appendix: notations and proofs

Let me switch the order of proof for simplification. I'll prove Proposition 2 first, and then show Proposition 1.

A.0.1 Proof of Proposition 2

Part 1:

Proof. Let's first prove if $\phi(c) = c_n$, then it is IC for Round n: Given $\phi(c) = c_n$ and one's preference is $\succeq$ and choices in Round 1 to $n-1$ are $c_1, \cdots, c_{n-1}$. For $x_n, y_n \in D_n$, assume that $x_n \succeq y_n, \forall y_n \in D_n$. then $\phi(c_1, \cdots, c_{n-1}, x_n) = x_n \succeq \phi(c_1, \cdots, c_{n-1}, y_n) = y_n, \forall y_n \in D_n$, therefore, $x_n \in C(D, \phi, \succeq)$, which means it's incentive compatible for Round n.

Then, let's show: If a payoff mechanism is IC for Round n, then $\phi(c) = c_n$

Step 1: $\phi(c) \neq \vec{\vec{m}}$, where $\vec{\vec{m}}$ is constant, irrelevant of choice c.

Suppose $\phi(c) \neq c_n$. Given one's preference is $\succeq$ and choices in Round 1 to $n-1$ are $c_1, \cdots, c_{n-1}$. For $x_n, y_n \in D_n$, without more restrictions about the preferences, we just assume the preference that $x_n \succ y_n$ and $y_n \in C(D, \phi, \succeq)$. This violates IC for Round n. However, if $\phi(c) = c_n$, then $\phi(c_1, \cdots, c_{n-1}, x_n) = x_n \succ \phi(c_1, \cdots, c_{n-1}, y_n) = y_n$, therefore, $x_n \in C(D, \phi, \succeq)$ and $y_n \notin C(D, \phi, \succeq)$. Thus, $\phi(c) = c_n$ satisfies IC for Round n.

□

Part 2:

Proof. Suppose $\exists i_0, 1 \leq i_0 < n$ such that $\{c_{i_0}\} \cap_{j=i_0+1,\cdots,n} D_j = \emptyset$, and $\forall i \neq i_0, 1 \leq i < n$, there exists $k_i, i < k_i \leq n$, where $c_i \in D_{k_i}$. Suppose $x_{i_0}, y_{i_0} \in D_{i_0}$. Assume a preference $\succeq$, $x_{i_0} \succ y_{i_0}, \forall y_{i_0} \in D_{i_0}$. Since $\{c_{i_0}\} \cap_{j=i_0+1,\cdots,n} D_j = \emptyset$, then $\{c_{i_0}\} \cap D_n = \emptyset$. Given the result from Part 1, if ϕ is IC for Round n if and only if $\phi(c) = c_n \in D_n$, so we have $\phi(c)$ is irrelevant of c_{i_0}. Thus, $x_{i_0}, y_{i_0} \in C(D, \phi, \succeq)$. However, IC for Round i_0 requires that $y_{i_0} \notin C(D, \phi, \succeq)$ since $x_{i_0} \succ y_{i_0}$. Contradiction.

□

Part 3:

Proof. From the definition of IC, we should have $\phi(s^*) = \phi(s_1^*, \cdots, s_n^*) \succeq \phi(c), s_i^* \succeq s_i, \forall s_i \in D_i, i = 1, \cdots, n, \forall c$ and $\phi(s^*) \succ \phi(c)$ if $c \notin \{s^*\}$. Since subjects are informed of all the lottery options at the beginning, suppose for a preference $\succeq$, $a \succ y, \forall y \in D \backslash \{a\}$ and $a \notin \{D_1\}$.

Since $\cup\{D_i\} = \mathbb{L}_0$, then there must be some $k, 1 < k \leq n$ where $a \in \{D_k\}$ but $a \notin \{D_i\}, \forall 1 \leq i < k$. Pick up the chain where a could be potentially involved: From Part 2, we know that there must exist a $k < k_1 \leq n$, such that $c_k \in \{D_{k_1}\}$. If $k_1 = n$, then the chain is $\{D_k, D_n\}$. If $k_1 < n$, then from Part 2, there must exist a $k_1 < k_2 \leq n$, such that $c_{k_1} \in \{D_{k_2}\}$. If $k_2 = n$, then such chain is $\{D_k, D_{k_1}, D_n\}$. If $k_2 < n$, repeat the procedure. After repeating a definite $m (m < n)$ times, we'll have $k_m = n$, then such chain is $\{D_k, D_{k_1}, \cdots, D_{k_{m-1}}, D_n\}$.

Suppose $x_1, y_1 \in D_1$. Assume a preference $\succeq$ with $x_1 \succ y_1$. Consider two choice lotteries vectors: $c' = s^* = (x_1, s_2^*, \cdots, s_n^*)$ and $c'' = (c_1'', \cdots, c_n'')$ where $c_1'' = y_1; c_i'' = a, \forall i = k, k_1, \cdots, k_{m-1}, n; c_j'' \in D_j, \forall j \in \{1, \cdots, n\} \backslash \{1, k, \cdots, k_{m-1}, n\}$. Firstly, we can see that $c' \in \{s^*\}, c'' \notin \{s^*\}$. Then, if ϕ is IC, we can get $\phi(c') = s_n^* = a$. On the other hand side, we also can get $\phi(c'') = c''_n = a$. Thus, we have $x_1, y_1 \in C(D, \phi, \succeq)$. However, IC requires $y_1 \notin C(D, \phi, \succeq)$.

□

A.0.2 Proof of Proposition 1

Proof. First we see that the ABC design satisfies all the necessary conditions for IC above. Then let's see why it's incentive compatible:

Step 1: $\phi(s_1^*, \cdots, s_n^*) = s_n^* \succeq \phi(s) = s_n, s_i^* \succeq s_i, \forall s_i \in D_i, i = 1, \cdots, n, \forall s \in \{c\}$**.** ($s^*$ is the weakly dominant strategy)

Now, let's prove: If an experiment is an ABC design experiment, with strategy $s^* \in \{(s_1^*, \cdots, s_n^*) : s_i^* \succeq s_i, \forall s_i \in D_i, \forall i = 1, \cdots, n\}$ and the given payoff mechanism $\phi : \phi(c) = c_n$, then $\phi(s^*) = s_n^* \succeq \phi(s), \forall s$. Given the nature of ABC and the strategy s^*, we have that $\{c_n\} = \{c_{n-1}, D_n\} = \{s_{n-1}^*, D_n\} = \{c_{n-2}, D_{n-1}, D_n\} = \{s_{n-2}^*, D_{n-1}, D_n\} = \cdots = \{D_1, \cdots, D_n\} = \{s_1^*, \cdots, s_{n-1}^*, D_n\}$. Since $c_n = s_n^*$, therefore $c_n = s_n^* \succeq s_1^*, c_n = s_n^* \succeq s_2^*, \cdots, c_n = s_n^* \succeq s_{n-1}^*$ and $c_n = s_n^* \succeq y_n, \forall y_n \in D$. Thus, $\phi(s^*) = s_n^* \succeq \phi(s) = s_n, \forall s$ where $s_n \in D$.

Step 2: $\{s^*\}$ **is the only weakly dominant strategy set.**(subjects may regret if deviating from $\{s^*\}$)

From Step 1, we know that with strategy s^*, a subject can ensure his payment as his most favorable lottery throughout the whole experiment. Now, let's see why it's strategy-proof.

With any well-behaved preference $\succeq$, suppose there exists some $c'' = (c''_1, \cdots, c''_n) \notin \{s^*\}$. Then, there exists at least one $k \in \{1, \cdots, n\}$, such that $x_k \succ c''_k$, where $c''_k, x_k \in D_k$. We show that $c''_k \notin C(D, \phi, \succeq)$

(1) $k = n$. We have $\phi(c''_1, \cdots, c''_n) = c''_n$ and $\phi(c''_1, \cdots, c''_{n-1}, x_n) = x_n \succ \phi(c'') = c''_n$. Therefore, $c''_k \notin C(D, \phi, \succeq)$.

(2) $k < n$. Given the nature of ABC, after making m choices where $m = 0, \cdots, n-1$ ($\{c_0\} = \emptyset$), to look forward, we have $\{c_{m+1}\} = \{D_{m+1}\} = \{c_m, D_{m+1}\}$, therefore $\{c_{m+2}\} =$

$\{D_{m+2}\} = \{c_{m+1}, D_{m+2}\} = \{c_m, D_{m+1}, D_{m+2}\}$. So on and so forth. Eventually, we have $\{c_n\} = \{D_n\} = \{c_{n-1}, D_n\} = \cdots = \{c_m, D_{m+1}, \cdots, D_n\}$

Since ABC is with no prior information, consider the scenario of where $x_k \succ y, \forall y \in \{D_{k+1}, \cdots, D_n\}$. In that sense, $\phi(c''_1, \cdots, c''_k, \cdots, c''_n) = c''_n \in \{c''_k, D_{k+1}, \cdots, D_n\}$, with the strategy $(c'_1, \cdots, x_k, x_k, \cdots, x_k)$, we have $\phi(c'_1, \cdots, x_k, x_k, \cdots, x_k) = x_k \succ \phi(c'') = c''_n$. Thus, $c''_k \notin C(D, \phi, \succeq)$.

$\square$

Appendix B

Subject Instruction for Experiment I

Instruction (ABC)

Individual Decision Making
All the decisions you will make in this experiment are individual ones, that is, you'll make the decisions only by yourself. Your decisions will only affect the money you get paid at the end of the experiment, not others' payoffs. Their decisions will not affect the money you get paid, either. NO talking is allowed in the experiment.

Making Choices
For each round, you'll choose between Option A and Option B. For example,
Round 1

<table>
<tr><td>Ball #</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td><td>18</td><td>19</td><td>20</td></tr>
<tr><td>Option</td><td colspan="10">$7</td><td colspan="10">$15</td></tr>
<tr><td>Option</td><td colspan="6">$0</td><td colspan="9">$10</td><td colspan="5">$20</td></tr>
</table>

Your payoff is determined by the number on the ball that is drawn from a box. In total, there are 20 balls in the box. In Option A, your payoff is $7 if the number on the drawn ball is 1-10; your payoff is $15 if the number on the drawn ball is 11-20. In Option B, your payoff is $0 if the number on the drawn ball is 1-6; your payoff is $10 if the number on the drawn ball is 7-15; your payoff is $20 if the number on the drawn ball is 16-20.

Procedure
After you make your choice in each round, the option you choose will carry on to the next round. It will automatically be one of the possible options you face. Think about a series of choices as a tournament: the loser is out, and the winner stays for the next round to play with a new one. For example, if you choose Option A in the example above, for the next round, you will face the same Option A but a different Option B:
Round 2

<table>
<tr><td>Ball #</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td><td>18</td><td>19</td><td>20</td></tr>
<tr><td>Option</td><td colspan="10">$7</td><td colspan="10">$15</td></tr>
<tr><td>Option</td><td colspan="20">$9</td></tr>
</table>

Your Options in Round 2 consists of what you chose in the previous round, Option A, combined with a new option, Option B. After making your choice in Round 2, say Option B, you will face one option that is exactly the same as Option B ($9 for sure) with a new option in the next round, Round 3, and so on and so forth. Your options in the last round will consist of what you chose in the second last round and a new option. You'll get paid for what you choose in the last round.

Your payoff is determined by the number on the ball that will be drawn from a 20-ball box. Remember that you'll never see again the option you don't choose. Once you give up that option, you give it up forever.

Payoff

There are 9 rounds in total. You'll get paid for the choice you make in the LAST ROUND, which is Round 9. After you make all the decisions, a ball will be drawn by you from the 20-ball box. The number on the ball will determine the money you get from your last choice. Remember that your choices in the previous rounds WILL affect the options you have at the last round.

Information

You are not informed about all the options before you make any choices. You only know the options you faced before, in the previous rounds, and the ones you are facing now, in the current round. You don't know the new options in the rounds you haven't come up to yet. However, the pool of options is fixed. You will encounter every option in the pool throughout the whole procedure. The option you don't choose in each round is the option you discard from the pool.

Your Best Strategy

Choosing your preferred option in each round will never harm you. Such a procedure will help you to eliminate your less preferred option, and the chosen option always stays. This strategy can ensure you to get paid for your best option since you always carry on your last chosen option, the current champion, to the next round and until choose your final champion in the end. If you chose a less favorable option in some round, since you don't know what comes next, and if you didn't meet any option better than the previous ones, you might regret ending up with and getting paid for that less favorable option.

Appendix C

Complete Path of Experiment I

For easier expression, define $S'_i = S_i$ and $R'_i = R_i$ for $i = 1, 4, 5$, and define $S'_2 = S_3$, $S'_3 = S_2$, $R'_2 = R_3$, $R'_3 = R_2$. Now under the first order stochastic dominance relations, we have: $S'_5 \succ^{SD} S'_4 \succ^{SD} S'_3 \succ^{SD} S'_2 \succ^{SD} S'_1$, and $R'_5 \succ^{SD} R'_4 \succ^{SD} R'_3 \succ^{SD} R'_2 \succ^{SD} R'_1$

The first round: $D_1 = \{S'_1, R'_1\}$. For the following even rounds, $D_{2k} = \{c_{2k-1}, S'_{k+1}\}|_{c_{2k-1}=S}$ and $D_{2k} = \{c_{2k-1}, R'_{k+1}\}|_{c_{2k-1}=R}$ for $k = 1, \cdots, 5$. For the following odd rounds, $D_{2k+1} = \{c_{2k}, R'_{k+1}\}|_{c_{2k}=S}$ and $D_{2k+1} = \{c_{2k}, S'_{k+1}\}|_{c_{2k}=R}$ for $k = 1, \cdots, 5$. It can be depicted as the following path. If subjects follow the first order stochastic dominance, then they should always be on the red path. The odd rounds of the red path are the target rounds.

Appendix D

Lottery List for Experiment II (from Harrison and Swarthout (2014))

	Prizes			Probabilities			Expected
No.	x1	x2	x3	p1	p2	p3	Value
1	5	10	20	0.5	0.5	0	7.5
2	5	10	20	0.25	0.75	0	8.75
3	5	20	10	0.75	0.25	0	8.75
4	10	20	5	1	0	0	10
5	5	10	20	0.25	0.5	0.25	11.25
6	5	20	10	0.5	0.5	0	12.5
7	10	20	5	0.75	0.25	0	12.5
8	5	35	20	0.75	0.25	0	12.5
9	10	20	5	0.5	0.5	0	15
10	5	20	10	0.25	0.75	0	16.25
11	10	35	5	0.75	0.25	0	16.25
12	10	20	35	0.25	0.75	0	17.5
13	10	20	35	0.5	0.25	0.25	18.75
14	5	35	10	0.5	0.5	0	20
15	20	35	5	1	0	0	20
16	5	70	10	0.75	0.25	0	21.25
17	10	20	35	0.25	0.5	0.25	21.25
18	10	35	5	0.5	0.5	0	22.5
19	20	35	5	0.75	0.25	0	23.75
20	10	20	35	0.25	0.25	0.5	25
21	10	70	20	0.75	0.25	0	25
22	5	35	10	0.25	0.75	0	27.5
23	20	35	5	0.5	0.5	0	27.5
24	5	20	70	0.25	0.5	0.25	28.75
25	10	35	20	0.25	0.75	0	28.75
26	20	35	70	0.25	0.75	0	31.25
27	20	70	5	0.75	0.25	0	32.5
28	35	70	5	1	0	0	35
29	20	35	70	0.5	0.25	0.25	36.25
30	5	70	10	0.5	0.5	0	37.5

31	10	70	20	0.5	0.5	0	40
32	20	35	70	0.25	0.5	0.25	40
33	35	70	5	0.75	0.25	0	43.75
34	20	70	5	0.5	0.5	0	45
35	35	70	5	0.5	0.5	0	52.5
36	5	70	20	0.25	0.75	0	53.75
37	10	70	35	0.25	0.75	0	55
38	20	70	35	0.25	0.75	0	57.5

Appendix E

Subject Instruction for Experiment II

Instruction (ABC)

Individual Decision Making

All the decisions you will make in this experiment are individual ones, that is, you'll make the decisions only by yourself. Your decisions will only affect the money you get paid at the end of the experiment, not others' payoffs. Their decisions will not affect the money you get paid, either. NO talking is allowed in the experiment.

Making Choices

For each round, you'll choose between Option A and Option B. For example, in Round 1,

Your payoff is determined by a randomly drawn number between 1 and 100 (each number is equally likely to occur). You will draw the number by throwing two 10-sided dice after you make all the decisions for 20 rounds. In Option A, your payoff is $7 if the number drawn is 1-50 (corresponding to the 50%); your payoff is $15 if the number drawn is 51-100 (corresponding to the 50%). In Option B, your payoff is $0 if the number drawn is 1-30 (corresponding to the 30%); your payoff is $10 if the number drawn is 31-75 (corresponding to the 45%); your payoff is $20 if the number drawn is 76-100 (corresponding to the 25%).

Procedure

After you make your choice in each round, the option you choose will carry on to the next round. It will automatically be one of the possible options you face. Think about a series of choices as a tournament: the loser is out, and the winner stays for the next round to play with a new one. For example, if you choose Option A in the example above, for the next round, you will face the same Option A but a different Option B:

Your Options in Round 2 consist of what you chose in the previous round, Option A, combined with a new option, Option B. After making your choice in Round 2, say Option B, you will face one option that is exactly the same as Option B ($9 for sure) with a new option in the next round, Round 3, and so on and so forth. Your options in the last round will consist of what you chose in the second last round and a new option. You'll get paid for what you choose in the last round.

Your payoff is determined by the number drawn by two 10-sided dice after you make all the choices for 20 rounds. Remember that you'll never see again the option you don't choose. Once you give up that option, you give it up forever.

Payoff

There are 20 rounds in total. You'll get paid for the choice you make in the LAST ROUND, which is Round 20. After you make all the decisions, you will throw two 10-sided dice. The number you draw will determine the money you get from your last choice. Remember that your choices in the previous rounds WILL affect the options you have in the last round. In addition, you will get the $7.50 show-up fee for just being here.

Information

You are not informed about all the options before you make any choices. You only know the options you faced before, in the previous rounds, and the ones you are facing now, in the current round. You don't know the new options in the rounds you haven't come up to yet. All the options you face are predetermined before you make any choices. That is, your choices will NOT affect the options you face in the experiment. You will not see the options you don't choose in the experiment again.

Your Best Strategy

Choosing your preferred option in each round will never harm you. Such a procedure will help you to eliminate your less preferred option, and the chosen option always stays. This strategy can ensure you to get paid for your best option since you always carry on your last chosen option, the current champion, to the next round and until choose your final champion in the end. If you chose a less favorable option in some round, since you don't know what comes next, and if you didn't meet any option better than the previous ones, you might regret ending up with and getting paid for that less favorable option.

Appendix F

Estimation Methods for Experiment II

The estimation methodology follows Harrison and Rutström (2008). First is to set up the parameters we would like to estimate, either parametric or non-parametric. Then consider different decision models:

F.1 Expected Utility Model

For a lottery $l = (x_1, p_1; \cdots ; x_K, p_K)$, we can calculate its expected utility with $U_k = u(x_k)$:

$$EU_i = \Sigma_{k=1,\cdots,K}(p_k \times U_k)$$

Given the binary lottery comparison in our case, the latent indexes with Fechner error noise μ are:

$$\nabla EU = (EU_B - EU_A)/\mu$$

After that, use the logistic function $\Phi(\cdot)$ to link to the observed choices:

$$\text{prob(choose lottery B)} = \Phi(\nabla EU)$$

. Eventually to estimate the parameters by maximize the conditional log-likelihood of

$$\ln L(u; y) = \sum_i [y_i \ln \Phi(\nabla EU) + (1 - y_i) \ln(1 - \Phi(\nabla EU))]$$

($y = 0$ if choose Option A, $y = 1$ if choose Option B)

F.2 Dual Expected Utility Theory Model

Yaari (1987) proposes a model with linear in prize and nonlinear in probability, which can be written as:

$$DU_i = \Sigma_{k=1,\cdots,K}(w_k \times x_k)$$

To calculate w_k, we need to array all the lotteries comonotonically based on the outcomes. For example, a lottery $l = (x_1, p_1; \cdots; x_K, p_K)$, to calculate its dual expected utility, here we arrange to make it as $x_1 \leq x_2 \leq \cdots \leq x_K$ with the corresponding probabilities $(p_1, \cdots, p_K)$. Given a probability weighting function $w(p)$, where $w(0) = 0, w(1) = 1, w(p)$ is increasing on $[0, 1]$. For both parametric or nonparametric estimation, the decision weight w_k is calculated as: $w_k = w(p_K + \cdots + p_k) - w(p_K + \cdots + p_{k+1})$.

And then similarly, we have:

$$\nabla DU = (DU_B - DU_A)/\mu$$

and

$$\ln L(u; y) = \sum_i [y_i \ln \Phi(\nabla DU) + (1 - y_i) \ln(1 - \Phi(\nabla DU))]$$

F.3 Rank Dependent Utility Model

RDU is the combination of EUT and RDU, with non-linearity on both prizes and probabilities, where

$$RDU_i = \Sigma_{k=1,\cdots,K}(w_k \times U_k)$$

So relatively

$$\nabla RDU = (RDU_B - RDU_A)/\mu$$

and

$$\ln L(u; y) = \sum_i [y_i \ln \Phi(\nabla RDU) + (1 - y_i) \ln(1 - \Phi(\nabla RDU))]$$

Appendix G

Result Table for Experiment II in Chapter 1

Data from 1-in-1 (75 obs) and ABC (1000 obs)

Parameter	Point Estimate	Standard Error	p-value	95% Confidence Interval	
		A. Expected Utility Theory (LL= -225.5)			
u_{10} constant	0.241	0.064	<0.001***	0.116	0.366
u_{10} pay1	-0.100	0.098	0.310	-0.293	0.093
u_{20} constant	0.439	0.054	<0.001***	0.333	0.546
u_{20} pay1	0.008	0.080	0.925	-0.148	0.163
u_{35} constant	0.672	0.036	<0.001***	0.602	0.743
u_{35} pay1	-0.028	0.076	0.708	-0.176	0.120
μ constant	0.069	0.012	<0.001***	0.044	0.093
μ pay1	0.020	0.030	0.499	-0.038	0.078
		B. Rank Dependent Utility Theory (LL= -219.8)			
u_{10} constant	0.211	0.063	0.001***	0.088	0.335
u_{10} pay1	-0.080	0.123	0.515	-0.321	0.161
u_{20} constant	0.392	0.066	<0.001***	0.263	0.520
u_{20} pay1	-0.036	0.175	0.835	-0.379	0.306
u_{35} constant	0.628	0.062	<0.001***	0.507	0.748
u_{35} pay1	-0.059	0.170	0.728	-0.393	0.275
$\varphi_{1/4}$ constant	0.275	0.061	<0.001***	0.156	0.394
$\varphi_{1/4}$ pay1	-0.028	0.138	0.840	-0.299	0.243
$\varphi_{1/2}$ constant	0.494	0.080	<0.001***	0.338	0.651
$\varphi_{1/2}$ pay1	-0.155	0.176	0.378	-0.500	0.189
$\varphi_{3/4}$ constant	0.694	0.063	<0.001***	0.572	0.817
$\varphi_{3/4}$ pay1	-0.036	0.154	0.816	-0.338	0.266
μ constant	0.067	0.011	<0.001***	0.045	0.089
μ pay1	-0.008	0.019	0.687	-0.045	0.029

Standard errors are clustered by individual. ***p<0.01, **p<0.05, *p<0.1

Appendix H

Full Structural Estimation Result Tables in Chapter 2

Table H.1: Estimated Results between Different Payoff Mechanisms: ABC vs One Round, RLIS

	Expected Utility Models				Rank Dependent Utility Models							
	CRRA		EP		CRRA&TK		CRRA&Prelec		EP&TK		EP&Prelec	
r												
One Round	0.0456	(0.0930)	-0.0751	(0.277)	0.0461	(0.0943)	0.0309	(0.105)	0.140	(0.121)	0.0699	(0.523)
RLIS	0.161***	(0.0391)	0.0832	(0.177)	0.188***	(0.0412)	0.206***	(0.0444)	0.176**	(0.0745)	0.202**	(0.0832)
constant	0.719***	(0.0533)	0.878***	(0.188)	0.644***	(0.0611)	0.730***	(0.0647)	0.774***	(0.0564)	0.787***	(0.0796)
α												
One Round			0.661	(2.435)					-1.248	(1.785)	-0.495	(5.120)
RLIS			-1.059	(1.845)					-1.605	(1.216)	-3.378	(2.170)
constant			-0.861	(2.470)					-0.431***	(0.0888)	-0.540***	(0.0833)
γ												
One Round					-0.0457	(0.125)			-0.0126	(0.126)		
RLIS					0.333***	(0.0896)			0.360***	(0.0938)		
constant					0.860***	(0.0627)			0.831***	(0.0729)		
η												
One Round							0.0841	(0.188)			0.0736	(0.506)
RLIS							0.113	(0.131)			0.004	(0.204)
constant							0.876***	(0.127)			0.979***	(0.195)
σ												
One Round							-0.081	(0.146)			-0.0236	(0.153)
RLIS							0.357***	(0.105)			0.424***	(0.115)
constant							0.865***	(0.024)			0.801***	(0.095)
μ												
constant	0.433***	(0.0680)	0.114	(0.112)	0.527***	(0.0928)	0.396***	(0.0782)	0.196	(0.136)	0.211	(0.206)
F-test (χ^2)												
One Round			0.08		0.43		0.83		5.31		1.39	
RLIS			0.34		30.64***		30.35***		18.29***		20.05***	
Log lik.	-3996.8076		-3996.5684		-3972.1101		-3966.0743		-3971.5127		-3965.6304	
N	7315		7315		7315		7315		7315		7315	

Standard errors in parentheses and clustered by individual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table H.2: Estimated Results between Different Payoff Mechanisms: RLIS vs One Round, ABC

		Expected Utility Models				Rank Dependent Utility Models							
		CRRA		EP		CRRA&TK		CRRA&Prelec		EP&TK		EP&Prelec	
r													
	One Round	-0.115	(0.0876)	-0.159	(0.211)	-0.142	(0.0878)	-0.175*	(0.0982)	-0.0359	(0.0913)	-3.266***	(0.223)
	ABC	-0.161***	(0.0391)	-0.0831	(0.193)	-0.188***	(0.0412)	-0.206***	(0.0444)	-0.177**	(0.0741)	-0.203**	(0.0896)
	constant	0.880***	(0.0497)	0.961***	(0.0353)	0.831***	(0.0545)	0.935***	(0.0642)	0.950***	(0.0317)	0.989***	(0.0180)
α													
	One Round			1.725	(2.135)					0.355	(1.644)	4.011*	(2.205)
	ABC			1.058	(1.924)					1.605	(1.215)	3.381	(2.209)
	constant			-1.922	(1.874)					-2.034	(1.255)	-3.915*	(2.211)
γ													
	One Round					-0.378***	(0.125)			-0.373***	(0.119)		
	ABC					-0.333***	(0.0896)			-0.360***	(0.0938)		
	constant					1.192***	(0.0593)			1.191***	(0.0598)		
η													
	One Round							-0.0294	(0.150)			3.430	(40.925)
	ABC							-0.113	(0.131)			-0.00416	(0.204)
	constant							0.990***	(0.0577)			0.983***	(0.0604)
σ													
	One Round							-0.438***	(0.135)			-0.879	(3.197)
	ABC							-0.357***	(0.105)			-0.424***	(0.115)
	constant							1.223***	(0.0633)			1.225***	(0.0638)
μ													
	constant	0.433***	(0.0680)	0.114	(0.120)	0.527***	(0.0928)	0.396***	(0.0782)	0.196	(0.136)	0.211	(0.201)
F test (χ^2)													
	One Round			0.65		11.10***		13.71***		9.99**		209493.45***	
	ABC			0.32		30.64***		30.35***		18.74***		19.00***	
Log. lik		-3996.8076		-3996.5684		-3972.1101		-3966.0743		-3971.5126		-3979.6276	
N		7315		7315		7315		7315		7315		7315	

Standard errors in parentheses and clustered by individual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table H.3: Estimations for Single Models with Allowance for Heterogeneity

	Expected Utility Models				Rank Dependent Utility Models							
	CRRA		EP		CRRA&TK		EP&TK		CRRA&Prelec		EP&Prelec	
r												
female	-0.0419	(0.0752)	-0.0209	(0.0401)	-0.0477	(0.0669)	-0.0512	(0.0592)	-0.0627	(0.0755)	-0.0436	(0.0572)
black	-0.0640	(0.0608)	-0.119	(0.0774)	-0.0756	(0.0578)	-0.148**	(0.0647)	-0.0768	(0.0603)	-0.108*	(0.0573)
age21	0.0314	(0.0739)	0.0643	(0.0502)	0.106	(0.0679)	0.0790	(0.0507)	0.0345	(0.0729)	0.0810***	(0.0268)
busiecon	0.0311	(0.0634)	-0.0568	(0.0533)	-0.0344	(0.0689)	-0.0936*	(0.0530)	0.0150	(0.0724)	-0.103	(0.113)
birthorder	-0.00193	(0.0330)	0.0641	(0.0421)	0.0330	(0.0337)	0.0830***	(0.0281)	0.0176	(0.0369)	0.0949***	(0.0309)
constant	0.803***	(0.159)	0.699***	(0.255)	0.478**	(0.218)	0.472	(0.443)	0.831***	(0.220)	0.597***	(0.156)
α												
female			0.0179	(0.196)			0.0445	(0.151)			-0.0202	(0.199)
black			0.401	(0.514)			0.184	(0.395)			0.237	(0.196)
age21			-0.321	(0.361)			-0.152	(0.285)			-0.350	(0.292)
busiecon			0.328	(0.388)			0.151	(0.302)			0.238	(0.203)
birthorder			-0.261	(0.307)			-0.104	(0.223)			-0.201	(0.215)
constant			0.217	(0.361)			-0.00417	(0.174)			0.524	(0.724)
γ												
female					-0.148	(0.158)	0.0532	(0.174)				
black					-0.405	(0.268)	0.0829	(0.167)				
age21					0.639*	(0.383)	-0.00582	(0.182)				
busiecon					-0.484*	(0.294)	0.0618	(0.210)				
birthorder					0.305**	(0.149)	0.0511	(0.121)				
constant					0.714***	(0.233)	0.579***	(0.196)				
η												
female									-0.960	(0.964)	-1.306	(1.391)
black									0.269	(0.942)	0.661	(1.563)
age21									-1.202	(1.036)	-1.060	(1.370)
busiecon									0.0432	(0.763)	-0.890	(0.829)
birthorder									-0.445	(0.542)	-0.231	(0.610)
constant									2.269	(1.475)	2.042	(1.693)
σ												
female									-0.145	(0.132)	-0.160	(0.178)
black									0.0157	(0.162)	0.261	(0.260)
age21									0.0492	(0.197)	-0.142	(0.209)
busiecon									-0.0779	(0.142)	0.0448	(0.222)
birthorder									0.151*	(0.0858)	0.0497	(0.132)
constant									0.710**	(0.299)	0.874**	(0.379)
μ												
constant	0.379**	(0.177)	0.0738	(0.102)	0.857	(0.540)	0.372	(0.622)	0.290	(0.185)	0.0359	(0.0680)
N	1000		1000		1000		1000		1000		1000	

Standard errors in parentheses and clustered by individual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Vita

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