Experiential and Neurobiological Influences on Economic Preferences and Risky Decision Making

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(ABSTRACT)

Economic preferences are fundamental to risky decision making and other economic decision-making. Unlike traditional economics, which routinely assumes that individuals are endowed with stable preferences and try to maximize the expected utility when facing risky decision-making problems, behavioral economics and neuroeconomics offer research strategies that help us explore the factors that influence economic preferences and risky decision-making process. This dissertation consists of three essays studying the underlying experiential influences on economic preferences and neurobiological effects on risky decision making.

Chapter 2 examines whether experiences during adolescence have a long-term effect on economic preferences. Between 1966 and 1976, China's Sent-Down Movement required seventeen million urban teenagers to spend several years living and working in rural areas. The program had a number of goals for participants, including learning empathy for rural laborers and developing collectivist values. The sent-down movement can be regarded as a natural experiment, which allow us to investigate whether this government policy was successful in effecting a lasting change to economic preferences. Using a modified Global Preference Survey and employing a regression discontinuity design, we find that the experience of being Sent-Down significantly changed participants' risk preferences, other regarding preferences, and attitude toward government.

Chapter 3 explores how the arousal system modulates attention and investment behavior. Experimental research shows that human decision making is shaped by emotions associated with an outcome's success or failure. Regret, for example, is a powerful predictor of future investment decisions in asset markets. Using a fictive learning model to capture regret, we examine changes in pupil diameter of participants performing a sequential investing task. By manipulating task uncertainty, we show that pupil dilation is positively correlated with both asset price variance and regret. In addition, pupil linked arousal is positively associated with the learning rate. We conclude that the pupil–linked arousal system helps regulate investment behavior in a dynamic market environment.

Chapter 4 explores the complex process by which people make risky choices. While traditional models, like expected utility theory, model choice as selection of the outcome with the highest probability weighted value, research shows that in some environments these models do a poor job of describing behavior. This study explores the role of attention, pupil-linked arousal and salience in risky choice. First, we replicate earlier findings that that choices are consistent with expected utility theory when the calculation is easy, however, as the calculation becomes harder, they make decisions by comparing unweighted payoffs and are attend to the salient option. Further, we find that pupil-linked arousal is associated with the level of cognitive effort needed to calculate expected utility. Finally we show that arousal reflects cognitive effort associated with resisted selecting more salient option.

Experiential and Neurobiological Influences on Economic Preferences and Risky Decision Making

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(GENERAL AUDIENCE ABSTRACT)

Economic decisions are those involving trade-offs where an individual must give up one item or possibility to get another. Economic preferences define which outcome an individual will value more, and helps explain why, for example, some people invest their money in high-risk and high-yield bonds while others keep their money in their savings account. Economists and other social scientists are interested in the differences between individuals' economic preferences, how they are formed and how they translate into peoples' decisions. Risky decision making is one common type of economic decision that people make daily, for example, investing in the stock market, gambling in casinos, buying lottery tickets or trying a new restaurant. We know that when two people make different decisions that sometimes it is because they have different preferences, and sometimes it is because they go about making decisions in different ways.

This dissertation explores whether people's early experiences have a long-term impact on economic preferences (Chapter 2), and investigate the roles that attention, emotional arousal and information salience play in risky decision making (Chapters 3 4) using research methods from behavioral economics, experimental economics and neuroeconomics.

The scientific mission of this dissertation is to deepen our understanding of how and why people make choices. We add to the evidence that economic preferences are not inborn and stable; instead, they are shaped by people's experiences. We also explore risky choices like investing money, and find that while people often try to minimize regret, our emotional arousal system significantly affects our attention patterns and behavior. In addition, when faced with decisions requiring calculations that are hard to do in your head, people make different decisions than when the calculations are easy. Overall, we paint a picture of human decision makers whose past experiences and current options determine both the nature of their choices and how they make them.

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Chapter 1

Introduction

This dissertation explores how an individual's experiences and neural system affect the process by which she makes decisions. Economic preferences are the basis for engaging in economic activities, and each individual has different economic preferences, for example, some people prefer to invest in high-risk and high-yield bonds while others keep their money in a savings account. Some people are willing to give up present rewards in exchange for greater rewards in the future, while others prefer to 'make merry while they can' (Mischel et al., 1989). Preferences are an important area of study for economists and other social scientists, including how and why they differ across individuals.

Researchers are also interested in the process by which people make choices. Risky decision making is prevalent in daily life, for example, investing in the stock market, gambling in casinos, buying lottery tickets and even deciding whether to try a new restaurant. When people make different risky choices it could either be because their risk preferences differ or because the process by which they arrived at the decision is different. Studying how people make decisions, including deciding what information to collect and how to use it to determine a choice, is another important area of study.

Economists have traditionally assumes that individuals are endowed with a endogenous and stable preferences, and that they make rational choices. In the case of risky decision making, this involves by gathering information about available options, then maximizing expected utility. More and more, however, research in behavioral economics, psychology and neuroeconomics have demonstrated that people's preferences and risky decision making processes are affected by additional, external factors (e.g. living environment, education, growth experience, income, etc.) (Falk et al., 2015; Basin and Verdier, 2000; Dohmen et al., 2012; Piketty, 1995; Malmendier and Nagel, 2011; Fuchs-Schundeln and Schundeln, 2015; Giuliano and Spilimbergo, 2014) and internal factors determined by brain function (Lohrenz et al., 2007; Chiu et al., 2008; Smith et al., 2014; Sokol-Hessner et al., 2009). This dissertation explores whether people's early experiences have a long-term impact on economic preferences (Chapter 2), as well as what role attention, emotional arousal and information salience play in dynamic investment behavior (Chapter 3) and static lottery choice behavior (Chapter 4) by adapting methods from behavioral economics, experimental economics, and neuroeconomics.

In chapter 2, we examine China's Sent-Down Movement, a government policy that required teenagers to spend time in rural areas in order to teach them collectivist values. We administered a large scale specialized survey which consisted of the Global Preference Survey (Falk et al., 2015) as well as some additional questions, to measure preferences (Andreoni and Miller, 2002). We then estimate the effects of the sent-down experience on preferences using a regression discontinuity (RD) approach using the birth cohort as the running variable, to help us control for selection bias. We find that the Sent-Down Movement significantly changed participants' economic preferences relative to those were not part of the program. In particular, those who were sent-down are more risk-averse, more likely to return others' kindness, and more altruistic. They are also less likely to support redistribution policies and trust the government. Our results are robust to alternative regression function specifications and bandwidth choices.

In Chapter 3, we created a dynamic investment environment where participants choose how much to invest in a risky asset in each period of a market. Every participant participates in two multi-period markets with different levels of price fluctuations for the risky asset. As participants make decisions we record their behavior, eye movements and pupil dilation. Results show that people do not maximize their expected profits by performing complex calculations, choosing instead to minimize regret (Lohrenz et al., 2007; Chiu et al., 2008). For example, when a participant invests less than they could have and the price of the asset rises, they realize that they would have earned more if they had invested it all. This may lead them to invest more next period. Previous research has shown that emotional arousal plays vital role in investment decision making (Smith et al., 2014; Sokol-Hessner et al., 2009). We find greater pupil dilation as market uncertainty increases. Additionally, greater pupil dilation is not only related to a higher learning rate from regret, but also predicts that the participant will decrease investment in the future. Pupil-linked arousal also modulates the information that people collect about the market and their portfolio. When emotional arousal is low, participants pay more attention to the risky asset; when emotional arousal is high, they tend to focus on information about past experience. Our experiment describes both how people make investment decisions and how the emotional arousal system modulates attention and behavior patterns.

Economists also study static risky choice. Chapter 4 examines how people choose between two risky alternatives and the role emotional arousal and information salience influence the process. In each of 120 trials, participants choose between two lotteries. Lotteries are divided into two types based on whether expected payoff is easy to calculate or difficult to calculate. Eye-tracking is used to record eye movement patterns and measure pupil dilation, an indication of participants' emotional arousal. We find that when the lottery's expected payoff is easy to calculate, both eye movement and behavior data indicate that the participants are calculating the expected payoff. They have a higher pupil dilation level, which shows that they utilize more cognitive effect to calculate. However, when the difficulty of calculation increases, they give up the calculation; instead, they begin to compare the payoffs of two lotteries, and choose the one with a larger payoff without thinking the probability that the payoff can be achieved. Our result shows that information saliency plays an essential role in risky decision-making. Defining that the standardized difference of lottery payoffs is the function of the payoff salience, we find that the lottery with salient payoff attract more attention of participants and have higher probability being selected. Besides, if the participants try to choose the non-salient option, she needs more cognitive control to overcome the attraction of salient payoff, which is shown as pupil dilation. Our findings confirm previous studies (Arieli et al., 2011; Aimone et al., 2016a), when the expected payoff is easy to calculate, people do the calculation and make decision base on expected payoff; However, if the expected payoff is difficult to calculate, people choose to compare component of lotteries. Further, we find what they used to compare is the payoff. The salient payoff attracts people's attention and increases the likelihood of being chosen. Finally, our results confirmed the role that pupil linked arousal system plays in this process.

Taken together these three chapters deepen our understanding of how economic preferences are formed and how risky decisions are made. We expand on previous work and show that economic preferences are not endogenous and stable; instead, they are shaped by the external environment that people experience. We also explore how people make investment decisions and lottery choice decision. We find that people make investment decisions, in part, by minimizing regret, and that emotional arousal system modulates people's attention patterns and behaviors significantly. We find that task difficulty affect people's decision-making process. In addition, we show that salients payoff attract decision makers' attention, thus increasing the likelihood that the associated lottery is selected. The arousal system plays a vital role in the process of expected utility calculation and in overcoming attraction.

Chapter 2

The impact of China's Sent-Down Movement on economic preferences

Sheryl Ball, Suqin Ge, Alec Smith, Wei Wang, and Xiaomeng Zhang

(ABSTRACT)

Between 1966 and 1976, China's Sent-Down Movement required seventeen million urban teenagers to spend several years living and working in rural areas. The program had a number of goals for participants, including learning empathy for rural laborers and developing collectivist values. The sent-down movement can be regarded as a natural experiment that allows us to investigate whether this government policy successfully affected a lasting change to economic preferences. Using a modified Global Preference Survey and employing a regression discontinuity design, we find that being sent down significantly changed participants' risk preferences, other-regarding preferences, and attitude toward government.

2.1 Introduction

Between 1966 and 1976, China's Sent-Down Movement required seventeen million urban teenagers to spend several years living and working in rural areas. The program had a number of goals for participants, including learning empathy for rural laborers and developing collectivist values. A rich literature in psychology and behavioral economics argues that one's personal experiences and environment have a significant influence on economic preferences (Falk et al., 2015; Basin and Verdier, 2000; Dohmen et al., 2012; Piketty, 1995; Malmendier and Nagel, 2011; Fuchs-Schundeln and Schundeln, 2015; Giuliano and Spilimbergo, 2014). Thus, China's Sent-Down Movement provides a case study on the ways in which a government program impacts program participants. This chapter investigates the effects of being sent-down, and quantifies differences in pro-social preferences, risk and time preferences, and attitudes towards government.

”Sent-down” is short for “Up to the mountains and down to the villages.” Between 1966 and 1976, one in three urban youth, who graduate from high school were forced to relocate to rural areas to perform manual labor and to receive ideological re-education by rural peasants (Li et al., 2010) for several years. Direct, large-scale effects of the movement include reducing teacher shortages in rural areas thus increasing rural education rates (Deng and Treiman, 1997). Studies (Chen et al., 2018; Lin, 2019) show that there is a spillover effect, which is that in-person-years of schooling increase in rural areas almost compensated the loss of the educational disruption in urban China during the Cultural Revolution. The achievement of education also lead to improvements in China's economic growth (Ministry of Education of the PRC, 2011; Sen, 2000),and increasing goods transfer to rural areas (Honig and Zhao, 2015) as well as improving rural medical care system (Wang, 1999; Rene, 2013). Using survey data, recent studies have documented long-term effects of program participation, both negative and positive. Sent-down individuals have a higher rate of chronic illnesses and mental problems (Gong et al., 2014; He, 2018), lower probability of having a successful marriage (He, 2018), and lower participation rate in political activities (Shi and Zhang, 2019). At the same time, they are more willing to invest in their children's education (Roland and Yang, 2016) and may have increased willingness to both persevere and face new opportunities (Zhou and Hou, 1999). While one might expect that a forced break in education and skill accumulation would have a negative impact on income, the experience seems to have resulted in neither (Xie et al., 2008; Zhou and Hou, 1999). Results on whether belief in whether one's effort pays off are mixed, with studies indicating both positive (Gong et al., 2017) and negative effects (Roland and Yang, 2016).

Although the Sent-Down Movement was aimed at changing people's values, however, there have been few causal studies of its success due to data limitations of most national surveys, which do not provide rich detail on individuals' economic preferences. We, therefore, administered a large scale specialized survey which consists of both the Global Preference Survey (Falk et al., 2015) and some standard economic experiments that elicit preferences (Andreoni and Miller, 2002). We then estimate the effects of the sent-down experience on an individuals' economics preferences using a regression discontinuity (RD) approach with the birth cohort as the running variable, to help us control for selection bias.

We find that the Sent-Down Movement significantly changed participants' economic preferences.

People who were sent-down are more risk-averse, more likely to return others' kindness and more altruistic. They also are less likely to support redistribution policies and trust the government. The results are robust to alternative regression function specifications and bandwidth choices.

Our paper makes two contributions to the literature. First, our paper adds to the literature studying China's Sent-Down Movement. Second, it adds to the literature on how personal experiences impact individuals' economic preferences. The chapter proceeds as follows: In Section 2, we provide the background of China's Sent-Down Movement. We discuss why the government launches this movement, who is eligible to be sent down, what the sent down youth did in the rural area, and identify specific preferences that the Chinese government wished to shape. In Section 3, we describe our survey and data. In Section 4, we discuss our approach to statistical inference, our empirical model, and its validity. We present the main results and several different robustness checks in Section 5, and conclude in Section 6.

2.2 Background

2.2.1 The goals of the Sent-Down Movement

The sent-down movement was part of the Cultural Revolution, which started on August 8 1966, aimed at driving out traditional or capitalist ideas, and replacing them with Chinese communism. While there is substantial disagreement about the precise motivation for sending teenagers to rural areas, one can think about the Sent-Down Movement as having had three goals (Dietrich, 1997; Pye, 1986). The first was to solve urban unemployment by redistributing labor to rural areas following the Great Chinese Famine. The second was that the Chinese Communist Party was concerned that pro-bourgeois thinking was prevalent among young people, and believed that this could be re-mediated if the youths were re-educated by workers and farmers who lived in more collectivist communities. Note that re-education was explicitly ideological rather than academic, as the urban youth already had greater academic achievement than the peasants. The third was that the Chinese government wanted to develop its rural areas, a goal which required labor resources to accomplish. An additional purpose of the movement was to diffuse fanaticism associated with the Red Guard, a student movement formed in support of the Cultural Revolution, by separating and relocating its members.

2.2.2 Who was sent-down

The large-scale Sent-Down Movement[1] started in 1966, and became an official policy in 1968. One third of the urban youth in the affected birth cohorts (1950-61) were sent down, totalling 17 million people (Deng and Treiman, 1997; Honig and Zhao, 2015; Li et al., 2010; Price, 2017; Yuan, 2017; He, 2018).

During this period, all primary and secondary schools were closed for two to three years. All universities were also closed from 1966 to 1971, However, the students who entered university before 1966 and had not graduated could stay in the school until they graduated and were assigned a job. After 1971 universities re-opened and began to admit students with new admission criteria, admitting students from families of workers, peasants, soldiers and Party cadres. High school graduates permitted to attend college only after being sent down, however (Deng and Treiman, 1997; Zhang et al., 2007).

2.2.3 The Sent-Down Experience

The send-down experience was a traumatic event for participants on a number of dimensions. First, living in a rural area is much different than an urban area. Next, the youth were separated from their families, and many were allowed visits for only a few weeks every three years. In the beginning, they were required to engage in harsh agricultural production; many people had to work 12 hours a day, 7 days a week (Zhou and Hou, 1999).

Eventually it was determined that the sent-down youth, who had no prior training or experience as farm laborers, were unsuited to the work. However, the sent-down youths had completed more formal schooling than rural residents. As the program evolve, therefore, the sent-down youth were reassigned to technical job such as study counselors, agricultural technicians, physicians, teachers, and even local leaders (Gu, 2009).

Some additional details about the movement were useful in planning our data analysis strategy. First, there is a birth data after which no one was sent down, establishing an abrupt difference between those born before and after that date. To see how we determine this date, one must first note that only teenagers who graduated from junior and senior high school, called ”the knowledgeable youth,” were eligible to be sent-down. According to China’s schooling policy, children had to be at least 7 years of age to enter primary school. It took at least 6, 3 and 3 years to finish primary, junior high and senior high school, respectively (Li et al., 2010). Hence the youngest sent down teenagers were 16 years old (7+6+3). The last year of the program was 1977. Hence, teenagers who born before September 1st 1961 were likely to be sent-down, but those born after September 1st were ineligible. Second, this movement was mandatory, which reduces any selection bias problem.

[1] A small scale, voluntary Sent-Down movement started in 1955. The “Voluntary Youth Team for Reclamation,” a group of 66 urban, teenage revolutionaries went to the “Great Northern Wilderness,”a bleak plain of Heilongjiang province close to Siberia, to reclaim the land. The Chinese government gave a national award to these young people to encourage this type of altruistic behavior

Unlike the Vietnam War draft in the United States, where draftees were disproportionately of low socioeconomic status due to high income men taking advantage of a college deferment program, participation in the Sent-Down Movement was affected neither by income, parent's education nor parental affiliation with the communist party (Zhou and Hou, 1999). In particular, despite separation and other hardships, many parents and youths would have chosen not to oppose this initiative for fear of consequences of appearing not to support the government. [2]

2.3 Data and Measurement

2.3.1 Preference measurements

We measure people's preferences using a web-based survey based on Falk et al. (2015)'s Global Preference Survey (GPS), the Chinese General Social Survey (CGSS) and Andreoni and Miller (2002)'s experiment. In addition, participants completed a demographic survey. Between March to July 2019 data was collected on Sojump (http://www.wjx.com), which is one of the most popular online survey platform in China, using their paid sample service. They randomly picked up registered users from their 2.6 million sample resources who lived in different cities in China and have diverse demographic backgrounds to send our survey. Studies from different discipline show that The Sojump sample was representative and reliable (Zhou et al., 2013). Before the start of data collection, our university's Institutional Review Board reviewed and approved the research procedure that monitors the research on human subjects. All subjects provided informed consent prior to participating. We collected 2501 response; however, 314 omitted critical information and 366 with rural household registration when they were born (who are ineligible for being sent-down) were deleted, leaving 1821 valid responses.

We measure eight kinds of preferences: risk preference, time preference, altruism, positive reciprocity, negative reciprocity, trust, redistribution preference, attitudes to equality and efficiency, and economic rationality measured by whether behavior is consistent with the Generalized Axiom of Revealed Preference (GARP). Most of the questions came from the Global Preferences Survey (Falk et al., 2015). This survey is the best way to measure the economic preference that we are interested in due to the difficulty of gathering the sent-down people from different places to participate in a standard economics experiment. The designers validate their survey questions using the experiments with financial incentives and give each question some weight to make sure this survey can capture the actual preferences without the real monetary reward. We added questions to measure four more preferences that we are interested in: trust in government (the question is from Chinese General Social Survey), trust in media, redistribution preferences, and attitude to trade-offs between equality and efficiency. In addition, participants made distributional choices by selecting points on a number of budget lines so that we could measure economic rationality using

[2] While even children of those with money and political connections would have been sent down, we can not eliminate the possibility that parents could not use their influence to have their children sent to rural areas that were closer to their family home, or find them assignments entailing less physical hardships.

Table 2.1: Survey description

Preference	Item description	Weight*	Source
Risk preference	Lottery choice task	0.53	GPS
	Qualitative survey question	0.47	
Patience	Inter-temporal choice task	0.71	GPS
	Qualitative survey question	0.29	
Positive reciprocity	Qualitative survey question	0.48	GPS
	Gift exchange task	0.52	
Negative reciprocity	Qualitative survey question: take revenge	0.37	GPS
	Qualitative survey question: punish unfair toward self	0.265	
	Qualitative survey question: punish unfair toward others	0.265	
Altruism	Qualitative survey question	0.46	GPS
	Altruism task	0.54	
Selfishness	Modified dictator game	1	Andreoni and Miller (2002)
Trust others intention	Qualitative survey question	1	GPS
Trust (government)	Qualitative survey question	1	CGSS
Trust (media)	Qualitative survey question	1	Our own question
Redistribution preference	Tax questions	1	Our own question
Equality vs Efficiency	Qualitative survey question	1	Our own question
Economic rationality	Modified dictator game	1	Andreoni and Miller (2002)

* In cases where more than one component is used to measure preferences we create an index using weights assigned by the designers of the Global Preference Survey (GPS) based on an experimental validation procedure.

GARP (Andreoni and Miller, 2002). The survey took about 30 minutes to complete, so we paid participants 22 RMB (about $3) or half of the average hourly wage rate of 40 RMB (National Bureau of Statistics of PRC, 2018).

2.3.2 Data

We collected demographic data from our participants, including whether they were sent-down, gender, income level, education level, whether they belong to a religious group group or a minority group, their father's occupation and their mother's occupation. We summarize the demographics and perform a t-test to test for demographic differences between the sent-down and control samples (Table 2.2). There are no significant differences in gender, ethnic group, education level, fathers' occupation, and mothers' occupation between the sent-down individuals and non-sent-down individuals. The only significant difference is that the sent-down cohort is older than the non-sent-down cohort because the people born after September 1961 were ineligible to be sent-down (Figure 2.1).

2.4 Method

Our goal is to determine whether there is a causal relationship between being sent-down and economic preferences. Let Y_i represent the economic preference of individual i and $sentdown_i$ be the treatment status, i.e., whether the individual was sent down. To motivate our approach,

Table 2.2: Summary statistics and t-test by sent-down status

	(1) Non-sent-down		(2) Sent-down		(3) Diff	
	mean	sd	mean	sd	b	t
Panel A: Self						
Age	58.83	8.29	65.28	5.31	-6.45***	(-19.02)
Female	0.50	0.50	0.49	0.50	0.01	(0.19)
Minority	0.06	0.23	0.05	0.22	0.01	(0.55)
Annual Income level	2.98	0.68	2.91	0.62	0.07*	(2.00)
Education level	3.51	0.80	3.37	0.81	0.14**	(3.21)
Non-religion	0.91	0.29	0.93	0.25	-0.03	(-1.82)
Panel B: Father's occup.						
Professionals	0.06	0.24	0.07	0.25	-0.00	(-0.24)
Military	0.04	0.20	0.04	0.20	0.00	(0.13)
Agriculture	0.40	0.49	0.40	0.49	-0.01	(-0.24)
Business	0.04	0.21	0.05	0.23	-0.01	(-0.72)
Leader	0.04	0.20	0.03	0.18	0.01	(0.87)
Worker	0.31	0.46	0.29	0.46	0.02	(0.79)
Non	0.03	0.18	0.04	0.20	-0.01	(-0.87)
Other	0.06	0.24	0.06	0.25	-0.00	(-0.18)
Panel C: Mother's occup.						
Professionals	0.01	0.11	0.02	0.14	-0.01	(-0.99)
Military	0.05	0.21	0.05	0.23	-0.01	(-0.42)
Agriculture	0.28	0.45	0.31	0.46	-0.03	(-1.04)
Business	0.09	0.29	0.09	0.29	-0.00	(-0.23)
Leader	0.09	0.28	0.08	0.28	0.00	(0.32)
Worker	0.19	0.39	0.20	0.40	-0.01	(-0.50)
Non	0.29	0.45	0.24	0.43	0.05	(1.93)
Other	0.00	0.07	0.00	0.05	0.00	(0.69)
Observations	1390		431		1821	

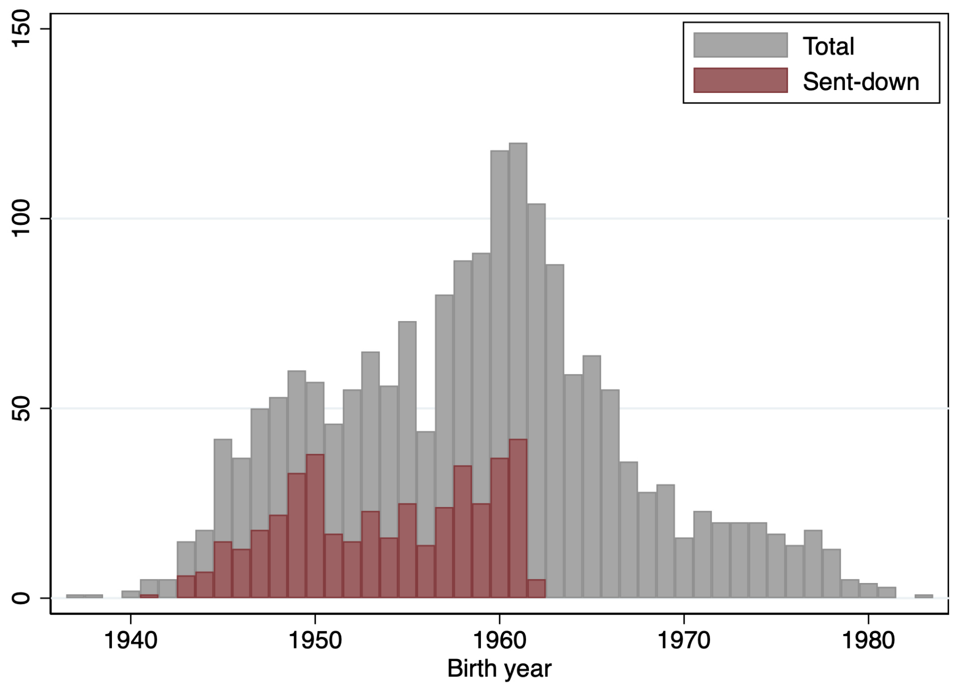

Figure 2.1: Distribution of birth year and percentage sent-down

consider an OLS regression.

$$Y_i = \beta_0 + \beta_1 sentdown + \varepsilon_i \tag{2.1}$$

Equation (2.1) compares the preferences of sent-down individuals to the preferences of non-sent-down individuals. In the event of non-random selection of individuals who were sent down, ordinary least squares has the potential to produce biased results. First, although participation in the sent down was compulsory, some individuals who were especially sympathetic to the government's goals volunteered to relocate themselves to the countryside. Second, even though the families of individuals who were sent-down did not differ by income, parent's education nor parental affiliation with the communist party, there may still have been families with the power to keep all of their children in the city (Zhou and Hou, 1999). Third, the government allowed multi-child families to keep one or more children in the city if they already sent some children down. We have no information on how families chose which children to send down, but we cannot exclude the possibility that the choice was based on the child's economic preferences, aka, that more altruistic children were sent-down. Any of these possibilities would bias our results if we conducted an ordinary least squares regression analysis.

For this reason, we employ a regression discontinuity design (RD). The RD approach is a quasi-experimental pre-test/post-test design strategy that is useful in establishing causality in which participants have not been assigned to conditions in a random manner. It takes advantage of a discontinuity in the data, in this case, the end of the Sent-Down Movement, and compares observations which lie on either side of this threshold. Since there are untreated observations on both sides of the program end date, we adapt a fuzzy RD design to identify the causal effect of the Sent-Down movement on individuals' economic preferences.

2.4.1 The regression discontinuity design

A fuzzy RD approach provides us with a research design that makes the discontinuity be an instrumental variable for the status of being sent-down, which can be regarded as a locally randomized experiment. In the fuzzy RD design, whether one is sent down partially depends on the location of one's running variable, in this case the birth year and month, relative to the cut-off point. The first consideration about setting the cut-off point is that around the point, there must be a discontinuity of the probability of being sent-down. The two key facts we emphasize in Section 2 help us to determine the cut-off point for birth cohort: (1) the last sent-down activity happened in 1977, (2) the teenagers who are eligible to be sent down must graduate from high-school graduates, and the schooling policy requires children who are at least seven years old in September to enter the primary school and spend at least 6 years and 3 years to complete the primary school and junior high school, meaning that students generally finished junior high school at age 16. Combining the compulsory schooling policy and the Sent-Down Movement, the last birth cohort affected by the movement was born before September 1st, 1961 meaning that they would have graduated from junior high school in the summer of 1977. Hence we set the cut-off point for the birth year and month is September

1961. The individuals who born before then had a chance of being sent-down, and anyone born after then was ineligible to be sent-down. We then compare the economic preferences of individuals born immediately before and after September 1961. The second necessary condition is that there is no confounding discontinuity at the cut-off point. What is the reason why we choose the end of the Sent-Down Movement as the cut-off, rather than the beginning. The beginning of the Sent-Down Movement faces a severe confounding discontinuity of the probability of entering college (Shi and Zhang, 2019). As we introduced in Section 2, the beginning of the Sent-Down movement is 1966 and at the same year, all of the universities were closed. Hence there is a discontinuous jump of being sent-down as well as a discontinuous drop of entering the college. Hence, we decide to use the end of Sent-Down Movement as the cut-off point.

We can define that:

$$P_r\left(\text{sentdown}_i = 1|x_i\right) = E\left(\text{sentdown}_i|x_i\right) = \begin{cases} g_0\left(x_i\right) & \text{if } x_i \leq x_0 \\ g_1\left(x_i\right) & \text{if } x_i > x_0 \end{cases} \tag{2.2}$$

where $g_0(x_i)$ is the density function of being sent-down before the cut-off and $g_1(x_i)$ is the density function of being sent-down after the cut-off. x_i is the running variable, the birth cohort, and x_0 is the cut-off point of the running variable, defined as the birth cohort of September 1961. We assume that $g_0\left(x_i\right) > g_1\left(x_i\right)$ at the cut-off point x_0.

$E[Y_{0i}]$ is the expected value of preferences of all the individuals if there was no Sent-Down Movement. We assume that around the cut-off point x_0, $E[Y_{0i}|x_0]$ is smooth and $E[Y_{0i}|x_0] = f(x_i)$. Suppose the effect of the treatment, being sent-down, is ρ, and we have $Y_{1i} = Y_{0i} + \rho D_i$, where $D_i = 1$ if the individual was sent-down and Y_{1i} is the preference of the sent-down individual. Now we have:

$$Y_i = f\left(x_i\right) + \rho D_i + \varepsilon_i \tag{2.3}$$

Since $E[Y_{0i}|x_0]$ is smooth at point x_0, we know that

$$\lim_{x_i \to x_0^+} E\left[f\left(x_0\right)\right] = \lim_{x_i \to x_0^-} E\left[f\left(x_0\right)\right] \tag{2.4}$$

Thus we have

$$\lim_{x_i \to x_0^+} E\left[Y_i|x_i = x_0\right] - \lim_{x_i \to x_0^-} E\left[Y_i|x_i = x_0\right] = \rho\left(\lim_{x_i \to x_0^+} E\left[D_i|x_i = x_0\right] - \lim_{x_i \to x_0^-} E\left[D_i|x_i = x_0\right]\right) \tag{2.5}$$

From equation (2.2), we know that the $E\left[D_i|x_i\right]$ is not smooth at the point x_0. So we can get that

$$\rho = \frac{\lim_{x_i \to x_0^+} E\left[Y_i|x_i = x_0\right] - \lim_{x_i \to x_0^-} E\left[Y_i|x_i = x_0\right]}{\lim_{x_i \to x_0^+} E\left[D_i|x_i = x_0\right] - \lim_{x_i \to x_0^-} E\left[D_i|x_i = x_0\right]} = \frac{\beta_1}{\alpha_1} \tag{2.6}$$

The empirical analysis implements a Fuzzy RD by using the two-stage least squares (2SLS) regression, making the discontinuity of the probability of being sent down an instrumental variable

(Hahn et al., 2001). The endogenous explanatory variable is the sent-down experience, and the IV is being born before September 1st, 1961. The first-stage of the 2SLS is to estimate the α_1 in equation (2.6) by

$$\min_{\alpha_0,\alpha_1,\alpha_2,\alpha_3} \sum_{i=1}^{N} K\left(\frac{x_i - x_0}{h}\right)[D_i - \alpha_0 - \alpha_1 T_i - \alpha_2 f(x_i - x_0) - \alpha_3 f(x_i - x_0) T_i]^2 \tag{2.7}$$

and the β_1 is estimated from

$$\min_{\beta_0,\beta_1,\beta_2,\beta_3} \sum_{i=1}^{N} K\left(\frac{x_i - x_0}{h}\right)[Y_i - \beta_0 - \beta_1 T_i - \beta_2 f(x_i - x_0) - \beta_3 f(x_i - x_0) T_i]^2 \tag{2.8}$$

where T_i is an indicator equal to one if $x_i \leq x_0$ and zero otherwise. h is the bandwidth selected according to Calonico et al. (2014) and $K\left(\frac{x_i - x_0}{h}\right)$ is a common triangle kernel weight suggested by Imbens and Lemieux (2008).

2.4.2 Validation of the RD design

The first important assumption of RD design is that there is no birth manipulation. Which means other than treatment status, there should not be any discontinuous differ between the people born two sides of the cut-off. In our case, it is reasonable to believe that people would not have known in 1961 that the there would be a movement in 1966, meaning that parents could not have deliberately timed the birth of children as to avoid having them sent down, so it is reasonable to treat relative birth dates as random. Nevertheless, we conduct formal validity checks. We start with an RD examination of density design by Cattaneo et al. (2018), and found that the P-value of the density of the birth cohort at the cutoff is 0.2518, so we fail to reject the null hypothesis that there is no birth manipulation at the cut-off point. This is consistent with our belief that parents were very unlikely to manipulate their children's birth dates.

The second validity test is checking whether the predetermined variables of the participants are smoothly distributed around the cut-off point. We collected four information as the predetermined variables. Which are gender, minority-status, father's occupation and mother's occupation. Figure 2.2 shows the distribution and local linear fit of these predetermined variables. We do not find any significant discontinuity in any of these variables around the cutoff from these virtual results. For more accurate test, we run the RD regression by using these predetermined variables as the dependent variables and the regression results are shown in Table 2.3. All of the coefficients are not significant, so we cannot reject the null hypothesis that the distribution of the predetermined variables is smooth and continuous around the cutoff point.

The third validity test is the confounding effect. We need to make sure there is no confounding discontinuous effect other than the Sent-Down Movement around the cut-off. The confounding change should satisfy two conditions. First, it must be discontinuous shock around the cutoff.

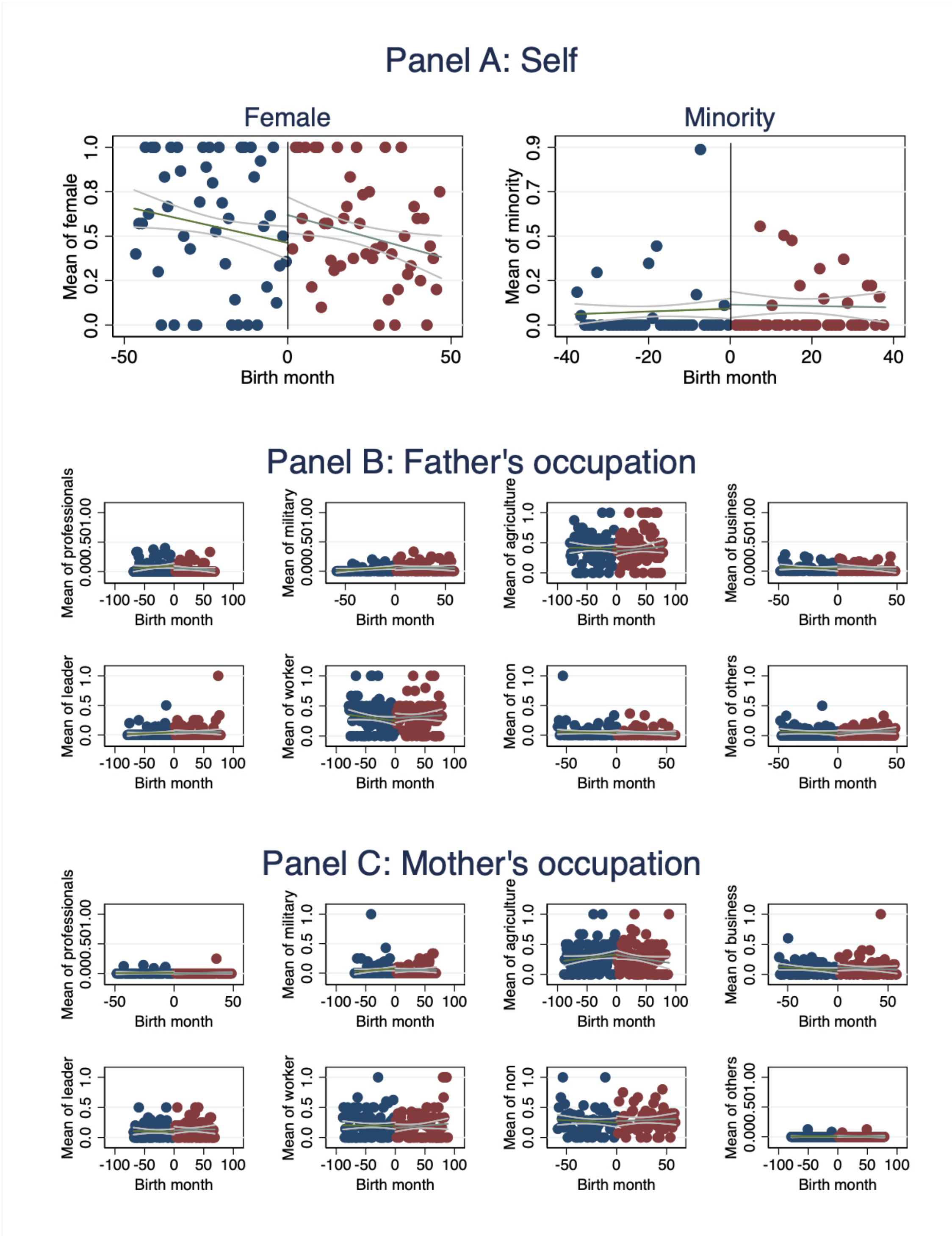

Figure 2.2: Demographic Variables: Each dot represents the mean value of the variables for the one month birth cohort. Green lines are the linear fits for each side of the cut-off; gray lines mark the 95% confidence interval.

Table 2.3: Continuity of demographic variables

Panel A: Self		
	(1)	(2)
VARIABLES	female	minority
RD_Estimate	0.105	-0.0440
	(0.0641)	(0.0300)
Eff. Observation	729	637
Robust p-value	0.0722	0.0890
Bandwith(month)	95.82	77.09

Panel B: Father's occup.								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	professionals	military	agriculture	business	leaders	workers	non	other
RD_Estimate	-0.0402	0.00515	-0.0244	0.0636*	0.000508	0.000742	0.00631	-0.00295
	(0.0344)	(0.0300)	(0.0594)	(0.0361)	(0.0233)	(0.0547)	(0.0273)	(0.0305)
Eff. Observation	947	909	1037	745	1063	1025	909	804
Robust p-value	0.308	0.929	0.789	0.0607	0.985	0.927	0.959	0.818
Bandwith(month)	140.1	130.9	162	96.51	168.8	159.2	131.9	107

Panel C: Mother's occup.								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	professionals	military	agriculture	business	leaders	workers	non	other
RD_Estimate	-0.0201	-0.0346	0.0148	0.0363	0.00755	-0.0341	0.0314	0.000663
	(0.0131)	(0.0282)	(0.0540)	(0.0370)	(0.0354)	(0.0460)	(0.0598)	(0.00903)
Eff. Observation	757	987	1079	871	968	1083	891	1013
Robust p-value	0.147	0.283	0.855	0.307	0.930	0.521	0.684	0.946
Bandwith(month)	98.40	151.8	175.2	119.4	145	176.6	124.3	157.9

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Second, it must have a significant influence on people's preferences. There are only four big shocks happened in this period and have an huge influence China's ordinary people (He, 2018; Shi and Zhang, 2019).

The first is Cultural Revolution from 1966 to 1976 causing the turmoil and change of Chinese society. The influence of the Cultural Revolution spread throughout China. We can rule this out, however, because both cohorts born before and after our cut-off experienced the Cultural Revolution. No one born around the cut-off was exempt from experiencing the Cultural Revolution. The only difference is they experienced the Cultural Revolution at different ages. Thus, we can control for the potential influence of the Cultural Revolution by controlling for the linear cohort trend.

A second possible confounding factor is the closure of all level schools from 1966 to 1967. However, the cohorts around the cut-off had not yet reached schooling age by 1966; They were not affected by the closure of schools.

A third possible confounding factor is college entrance suspension. In 1966-1969, all of the universities were closed entirely. The college enrollment resumed in September 1970. This caused two discontinuity of the probability of entering the college. The first in September 1966, the college admissions rate dropped to 0 suddenly, and the second in September 1970, college enrollment jumped from 0 to a positive number. However, these two discontinuity changes corresponded to the birth cohort cut-off of September 1947 and September 1950, which are much earlier than the cut-off for the Sent-Down Movement, September 1961.

A fourth possible confounding factor is the resuming of the national college entrance examination. During the Cultural Revolution, the universities admitted students through recommendations rather than test-based examinations. After 1977, the national college entrance examination was resumed (Shi and Zhang, 2019). This led to a discontinuous opportunity to be admitted by the college for students who graduated from senior high school before 1976 and those who graduated from senior high school after 1977 (Roland and Yang, 2016). This corresponds to the birth cohort cut-off of September 1958, which is also much earlier than the cut-off for the Sent-Down Movement.

2.5 Result

2.5.1 OLS results

As we mentioned above, OLS is not a good tool to identify the causal effect due to the selection bias problem. However, it can demonstrate the correlation between sent-down experience and preference. The difference between the OLS and RD can help us distinguish the source of the self selection bias and it might help shed light on differing results from earlier studies (He, 2018; Zhou and Hou, 1999; Harmel and Yeh, 2016; Xie et al., 2008; Roland and Yang, 2016). We first run a simple OLS regression and use age, gender, education, income, minority status and religious status as control variables. The OLS results show that sent-down individuals are different in every preference we measured. However, as discussed above, we suspect that OLS might suffer from self-selection bias.

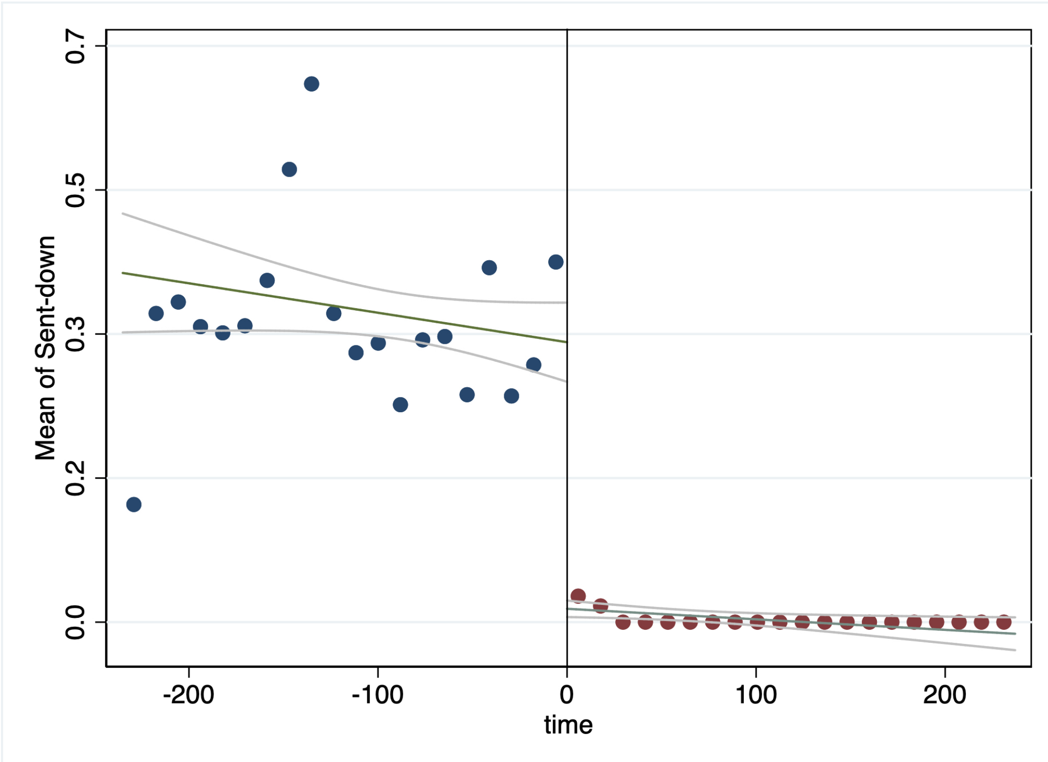

Figure 2.3: Distribution of sent-down probability: Each dot represents the proportion of people who were sent-down within each year cohort, and the green lines are the linear fits for each side of the cut-off, and the gray lines mark the 95% confidence interval.

In order to measure the Sent-Down Movement's causal effect on economic preferences, we present the RD design results next.

2.5.2 First stage results of RD design

Figure 2.3 plots the relationship between the proportion of respondents who report being sent-down and birth cohort. The first-stage regression shows that people born before the cut-off had a 44% higher probability of having been sent-down than those born after (P=0.000). This confirms that our cut-off serves as a valid instrument for the sent-down experience.

2.5.3 Main results

The regression results in Table 2.4 are consistent with the hypothesis that the experience of being sent-down changed participants' economic preferences. The birth cohort before the cut-off, the eligibility of being sent down, is used as an instrumental variable for the variable sent-down. The coefficients of sent-down are significantly positive for risk aversion (P=0.010), positive reciprocity (P=0.001), and altruism (P=0.042) and significantly negative for trust government (P=0.001), selfish (P=0.047) and redistribution preference (P=0.000). We find no effect of patience, negative reciprocity, trust others, economic rationality, and attitude to trade offs between equality and efficiency.

Comparing the RD design results to those from OLS shows that two results have switched signs. While the OLS results demonstrate that sent-down individuals are more likely to trust government and support redistribution policy, however the RD design shows that Sent-Down Movement made individuals less likely to trust government and support redistribution policy. This may be because some people who were highly sympathetic to the government policy volunteered to relocate themselves to the countryside (Zhang et al., 2007; Zhou and Hou, 1999). This suggests that statistical bias provides an explanation for why several previous studies (Zhou and Hou, 1999) showed the sent-down individuals trust government more while others (Harmel and Yeh, 2016; He, 2018) showed they trust government less.

Figure 2.4 provides visual evidence that confirms the regression results. Seven significant results, risk aversion, positive reciprocity, altruism, trust to government, trust to media, selfishness and preference of redistribution policy, change sharply at the cut-off in the figure.

2.5.4 Robustness

Regression with control variables

Previous studies have shown that individuals' socioeconomic status influences their preferences (Falk et al., 2015; Eckel and Grossman, 2002; Rao, 2014). Hence, we also control for the demographic variables in a local linear regression, including gender, minority status, income level, education level, father's occupation and mother's occupation, which may influence economic preferences. Results are shown in Table 2.5, and are similar to the baseline results in Table 2.4.

Alternative bandwidths

The bandwidth choice is an important work in the RD approach. The shorter bandwidth induces the smaller bias but larger variances. The longer bandwith can reduce the variances by increasing the bias. In the main results, we use the optimal bandwidth developing by Cattaneo et al. (2018). In this sub-section, we test the sensitivity of the effect of the Sent-Down movement to the bandwidth choice, we use different bandwidths ranging from $h^* - 18months$ to $h^* + 18months$ to do the RD regression, where h^* denotes the optimal bandwidth Cattaneo et al. (2018). The significant coefficients with optimal bandwidth are also statistically significant with different bandwidth (Figure 2.5).

Table 2.4: Baseline results

VARIABLES	(1) risk averse	(2) patient	(3) positive reciprocity	(4) negative reciprocity	(5) altruism (GPS)	(6) trust others
RD__Estimate	0.344***	0.0213	0.979***	-0.158	0.244**	-0.109
	(0.133)	(0.123)	(0.183)	(0.109)	(0.119)	(0.159)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	578	1090	987	956	909	902
Conventional Std. Err.	0.133	0.123	0.183	0.109	0.119	0.159
Conventional p-value	0.00996	0.863	9.43e-08	0.148	0.0406	0.491
Robust p-value	0.00996	0.257	0.00121	0.130	0.0429	0.570
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
Bandwith(month)	68.18	179.5	151.6	142.6	130.2	129
VARIABLES	(7) trust government	(8) trust media	(9) equality vs efficiency	(10) selfish (dictator game)	(11) redistribution policy	(12) CCEI
RD__Estimate	-0.618***	-0.161	-0.528**	-0.493*	-0.741***	0.00124
	(0.176)	(0.151)	(0.221)	(0.263)	(0.137)	(0.00336)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	891	947	830	860	765	882
Conventional Std. Err.	0.176	0.151	0.221	0.263	0.137	0.00336
Conventional p-value	0.000447	0.288	0.0171	0.0610	5.85e-08	0.713
Robust p-value	0.000558	0.135	0.00892	0.0468	1.30e-05	0.495
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
Bandwith(month)	125.8	141.9	111.7	116.4	101.7	122.3

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

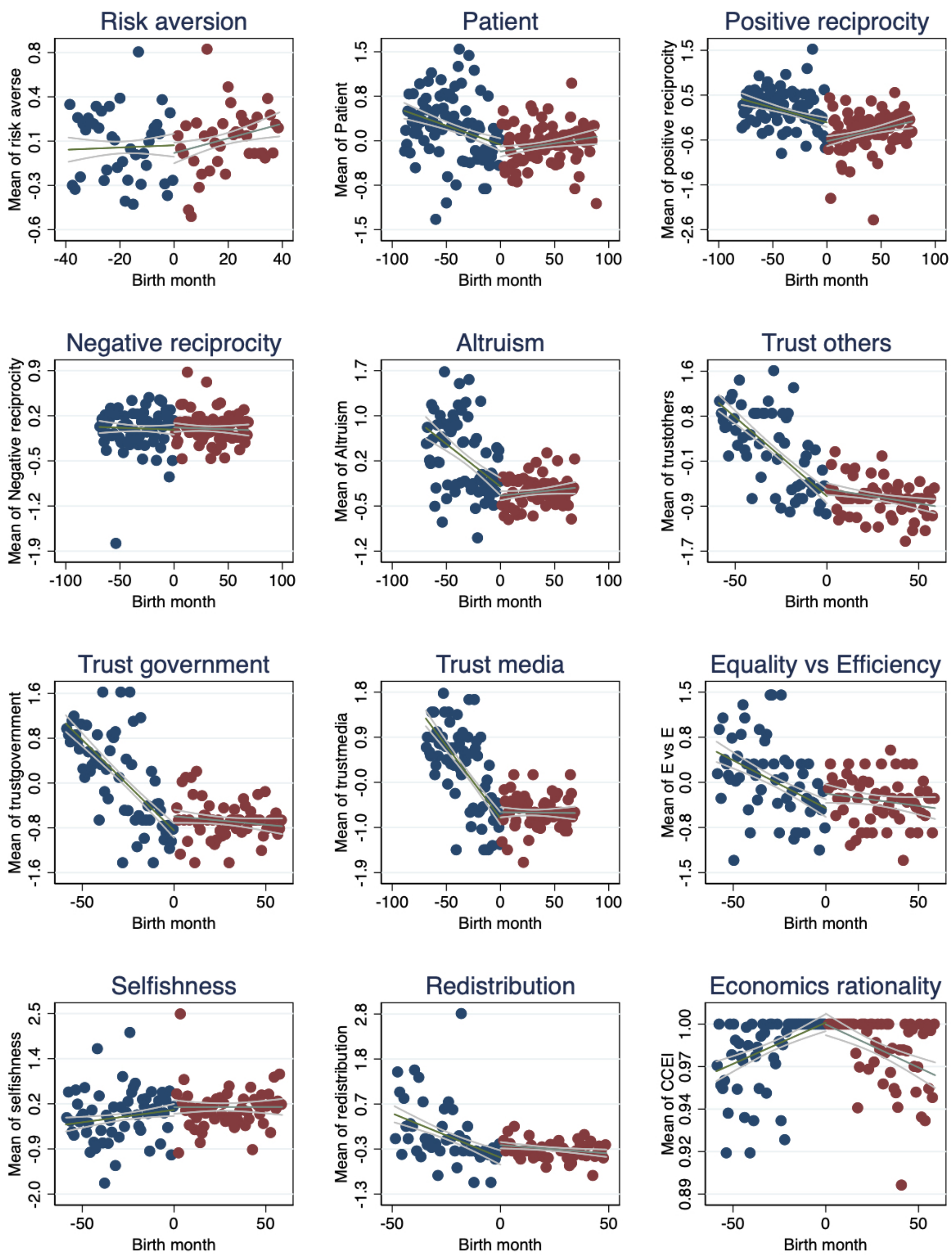

Figure 2.4: Baseline results: Each dot represents the mean value of the variables measuring each economic preference within a one month birth cohort, and the green lines are the linear fits for each side of the cut-off, and the gray lines mark the 95% confidence interval. The bandwidth is chosen by using the method of Cattaneo et al. (2018).

Table 2.5: Robustness (1): control variables

VARIABLES	(1) risk averse	(2) patient	(3) positive reciprocity	(4) negative reciprocity	(5) altruism (GPS)	(6) trust others
RD__Estimate	0.235**	-0.0254	0.906***	-0.110	0.260**	-0.151
	(0.114)	(0.124)	(0.179)	(0.105)	(0.122)	(0.156)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	956	968	983	942	909	909
Conventional Std. Err.	0.114	0.124	0.179	0.105	0.122	0.156
Conventional p-value	0.0398	0.838	4.26e-07	0.295	0.0324	0.332
Robust p-value	0.00859	0.211	0.000882	0.210	0.106	0.174
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
Bandwith(month)	142.9	145.8	149.2	138.9	130.5	130.2
VARIABLES	(7) trust government	(8) trust media	(9) equality vs efficiency	(10) selfish (dictator game)	(11) redistribution policy	(12) CCEI
RD__Estimate	-0.622***	-0.165	-0.414*	-0.513**	-0.769***	0.000714
	(0.178)	(0.150)	(0.212)	(0.236)	(0.138)	(0.00350)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	871	916	902	925	871	882
Conventional Std. Err.	0.178	0.150	0.212	0.236	0.138	0.00350
Conventional p-value	0.000483	0.269	0.0506	0.0297	2.43e-08	0.838
Robust p-value	0.00102	0.353	0.0159	0.0415	6.74e-06	0.902
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
Bandwith(month)	118.2	132.2	129	134.3	118.3	122.9

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

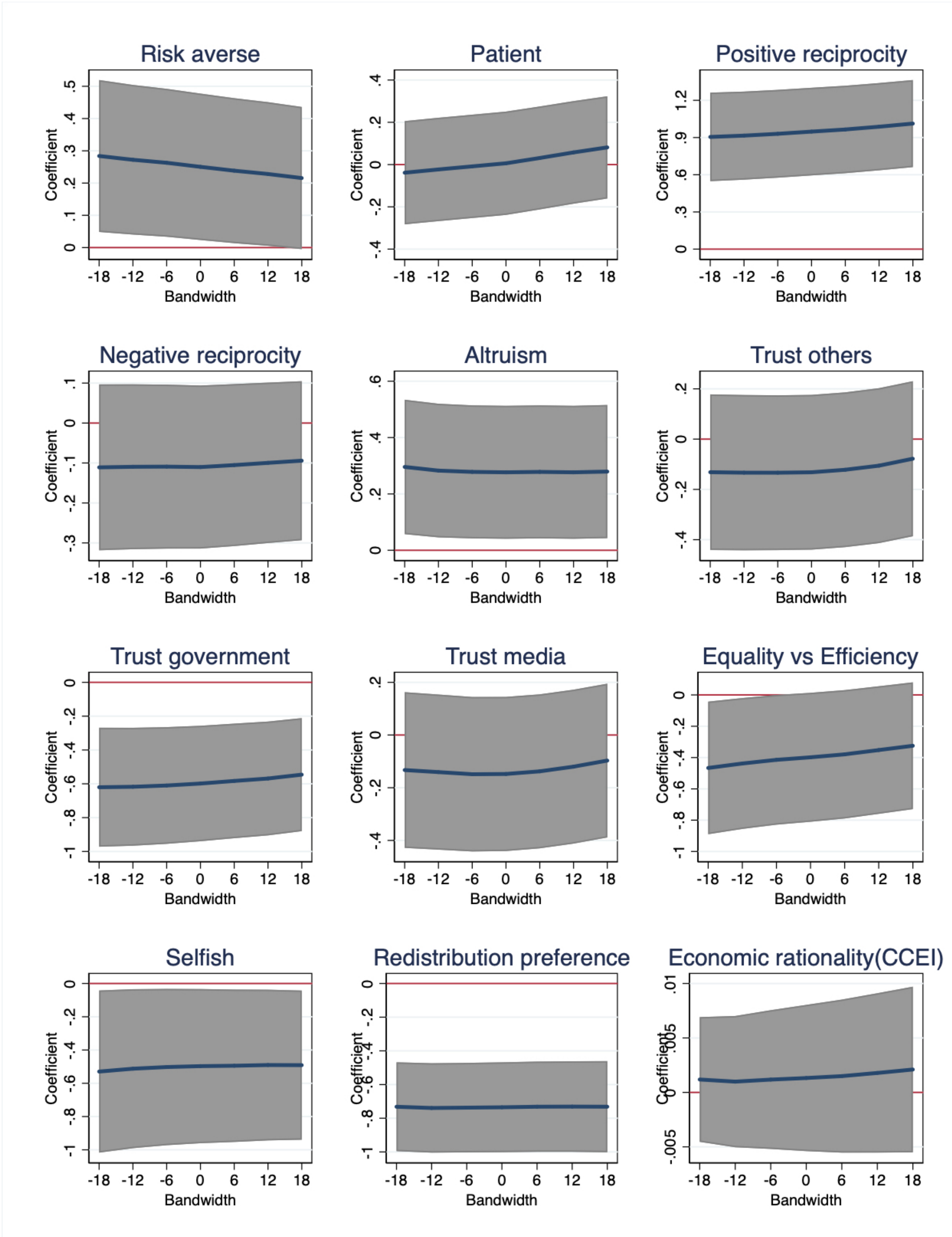

Figure 2.5: Robustness (2): different bandwidth

Table 2.6: Robustness (3): Epanechnikov kernel function

VARIABLES	(1) risk averse	(2) patient	(3) positive reciprocity	(4) negative reciprocity	(5) altruism (GPS)	(6) trust others
RD_Estimate	0.212*	-0.0570	0.951***	-0.112	0.228*	-0.176
	(0.115)	(0.130)	(0.184)	(0.109)	(0.127)	(0.164)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	942	860	930	871	909	877
Conventional Std. Err.	0.115	0.130	0.184	0.109	0.127	0.164
Conventional p-value	0.0641	0.662	2.44e-07	0.307	0.0730	0.285
Robust p-value	0.0130	0.163	0.00116	0.269	0.358	0.0428
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
Bandwith(month)	139.9	116.6	137.5	118.5	130.9	121.5
VARIABLES	trust government	trust media	equality vs efficiency	selfishness	redistribution	CCEI
RD_Estimate	-0.610***	-0.207	-0.521**	-0.396*	-0.719***	0.000915
	(0.181)	(0.155)	(0.225)	(0.229)	(0.145)	(0.00425)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	851	902	830	925	930	871
Conventional Std. Err.	0.181	0.155	0.225	0.229	0.145	0.00425
Conventional p-value	0.000729	0.181	0.0208	0.0831	7.57e-07	0.830
Robust p-value	0.00162	0.178	0.0103	0.150	3.05e-05	0.961
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
Bandwith(month)	115.2	128.5	110.8	134.4	136.8	120

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Alternative kernel function

In the main results, we use the common Triangular kernel function. To test the sensitivity of the estimate to the kernel function, we use the Epanechnikov kernel function as an alternative. The coefficients of sent-down are still very stable (Table 2.6).

Local polynomial estimation

Gelman and Imbens (2014) suggest that researchers use local linear or local quadratic estimation in the RD design. In the main results, we use the local linear regression; in this sub-section, we use local quadratic regression as a robustness check. Almost all of the effects of the sent-down experience on economic preferences remain statistically significant under this specification (Table 2.7).

Table 2.7: Robustness (4): Local polynomial estimation

VARIABLES	(1) risk averse	(2) patient	(3) positive reciprocity	(4) negative reciprocity	(5) altruism (GPS)	(6) trust others
RD_Estimate	0.340***	-0.221	0.847***	-0.148	0.421***	0.0336
	(0.127)	(0.146)	(0.195)	(0.117)	(0.142)	(0.169)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	1322	896	1267	1294	983	916
Conventional Std. Err.	0.127	0.146	0.195	0.117	0.142	0.169
Conventional p-value	0.00726	0.132	1.46e-05	0.206	0.00303	
Robust p-value	0.0114	0.143	0.00538	0.170	0.000174	0.236
Order Loc. Poly. (p)	2	2	2	2	2	2
Order Bias (q)	3	3	3	3	3	3
Bandwith(month)	246.4	127.5	228.1	240	148.3	132.1
VARIABLES	(7) trust government	(8) trust media	(9) equality vs efficiency	(10) selfishness	(11) redistribution	(12) CCEI
RD_Estimate	-0.864***	-0.154	-0.630***	-1.064***	-0.886***	0.000197
	(0.204)	(0.162)	(0.243)	(0.340)	(0.167)	(0.00400)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	1262	1054	1219	871	1201	1181
Conventional Std. Err.	0.204	0.162	0.243	0.340	0.167	0.00400
Conventional p-value	2.38e-05	0.341	0.00961	0.00175	1.18e-07	0.961
Robust p-value	0.000178	0.496	0.0122	0.000632	0.000145	0.993
Order Loc. Poly. (p)	2	2	2	2	2	2
Order Bias (q)	3	3	3	3	3	3
Bandwith(month)	226.4	164.7	213.2	119.7	206.7	201.5

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Robustness (5): Send-down duration as an alternative independent variable

VARIABLES	(1) risk averse	(2) patient	(3) positive reciprocity	(4) negative reciprocity	(5) altruism (GPS)	(6) trust others
RD_Estimate	0.0674***	-0.00578	0.184***	-0.0292	0.0447**	-0.0188
	(0.0258)	(0.0228)	(0.0342)	(0.0198)	(0.0223)	(0.0292)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	565	1045	1037	983	942	930
Conventional Std. Err.	0.0258	0.0228	0.0342	0.0198	0.0223	0.0292
Conventional p-value	0.00896	0.799	7.01e-08	0.140	0.0451	0.520
Robust p-value	0.00916	0.206	0.00119	0.139	0.0536	0.533
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
Bandwith(month)	66.79	163.9	160.1	148.2	138.7	137.2
VARIABLES	trust government	trust media	equality vs efficiency	selfishness	redistribution	CCEI
RD_Estimate	-0.111***	-0.0280	-0.0962**	-0.0952*	-0.137***	0.000281
	(0.0322)	(0.0276)	(0.0410)	(0.0488)	(0.0252)	(0.000667)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
Eff. Observation	909	968	839	839	765	916
Conventional Std. Err.	0.0322	0.0276	0.0410	0.0488	0.0252	0.000666
Conventional p-value	0.000559	0.310	0.0191	0.0508	5.59e-08	0.674
Robust p-value	0.000562	0.277	0.00991	0.0326	1.02e-05	0.416
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
Bandwith(month)	130.7	144.3	113.3	112.9	101.8	132.2

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Send-down duration as an alternative independent variable

Thus far, we use a dummy variable that whether the individuals were sent-down as the main independent variable. It is reasonable to believe that if the people stayed in the countryside longer during the Sent-Down Movement would be affected more, Hence, we use time spent in the countryside as the main independent variable to conduct the RD regression. Estimation results are reported in Table 2.8. All of the coefficients are stable, which proves our hypothesis that the longer the individuals were sent-down, the more their preferences changed.

2.6 Discussion

By examining how political movements influence people's preferences, this paper uses the Sent-Down Movement in China as a natural experiment to study the impact of policy designed to change people's economic preferences by collecting survey data using the Global Preferences Survey, and then exploiting the fuzzy RD design to estimate the causal effect of the policy.

Our results show that the sent-down experiences significantly change people's economic preferences.

It makes people become more risk averse, altruistic and more likely to engage in positive reciprocity. However they are less likely to trust government and support the redistribution policy.

Economic preferences play a fundamental role in human societies by underlying the decision making processes and behavior, and by influencing interactions within societies and markets. A rich literature of psychology and behavioral economics argues that personal experiences and environment have a significant influence on economic preferences.

Studies have shown that many types of large scale events can influence people's preferences. Living through a time characterized social disorder or war makes people become more risk averse (Kim and Lee, 2014). Experiencing an economic depression can make residents more risk-averse (Malmendier and Nagel, 2011) and support a redistribution policy more (Giuliano and Spilimbergo, 2014). Risk and time preferences depend on the stage of economic development (Tanaka et al., 2010). In wealthier villages in Vietnam, people are less loss-averse and more patient. Individuals' preferences are also affected by political institutions. Alesina and La Ferrara (2001) show that social mobility and property ownership change people's attitudes toward an economic redistribution policy. Fuchs-Schundeln and Schundeln (2015) find that people who live in a democratic country will more strongly support democracy. Miguel et al. (2010) find that people who have experienced civil war would become more violent. A field experiment by Alesina and Fuchs-Schundeln (2007) shows that the older cohorts who live in East Germany are more likely to favor an economic redistribution policy and government intervention than those who live in West Germany, however, younger cohort who were born after Germany was merged do not display these preference differences. By conducting Ultimatum game experiments in 15 small societies, Henrich et al. (2001) find that forms of production influence people's preferences. Cooperative production forms induce higher offer and higher low-offer rejection rate, independent production forms are associated with lower offer and lower low-offer rejection. Studies also find that age (Guiso et al., 2008; Dohmen et al., 2017), peers (Rao, 2014) and school curriculum (Cantoni et al., 2017) change individuals' economic preferences. Interests and beliefs of the public also be altered by government policy (Campbell, 2012).

Given our findings it is natural to explore mechanisms through which preferences were changed, which we do by preference type. Two possible explanations can help to understand why sent-down individuals are more altruistic. First, as we mentioned, the Sent-Down Movement aimed to make youths more altruistic; hence, people who were sent-down received more education on the importance of altruism. They were only allowed to read books that taught people to be pro-socialism and altruistic. The second reason is that hard life and harsh work in rural areas requires people to help each other and support the collective effort in order to survive. Thus altruism and group loyalty may be evolutionarily successful strategies (Simon, 1993). Henrich et al. (2001) also shows that societies that collectively perform harsh work such as hunting are more altruistic.

There are two possible reasons why sent-down people are more willing to return others' kindness. The first reason is that the sent-down youth had higher academic achievement than rural farmers, hence they brought needed skills with them and frequently worked as teachers, technicians, or physicians. In return local residents helps them to adapt to the hard conditions they found in rural area. In response, the sent-down youth learned to return others' kindness. The second reason is similar to mechanism which may have produced altruism: positive reciprocity may have increased group loyalty, and group loyalty helps people survive during hard times (Zhang et al., 2007; Zhou and Hou, 1999; Yang, 2003). Note that this did not translate into government led reciprocity - However, those who were sent-down people support redistribution policy and trust the government less. We speculate that this is due to unhappy experiences associated with being sent-down.

Thus the findings of this paper have important policy implications that government policies may have intended consequences in that they not only have direct and planned, but may also have unintended negative consequences on citizen's long term preferences. Although our paper is based on a specific policy adopted in China, the conclusions of our paper contribute to our understanding of the effect government can have on individual preferences. It suggests that other government policies, such as De-Sinicization in some East Asia Countries or regions, or social disorder such as Arab Spring, may lead to both good and bad long-term preference changes.

Chapter 3

Pupil-linked arousal modulates attention and fictive learning in sequential investing

Xiaomeng Zhang, Sheryl Bal and Alec Smith

(ABSTRACT)

Experimental research shows that human decision making is shaped by emotions associated with an outcome's success or failure. Regret, for example, is a powerful predictor of future investment decisions in asset markets. Using a fictive learning model to capture regret, we examine changes in pupil diameter of human participants performing a sequential investing task. By manipulating task uncertainty, we show that pupil dilation is positively correlated with both asset price variance and regret. In addition, pupil linked arousal is positively associated with the learning rate. We conclude that the pupil–linked arousal system helps regulate investment behavior in a dynamic market environment.

3.1 Introduction

How individuals make investment decisions is an important question in economics, finance, and other behavioral sciences. Because asset prices are uncertain, research has explored how people learn about asset values and decide when, and how much to invest. One model of valuation and choice is fictive learning, in which decisions are directed by ”fictive” outcomes, meaning outcomes that have not been experienced. Here individuals adjust their behavior in response to fictive errors, the difference between received and maximum possible rewards (Lohrenz et al., 2007; Chiu et al., 2008; Coricelli et al., 2005; Camille et al., 2004; Hazan and Kale, 2015; Frydman and Camerer, 2016; Gu et al., 2014; Bault et al., 2016). Since regret is an emotion associated with missed opportunity, a fictive learning model is consistent with the notion that investment decisions involve affective or emotional arousal (Sokol-Hessner et al., 2009; Smith et al., 2014; Shiv et al., 2005). Arousal systems include the noradrenergic brainstem nucleus locus coeruleus (Aston-Jones and Cohen, 2005; Nieuwenhuis et al., 2011; Jepma and Nieuwenhuis, 2011; Gilzenrat et al., 2010), which affects pupil diameter, and is an important component of affective responses (Bradley et al., 2008; Preuschoff et al., 2011), is thought to guide the focus of attention (Coull et al., 1997; Sara, 2009), and is known to modulate information processing such as learning, inferring, and predicting (Nassar et al., 2013, 2010; Urai et al., 2017; Aston-Jones and Cohen, 2005; Murphy et al., 2016; Eldar et al., 2013). Motivated by these findings, we compared the Bayesian optimal model and the fictive learning model, examined whether increased autonomic arousal, as measured by pupil dilation, would lead to increased fictive learning, and explored how this is reflected in choice, We find evidence that the arousal system plays a computationally complex roles in making investment decisions.

We used a sequential investing task to create a learning environment with quantifiable fictive errors and eye-tracking to measure eye movement and record changes in pupil diameter as indicators of arousal in 67 human participants (Fig. 3.1a) (Wang J Tao-yi and Camerer, 2010; Krajbich and Rangel, 2011). The sequential investing task has two 48-trial blocks which differed by the level of price variation, creating a “low noise block” and a “high noise block” and participants saw these blocks in different orders. Each trial consisted of a number of steps: first participants allocated their endowment between a risky asset and cash by moving a centrally placed slider bar; next the new price of the risky asset was revealed; following this, participants viewed a graph of the price history of the asset; and finally the participant’s saw a portfolio summary which summarized information about the market and their earnings (Fig. 1a). The risky asset price followed a two-state (good or bad) Markov-switching Gaussian random walk with a state switching probability of 20%, where $r_t = \mu dt + \sigma dZ_t$ in the good state and $r_t = -\mu dt + \sigma dZ_t$ in the bad state. Here r_t is the price change rate in trial t, μ is equal to 5% and $Z(t)$ is white noise. σ differs between the blocks, taking the value 0.05 in low noise block and 0.15 in the high noise block. In the low noise block, the drift is small so it is easy to detect state switches, however, this is not the case in the high noise block. A sample price history for each block is found in Figure 3.1b [for more market details, see Methods]. Participants were initially randomly assigned to either the good state or the bad state. Note that if the asset price increased, participants made the most money if they invested their entire endowment, whereas if the asset price decreased, they avoided losing money if they invested nothing. This structure allows us to calculate the fictive error: $f^+ = (100\% * r_t^+) - (Allocation * r_t^+)$

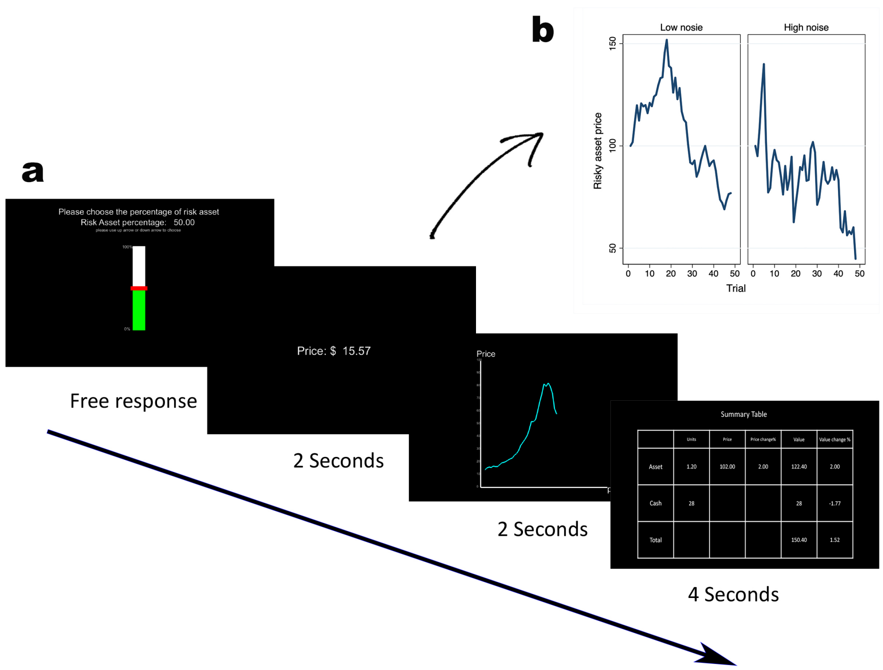

Figure 3.1: a). Timing of a trial of the sequential investing task. Each trial began with a free response period in which the participant chose the percentage of her total endowment to allocate to the risky asset. Next, the new price of the risky asset was revealed for 2s. Then the price history was displayed, followed by a summary table of participant's portfolios. b). Sample price histories for both the high and low noise blocks illustrating that the high noise block has greater price variation.

and $f^- = (0\% * r_t^-) - (Allocation * r_t^-)$. Here r^+ is the positive risky asset return, r^- is negative risky asset return, $Allocation$ is the percentage of the current portfolio invested in the risky asset, $Allocation * r_t^+$ is the experienced gain for positive return, and $Allocation * r_t^-$ is the experienced loss for negative returns.

3.2 Results

We begin with behavioral results on trial-to-trial investment behavior. As hypothesized, in the "low noise" block, we find that participants invest more in the good state than the bad state (z-scored allocation 0.095 vs. -0.212, P=0.000). In the high noise block, it is difficult for participants to determine which state they are in, thus, we observe no differences in investment behavior states (z-scored allocation 0.091 vs -0.013, P=0.126; Fig. 3.2a). Participants' investment density between the two states in the "low noise" block is significantly different (P=0.000,Kolmogorov-Smirnov test

(Lilliefors, 1967)); they make more “all-out” decisions in which they allocate 0% of their total portfolio to the risky asset in the bad state (Average 3.1 vs. 1.6, P=0.036). However in the “high noise” block the participants investment density has no significant difference between two states (P=0.159, Kolmogorov-Smirnov test) (Fig. 3.2b). Which suggested that in ”low-noise” block, participants were more confident, hence they reduce their investment rapidly when they are in bad state. However, in the ”high noise” block, the high level of price uncertainty makes it difficult for the subject to determine whether the change was caused by the state change or by the noise. As a result, their strategy adjustment becomes cautious and slow.

We next analyze decision-related pupil dilation (and, by inference, brainstem activity)(de Gee et al., 2014) to uncertainty in the market price. Previous research (Nassar et al., 2013; Jepma and Nieuwenhuis, 2011; Richer and Beatty, 1987) has suggested that changes in pupil diameter reflect the cognitive effort that individuals use to deal with task uncertainty. Once the investment decision is made for a trial, we measure pupil dilation during the 2s interval in which the new asset price was displayed using an iso-liminant display. By standardizing pupil diameter within participants to control for individual variation, we create a z-scored pupil size variable and find that pupil size in the “high noise” block is significantly larger than in the “low noise block” (0.158 vs. -0.038, P=0.006; Fig. 3.2c).

As a first pass at selecting between our two candidate decision-making models, we next explored the process by which participants made their investment decisions by noting to which information participants attended. By recording participants’ gaze–fixations during the 4s summary table, we learn that the two items to which they most attended were asset price change percentage (15.16% of total time) and total portfolio value (17.73% of total time; Fig. 3.2d). We consider two established behavioral models, the Bayesian investment model and the fictive learning model (Cyert et al., 1978; Lohrenz et al., 2007; Chiu et al., 2008). The only instrumental information for the Bayesian investment model is the risky asset price change percentage, accounts for 15.16% of participants’ total attention. For fictive learning participants also need the risky asset price change and their total portfolio value in order to determine the fictive outcome and calculate fictive error, for example, if the price increased in trial t, they have X cash and the risky asset price change is r, the fictive outcome is $X(1 + r)$.

A second model selection approach relies only upon behavioral data. Since the Bayesian investor’s objective is to maximize the expected final value of their asset portfolio and investing in the good state is more lucrative than in the bad state the investor would use the asset price return to update their beliefs about the probability that they are in a good state (Eq. 3.3 in Methods). Decisions are then based only upon this estimated probability and their risk aversion parameter. Assuming that participants have a Constant Relative Risk Aversion (CRRA) utility function (Eq.3.4 in Methods). We can then calculate the optimal Bayesian strategy based on the current probability of being in the good state for the different risk aversion level participant in both blocks (Eq. 3.12 in Method section, Fig. 3.3a). Using individual risk aversion parameters determined on the first day of the experiment (see Methods) we compare the optimal investment decision for each participant with actual choices and find that they are significantly different (P=0.000, Kolmogorov-Smirnov test; Fig. 3.3b).

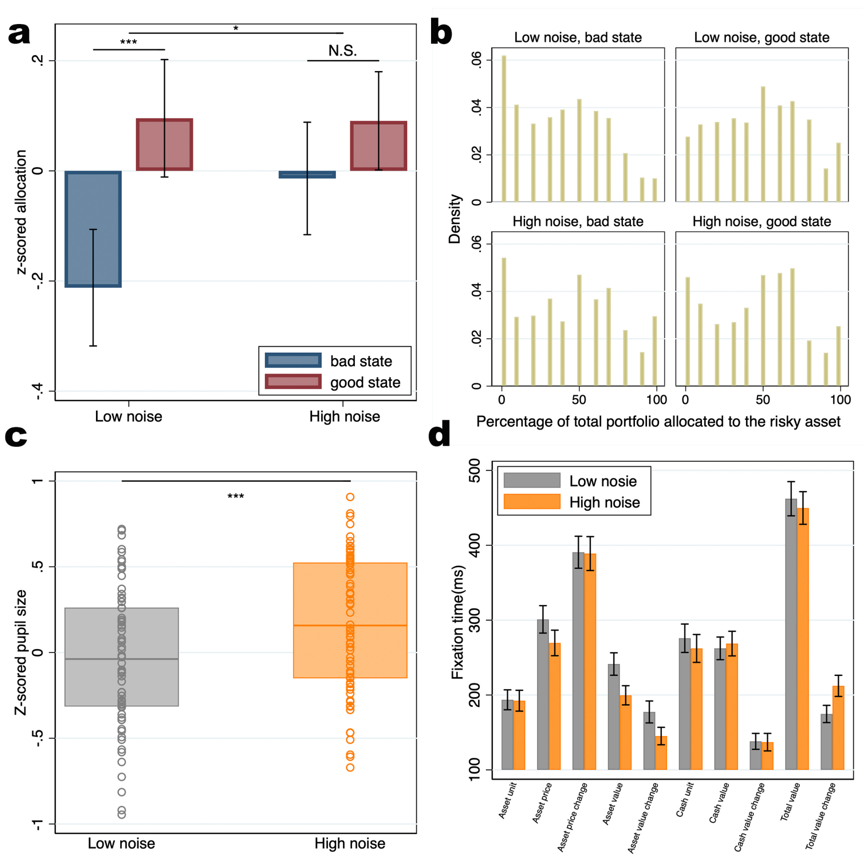

Figure 3.2: *P<.1, **P<.05, ***P<.01. Error bars indicate 95% confidence intervals. a) In the low noise block we find that participants invest more in the good state than the bad state (z-scored allocation 0.095 vs. -0.212, P=0.000). In the high noise block, it is difficult for participants to determine whether they are in the good or bad state, and we observe no differences in investment behavior (z-scored allocation 0.091 vs -0.013, P=0.126). b) A Two-sample Kolmogorov-Smirnov test for equality of distribution functions shows that the investment distributions between the two states in the low noise block are significantly different (P=0.000), however, this is not the case in the high noise block (P=0.159) c). Z-scored pupil size is significantly larger in high noise block (z-scored pupil size 0.158 vs -0.038, P=0.006), demonstrating a link between uncertainty and pupil-linked arousal. d) Participants' attention allocation shows participants pay the most attention to total value (17.73%) and risky asset price change (15.16%).

A third approach takes advantage of pupil dilation data and the Bayesian investor, they would have less arousal when the market price change is large in either direction because it is easier to determine whether they are in the good or bad state. This implies that pupil dilation should have an inverse u-shaped relationship with the market price change. Instead, we find that participants' pupil diameter shows an u-shaped relationship in risky asset returns (Fig. 3.3c), indicating that large price changes are associated with higher arousal, the opposite of the expected result. Furthermore, we find that pupil dilation predicts one trial forward decreases in investment ($\rho = -0.068$, P<0.000, Fig. 3.3d). Since the price process is random, this result is more consistent with fictive learning or emotion driven behavior than Bayesian modeling, consistent with prior work that showed. Meanwhile, study has shown that an increase in pupil-linked arousal boosts the participants' tendency to alternate choices in a subsequent trial (Urai et al., 2017).

Next, we consider the fictive learning model where the investor's objective is to minimize regret. To minimize regret and investor who invested less than their entire endowment and saw a price increase should invest more in a subsequent trial following one without considering the likelihood that the price will increase further. This implies that a large price change would cause more regret, which would induce a higher level of arousal. This is consistent with our pupil diameter data. We also fit our behavioral data to this fictive learning model. To assess the impact of fictive error, $f^+ = (100\% * r_t^+) - (Allocation_t * r_t^+)$ and $f^- = (0\% * r_t^-) - (Allocation_t * r_t^-)$ on participants' behavior, we conducted linear fixed-effects multiple regression analyses on the series of risky asset's return from each participant. In the trial t, the percentage of current portfolio invested in the risky asset is denoted as $Allocation_t$ .The risky asset's return is r_t . Therefore, when the risky asset's price p_t increases at trial t, the market returns are positive and can be expressed as $r_t^+ = (p_t - p_{t-1})/p_t > 0$; while the risky asset's price p_t decreases in the trial t, the negative returns are defined as $r_t^- = (p_t - p_{t-1})/p_t < 0$. participant gains then become $Allocation_t * r_t^+$ for positive market returns, and losses are $Allocation_t * r_t^-$for negative market returns. Using the variables defined above, the following multiple regression was performed:

$$Allocation_{t+1} = \beta_0 + \beta_1 Allocation_t + \beta_2 r_t^+ + \beta_3 r_t^- + \beta_4 Allocation_t * r_t^+ + \beta_5 Allocation_t * r_t^- \qquad (3.1)$$

The results of this multiple regression are shown in Table 3.1. The only variable that does not have a significant influence on the next trial allocation is negative price return r^-. The other four terms significantly predict the next trial allocation $Allocation_{t+1}$: the current allocation to the risky asset $Allocationt$, positive changes in the market r_t^+ and the effects of fictive errors $1 * r_t^+ - Allocation_t * r_t^+$(gain) and $0 * r_t^- - Allocation_t * r_t^-$(loss). These results suggest that participant behavior are consistent with the fictive learning model,

These behavioral findings were paralleled by pupil responses except the positive fictive error term. Two things caused pupil dilation, namely, positive changes in the market r_t^+ ($\rho = 1.54$, P=0.007, a fixed effect regression) and the negative fictive errors $0 - Allocation * r_t^-$ ($\rho = -1.89$, P=0.049, a fixed effect regression) (Fig. 3.4a and 3.4b). Which suggested that the arousal system is more sensitive to the regret in losses than in gains. In other words, when the participants experienced the gains, the regret for not having invested more did not cause the pupil dilation, however, if the participants suffer the loss, the regret for not having invested less caused high-level pupil-dilation. The attention data also support this finding; in the gain trials, they pay more attention to risky

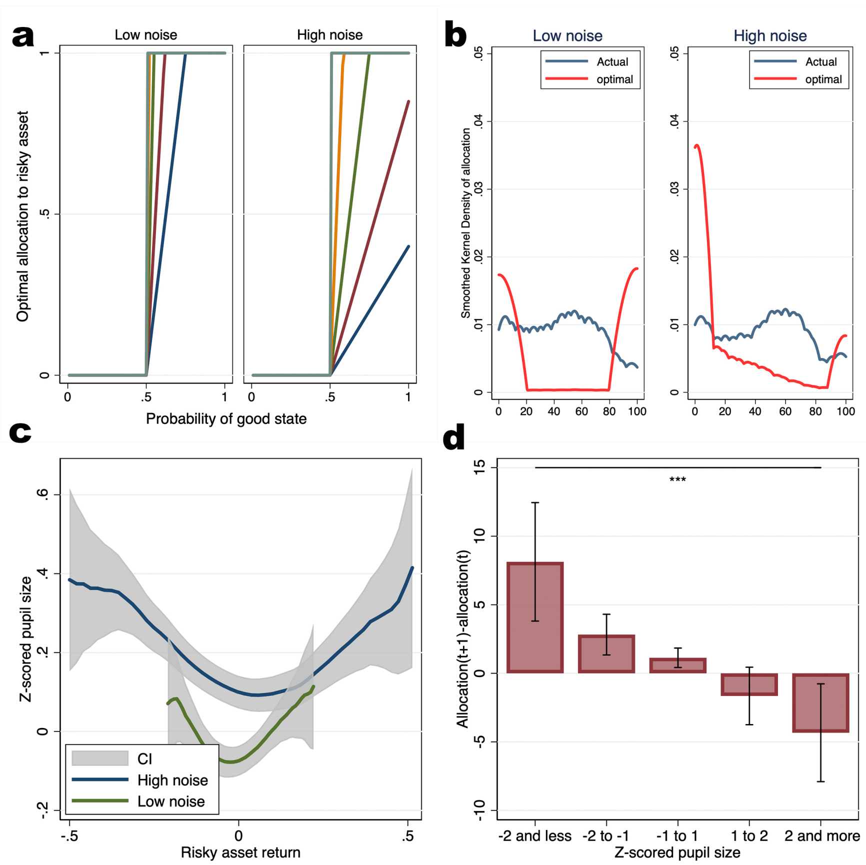

Figure 3.3: *P<.1, **P<.05, ***P<.01. Error bars indicate 95% confidence intervals. a) The relationship between Bayesian probability of good state and optimal allocation to the risky asset for different risk-averse level participants: green is a risk neutral investor with risk aversion parameter λ=0 who invests 100% in the risky asset when the probability of good state is > 50% and none probability < 50%. Other lines represent investors with increasing levels of risk aversion , yellow λ=0.3, dark green λ=0.5, λ=0.7 and blue is the most risk averse with λ=0.9. b). The density of optimal allocation (red) and actual allocation (blue). Participants' behavior significantly differs from optimal (P=0.000). c) Pupil dilation is quadratic in risky asset returns. d) Pupil dilation predicts future decreases in investment (P=0.000)

Table 3.1: Behavioral regression

Variable	Coefficient	SE	t-value	p-value
$Allocation_t$	0.52	0.05	10.14	0.000
r^+	0.80	0.18	4.43	0.000
r^-	-0.20	0.13	-1.53	0.132
$Allocation_t * r^+$	-0.54	0.25	-2.16	0.034
$Allocation_t * r^-$	-0.61	0.27	-2.29	0.026
$cons$	0.21	0.02	9.23	0.000

Results of linear multiple regression of $Allocation_{t+1}$, next allocation to risky asset, on indicated variables: $Allocation_t$ is allocation to risky asset at period t,$r^+ = max(r, 0)$, where r is the current market return, $r^- = max(-r, 0)$, and $Allocation_t * r^+$ is the return that the investors experienced for the positive market case, and similarly for $Allocation_t * r^-$. Fixed effects over participants, n= 67.

asset price (P=0.002, paired t-test), risky asset value (P=0.001, paired t-test), and risky asset value change percentage (P=0.002, paired t-test), which means they pay more attention to the risky assets information to enjoy the increase. Whereas in the loss trials, they pay more attention to the cash unit (P=0.034, paired t-test) and the total value changed percentage of their portfolio (P=0.014, paired t-test) (Fig. 3.4d) to calculate the fictive outcome.

Given the result that the participants behavior and pupil-linked arousal are driven by negative fictive error and the studies (Nassar et al., 2010, 2013; Behrens et al., 2007) that have shown that pupil-linked arousal is positively related to the learning rate. We wondered whether the pupil-linked arousal could increase the learning rate from the fictive error. In order to test whether the pupil-linked arousal caused by negative fictive error would induce an increased learning rate from the negative fictive error, we perform one additional regression analysis with an interaction term between the z-scored pupil size and all other variables (Table 3.2). The pupil diameter is significantly related to the learning rate from the negative fictive error ($Allocation * r_t^-$, P=0.007), which means that pupil-linked arousal significantly increases the learning rate from the regret (Fig. 3.4c). It also modulates the participants' attention in the high arousal trials. They have more eye-movements between the asset price and its change percentage (P=0.009, paired t-test), and between the total portfolio value and its change percentage (P=0.018, paired t-test). These kinds of eye-movements suggest that the participants pay more attention to compare the actual outcome and the fictive outcome when arousal level increases (Fig. 3.4e).

3.3 Discussion

Our work demonstrates that decision-makers learn from fictive error signals and that increased autonomic arousal is associated with increased learning. We first examined whether investors'

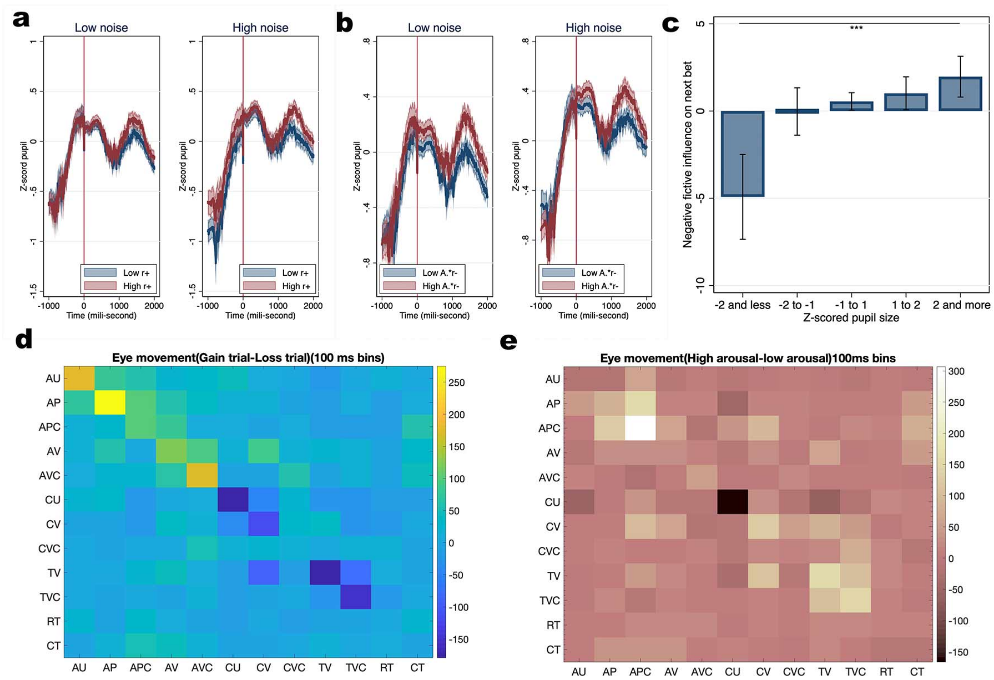

Figure 3.4: *P<.1, **P<.05, ***P<.01. Error bars indicate 95% confidence intervals. a) The high market return caused pupil dilation in the gain trials. The red line is the average z-scored pupil size against time when the participants experienced the high market return and the blue line is average z-scored pupil size against time when the participants experienced the low market return. The colorful areas are the 95% confidence intervals b). The large fictive error caused pupil dilation in the loss trials. The red line is the average z-scored pupil size against time when the participants had larger fictive errors and the blue line is average z-scored pupil size against time when the participants had larger fictive errors. The colorful areas are the 95% confidence intervals c) The pupil linked arousal increases the learning rate from negative fictive error (P=0.007). d) The eye-movement pattern shows that in the gain trials, the participants pay more attention to risky asset price (P=0.002), risky asset value (P=0.001), and risky asset value change percentage (P=0.002), while in loss trials, they pay more attention to cash unit (P=0.034) and the total value changed percentage of their portfolio (P=0.014). e) The eye-movement pattern shows that in the trials with high arousal level, the participants has more eye-movements between the asset price and its change percentage (P=0.009), and between the total portfolio value and its change percentage (P=0.018). which can be used to compare the actual market change and the fictive change.

Table 3.2: Structural fictive learning model with arousal

Variable	Coefficient	SE	t-value	p-value
$Allocation_t$	0.52	0.05	10.18	0.000
$zpupil$	-0.01	0.01	-0.77	0.446
r^+	0.77	0.18	4.26	0.000
r^-	-0.25	0.12	-2.03	0.046
$Allocation_t * r^+$	-0.44	0.25	-1.76	0.083
$Allocation_t * r^-$	-0.46	0.25	-1.85	0.068
$zpupil * r^+$	0.13	0.13	0.96	0.341
$zpupil * r^-$	0.26	0.09	2.93	0.005
$zpupil * allocation_t * r^+$	-0.31	0.19	-1.63	0.108
$zpupil * allocation_t * r^-$	-0.48	0.17	-2.78	0.007
$cons$	0.21	0.02	9.41	0.000

Results of linear multiple regression of $Allocation_{t+1}$, next allocation to risky asset,on indicated variables: $Allocation_t$ is allocation to risky asset at period t,$zpupil$ is normalized pupil size at period t, $r^+ = max(r,0)$, where r is the current market return, $r^- = max(-r,0)$, and $Allocation_t * r^+$ is the actual investor return for the positive market case, and similarly for $Allocation_t * r^-$.$zpupil * allocation_t * r^+$ is the interaction of arousal(pupil-size) and positive fictive error at period t and similarly for $zpupil * allocation_t * r^-$. Fixed effects over participants, n= 67.

behavior was driven by regret. Consistent with the outcomes of previous work (Lohrenz et al., 2007; Gu et al., 2014; Chiu et al., 2008), we find that investing decisions are driven by fictive error signals, suggesting that fictive learning more accurately models behavior than Bayesian investment. In addition, we find that negative fictive error has more influence on both behavior and arousal than the positive fictive error, suggesting that the arousal system is more sensitive to regret in losses than in gains, a result that contributes to our understanding of loss aversion (Tversky and Kahneman, 1991; Sokol-Hessner et al., 2009).

Second, we established the relationship between autonomic arousal and fictive learning. Eye-tracking data confirmed assumptions of the fictive learning model, namely, that fictive learners pays the most attention to the total value of portfolio, and exhibits signs of learning in their pupillary response: (i) Pupil dilation can be caused by the increase of the difficulty and uncertainty of the task (Jepma and Nieuwenhuis, 2011; Nassar et al., 2013; Richer and Beatty, 1987), which confirmed the idea that pupil dilation reflects the amount of cognitive effort in the learning process (Kahneman and Beatty, 1966). (ii) Negative fictive error was positively correlated with pupil dilation, a relationship consistent with pupillometry studies that showed the pupil responses to surprise associated with the risky prediction error (Raisig et al., 2010; Preuschoff et al., 2011). (iii) Pupil-linked arousal is positively associated with the fictive learning rate. These findings suggest that pupil-linked arousal systems encode both uncertainty and regret signals that facilitate learning behaviors. (iv) Pupil-linked arousal play an important role in modulating attention (Coull et al., 1997; Sara, 2009).

More generally, our results further confirm that, the brain regions of arousal and autonomic function modulate the attention patterns and regulate the influence of emotion on learning process (Critchley et al., 2001; Nassar et al., 2013; Jepma and Nieuwenhuis, 2011; Preuschoff et al., 2011; Behrens et al., 2007). These areas likely include not only the locus coeruleus but also the anterior cingulate cortex (Smith et al., 2014), whose activity encodes several signals including unsigned prediction errors and learning rates (Behrens et al., 2007; Nassar et al., 2013; Aston-Jones and Cohen, 2005; Krugel et al., 2009; Matsumoto et al., 2007). This provides supporting evidence for the Yerkes–Dodson "inverted U" relationship (Yerkes and Dodson, 1908) between arousal level and learning rate.

3.4 Methods

3.4.1 Participants

Sixty-seven participants (33 female, 34 male; ages=18–61 years), who had normal or corrected-to-normal vision, completed this study. The experiment protocol was approved by the Institutional Review Board of Virginia Tech and was carried out in accordance with institutional and federal regulations and guidelines concerning the protection of human subjects. Informed consent was obtained from all participants. This experiment was conducted in two parts, and participants were given \$5 show-up compensation for the first part and a \$10 compensation for the second part, in addition to receiving up to \$95 based on the interaction of their decisions and random chance. All data collection took place in the Virginia Tech Economics Lab.

3.4.2 Task

The first part of the study consisted of a variation of a lottery choice experiment to measure risk preferences Eckel and Grossman (2002) conducted using oTree Holzmeister (2017); Chen and Wicken (2016) without eye-tracking. One week later, the participants returned for the second part of our experiment where, after receiving instructions, the participants were placed in front of an eye-tracker using a chin rest to improve data precision. Following camera calibration and validation, performed the primary investment test. All of the participants participated in both blocks, "high noise" and "low noise" in randomly order. At the beginning of each block, there were eight passive viewing trials to help participants become familiar with the price process. Next were 40 trials for each condition where participants made investment decisions. Figure 1a shows the events and timing for each trial. The participants began the experiment with 50 experimental dollars in cash and 50 experimental dollars worth of the risky asset. In each trial, participants used buttons on a video game controller to move a slider bar to indicate the percentage of her total allocation, from

0-100% she wished to invest in the risky asset Lohrenz et al. (2007); Chiu et al. (2008). After making a decision, the participant used the red button on the controller to submit her allocation after which the new price of the risky asset was revealed and the price graph updated. Finally participants saw a tabular summary of their portfolio showing the most recent price of the risky asset, the value of the participant's holdings, and additional information, including the most recent percent change of the price of the risky asset and the overall portfolio.

The participants were instructed to make a decision in each trial to maximize their final portfolio, which is what they would be paid. The participants must make a prediction of the next trial's risky asset price according to the price change rate they have seen and the price rule they have known. They would allocate their asset to maximize their pay off. We recorded their pupil diameters when they saw the price, which is the necessary information for making a prediction.

3.4.3 Price process

The price of cash is constant in our experiment, and the interest rate of cash is 0. For the risky asset, there are two states, good state or bad state; the participant was randomly set in a good state or a bad state at the beginning of the experiment, which was not known by the participants. If she was in a good state, there is an 80% chance she would stay in a good state and a 20% chance she would change to a bad state in the next trial. The same goes for a bad state: There is an 80% chance of staying in a bad state and a 20% chance of changing state. The switch rate matrix is shown in Table 3. The price process of the risky asset obeyed the following rules: $r_t = \mu dt + \sigma dZ_t$ in good state and $r_t = -\mu dt + \sigma dZ_t$ in bad state, where r_t is the price change rate in trial t, μ is equal to 5% in our experiment and $Z(t)$ is a standard white noise. σ differs in two conditions: In the low noise condition, σ is 0.05 while in the high noise condition, σ is equal to 0.15.

Table 3.3: State switch rate matrix

		state	$t+1$
		good state	bad state
state t	good state	0.8	0.2
	bad state	0.2	0.8

The price process mentioned previously was fully known by the participants except whether they were set in a good state or a bad state at the beginning of the experiment.

3.4.4 Pupil-diameter measurements

We applied a frequency of 1000 HZ to record the participants' pupil size of the right eye throughout the task using EyeLink 1000 Desktop Mount (SR Research) . Participants were seated in a quiet room, with their head positioned on a chin rest 50 cm in front of the computer screen. We use the maximum pupil size during the 2-s price-viewing period for each trial allowing us to calculate a z-score over 96 max pupil measurements for each participant.

3.4.5 Bayesian investment model

Since an investor whose behavior is consistent with a Bayesian investment model needs well-defined probability that she is in the good state in each period we here show the calculation of that probability. Formally, let r_t be the price change rate of the risky asset the participant observed in the period t. According to r_t, a Bayesian investor would assign probability $q_t = Pr(s_t = good|r_t.r_{t-1},...,r2,r1)$ to that this trial is in the good state. Hence when a Bayesian investor observed the price change rate is r_t in trial t, she has

$$q_t(q_{t-1}, r_t) = \frac{Pr(r_t|s_t = good)Pr(s_t = good|q_{t-1})}{Pr(r_t|s_t = good)Pr(s_t = good|q_{t-1}) + Pr(r_t|s_t = bad)Pr(s_t = bad|q_{t-1})} \tag{3.2}$$

As previously discussed, in a good state, $r_t = \mu dt + \sigma dZ_t$. Let the distribution function of r_t in a good state $Pr(r_t|s_t = good)$ is $f_{good}(r_t) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(r_t-\mu)^2}{2\sigma^2}}$. Similarly, in a bad state, $r_t = -\mu dt + \sigma dZ_t$, $Pr(r_t|s_t = bad)$ is $f_{bad}(r_t) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(r_t+\mu)^2}{2\sigma^2}}$. As Table 3 shows, the state switch rate is $p = 0.2$, so given the updated belief of probability that the previous trial is in a good state q_{t-1}, $Pr(s_t = good|q_{t-1}) = (1-p)q_{t-1} + p(1-q_{t-1})$ and $Pr(s_t = bad|q_{t-1}) = pq_{t-1} + (1-p)(1-q_{t-1})$. Therefore, we can re-write Eq.3.2 as follows:

$$q_t(q_{t-1}, r_t) = \frac{f_{good}(r_t)((1-p)q_{t-1} + p(1-q_t))}{f_{good}(r_t)((1-p)q_{t-1} + p(1-q_t)) + f_{bad}(r_t)(pq_t + (1-p)(1-q_t))} \tag{3.3}$$

The optimal strategy of an investor is based on the beliefs of probability that trial t is in a good state. If she thought the trial t is in a good state, there is an 80% chance that trial $t+1$ is also in a good state and that the price of the risky asset would increase in the future and that it is better to increase the holding of the risky asset.

The functional form for a Constant Relative Risk Aversion (CRRA) utility function is shown below:

$$U(x) = \frac{1}{1-\lambda}x^{1-\lambda} \tag{3.4}$$

The investor starts with a positive initial wealth X_0 and chooses, at each time t, $0 < t \leq T$, to invest a fraction π_t of his wealth in the risky asset so as to maximize the expected utility of her terminal wealth X_{T+1}

$$\max_{\pi_t} E(U(X_{T+1})) \tag{3.5}$$

s.t.

$$dX_t = X_t\pi_t\begin{bmatrix}\mu dt + \pi_t\sigma dW(t) & -\mu dt + \pi_t\sigma dW(t)\end{bmatrix}\begin{bmatrix}q_{t-1}(1-p) + (1-q_{t-1})p \\ q_{t-1}p + (1-q_{t-1})(1-p)\end{bmatrix} \tag{3.6}$$

$$q_0 = q \tag{3.7}$$

$$X_0 = x_0 \tag{3.8}$$

In order to simplify the model and without loss of generality, we assume that the participants will maximize their one trial forward payoff instead of the final payoff. To keep the utility function consistent, the objective function of this myopic dynamics model should be:

$$\max_{\pi_t} E(U(X_{t+1})) \tag{3.9}$$

for the participant at trial t.

As we showed before, the participant still needs to guess whether she is in a good state or bad state to maximize the one trial forward payoff. Hence the expected utility function can be re-written as

$$E(U(w_{t+1})) = \begin{bmatrix} \mathbb{E}(w_{t+1}|state_t = good) & \mathbb{E}(w_{t+1}|state_t = bad) \end{bmatrix} \begin{bmatrix} q_{t-1}(1-p) + (1-q_{t-1})p \\ q_{t-1}p + (1-q_{t-1})(1-p) \end{bmatrix} \tag{3.10}$$

The first order condition of the objective function is:

$$0 = \begin{bmatrix} \mathbb{E}[(1+\pi_T r_t)^{-\lambda} r_t | state_t = good, q_{t-1}] & \mathbb{E}[(1+\pi_t r_t)^{-\lambda} r_t | state_t = bad, q_{t-1}] \end{bmatrix} \begin{bmatrix} q_{t-1}(1-p) + (1-q_{t-1})p \\ q_{t-1}p + (1-q_{t-1})(1-p) \end{bmatrix} \tag{3.11}$$

The myopic optimal strategy of this investment experiment satisfies:

$$0 = \begin{bmatrix} \int_{-\infty}^{\infty} (1+\pi_t r_t)^{-\lambda} r_t \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(r_t-\mu)^2}{2\sigma^2}} dr_t & \int_{-\infty}^{\infty} (1+\pi_t r_t)^{-\lambda} r_t \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(r_t+\mu)^2}{2\sigma^2}} dr_t \end{bmatrix} \begin{bmatrix} q_{t-1}(1-p) + (1-q_{t-1})p \\ q_{t-1}p + (1-q_{t-1})(1-p) \end{bmatrix} \tag{3.12}$$

We determined each participant's risk preference parameter λ from the risk elicitation task conducted on the first day of the experiment, which was then used to calculate the optimal allocation to the risky asset for each participant in each trial (Fig. 3.2a).

Chapter 4

Arousal, attention and lottery choice

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(ABSTRACT)

This research explores the complex process by which people make risky choices. While traditional models, like expected utility theory, model choice as selection of the outcome with the highest probability weighted value, research shows that in some environments these models do a poor job of describing behavior. This study explores the role of attention, pupil-linked arousal and salience in risky choice. First, we replicate earlier findings that that choices are consistent with expected utility theory when the calculation is easy, however, as the calculation becomes harder, they make decisions by comparing unweighted payoffs and are attend to the salient option. Further, we find that pupil-linked arousal is associated with the level of cognitive effort needed to calculate expected utility. Finally we show that arousal reflects cognitive effort associated with resisted selecting more salient option.

4.1 Introduction

Uncertainty is often a consideration when making major decisions in domains such as investment, insurance, health and education, as well as minor decisions like whether to try a new restaurant. Expected utility theory is the standard economic theory of choice under risk; it both models risky decision-making and allows researchers to estimate individuals' risk preferences. Motivated by recent work that shows that Expected Utility Theory does not reliably explain risky choice, this research explores the complex process by which make decisions. We find that attention, pupil-linked arousal and salience each play a role in the choice process.

Calculation difficulty (Arieli et al., 2011), choice architecture (Aimone et al., 2016b), age (O'Brien and Hess, 2019) and lack of a MAOA-L gene (Frydman et al., 2010) are associated with reduced chance of using an Expected Utility Theory consistent decision process when making risky choices. Eye-tracking studies show that, in addition to eye movements needed to evaluate each lottery, participants also use component comparison procedures in which attributes are compared across lotteries (Arieli et al., 2011; Aimone et al., 2016a,b; Krajbich et al., 2010). Evidence on component comparison-procedures opens the door to models such as salience theory, in which lottery attributes are compared and more salient attributes grab more of an individual's attention and limited cognitive resources (Bordalo et al., 2012; Frydman and Mormann, 2018) Thus both attention and emotional arousal play an important role in risky decision making (Sokol-Hessner et al., 2009; Smith et al., 2014; Shiv et al., 2005; Krajbich et al., 2010).

To explore individuals' risky decision making procedures, we combine methods and theories from neuroscience, psychology and economics (Fehr and Rangel, 2011). We manipulate stimulus presentation style and expected utility calculation difficulty while measuring both eye-movement and pupil diameter. Pupil diameter is an important indicator of affective arousal (Bradley et al., 2008; Preuschoff et al., 2011) which is thought to guide the focus of attention (Coull et al., 1997; Sara, 2009) and is known to modulate information processing (Nassar et al., 2010; Aston-Jones and Cohen, 2005; Eldar et al., 2013; Murphy et al., 2016). We find that when expected utility computations are easier, participants have significantly more eye movements between payoffs and probabilities, which is consistent with expected utility maximization. Interestingly, we also find more pupil dilation when expected utility calculations were easier. Defining salience as the normalized distance between the two payoffs, we find that increasing the salience of the riskier lottery increases its fixation duration as well as its likelihood of being selected. Finally, we find that pupil linked arousal is associated with increased risk avoidance when the riskier option is more salient.

The article proceeds as follows. In Section 2, we introduce our experimental design and methods. In Section 3, we present our main results. Discussion and conclusions are found in Section 4.

4.2 Experiment Design and Methods

Fifty participants (26 males and 24 females, age from 18 to 54) who had normal or corrected-to-normal vision made a series of 120 decisions that involved choosing between two lotteries. Each lottery had a chance of earning a prize and a chance of earning nothing. While participants made decisions their eye movement and pupil diameter were measured via eye tracker (1000Hz EyeLink 1000 plus, SR Research). Participants received compensation of $10 plus earnings from a randomly selected lottery outcome, resulting in average earning of $20.33. All experimental procedures were reviewed by the Virginia Tech Institutional Review board and all participants provided informed consent.

Each experimental trial (Figure 4.1a), began with the presentation of a fixation cross for 2 seconds, followed by a phase in which they viewed the 2 lotteries from which they would choose for 6 seconds while eye movements were tracked. This was then followed by a free response period in which two grey boxes appeared to indicate that participants could make a choice using the arrow key on the keyboard. Once a lottery was selective, the grey box outside the chosen alternative turned red, and participants hit the enter key to confirm their decision.

In our within-subject design, the treatment concerned whether expected payoff computations were easy or hard. Easy lotteries had at most 3 non-zero digits, for example, $3 at a 90% probability, while hard lotteries had at least 4 non-zero digits, for example, $3.7 at an 89% probability. Participants were presented with four blocks of lotteries (two easy and two hard) which were randomly presented, alternating block difficulty. Within each block lotteries were varied so that the risky lottery did not always have the highest average payoff, and so that there was significant variation in probabilities across lotteries. In order to keep the blocks similar except for calculation difficulty, lotteries in the hard block were generated by adding small, random perturbations to the payoffs and/or probabilities of the gambles in the easy blocks.

In previous studies(Arieli et al., 2011; Aimone et al., 2016a,b), information for each lottery was presented vertically, so that one lottery was in the left column and the other is on the right. To control for the potential confounding effect of reading habit, we use four presentation styles so that lotteries were presented vertically in some rounds and horizontally in others (Figure 4.1b).

To identify and categorize eye-movements, we divide the screen into four quarters: top left, bottom left, top right and bottom right. We analyze six types of eye movements based on the two quarters viewed: Payoff 1-Probability 1, Payoff 1-Payoff 2, etc., and record the time that participants spent on each type of eye-movement to uncover their decision making procedure. Remember that in order to calculate the expected utility of a lottery, a participant needs to consider both the probability and the payoff, hence the greater the percentage of time spent on Payoff 1-Probability 1 and Payoff 2-Probability 2, the more consistent eye movements are with expected utility theory (EU eye-movement). Similarly, the more time a participant spends comparing the attributes of lotteries, Payoff 1-Payoff 2 and Probability 1-Probability 2, the more consistent their eye movements are with component comparison (Figure 4.2).

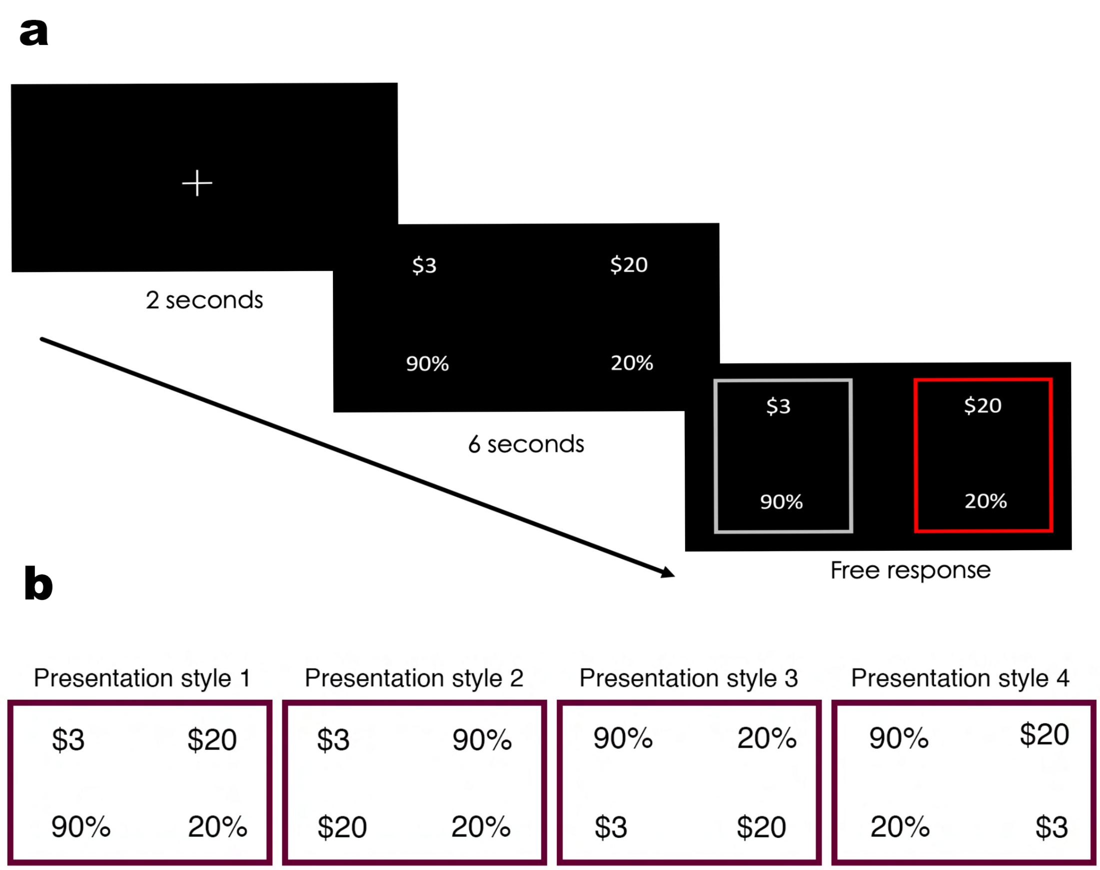

Figure 4.1: a) Sequence of events during a single trial. b) Choice presentation styles used in this study.

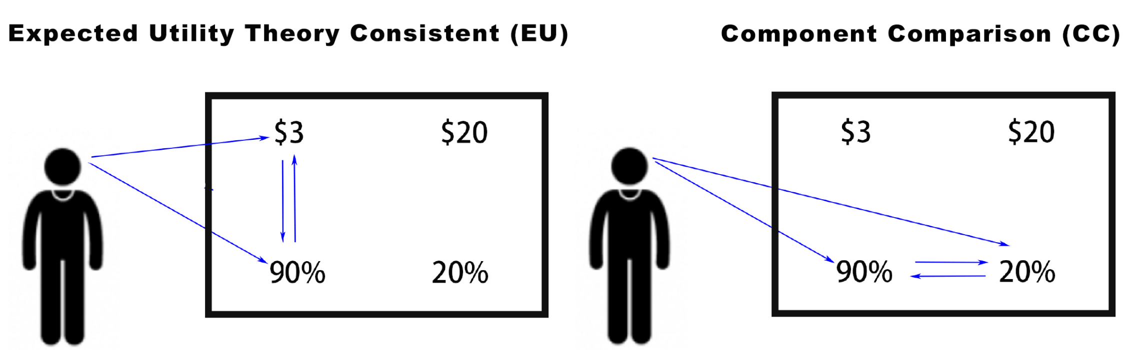

Figure 4.2: Eye movements in the experiment by evaluation procedure

4.3 Results

We begin with behavioral results. We first compare choice frequency for the lottery with the higher expected monetary value (EMV), a special case of expected utility where the utility function is linear. We find no significant difference in the frequency of EMV choices between easy and hard blocks (P=0.195, paired t-test,Figure 4.3a). Participants chose the risky (high payoff and lower probability) lottery significantly more often in the hard blocks (P=0.023, paired t-test, Figure 4.3a). Although participants choose a similar amount of high EMV lotteries between two kinds of blocks, the structure of the high EMV choices are significantly different. In the hard blocks, participants chose more risky lotteries with low EMV (P=0.000, paired t-test,Figure 4.3b), more safe lotteries with high EMV (P=0.016, paired t-test,Figure 4.3b), but fewer safe lotteries with low EMV (P=0.000, paired t-test, Figure 4.3b). Given that the risky lotteries have a larger payoff and lower probability, selecting more risky lotteries with lower EMV suggests that participants may be attracted by the payoff and choose it even when the EMV is lower, so that payoff salience might play an important role in the decision making-process.

To infer the choice procedures used by participants we compare their eye movement patterns. Previous studies have established that eye tracking can be used to examining choice procedures to understand decision making processes (Arieli et al., 2011; Aimone et al., 2016a; Reutskaja et al., 2011; Wang et al., 2010). The percentage of time engaged in EU consistent eye movement in easy blocks is significantly higher than that in the hard blocks (P=0.000) while the percentage of time engaged in CC eye movement in easy blocks is significantly lower than that in the hard blocks (P=0.000, Figure 4.3c). To confirm this finding and identify attributes comparisons in the hard blocks, we compared eye movements between attributes in both types of blocks. We calculate the proportional eye transition duration from time t ms to time $t+1$ ms between attributes in the easy block and it subtracted from that of the hard block (Figure 4.3d). In the easy blocks, participants spend more time looking back and forth between the lottery's payoff and its probability (EU consistent eye movement, P=0.022). In the hard block, they spend significantly more time looking between the payoff in each lottery (P=0.000). This is consistent with Arieli et al. (2011)'s results: if the lottery's expected utility is easy to calculate, participants spend time to calculate it and use the results to arrive at their decision. As the calculation difficulty increases, however, participants give up doing calculations and make decisions based on most frequently on comparing payoffs, and less frequently on comparing probabilities.

Research has shown that pupil dilation reflects cognitive effort (Kahneman and Beatty, 1966). We measure pupil dilation during the 6s lottery observation period. By standardizing pupil diameter within participants to control for individual variation, we create a z-scored pupil size variable to use in our analysis. We first conducted a fixed effects regression where z-scored pupil size is modeled as a function of average time engaged in EU eye-movement across all trials. We find that there is a positive relationship between the time engaged in the EU eye-movement and the z-scored pupil size, which suggests that when participants try to calculate the expected utility of a lottery, they exert more cognitive effect (P=0.03, Figure 4.4a). This result is consistent with recent studies that show that multiplication problems evoke pupil dilation (Ahern and Beatty, 1979; Boersma et al., 1970; Hess and Polt, 1964; Klingner et al., 2011; Payne et al., 1968; Schaefer et al., 1968).

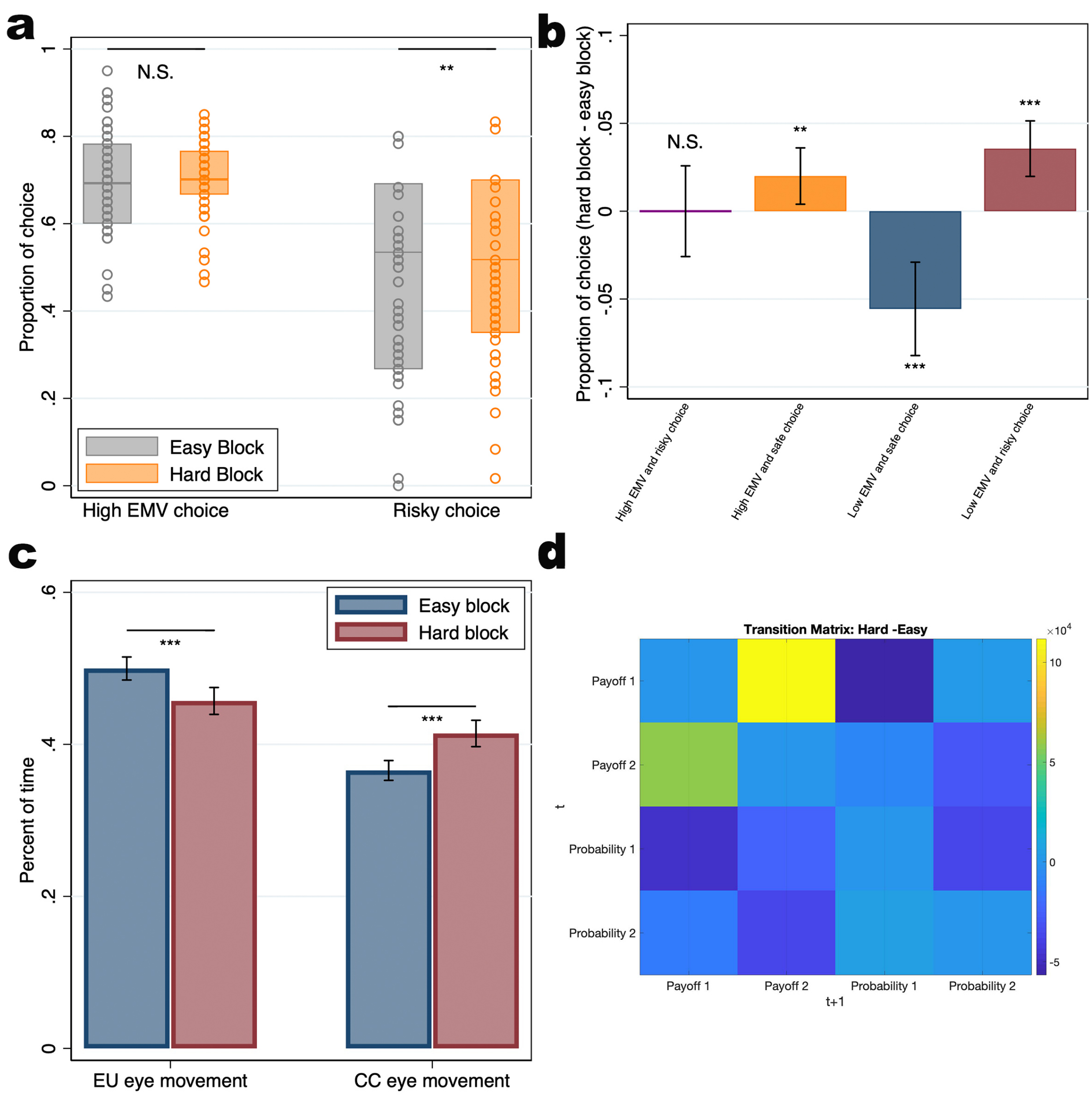

Figure 4.3: $*P < .1, **P < .05, ***P < .01$. Error bars indicate 95% confidence intervals. a) We find participants chose the same proportion of high EMV choice (P=0.195). However, in the hard block we find that participants chose more risky lotteries (P=0.023). b) The difference of choice structure between two blocks. In the hard block, the participants chose significantly more high EMV safe lottery (P=0.016) and low EMV risky lottery (P=0.000), but less low EMV safe lottery (P=0.000). c) Percentage of time engaged in EU or CC eye movement. In the hard block, the participants spend less time on EU eye movement (P=0.004) but more time on CC eye movement (P=0.000) d) Transition Matrix. Proportional transition duration from time t to time $t+1$ between attributes in the Easy Block is subtracted from that of the Hard Block. Each row (column) represents one of the four attributes. In the hard block, participants spend more time looking back and forth between payoffs(P=0.000) and less time between the lottery's payoff and its probability that can be achieved (P=0.022).

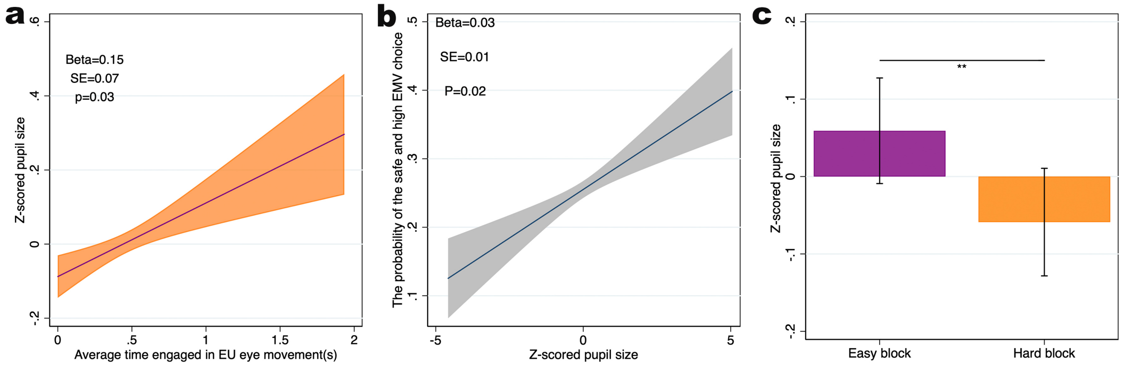

Figure 4.4: $*P < .1, **P < .05, ***P < .01$. Error bars indicate 95% confidence intervals. a) A fixed effects regression modeled z-scored pupil size as a function of average time engaged in EU eye-movement across all trials (P=0.03). b) A fixed effects regression modeled safe choice with high EMV as a function of z-scored pupil size across all trials (P=0.02). c) Pupil size (z-scored) for hard and easy blocks. In the easy block, the average pupil size is significantly larger (P=0.02).

In some trials, the safe lottery has the higher EMV, and in other trials, the risky lottery has the higher EMV. For example, if the safe lottery yields the prize \$5 with probability 60% and the risky lottery yields the prize \$7 with probability 40%, the safe lottery has a higher EMV. But in another example, the safe lottery yields the prize \$3 with probability 70% and the risky lottery yields the prize \$8 with probability 30%, which means the risky lottery has a higher EMV. We ran another fixed effects regression where the probability that the safe lottery with high EMV is chosen is modeled as a function of z-scored pupil size across all trials. We found that the increases the pupil dilation induce the increase of the probability that the safe lottery with high EMV is chosen (P=0.02, Figure 4.4b). Because the safe lottery with high EMV allows people get a higher expected payoff with taking less risk, it is a better choice comparing to the risky low EMV alternative. This result shows that pupil linked arousal, which is the indicator of cognitive effect, improves choice quality. This link to choice quality holds because choosing the safe lottery with high EMV suggests that participants are successful in identifying the high EMV even if the other alternative has a higher payoff. Finally, we find that the participants have a larger average pupil size in the easy block (P=0.02, Figure 4.4c), which provide additional support that participants use cognitive effort to calculate the expected utility in the easy block.

We next explore whether salience theory can explain the risky decision making process. First, we adapt the salience function from Bordalo et al. (2012). Assume the payoff of the lottery i is x_i and the payoff of the lottery j is x_j. The payoff salience function of the lottery i is defined as

$$\frac{|x_i - x_j|}{|x_i| + |x_j| + \sigma} \tag{4.1}$$

where σ is a non-negative number that captures the difference in salience. In this study, we use a simplified salience function (Frydman and Mormann, 2018) that assumes that σ equals 0 for everyone, so that the salience function measures lottery differences instead of both lottery

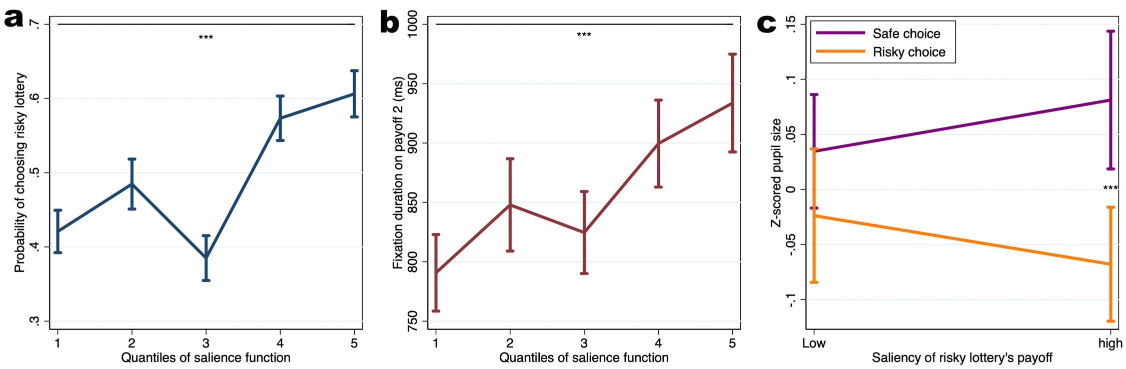

Figure 4.5: $*P<.1, **P<.05, ***P<.01$. Error bars indicate 95% confidence intervals. a) We found that increasing the saliency of the riskier lottery increases its likelihood of being selected (P=0.000). b) We found that increasing the saliency of the riskier lottery increases its fixation duration (P=0.000). c) Pupil dilation increase with saliency of risky lottery if participants chose the safe lottery (P=0.000).

differences and individual differences. The payoff salience function of lottery i increases in the distance between the payoff x_i and the payoff x_j of the alternative lottery which is captured by term $|x_i - x_j|$ and decreases as the absolute payoff gets farther from zero, as captured by the term $|x_i| + |x_j|$. Thus, the salience function can be thought of as the normalized distance between the two payoffs. Assume the payoff of the risky lottery is x_r and the payoff of the safe lottery is x_s. We then define the payoff salience function of the risky lottery as $\frac{|x_r - x_s|}{|x_r| + |x_s|}$. We run a fixed effects regression, and find that increasing the salience of the risky lottery increases its likelihood of being selected (P=0.000) as well as its fixation duration (P=0.000). Combining these two findings, we can conclude that payoffs salience plays an important role in the risky decision-making process. The more salient option attracts participants' attention and make them more likely to select a risky lottery.

The data on pupil linked arousal system is also consistent with these findings. We find that if the risky lottery is not salient, pupil size is not significantly different between the risky choice and the safe choice (P=0.151). However, if the risky lottery is salient, participants have significantly larger pupil size when choosing the safe lottery (P=0.000). This confirms that pupil dilation is an indicator of the inhibition cognitive effect, which refers to the cognitive effort that is used to overcome dominant or automatic responses (Brown et al., 2014; Cohen and Henik, 2015; D'Ascenzo et al., 2016; Geva et al., 2013; Hasshim and Parris, 2015; Laeng et al., 2011; Reinhard and Lachnit, 2002; Richer et al., 1983; Rondeel et al., 2015; Schacht et al., 2010; Scharinger et al., 2010; Siegle et al., 2008; Steinhauer et al., 2004; Wendt et al., 2014; van Bochove et al., 2013). If the risky lottery's payoff is salient, participants are automatically attracted to this option and select it. Hence, if they need to choose the safe lottery, they need more cognitive effort to overcome this attractiveness, which leads to the higher level pupil dilation. To sum up, our experimental data provide evidence in favor of salience theory, where a salient payoff makes participants overweight it (more attention and more likely to be chosen). Also, we provide evidence that more cognitive effect will be used to conquer these automatic responses of choosing the more salient option.

4.4 Discussion and Conclusion

In this work we first confirm prior findings that participants have more EU consistent eye movement when the calculation is easy, which suggests that participants integrate probabilities and payoffs into subjective values. However, when the EU calculation is hard, participants spend more time comparing the components of two lotteries. (Arieli et al., 2011; Aimone et al., 2016a). We also identify the component that is mainly used in making such comparisons: the payoffs.

Second, we established the relationship between the autonomic arousal system and the risky lottery choice process. We find that pupil dilation is an indicator of participants cognitive effort to calculate expected utility (Ahern and Beatty, 1979; Boersma et al., 1970; Hess and Polt, 1964; Klingner et al., 2011; Payne et al., 1968; Schaefer et al., 1968). When participants have more EU consistent eye movement, they have a higher pupil dilation level, which predicts the safe lottery with high EMV is chosen.

Our results also highlight the important role of top down salience in the choice process, which guides decision-makers towards looking at and selecting the more salient alternative. Interestingly, we also find that a higher arousal level is associated with choosing the less salient alternative, which suggests that choosing the less salient alternative requires a higher level of cognitive control. These results demonstrate that comprehensive choice process models of decision making under uncertainty need to integrate information about physiological states with the computation of subjective value.

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Appendix A

Appendix to Chapter 2

A.1 First page of the survey (screen shot)

VT EL Virginia Tech Economics Laboratory

您现在正在参与的是全球偏好调查，此项调查由Alec Smith博士（E-mail: alecsmith@vt.edu）和Xiaomeng Zhang（E-mail: xiaomeng@vt.edu） 设计运行。参与者必须年满 18 岁。

此项调查需要**15分钟**完成，无任何风险。

实验**完全匿名**，只有实验员可以看到您的回复， 我们不会要求您的身份信息（姓名、地址，E-mail 等）。

如果您有任何疑问，可以联系研究人员。

如果您觉得您的权益被伤害，可以联系弗吉尼亚理工学术审核委员会irb@vt.edu。

在问卷过程中，您**可以随时退出**。

*** 如果您确定参与，请选择“继续”。退出请选择“退出”。**

○ 继续

○ 退出

下一页

A.2 Questions' detail

Risk preferences were elicited through a series of related quantitative questions and one self-assessment question. The quantitative questions asked participants to decide either to receive a guaranteed 300RMB ($47) payment or a 50% chance of receiving an x RMB payment, and a 50% chance of receiving nothing, in a lottery. The guaranteed payment was fixed, and the x payment increased or decreased depending on the previous answer. The exposition of the entire sequence of binary decisions is shown in the Appendix. The self-assessment question is: "How much do you agree that you would like to take risk?" This was a 10 scale question, with 10 being "Very willing to take risks" and 0 being "Completely unwilling to take risks."

Time preferences were queried the same way as risk preferences. A series of related quantitative questions and one self-assessment question were used to elicit individual's time preference. The quantitative questions made participants decide to receive 100 RMB ($16) today or x RMB, where $x > 100$, in 12 months. The immediate payment was fixed and the x increased or decreased depending upon the previous answer. The exposition of the entire sequence of binary decisions is shown in the Appendix. The self-assessment question is: "How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?"This was a 10 scale question, with 10 being "Very willing to do so" and 0 being "Completely unwilling to do so."

Positive reciprocity was measured by a self-assessment question and a gift in exchange for help question. The self-assessment question was, "When someone does me a favor, I am willing to return it." 10 meant very willing to do so, and 0 meant unwilling to do so. The gift in exchange for help question asked participants how large a gift they would give to a stranger who spent 16 RMB to help them as a "thank you" present.

Negative reciprocity was elicited by several self-assessment questions, which were "If I am treated very unjustly, I will take revenge at the first occasion, even if there is a cost to do so," and "How willing are you to punish someone who treats you unfairly, even if there may be costs for you?" and "How willing are you to punish someone who treats others unfairly, even if there may be costs for you?"

Altruism was measured by a self-assessment question and a donation decision question. The self-assessment question was "How willing are you to give to good causes without expecting anything in return?" The donation decision question asked participates how much money they would donate to charity if they were given 800 RMB to spend.

Selfish was measured by 11 modified dictator games. The participants were asked to divide the money between themselves and another participant at different price ratio. We use their decision to estimate a CES utility model, which is $U_s = \left(a\pi_s^\rho + (1-a)\pi_o^\rho\right)^{1/p}$, the term a can be used to measure the selfish.

Trust was divided into three categories: trust others, trust government, and trust media, which were measured by three 10-scale self-assessment question which are: "I assume that people have only the best intentions." ,"I assume that government is trustful.", and "I assume that media is trustful." 10 meant very agree and 0 meant totally disagree.

Redistribution preference was measured by two taxes questions. We ask the participants how many percentages do they think the top 1% richest people should be taxed of their total income.

Attitudes to equality and efficiency was measured by two 10 scale questions, which are: "Government should slow down the growth rate to insure equality" , with 10 being "Very agree" and 0 being "Completely disagree."

Economic rationality was measured from the 11 modified dictator games. We can find whether they violated the reveal preference axioms. Also we use the Critical Cost Efficiency Index (CCEI) to measure the severity of the violation.

A.3 Number of Sent-Down Individuals Estimated from CFPS 2010

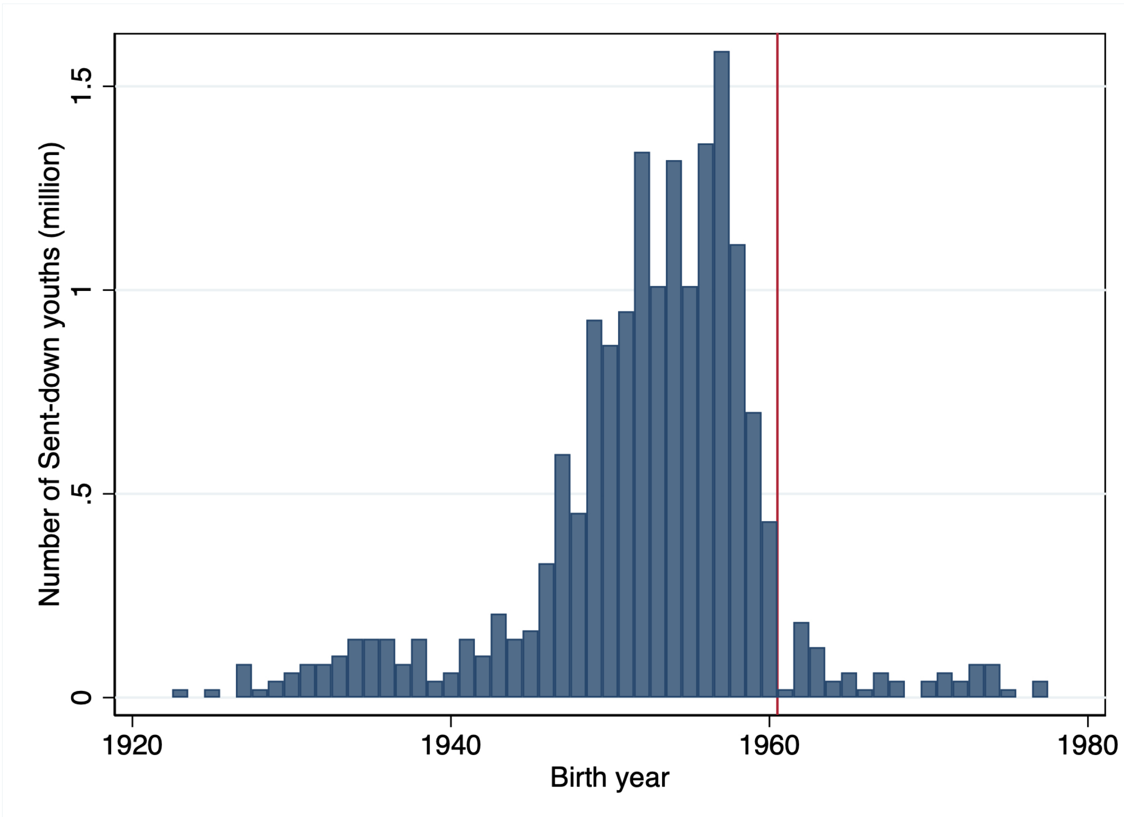

Figure A.1: Number of the Sent-Down individuals form 2010 wave of the China Family Panel Study (CFPS), which prove that individuals who born after 1961 has a lower probability to be sent-down.

A.4 Summary statistics

Table A.1: Summary statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Sent-down	1,821	0.237	0.425	0	1
Sent-down duration	1,821	1.042	2.075	0	10
Birth year	1,821	1,959	8.160	1,937	1,983
Single-child	1,821	0.0395	0.195	0	1
Female	1,821	0.496	0.500	0	1
Non-religion	1,821	0.913	0.282	0	1
Minority	1,821	0.0538	0.226	0	1
Income level(thousand RMB)					
5 or lower	1,821	0.00934	0.0962	0	1
5-10	1,821	0.196	0.397	0	1
10-50	1,821	0.631	0.483	0	1
50-100	1,821	0.149	0.356	0	1
100-500	1,821	0.0132	0.114	0	1
more than 500	1,821	0.00165	0.0406	0	1
Education level					
Non	1,821	0.0192	0.137	0	1
Primary school	1,821	0.0851	0.279	0	1
Some high school	1,821	0.338	0.473	0	1
High school diploma	1,821	0.526	0.499	0	1
Some college or associate degree	1,821	0.0242	0.154	0	1
Bachelor	1,821	0.00494	0.0701	0	1
Master	1,821	0.00110	0.0331	0	1
Doctor	1,821	0.00110	0.0331	0	1
Father's occupation					
Professionals	1,821	0.0648	0.246	0	1
Military	1,821	0.0428	0.203	0	1
Agriculture	1,821	0.399	0.490	0	1
Business	1,821	0.0467	0.211	0	1
Leading cadres[2]	1,821	0.0417	0.200	0	1
Worker	1,821	0.308	0.462	0	1
Non	1,821	0.0346	0.183	0	1
Other	1,821	0.0632	0.243	0	1
Mother's occupation					
Professionals	1,821	0.0132	0.114	0	1
Military	1,821	0.0494	0.217	0	1
Agriculture	1,821	0.286	0.452	0	1
Business	1,821	0.0901	0.286	0	1
Leading cadres	1,821	0.124	0.330	0	1
Worker	1,821	0.191	0.393	0	1
Non	1,821	0.279	0.449	0	1
Other	1,821	0.00384	0.0619	0	1

A.5 Tree for the staircase risk task

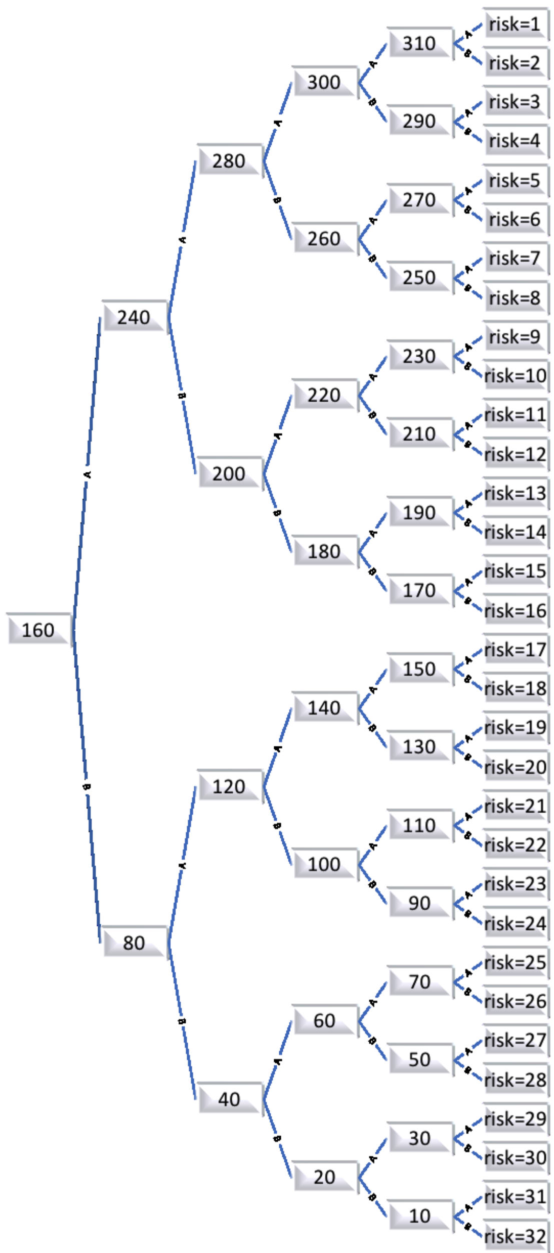

Figure A.2: Tree for the staircase risk task (numbers = sure payment, A = choice of sure payment, B = choice of lottery)

A.6 Tree for the staircase time task

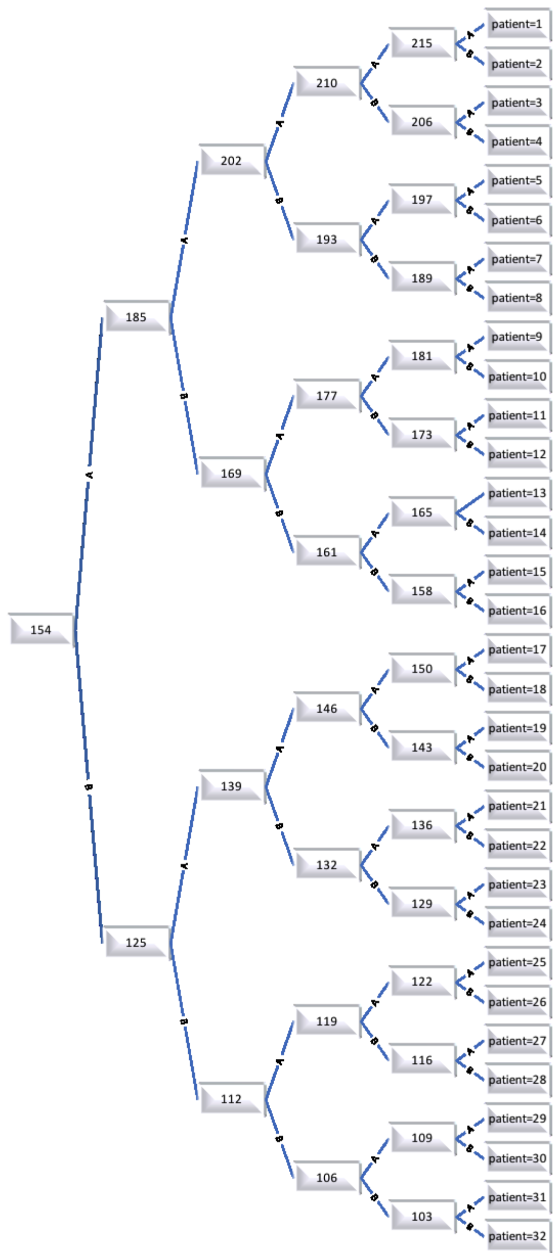

Figure A.3: Tree for the staircase time task (numbers = payment in 12 months, A =choice of 100 RMB today, B = choice of x RMB in 12 months)

A.7 Modified dictator game

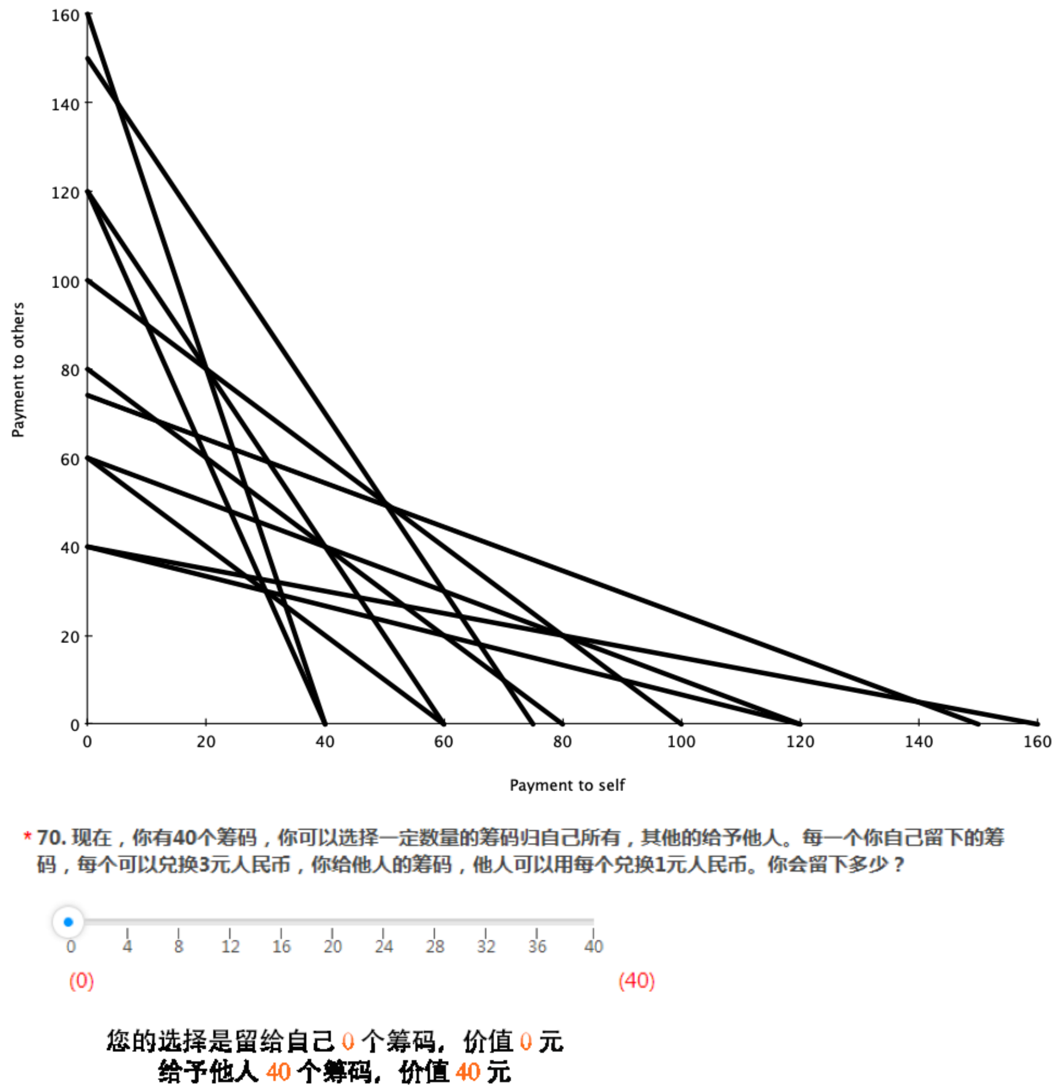

Figure A.4: The participants chose the payment to themselves and others among the budget lines in top figure. The screen shot of the decision making page is shown in bottom figure.

A.8 OLS results(1)

Table A.2: OLS results(1)

VARIABLES	(1) risk averse	(2) patient	(3) pos. reciprocity	(4) neg. reciprocity	(5) altruism	(6) trust others
sent down	0.0772***	0.453***	0.420***	0.141***	0.441***	0.397***
	(0.0276)	(0.0407)	(0.0417)	(0.0274)	(0.0436)	(0.0485)
age	0.00856***	0.0122***	0.0206***	-0.00301*	0.0330***	0.0701***
	(0.00166)	(0.00245)	(0.00251)	(0.00164)	(0.00262)	(0.00292)
female	0.00852	0.134***	0.00862	0.0687***	0.0494	0.0447
	(0.0226)	(0.0333)	(0.0341)	(0.0224)	(0.0357)	(0.0397)
education level	0.0671***	0.244***	-0.0292	0.0646***	0.139***	0.0578**
	(0.0167)	(0.0246)	(0.0252)	(0.0165)	(0.0264)	(0.0293)
income level	-0.0161	0.175***	0.0796***	0.0555***	0.163***	0.0408
	(0.0181)	(0.0268)	(0.0274)	(0.0180)	(0.0287)	(0.0319)
minority	0.143**	0.0317	0.0636	0.00716	-0.0443	-0.0111
	(0.0579)	(0.0855)	(0.0876)	(0.0574)	(0.0916)	(0.102)
non religion	0.363***	-0.219	0.111	0.186*	0.238	0.0443
	(0.107)	(0.158)	(0.162)	(0.106)	(0.169)	(0.188)
father.professionals	-0.00798	-0.00538	0.0809	0.0170	0.102	0.118
	(0.0613)	(0.0905)	(0.0927)	(0.0608)	(0.0969)	(0.108)
father.military	0.00833	0.0474	-0.140	-0.0808	0.0819	-0.0191
	(0.0686)	(0.101)	(0.104)	(0.0681)	(0.109)	(0.121)
father.agriculture	-0.0104	0.111	-0.00373	-0.00487	0.138*	0.0106
	(0.0471)	(0.0695)	(0.0712)	(0.0467)	(0.0744)	(0.0828)
father.business	-0.0342	-0.0446	-0.245**	0.0881	0.0610	-0.0521
	(0.0670)	(0.0989)	(0.101)	(0.0664)	(0.106)	(0.118)
father.leader	-0.0497	0.277	0.0570	0.104	0.411*	-0.185
	(0.133)	(0.197)	(0.202)	(0.132)	(0.211)	(0.235)
father.worker	0.0255	0.125*	0.0434	0.0464	0.114	0.0508
	(0.0480)	(0.0708)	(0.0725)	(0.0476)	(0.0758)	(0.0843)
father.non	-0.0656	0.198*	0.0586	0.0549	0.165	-0.0501
	(0.0735)	(0.108)	(0.111)	(0.0728)	(0.116)	(0.129)
mother.leader	0.103	-0.341*	-0.0729	-0.0990	-0.216	0.0802
	(0.127)	(0.188)	(0.192)	(0.126)	(0.201)	(0.224)
mother.worker	0.136	-0.321*	-0.0765	-0.0515	-0.0400	0.0883
	(0.123)	(0.182)	(0.186)	(0.122)	(0.195)	(0.217)
mother.professionals	-0.00734	-0.213	-0.140	0.0889	-0.225	-0.0378
	(0.154)	(0.228)	(0.233)	(0.153)	(0.244)	(0.271)
mother.military	0.225*	-0.215	-0.0664	-0.00436	-0.0899	0.132
	(0.131)	(0.193)	(0.198)	(0.130)	(0.207)	(0.230)
mother.agriculture	0.0843	-0.321*	-0.157	-0.0454	-0.0739	0.0446
	(0.122)	(0.181)	(0.185)	(0.121)	(0.194)	(0.215)
mother.business	0.112	-0.343*	-0.229	0.0118	-0.145	0.0911
	(0.126)	(0.187)	(0.191)	(0.125)	(0.200)	(0.222)
mother.non	0.109	-0.320*	-0.150	-0.0335	-0.0742	0.105
	(0.122)	(0.181)	(0.185)	(0.121)	(0.194)	(0.215)
Constant	-1.185***	-1.775***	-1.440***	-0.432**	-3.284***	-4.773***
	(0.213)	(0.315)	(0.322)	(0.211)	(0.337)	(0.375)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
R-squared	0.046	0.180	0.157	0.061	0.203	0.371

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.9 OLS results(2)

Table A.3: OLS results(2)

VARIABLES	(1) trust government	(2) trust media	(3) Equality vs Efficiency	(4) selfishness	(5) redistribution	(6) CCEI
sent-down	0.467***	0.420***	0.498***	-0.0515	0.686***	-0.00369
	(0.0484)	(0.0489)	(0.0574)	(0.0555)	(0.0573)	(0.00233)
age	0.0671***	0.0649***	0.0221***	-0.0528***	0.0307***	-0.000508***
	(0.00291)	(0.00294)	(0.00345)	(0.00334)	(0.00345)	(0.000140)
female	0.0647	0.0650	0.0291	0.00978	0.0267	0.00242
	(0.0396)	(0.0400)	(0.0469)	(0.0454)	(0.0468)	(0.00191)
education level	0.0252	0.00618	-0.0494	-0.277***	0.0825**	-0.00222
	(0.0293)	(0.0296)	(0.0347)	(0.0336)	(0.0346)	(0.00141)
income level	0.0368	0.0315	0.134***	0.0464	0.000873	0.00280*
	(0.0318)	(0.0322)	(0.0377)	(0.0365)	(0.0377)	(0.00153)
minority	0.0134	-0.00927	0.0232	-0.346***	0.0559	-0.00359
	(0.102)	(0.103)	(0.121)	(0.117)	(0.120)	(0.00490)
non religion	0.280	0.0316	0.489**	-0.147	-0.0373	-0.0117
	(0.188)	(0.190)	(0.222)	(0.215)	(0.222)	(0.00904)
father.professionals	0.0811	0.151	0.0833	-0.0511	0.0521	0.00917*
	(0.108)	(0.109)	(0.127)	(0.123)	(0.127)	(0.00519)
father.military	-0.106	-0.0259	0.0109	-0.0675	-0.0566	-0.00737
	(0.121)	(0.122)	(0.143)	(0.138)	(0.143)	(0.00581)
father.agriculture	0.0768	0.213**	-0.00412	-0.0539	0.108	0.00356
	(0.0826)	(0.0835)	(0.0979)	(0.0948)	(0.0978)	(0.00398)
father.business	0.0530	0.0730	-0.161	-0.0207	-0.154	-0.00113
	(0.118)	(0.119)	(0.139)	(0.135)	(0.139)	(0.00567)
father.leader	0.151	-0.0146	-0.0105	0.0963	0.478*	-0.00771
	(0.234)	(0.237)	(0.277)	(0.269)	(0.277)	(0.0113)
father.worker	0.0960	0.150*	0.00829	-0.0738	0.0615	0.000638
	(0.0842)	(0.0851)	(0.0998)	(0.0966)	(0.0996)	(0.00406)
father.non	0.00152	0.0471	-0.216	0.0130	-0.00279	0.00387
	(0.129)	(0.130)	(0.153)	(0.148)	(0.153)	(0.00622)
mother.leader	-0.175	0.0972	0.192	-0.275	-0.490*	0.0104
	(0.223)	(0.226)	(0.264)	(0.256)	(0.264)	(0.0108)
mother.worker	-0.103	0.0927	0.164	-0.447*	-0.482*	0.00939
	(0.216)	(0.219)	(0.256)	(0.248)	(0.256)	(0.0104)
mother.professionals	0.0384	-0.149	0.146	-0.379	-0.401	0.00259
	(0.271)	(0.274)	(0.321)	(0.311)	(0.321)	(0.0131)
mother.military	-0.168	0.111	0.328	-0.455*	-0.515*	0.00502
	(0.229)	(0.232)	(0.272)	(0.263)	(0.271)	(0.0111)
mother.agriculture	-0.0851	0.130	0.158	-0.374	-0.553**	0.00611
	(0.215)	(0.217)	(0.255)	(0.246)	(0.254)	(0.0104)
mother.business	-0.0370	0.117	0.173	-0.413	-0.440*	0.00848
	(0.222)	(0.224)	(0.263)	(0.255)	(0.263)	(0.0107)
mother.non	-0.0494	0.0888	0.216	-0.407*	-0.576**	0.00557
	(0.215)	(0.217)	(0.255)	(0.247)	(0.254)	(0.0104)
Constant	-4.598***	-4.398***	-2.311***	4.625***	-1.760***	1.015***
	(0.374)	(0.378)	(0.444)	(0.429)	(0.443)	(0.0180)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
R-squared	0.377	0.357	0.114	0.156	0.172	0.028

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix B

Appendix to Chapter 3

B.1 Summary Statistics for demographics

Table B.1: Summary Statistics for demographics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Age	67	24.06	9.28	18	61
Female	67	0.49	0.50	0	1
Race					
Native American	67	0.03	0.17	0	1
Asian	67	0.25	0.44	0	1
African American	67	0.10	0.32	0	1
pacific islander	67	0.01	0.12	0	1
White	67	0.54	0.50	0	1
Other	67	0.06	0.24	0	1
Income					
Significantly higher	67	0.15	0.36	0	1
Somewhat hgher	67	0.21	0.41	0	1
About the same	67	0.42	0.50	0	1
Somewhat lower	67	0.19	0.40	0	1
Significantly lower	67	0.03	0.17	0	1
Job					
Non	67	0.42	0.50	0	1
Part-time job	67	0.39	0.49	0	1
Full-time job	67	0.19	0.40	0	1
Major					
Agriculture and Life Science	67	0.09	0.29	0	1
Business other than Economics	67	0.21	0.41	0	1
Economics (either in COB or COS)	67	0.13	0.34	0	1
Engineering	67	0.24	0.43	0	1
Liberal Arts and Human Sciences	67	0.15	0.36	0	1
Natural Resources and Environment	67	0.03	0.17	0	1
Science other than Economics	67	0.15	0.36	0	1

B.2 Pupil influence Regression

Table B.2: Pupil influence Regression

Variable	Coefficient	SE	t-value	p-value
$Allocation_t$	0.27	0.14	1.89	0.063
r^+	1.54	0.55	2.79	0.007
r^-	-0.71	0.49	-1.46	0.148
$Allocation_t * r^+$	-0.71	0.91	-0.77	4.442
$Allocation_t * r^-$	-1.89	0.94	-2.01	0.049
$cons$	-0.19	0.07	-2.64	0.010

B.3 Pupil dilation predicts decreased future invest

Table B.3: Pupil dilation predict decrease future invest

	(1)
VARIABLES	$Allocation_{t+1} - Allocation_t$
Z-scored pupil size	-2.344***
	(0.491)
Constant	0.0784***
	(0.0293)
Observations	5,184
Number of blocks	134
R-squared	0.006

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B.4 Price history

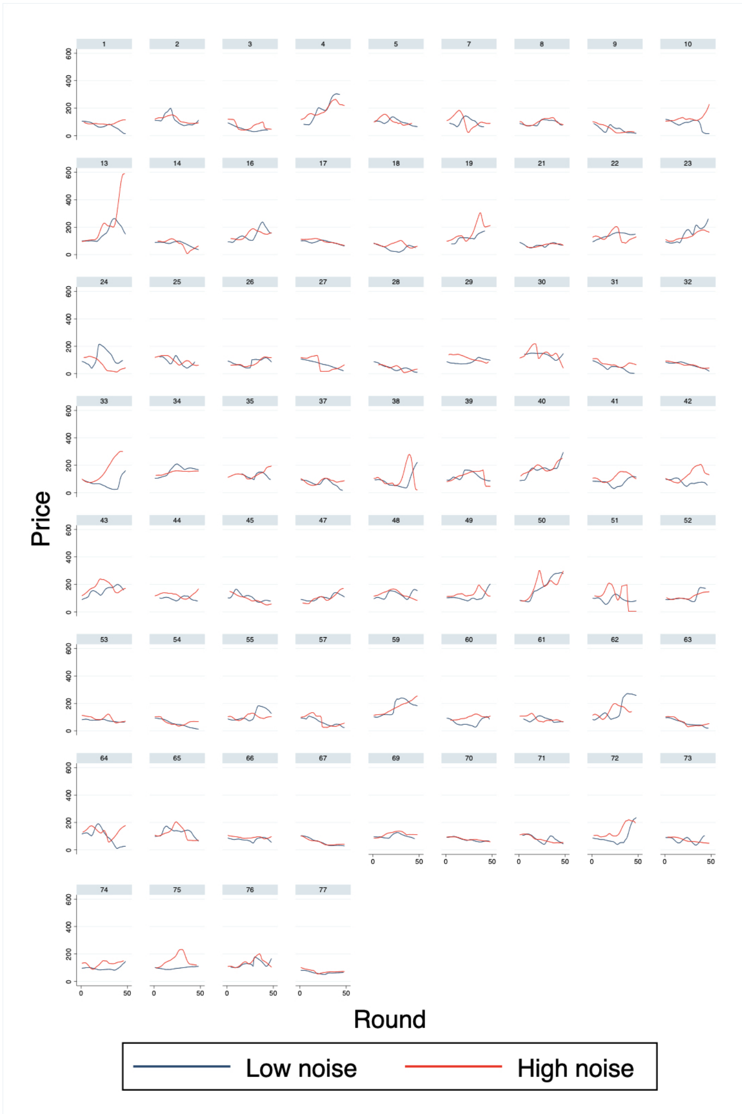

Figure B.1: Price history

Appendix C

Appendix to Chapter 4

C.1 Summary statistics

Table C.1: Summary statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Age	50	23.50	6.485	18	54
Female	50	0.480	0.505	0	1
Race					
Asian	50	0.200	0.404	0	1
Africa American	50	0.060	0.240	0	1
other	50	0.040	0.198	0	1
white	50	0.700	0.463	0	1
Income					
Significant higher	50	0.080	0.274	0	1
Somewhat higher	50	0.260	0.443	0	1
About the same	50	0.420	0.499	0	1
Somewhat lower	50	0.160	0.370	0	1
Significant lower	50	0.080	0.274	0	1
Major					
Agriculture and Life Science	50	0.100	0.303	0	1
Architecture and Urban Studies	50	0.040	0.198	0	1
Business	50	0.180	0.388	0	1
Economics	50	0.020	0.141	0	1
Engineering	50	0.300	0.463	0	1
Liberal Arts and Human Sciences	50	0.160	0.370	0	1
Science	50	0.200	0.404	0	1

C.2 Two fixed effect regression about pupil

Table C.2: Two fixed effect regression results on pupil dilation

VARIABLES	(1) Z-scored pupil	(2) Safe and high EMV choice
EU eye movement	0.156**	
	(0.0706)	
Z-scored pupil		0.0297**
		(0.0117)
Constant	-0.0696**	0.255***
	(0.0330)	(3.63e-05)
Observations	4,811	4,811
R-squared	0.002	0.005
Number of subject	50	50

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

C.3 Two fixed effect regression on salience

Table C.3: Two fixed effect regression about salience

	(1)	(2)
VARIABLES	Gaze fixation on salience payoff	Salience lottery is chosen
salience	301.8***	0.446***
	(45.66)	(0.0611)
Constant	806.7***	0.302***
	(19.45)	(0.0260)
Observations	5,000	5,000
R-squared	0.013	0.041
Number of subject	50	50

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1