THE BEHAVIORAL DEVELOPMENT ECONOMICS OF POVERTY AND RISK

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Sunsiree Kosindesha

December 2020

THE BEHAVIORAL DEVELOPMENT ECONOMICS OF POVERTY AND RISK

Sunsiree Kosindesha, Ph.D.

Cornell University 2020

This dissertation explores the behavioral development economics of poverty and risk from three perspectives. Chapter one focuses on the first perspective concentrating on the psychology of poverty and risk preferences. The second perspective studied in chapter two looks at poverty from the lens of flood experiences, and at risk from the angle of belief, instead of risk preferences. The third perspective presented in chapter three approaches the issue of poverty and risk by applying traditional poverty measures intertwining with reference-dependent utility to a set of data.

The first chapter, "Do Financial Worries Change Risk Preferences Under Prospect Theory?" focuses on the causal nexus of induced financial concerns on probability weighting and loss aversion. Contrary to the standard assumption treating risk preferences as traits, we have learned that risk preferences might be malleable in recent years. However, we have yet to know the specific role of the occupation of mind by financial strain on the alteration of risk preferences. The empirical tracing of corresponding causal path through cognition and emotion has been suggested. To fill these gaps in the literature, chapter one asks whether financial concerns make people more overweigh small probabilities, more underweigh large probabilities, and more loss averse. Additionally, whether possible mechanisms behind the effects, if exist, change in cognitive ability, and change in emotion is empirically tested. To answer the questions, the state of mind of 583 subjects was primed with scenarios aimed to induce

financial worries or nonfinancial worries in an online experiment. Each type of primed concerns involves two levels of intended intensity: "hard" and "easy." We found that financial hard priming makes subjects have a higher level of overweighting of probabilities than nonfinancial priming. Financial hard priming causes subjects to be more loss averse when compared to financial easy priming. Moreover, "poverty" status moderates the average treatment effect of priming on risk preferences. The "poor" have a higher level of overweighting than the "nonpoor." Additionally, the "poverty"-moderated marginal effects of financial hard priming on the level of overweighting of probabilities is mediated by cognitive fatigue. The more cognitive fatigue is, the higher the level of the overweighting becomes.

Given that it might be impossible to disentangle risk preferences from beliefs, the second chapter, "The Effect of the Salience of Flood Experiences on Subjective Probability of megaflood," aims to understand how heuristics could play a role in forming belief concerning the likelihood of relatively rare event. Partaking in the attempt to better understand the psychology of small-probability events, chapter two explores how Cambodian rice farmers, who have mixed experiences of floods with different levels of salience, form their observed beliefs over the probability of megaflood event. This should help better understand the role of availability heuristics(Tversky and Kahneman (1974)) in the over-or under-estimation of small probabilities in a real setting. Specifically, whether the salience of flood shocks encountered by rice farmers affects their subjective beliefs on the probability of extreme flood event; and whether flood shocks that are more salient to the farmers makes them have higher subjective probability on future extreme flood event are explored in this chapter. It is found that there is no recency effect of the occurrence of floods on the subjective

belief of the occurrence of megaflood. However, shocks that are more salient, in terms of the extremeness of flood loss, make farmers have a higher subjective probability of megaflood event. This is indicative of the role of availability heuristics (Tversky and Kahneman (1974)) and the salience theory of choice under risk(Bordalo et al. (2012))

In the third chapter, "What More Can Reference-Dependent Poverty Measures Tell Us?: Application to Thai Economy Using Townsend-Thai Panel Data", reference-dependent utility and loss aversion are instilled into traditional poverty measure. The objectives of chapter three are to apply the reference-dependent poverty measures proposed in Jäntti et al. (2014) to Thai data with further consideration on the design of reference point; and to compare the designs of two existing measures, of Günther and Maier (2014) and of Jäntti et al. (2014), both of which apply the reference-dependent utility from Kőszegi and Rabin (2006). From Townsend-Thai household panel data over the year 2000 to 2011, It is found that Prospect-theory based poverty measures, based on 'equivalent income' as proposed by Jäntti et al. (2014), are mostly higher than conventional FGT measures, but are with similar trend. By building in loss aversion into the poverty measures, the economic insecurity of the vulnerable who have had income around the poverty line and have experienced income loss, with magnitude significant enough, is now reflected in the overall level of reference-dependent poverty. We can learn more from reference-dependent poverty measure the nature of "poverty" around the poverty line: the churning in income versus the persistency of poverty.

BIOGRAPHICAL SKETCH

Sunsiree Kosindesha is a Ph.D. candidate in Economics at Cornell University. She earned her Bachelor of Arts in Economics (*summa cum laude*) and Master of Arts in Economics from Thammasat University, Bangkok, Thailand. She has also been holding a lecturer position at the Faculty of Economics, Thammasat University, who helped provide financial support for her doctoral endeavor.

To mom, dad, and my learning journey

For wisdom, love, and life

ACKNOWLEDGEMENTS

Throughout this long quest for knowledge, I have been and forever will be grateful to Prof. Ravi Kanbur, who has provided guidance and helps with utmost patience. Open doors to his office hours, kindly designed to provide advisees chances to update with work and life on a regular basis, have been a pillar for me to hold on to, both to grow intellectually and to survive some gloomy days of Ph.D. life. I wouldn't have been able to pull this journey through without the given opportunities to learn from his wisdom and without his kindest moral and financial support, all of which I will always be in his debt.

I sincerely appreciate precious and fruitful discussions with Prof. David Just. Chances to learn from him have been the engraved rewarding gifts of my academic voyage. Not only have I learned from his invaluable insightful advices, but also I am blessed that I have had a chance to meet a caring and loving intellectual whose beacon has lighted my path out of the maze of ignorance.

I am truly thankful for Prof. Jim Berry's time invested and straightforward comments when I needed a wakeup call the most. The comments helped urge me to dare to change and to take a route to a better destination. His encouragement that the effort showed meant a lot and will be treasured in my memory.

Wisdom, teaching, generosity, advices, comments, and highly valued time from Prof. Chris Barrett, Prof. Brian Dillon, Prof. Ted O'Donoghue, Prof. Nancy Chau, Prof. Sommarat Chantarat, Prof. Joe Guinness, Prof. Asim Khwaja, Prof. Jukka Pirttilä, Prof. George Jakubson, Prof. Kaushik Basu, Prof. Francesca Molinari, Prof. Levon Barseghyan, Prof. Vivian Zayas, and from Prof. Dan Benjamin, have inspired me, helped me to learn, and built my work and myself up brick by brick. They are greatly appreciated.

Dear Mom and Dad, my first teachers and my lifelong supporters, you are my world and my home sweet home. Thank you for your endless tender love and care, for your sacrifices, and for being the wind beneath my wings. Now it's time for me to take great care of you both in return.

If it weren't because of Cornell Econ, then we wouldn't have met. I am glad that I know and have you as my colleague and my friend, Fikri Pitsuwan. Thank you for being a lighthouse, and I wish you arrive at the right destination no matter which train you take. Importantly, I also would like to extend my gratitude to Sakulrat Bovornsantisuth for the unexpected help in making the last stage of my project happen; Xin Gao for our long walk in Ithaca and her honest and free spirit; Christina Korting, Matt McGranaghan, Jason Somerville, and Elina Hur, for kindly sharing their works and expertise; Chayanee Chawanote and Pimbucha Rusmevichientong for being there sisterly and academically throughout the years; Sra Chuenchoksan for the Wegman family; Heidi Verheggen, Christine Coyer, and Susan Ye for making my first fall, winter, and spring in Ithaca more bearable; last but not least, Bunyarit Meksiriporn for his loving friendship and caring mentorship.

Cold Ithaca is warmer with friendship given to me from Som, pPew, Ming, Billy, Nid, Anto, Hize, Kai, Mas, Borworn, Ing, Game, Sherry, Pow, Next, Keng, Ja, pMook, May, Ped, Peng, Nong, Fay, Chris, Ly, Note, Nahm, Oath, Belle, Orn, pM and M's kitchen, Namhom, Zara, Sine, Paeng, Top, Nok, Mook, pNatt, Yanan Li, Wendy Xu, Mehreen Mookerjee, Sanket Roy, Maricar Mabutas, Yang Zhang, Lin Xu, Dan Reeves, Miriam Larson-Koester, Sherry Zhang, Lawrence Jin, Zhenda Yin, Jeff Swigert, Todd Jones, Sarah Prenovitz, June Pan, Liyuan Cui, Priya Mukherjee, Leigh Wedenoja, Cen Chen, Anne Ruohonen, Sandra Schenk, P.P., Pichie, pRung, pYuwi, nMark, Mo, friends I met at Cornell, and

Shonda Rhimes of Grey's Anatomy.

I have received tremendous helps from and would like to heartily thank Rhonda Kinley of Cornell grad school; Brandon Jameson and Jesse Turner of Qualtrics team; Felix Henninger of lab.js; Sue Snyder formerly of Dyson School of AEM; Ariel Scotes, formerly of the Cornell Legal Research Clinic; Prof. Ronald Rychlak of the University of Mississippi School of Law; and Derina Samuel of Cornell's Center for Teaching Innovation.

I would like to express my deepest gratitude to the Faculty of economics at Thammasat University who helped provide funding that made this journey possible; and to Ajarn Arayah, Ajarn Pranee, Ajarn Anin, Ajarn Chalothorn, Ajarn Phongthorn, Ajarn Jakrapong, Ajarn Apichat, Ajarn Patamawadee, Ajarn Bhanupong, Ajarn Praipol, Ajarn Nat, Ajarn Pokpong, Ajarn Pawin, Ajarn Sittisak, Ajarn Chaiyuth, Ajarn Joop, Ajarn Fai, and to Ajarn Anan, who have trained me and provided the needed supports to begin and survive my Ph.D.

Lastly, I have enjoyed everything Cornell University is, despite my own struggles to shatter the glass box. With hope and fear, flight and fight, darkness and light, it has been a memorable wonderful bittersweet ride that will shape who I am for the rest of my life. Thank you, Cornell University and everyone in it, for the enriching experiences of my learning journey!

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

DO FINANCIAL WORRIES CHANGE RISK PREFERENCES UNDER PROSPECT THEORY?

Abstract

We manipulated subjects' state of mind by priming them with scenarios designed to induce financial worries or nonfinancial worries in an online experiment among subjects who lived in New York State. Each type of priming involved two levels of intended intensity of concerns: "hard" and "easy." Subjects were randomly assigned into one out of four conditions based on types and levels of the priming. With these triggered concerns, we test whether intent-to-treat financial worries cause subjects to more overweigh small probabilities, to more underweigh large probabilities, and to be more loss-averse. Apart from traditional experimental lotteries, real lottery tickets, comprising of WIN4, NUMBERS, and Megamillions JtJ were used to study changes in risk preferences. This helps us to better understand how having concerns changes how people weigh extremely small probabilities of positive events in real lotteries. Based on the implications of Dual-Process theory, we also test whether the effects of financial worries on risk preferences, if exist, are mediated by change in cognition and affect. We found that financial hard priming makes subjects have a higher level of overweighting of probabilities when compared to nonfinancial primings, and causes subjects to be more loss averse when compared to financial easy priming. The higher level of overweighting of probabilities is moderated by poverty status in the sample. Additionally, one of these moderated marginal effects of financial hard priming is found to be mediated by cognitive fatigue.

1.1 Introduction

"Do economic situations and living conditions create preferences?" a question inspired by the idea of endogenous preferences suggested by Bowles (1998)?; "Does poverty put the poor in special circumstances that shape their preferences?" According to the standard economic theory of decision under uncertainty, people choose to act in their best interests, given their circumstances and exogenous risk preferences. How much you like or hate risk, loss, and view probabilities don't depend on how much wealth you possess. On the flip side of this idea, this paper studies whether having a state of mind of the poor causes people to change their risk preferences. Specifically, we try to test whether financial concerns make people more overweigh small probabilities, more underweigh large probabilities, and more loss averse. To shed some light on the mechanism of such effects, we test if possible channels are change in cognitive ability and change in emotion. Cognition and emotion are factors controlling the interplay between the deliberative and the affective processes in the brain suggested by dual process theory(Loewenstein et al., 2015).

Our experimental design is to first prime subjects with financial concerns and nonfinancial concerns. Each frame of concerns has two levels, easy and hard. These were designed with the intention to construct variation in cognitive load and in the level of affect. The idea behind the pathway from having financial concerns to cognitive ability follows a seminal paper by Mani et al. (2013a), who tried to establish that "poverty impedes cognitive function." Building on the design of both Mani et al. (2013a) and Lichand and Mani (2016), we take those primed with nonfinancial concerns and those with easy financial concerns as control groups. Then, individual risk preferences are elicited, using experi-

mental lotteries and real lottery tickets available in the official lottery market in the State of New York. Then, cognitive ability and affect are measured.

Studying the effect of preoccupation of financial concerns on one's mind on her risk preferences could help us to better our understandings of the psychological lives of the poor(Schilbach et al., 2016), accordingly on resulting behaviors. The popularity of lottery playing among the poor(Ariyabuddhiphongs and Chanchalermporn, 2007; Blalock et al., 2007; Haisley et al., 2008;) even with the extremely low chance of winning might be partly explained by the higher level of overweighting of small probabilities among the poor, relative to the rich. The underweighting of the high probability of success in technology adoption and loss aversion might keep the poor from adopting new technologies, like more effective farming techniques. Moreover, impoverished individuals who rely heavily on labor income and cannot afford job loss due to health problems might choose to remain health uninsured because they underweigh the illness probability(Schneider, 2004).

The facets of literature that we aim to contribute are as the followings. Firstly, the idea that poverty, its cultures, and its psychologies could shape the poor's preferences, as well as economic decision making has been proposed by Bertrand et al. (2004), Shah et al. (2012), Mullainathan and Shafir (2013), Haushofer and Fehr (2014), Schilbach et al. (2016), and Dean et al. (2017). A determinant of such effect that has been pointed out is cognitive capacity, hence bandwidth, which is a limited resource. Empirically, Tanaka et al. (2010), Yesuf and Bluffstone (2009a), and Guiso and Paiella (2008) showed that wealth, hence poverty, is related to risk preferences. It has been found that poor people are likely to be more risk-averse. Furthermore, collections of studies have explored

the relationship between income and cognitive ability(such as Carvalho et al., 2016; Mani et al., 2013a; Spears, 2011), and the relation between cognitive ability and risk preferences (such as Benjamin et al., 2013; Deck and Jahedi, 2015; Dohmen et al., 2010). In the literature, mixed evidence regarding whether poverty impeded cognitive ability and whether higher cognitive load changed risk preferences were studied separately. Putting these pieces of jigsaw together, this paper contributes to the literature by exploring the role of cognitive ability as a channel through which poverty mindset could causally affect risk preferences. We address directly to the mentioned links by studying cognitive load and reduced bandwidth induced by financial concerns, the central concerns of the life of the poor. This might help provide further insights from when we study cognitive load that is directly manipulated by cognitive-load tasks like memorization of digits (McManus, 2014; Deck and Jahedi, 2015), or when exploiting natural variation of result of IQ test in samples (Dohmen et al., 2010; Benjamin et al., 2013). This is because how financial concerns reduce bandwidth might be different from how direct cognitive-load tasks reduce bandwidth.

Secondly, by exploring the causal linkage from a scarcity mindset to cognitive load then to risk preferences under prospect theory, we also test predictions of Dual process theory(Loewenstein et al., 2015; Schilbach et al., 2016). The hypothesis is that poverty-related concerns consume mental resources, leading the affective process(system I) to have more influence than the deliberative process(system II). Accordingly, as predicted by Dual process theory, poorer individuals depart from standard rationality in expected utility theory and show stronger insensitivity to probabilities and a higher level of loss aversion.

Thirdly, by understanding a factor determining the degree of overweight-

ing of small probabilities, we help better the understanding of heterogeneity of probability weighting (Etchart-Vincent, 2009; Glöckner and Pachur, 2012). Moreover, we fill in the literature gap on the determinants of the weighting of small probabilities of rare events, as pointed out by Barberis (2013). This is done using real lottery tickets, which are gambles for much larger prizes with much lower probabilities than usual stakes used in lab experiments. Additionally, this fits into the literature on understanding the stability of risk preferences(Barseghyan et al., 2018).

Lastly, the priming of financial concerns to make people feel poor helps us tap into the area of works needed to clarify what it means to 'feel poor' and what 'perception of poverty' is, as mentioned in Schilbach et al. (2016).

1.2 Literature Review

The potentially bidirectional relationship between economic environment and economic decision-makings have been studied extensively, for example, in the long strand of literature for poverty trap. The literature relating differences in economic behaviors and economic circumstances to differences in risk preferences, cognitive ability, and emotion has been advancing piece by piece, when observed measures of these latent confounding factors have been developed and increasingly used overtime.

The most relevant paper that shared the same spirit as this study are Carvalho et al. (2016) and Dalton et al. (2020), whose works were methodologically inspired by the experimental design to capture the psychology of poverty by Mani et al. (2013a). Carvalho et al. (2016) studied the causal effect of financial

resources on cognitive function and risk-related choice task among low income US households. This is done by comparing the choices of subjects before payday and those of subjects after payday[1]. By using interval regression, the paper didn't find the effect of financial resource on CRRA parameters[2], on asset allocation, or on loss aversion[3]. Also, the treatment effect of payday resource on cognitive function wasn't found. The paper didn't try to establish cognitive ability as mediator through which changes in financial resources affected risk preference. Dalton et al. (2020) experimentally induced financial worries[4] among about 120 Vietnamese small business owners, and tried to find its effect on risk aversion, measured by proportion of endowed money allocated to risky prospect in an investment game(Gneezy and Potters, 1997). The paper also tried to find the effect of these financial worries on fluid intelligence measured by Raven's Progressive matrices. On the contrary to Carvalho et al. (2016), Dalton et al. (2020) found that risk aversion reduced as a result of higher financial worries, especially among smaller business owners. As for the priming effect on cognition, null effect was shown to be the case in both studies. The effect came from comparing the outcome variables in financial hard condition versus in financial easy condition.

For the effect of financial concerns on cognitive ability, the paper that found such effect is Mani et al. (2013a). Mani et al. (2013a) primed 101 subjects at New

[1]In study 2 of Carvalho et al. (2016), priming questions by Mani et al. (2013a) were adapted to multiple-choice questions and randomly assigned to 10% of the respondents (group II). However, group II were not given risk choice task. They worked on priming questions, numerical Stroop task, and financial circumstance questions. To note, in study 2, participants worked on questions about subjective perceptions of financial strain and the before-payday group were more financially concerned than the after-payday group.

[2]CRRA parameter is elicited using Eckel and Grossman (2002) in study 1 and Choi et al. (2014) in study 2. In both cases, there was no variation in probability.

[3]Loss aversion was studied by using the lottery choice task in Fehr and Goette (2007).

[4]The paper had manipulation check done by OLS regressions of individual fraction answering 'yes' to financial worry questions on treatment dummy. The financial worry questions were asked as follow-up questions after each scenario.

Jersey mall with financial concerns and found that the poor when primed with hard financial condition performed significantly worse on cognitive tasks than the rich when primed with the hard condition, that is the interaction between income and priming statistically significantly reduced cognitive performance. The overall effects found in Mani et al. (2013a)has large effect size with Cohen's d ranged from 0.88 to 0.94. Another paper that found the effect is Lichand and Mani (2016) who primed 2,822 Brazilian farmers about drought and found that the priming[5], which led to higher worry about future rainfall, statistically significantly affected the cognitive function. The same patterns of effect were also found by Joy (2017) among 127 psychology students at Midwestern university. Other papers that are in the same spirit are Graves (2015)(89 fishermen in Tanzania) and Dalton et al. (2016) (127 shop owners in Vietnam), on the contrary, found no such effect. As for the relation between cognitive ability and risk preferences, Dohmen et al. (2010) found that individuals with higher cognitive ability, measured by IQ test, are more risk-loving in the lottery experiments. However, this paper didn't focus on establishing causality.

In a big picture, this study links four constructs together: financial thought, cognitive ability and affect, and risk preferences. In order to understand what literature has done regarding each link, the content is separated into 5 parts as the following.

[5]as well as the interaction of priming and income per capita

1.2.1 Relation between income and risk preferences in prospect theory

Many studies have explored relationship between socioeconomic characteristics, including income, and risk preferences, both in the scope of expected utility theory (for example, Binswanger, 1980, 1981) and prospect theory. In this subsection, we only focus on literature for the latter in which probability weighting function, loss aversion, and curvature of value function were elicited. Scoping to Prospect theory helps widen possible sources of risk-aversive or risk-seeking behavior, that might originate from other parts of risk preferences than concavity/convexity of utility function. To study the relationship, parameters of cumulative prospect theory- probability weighting function, loss aversion, and curvature of utility function- are estimated, while demographics about income was also collected. Some studies found that the higher the household income and/or wealth, the less the overweighting level of small probabilities, hence more sensitivity to probabilities (Donkers et al., 2001, Freudenreich et al., 2017, Rieger et al., 2017). Donkers et al. (2001) found such pattern within a Dutch household survey(the result is for individual level and in table 5 of the paper), while Freudenreich et al. (2017) was for maize farmers in southern Mexico, using asset index as a measure of wealth (the result in table 9). At country level, Rieger et al. (2017) performed a cross-country comparison and found that wealthier countries (measured by higher log of GDP per capita) had less probability weighting, i.e. more sensitive to probabilities (table 12). However, Vieider et al. (2019), assuming linear value function while allowing for probability weighting and loss aversion, found that, in Vietnamese villages, risk tolerance is positively correlated with income within the sample, but does not correlate

with wealth (table 3 and 4). Because of linear value function, risk tolerance roots from how probabilities are weighted, meaning that higher risk tolerance is consistent with higher level of the overweighting of small probabilities. In other words, contrary to results with previous studies, Vieider et al. (2019) found that household with higher income would have higher level of the overweighting of small probabilities. Additionally, loss aversion was also found to decrease when income increased. This result is in line with the finding by Tanaka et al. (2010), a seminal paper in this area, who, by using two stage least square, found that individuals residing in wealthier villages in Vietnam were less loss averse(table 5).

Relating to this literature, the relationship between income and risk preference might be underlying the relationship between poverty and lottery buying. A study by Haisley et al. (2008) explored experimentally whether subjective feelings of poverty (experiment 1) or being primed that lottery provided equal chances(experiment 2) lead to increase in lottery purchase. Both experiments found positive treatment effects.

1.2.2 Relation between income and cognitive function

The previously unexamined effects of income, hence poverty, or scarcity on cognitive function probably came into economists' attention because of two seminal papers by Mani et al. (2013a) and Shah et al. (2012). Both paper tried to establish that "poverty-related concerns" or "having too little" led to decreased performance in cognitive tasks, indicating cognitive fatigue. Though sharing very similar hypothesis, the designs of the experiment aimed to capture poverty or

scarcity were in different ways. Mani et al. (2013a) tried to embrace how financial thoughts occupy the poor's mind, and this was done by priming subjects with financial scenarios. In a different route, Shah et al. (2012) literally created scarcity by assigning smaller or larger budgets to subjects.

Exploring into more details of Mani et al. (2013a)'s experiments using priming, adults, recruited at a New Jersey mall, were assigned to read one of two series of questions about financial scenarios, called "hard" or "easy". The two series were different in their intended activation of financial concerns. Cognitive tasks, Raven's Progressive Matrices and Hearts and Flowers task(a spatial compatibility task) were used to measure cognitive function while or after subjects answered the questions. Median split on income was used to determine whether subjects were "poor" or not. The paper found that experimentally induced thoughts about finances decreased cognitive performance among the poor but not among the better-off subjects[6].

To answer the same research question as in Mani et al. (2013a) with a larger sample and with more features of cognition examined[7], Lichand and Mani (2016) implemented, in a state in Northeast Brazil, a similar priming methodology that was experimentally implemented in New Jersey mall by Mani et al. (2013a). However, Lichand and Mani (2016) had different design for control condition which is about daily life matters, specifically prime-time soap opera

[6]Wicherts and Scholten (2013) commented Mani et al. (2013a) on the drawbacks of using median split to define "poor" status, instead of using continuous income, and on the ceiling effects in cognitive tasks. Mani et al. (2013b) responded by showing that the results hold when using continuous income and that the main effects was driven by ceiling effect.

[7]Mani et al. (2013a) sample size ranged from about 100 participants for experiments in New Jersey mall to 464 sugarcane farmers in the field studies in India. In Lichand and Mani (2016), 2,822 farmers responded to at least one phone call for data collection. While Mani et al. (2013a) used Raven's Progressive matrices, Heart and Flower task, and Numerical Stroop task, Lichand and Mani (2016) explored more channels through which the effect on cognition could occur by using audio digit span, audio Stroop task, questions to measure anchoring, focus and tunneling, and framing.

or sleep time, instead of using the same financial frame with different activation level as in Mani et al. (2013a). The treatment became about rainfall or drought. Furthermore, in the revised version, Lichand and Mani (2020) augmented original data collection by cross-matching with Brazil's conditional cash transfer program(Bolsa Família) data. This augmentation is in line with the design of Carvalho et al. (2016), and is to differentiate the effect due to low level in income, from the variation in income. In sum, the study culminated in exploiting three main sources of variation in the same sample: exogenous rainfall variation at municipal levels, priming on drought-related concerns at phone-call level in phone survey, and random variation in farmer's Bolsa Família payment. Some patterns of the results of the paper replicated the findings by Mani et al. (2013a) and Carvalho et al. (2016). Resembling to Mani et al. (2013a), the poorer municipality's per capita income was, the higher predicted adverse effect of the priming on cognition became (in figure 5, panel 5 of Lichand and Mani (2020)). Importantly, the study found the priming effect on cognitive load, without any moderation of income (table 3 & 5). On the other hand, like Carvalho et al. (2016), the study didn't find statistically significant before-after payday effect on cognitive load for 3-days window (table 6).

Varieties of methodologies have been used to study the effects of scarcity on many ways the brain works. Shah et al. (2012) gave different participants different amounts of in-game resources to play incentivized game. Players with smaller budgeted chances to play games showed more cognitive fatigue in Dots-Mixes task. Those with smaller budget to get it right also spent longer on the first round of the game, and ended up performed better, while overborrowed her own future resources to be used in the game. The study suggests that scarcity causes change in attention allocation. It increases focus on the problems

that scarcity is made salient. This tunneling, at the same time, leads to neglects of other aspects of the problem. Another aspect of how income can change how the mind works is studied by Shah et al. (2015). Through many experiments, Shah et al. (2015) showed that the poor were less susceptible to framing effects. Additionally, in line with Mani et al. (2013a), Spears (2011) used a lab-in-the field to show that making choices under literally smaller budget yielded worse performance in numerical Stroop task.

Not only scarcity changes cognitive capacity and causes reallocation of cognitive resources across problems, it also has an effect on the nature of the content of cognition as shown by the work of Shah et al. (2018). Monetary concerns were found to be easily triggered, to be persistently occupied the poor's mind, and to shape how connections were made. The participants in Shah et al. (2012), Shah et al. (2015), and Shah et al. (2018) were recruited largely from Amazon's Mechanical Turk.

The application of understanding of the relationship between income and cognitive ability in educational context has been studied by Duquennois (2019), Destin and Svoboda (2018), Hackman and Farah (2009), Lipina et al. (2013), and Mezzacappa (2004). Duquennois (2019) exploited US ASSISTments online homework platform and International Mathematics and Science Study (TIMSS) exam to provide an evidence of power of poverty in capturing attention of low socio-economic status students when working on mathematics exam questions that are monetary salient. In line with this, Destin and Svoboda (2018) showed that making educational financial burden salient in students' mind, together with identity conflict, worsened the students' cognitive functioning in Stroop task. Moreover, Mezzacappa (2004), Hackman and Farah (2009), and Lipina

et al. (2013) suggested that childhood poverty affected language, executive function, and neural processing. This cost of child poverty on long-term cognitive performance might be due to the fact that lower socioeconomic children encounter differences in cultural factors, peri-and postnatal health and nutrition, home environment and stimulation, and social and physical resources in the neighborhood.

1.2.3 Relation between cognitive function and risk preferences

In traditional economic theory, risk preferences are latent traits determining risky choices across all contexts. Cognitive ability is usually also assumed to be a primitive in an economic model, and is normally thought of as being independent of risk preferences. A possibility of the causal effect of cognitive ability on risk preferences, and decision making under uncertainty, has been theoretically discussed and empirically examined by many studies, such as those by Dohmen et al. (2010), Benjamin et al. (2013), Dohmen et al. (2018), Andersson et al. (2016), Deck and Jahedi (2015), Pachur et al. (2017), Gerhardt et al. (2016), and Choi et al. (2018).

Dohmen et al. (2018) pointed out a pattern found in studies exploring the linkages between cognitive ability and measured risk preferences from risky choices in and out of laboratory and from self-reported willingness to take risk. The pattern is that cognitive ability relates with risk avoidance when situation is disadvantageous and risk seeking when advantageous. Cognitive ability in solving quantitative problem is especially related to elicited risk preferences. Theoretically, as pointed out by Benjamin et al. (2013), a dual-process model is

one possible mechanism why cognitive ability might impact risk preferences through its weakening or strengthening control over deliberative process. Experimentally, Benjamin et al. (2013) manipulated cognitive load among Chilean high-school students and saw whether the load had effects on small-stakes risk preferences to deviate from expected-wealth maximizing behavior. The paper found that cognitive load increased possibility of behavior away from expected-wealth maximization, increasing small-stake risk aversion. That higher cognitive load corresponds to higher risk aversion was also found by Deck and Jahedi (2015) and Gerhardt et al. (2016). In addition, Dohmen et al. (2010) found that, among representative German adults, lower speed of processing related with higher risk aversion, controlling for possible confounding factors such as personal traits. Pachur et al. (2017) tried to examine the relationship between numeracy, fluid abilities, crystallized abilities, positive and negative affect- and loss aversion, probability sensitivity, as well as probability optimism. It was indicated that higher crystallized abilities related with lower loss aversion; and that higher fluid abilities and higher negative affect reduced probability optimism. This negative correlation between cognitive ability and probability insensitivity was also reported by Choi et al. (2018). Moreover, from the study by Pachur et al. (2017), negative affect should be another confounding factor we need to consider when learning how cognitive ability determines risky choices.

Challenges in studying the relationship between cognitive ability, cognitive capacity, or cognitive load and risk preferences are such as the one pointed out by Andersson et al. (2016). Low cognitive ability or high cognitive load might be its own obstacle to get the relationship correctly. This is because noise in risky choices used to elicit risk preferences might be dependent on cognitive ability. Moreover, the noises could depend on the design of risky choice task. That is,

apart from the relationship between two latent variables that we need to learn, the research must also be done on the tool to elicit the latent risk preferences, so that it is not influenced by variation in cognitive ability.

1.2.4 Relations between income, cognitive function, and risk preferences

The relationships among income (and poverty), cognitive function, and corresponding decision-making are potentially bidirectional among each other in a circle of poverty. Connecting poverty, cognitive function, and related outcomes, Schilbach et al. (2016) emphasize the importance in enriching the understanding of the psychological lives of the poor by understanding "bandwidth,"- limited mental reserve or capacity for effortful thought. "Bandwidth" is defined as an umbrella term composing of psychological constructs that underlie brain's capacity for decision-making. Nutrition, alcohol and monetary concerns are considered one of many factors that can determine bandwidth which could accordingly govern decision-making, productivity, utility, and so on. Dean et al. (2017) develop more on this line of work by elaborating possible causes and effects of change in cognitive function, especially in the lives of the poor. Compositions and measures of cognitive functions and potential theoretical pathways to behaviors are discussed in details. Impact of Cognitive Functions on Economic Outcomes is suggested to work through various components such as attention, inhibitory control, memory, and higher-order executive functions. Many potential theoretical pathways are suggested such as rational inattention, salience, selective attention, quasi-hyperbolic discounting, and dual-self models.

The relationships among monetary concerns, resulting cognitive load, and risk preferences are one part of these rather complicated web of potential interplays upstreaming and downstreaming from change in cognitive function, waiting to be researched. One candidate for the theoretical framework that can help guide the design of study is the theoretical model and predictions proposed in Loewenstein et al. (2015). In this model, cognition is largely used in deliberative process, while affect and emotion largely drive affective process. The two processes together determine choice behavior. Cost of mobilizing will power is constructed to moderate the relative strength between these two processes. This cost is the key to analyze possible pathway from poverty and income to risk preferences because the cost is designed to be dependent on cognitive load, which can be changed due to financial pressure. The more the cognitive load is, the more risk preferences depart from standard rationality of expected utility theory.

1.2.5 Relation between income, affect, and risk preference

In the past two decades, immediate emotion, experienced at the time of decision-making, has been increasingly recognized as a possible factor determining economic behavior. Embracing the role of immediate emotion into economic modeling is believed to improve predictive accuracy of formal modeling(Loewenstein, 2000; Loewenstein and Lerner, 2003). Lerner et al. (2015) provide theoretical framework dubbed "the emotion-imbued choice(EIC) model" which scopes the influences of integral emotions and incidental emotions. Emotional valence, the content of thought, the depth of thought, goal activation help shape the influence of emotion on decision-making.

For decision under uncertainty and the role of emotion, the "Risk-as-feeling" hypothesis (Loewenstein et al., 2001) highlights the interplay between cognitive evaluation and feelings when evaluating anticipated outcomes and emotions, subjective probabilities. Vividness, immediacy, and background mood can also determine "feelings" which could have the direct effect on behavior and outcome. The work of Rottenstreich and Hsee (2001) augment the concept of diminishing sensitivity in probability weighting function in Prospect theory, by breaking the assumption of probability-outcome independence for outcomes with different affective values. Lotteries with affect-rich outcomes is hypothesized to have weighting functions that are more S-shaped than lotteries with affect-poor outcomes. In this perspective, the weighting function captures the weight of feelings of hope or fear, evoked by the nature of the outcomes of the prospects.

Stepping forward to relationships between income, affect, and risk preferences, Haushofer and Fehr (2014) discuss the evidences suggesting that poverty and its related cognitive load may lead to stress and negative affective states, which may result in myopia and risk aversion. Such evidences linking poverty and affects, mentioned in the review, are such as (a.) positive effects of unconditional cash transfer program on happiness and life satisfaction, and its negative effects on stress and depression (Haushofer and Shapiro, 2016); (b.) positive effect of random negative income shocks to farmers from drought on stress levels. Moreover, the review also mentions the evidence of an experimental induced stress and fear leading to higher risk aversion.

As in the relations between income, cognitive function, and risk preferences, Loewenstein et al. (2015) also provide a theoretical framework to analyze the

effect of income to risk preferences (and time preferences) through immediate emotion. The intensity of affective motivation is included in the model to moderate the motivational function, which is the key construct to explain departure from goal-oriented outcome.

Cognition and emotion are closely linked as there might be potential interplay between the two. To explore this link, Joy (2017) experimentally manipulated financial stressor by having participants think about scenarios, and investigated whether worries mediated the effect of the stressors on performance of financial emotional Stroop test (FEST, Shapiro and Burchell, 2012) and Raven's Advanced Progressive Matrixes. Current Worry Index was found to have a statistically significant effect on cognitive performance, controlling for adjusted household income or material hardship, dummy for treatment condition and its corresponding interaction(Table 2 and 3 in the paper). In similar theme but from different angle, Viseu et al. (2018) used self-report questionnaires to evaluate the relationship between economic stress factors and stress, anxiety, and depression, and found positive correlations. Additionally, Jimenez (2017) had participants look at video with images of poverty and measured emotion by face recognition. The study found that poverty video raised the level of feeling guilty, ashamed, sad, fearful, hostile, upset, as well as, attentive.

The effect of immediate emotion on risk preferences is studied by Conte et al. (2018) who ran an experiment using film clips as emotion induction. Subjects were randomly assigned into one of five treatments- a joviality treatment, a sadness treatment, a fear treatment, an anger treatment or a neutral treatment, then made 100 pairwise lottery choice problems. Conte et al. (2018) found that joviality, sadness, fear and anger reduced risk aversion, compared to the neutral

treatment, while joviality and fear changed probability weighting.

1.3 Dual-Process theory and testable predictions

We follow theoretical framework of dual-process theory in Loewenstein et al. (2015) who provided qualitative predictions for directional impact of cognitive load. In this section, a model for risky decision making in Loewenstein et al., 2015(p. 65-70) is briefly summarized and restated here in the same mathematical expression. The model is as follows.

Individual maximizes the objective function $V(x)$ which is the weighted value function between the deliberative system's utility function $U(x)$ and the affective process's motivational function $M(x, a_M)$. The weight is the cost to the deliberative process of mobilizing willpower which is represented by the cost function $h(W, \sigma)$, where W is the stock of willpower and σ is cognitive load. The cost h is assumed to be increasing in cognitive load σ. The value function in affective process contains the affective intensity of money a_M. A person chooses option $x \in X$ that maximizes:

$$U(x) + h(W, \sigma) * M(x, a_M) \tag{1.1}$$

, each option x in choice set X is a lottery $x \equiv (x_{1,} p_1; ...; x_N, p_N)$, where for the state of nature $i = 1, .., N$, outcome x_i occurs with probability p_i. There are N states of nature. Loewenstein et al. (2015) assumed that the deliberative process evaluated risky prospect according to expected utility theory. That is, $U(x) = \sum p_i u(x_i)$. Moreover, the affective system incorporated probability weighting and loss aversion as in Prospect theory (Kahneman and Tversky, 1979a). Accordingly,

the motivational function is $M(x, a_M) = \sum w(p_i)v(x_i, a_M)$, where $w(p_i)$ is nonlinear probability-weighting function with $dw/dp < 1$ for $p \in (0, 1)$, and $v(x_i, a_M)$ includes loss aversion. The person chooses lottery x to maximize the weighted value function:

$$\max_x V(x) \equiv \max_x \sum p_i u(x_i) + h(W, \sigma) * \left[\sum w(p_i)v(x_i, a_M)\right] \tag{1.2}$$

, where $v(x_i, a_M) = a_M u(x_i)$ if x_i is a gain, and $v(x_i, a_M) = -a_M \lambda u(-x_i)$ if x_i is a loss, i.e. $x_i < 0$. The variable $\lambda > 1$ reflects the degree of loss aversion.

The intuition from this model that we aim to test is that unrelated[8] cognitive load will increase behavioral tendencies of insensitivity to change in probability and loss aversion because it magnifies the influence of the affective process against the deliberative process when making decision under uncertainty.

We consider two cases. The first one is certainty equivalent for pure-gain simple monetary gamble $(\$Z, p; \$0, 1 - p)$ with $Z > 0$, occurring with probability p. The second one is the probability to accept mixed (gain-loss) gambles $(\$G, p; -\$L, 1 - p)$ with $G, L > 0$. The pure gain gamble allows us to focus on the determinants of probability weighting, while the mixed gamble allows us to consider the role of loss aversion.

[8]Being 'unrelated', here, means the cognitive load provides no related information with the risky choice in consideration.

1.3.1 Monetary certainty equivalent for pure-gain monetary gambles

We will derive monetary certainty equivalent for pure gain monetary gamble with general case for utility function $u(\cdot)$ (the linear utility case is discussed in Loewenstein et al. (2015)). The certainty equivalent is determined by the amount of money that the person is indifferent between the gamble and such amount. That is, the amount $\$CE$ for gamble $(\$Z, p; \$0, 1-p)$ with $Z > 0$, occurring with probability p is the amount that satisfies the following equation.

$$u(CE) + h(W,\sigma)((w(p) + w(1-p))a_M u(CE) = pu(Z) + h(W,\sigma)w(p)a_M u(Z) \tag{1.3}$$

Therefore,

$$u(CE) = \frac{p + h(W,\sigma)a_M w(p)}{1 + h(W,\sigma)a_M(w(p) + w(1-p))}u(Z) \tag{1.4}$$

Note that, under expected utility theory, i.e. if the affective process has no influence toward the person's decision, we will have that $u(CE) = pu(Z)$.

From equation (1.4), we have that:

$$u(CE) = \frac{1 + h(W,\sigma)a_M(w(p)/p)}{1 + h(W,\sigma)a_M(w(p) + w(1-p))}pu(Z) \tag{1.5}$$

From equation (1.5), for small probabilities with $w(p) > p$ and with sub-certainty property of Prospect theory(Kahneman and Tversky, 1979a) having

$w(p) + w(1-p) < 1$, we have that $u(CE) > pu(Z)$. If $u(\cdot)$ is monotonically increasing, we have that $CE > pZ$. This expresses the influence of affective process, the source of overweighting of small probabilities.

On the contrary, for large probabilities with $w(p) < p$, when $\frac{w(p)}{p} < \frac{w(1-p)}{1-p}$, we have that $u(CE) < pu(Z)$. If $u(\cdot)$ is monotonically increasing, we have that $CE < pZ$, expressing the underweighting of large probabilities.

We focus on the case where there is increase in cognitive load σ. From equation (1.5), we have following prediction, a part of which stated in *'Risky Choice Prediction #1 (R-1)'* in Loewenstein et al. (2015), that will be what we are trying to test in this paper.

Prediction#1 : For simple pure-gain monetary gamble, an increase in cognitive load σ, hence an increase in the cost of mobilizing willpower $h(W, \sigma)$, will increase CE when $CE > pZ$ and decrease CE when $CE < pZ$.

This means that, for a given level of risk aversion as expressed in $u(\cdot)$, an increase in cognitive load σ will increase the level of overweighting of small probabilities, and increase the level of underweighting of large probabilities. If the weighting function $w(p)$ is linear with $0 < w'(p) < 1$, the function will be less steeper when there is an increase in cognitive load.

1.3.2 Decision to accept or reject mixed gamble with gain and loss

Consider a gamble ($\$G, p; -\$L, 1-p$) with $G, L > 0$. To accept such gamble, a person must have that the gamble gives positive weighted value function. That is, the person will accept the gamble when:

$$\{[pu(G) + (1-p)u(-L)] + h(W,\sigma)\,[w(p)a_M u(G) - w(1-p)a_M \lambda u(L)]\} > 0 \tag{1.6}$$

From equation (1.6), we can understand the competing forces between the deliberative and affective processes via following equation:

$$\frac{pu(G) + (1-p)u(-L)}{h(W,\sigma)} > w(1-p)a_M \lambda u(L) - w(p)a_M u(G) \tag{1.7}$$

Equation (1.7) says that expected utility from the gamble per one unit of cost of mobilizing willpower must be more than weighted feeling of loss and loss aversion that is not compensated by weighted feeling from gain. Accordingly, as the cognitive load σ increases, the cost of mobilizing willpower increases. This makes the expected utility from deliberative system per unit cost reduce, hence the person is more likely to reject the gamble. This is especially when we consider small-probability loss and large-probability gain. This intuition can also be clearly understood if we assume that the utility $u(\cdot)$ if linear and with the probability of winning equal to 1/2. That is, let us consider gamble ($\$G, 1/2; -\$L, 1/2$), equation (1.6) reduces to:

$$\left[\frac{1}{2}G + \frac{1}{2}(-L)\right] + h(W,\sigma)\left[w(\frac{1}{2})a_M G + w(\frac{1}{2})(-a_M \lambda L)\right] > 0 \tag{1.8}$$

As in *Risky Choice Prediction #5 (R-5)* in Loewenstein et al. (2015), we have another prediction that can be tested in this paper. We restate the prediction here:

***Prediction*#2:** When facing 50-50 gain-loss gambles with $L < G < \lambda L$, an increase in $h(W,\sigma)$ will make it more likely that the person rejects the gamble. [9]

With $L < G < \lambda L$, the increase in cognitive load will increase the weight of loss aversion in the decision whether to accept or reject the gamble.

The main objectives of this paper are to test if cognitive load increases the overweighting of small probabilities, the underweighting of large probabilities, and loss aversion. These are what suggested from *Prediction#1* and *Prediction#2.* Importantly, our specific interest is at the increase in cognitive load from financial concerns. To this end, probability weighting function and coefficient of loss aversion will be estimated from certainty equivalent elicited from individual's lottery choices. The cost of mobilizing willpower, $h(W,\sigma)$ will not be estimated in this study.

[9] If we assume that $u(x) = x^\alpha$, then the prediction is for gambles with $L^\alpha < G^\alpha < \lambda L^\alpha$.

1.4 Experimental design

Three essential components of experimental design[10] are the priming of concerns, the measurement of cognitive ability and affect, and risk-preference elicitation. Each component is discussed in the following.

1.4.1 Priming subjects with financial and nonfinancial concerns

Each subject is randomly assigned into one out of four conditions, composing of 'financial easy' condition (denoted later as 'fe'), 'financial hard' condition ('fh'), 'nonfinancial easy' condition ('nfe'), and 'nonfinancial hard' condition ('nfh'). Each condition contains questions, in four scenarios, that are intended to ask in order to bring mentioned events to the top of mind. To capture the effect of having concerns that are framed as financial, we compare the conditions that make subjects worried about financial events, with the conditions that make subjects worried about nonfinancial events. In the same spirit as the design of the control group of Lichand and Mani (2016), the ideas behind the design of nonfinancial concerns were that they should be important enough to have subjects' thought occupied, but should not make one systematically worry about monetary issues. As equally importantly, to capture the effect of higher financial demand, we have two levels of monetary concerns in financial frame, corresponding with two levels of non-monetary concerns in nonfinancial frame. These two levels of

[10] Preregistrations of this study are at AEA RCT and OSF with the following references:

1. Just, David and Sunsiree Kosindesha. 2020. "Do Financial Worries Change Risk Preferences Under Prospect Theory?: An Implication of Dual-Process Theory." AEA RCT Registry. May 01. https://doi.org/10.1257/rct.5124-1.5.
2. Kosindesha, Sunsiree, and David Just. 2019. "Do Financial Worries Change Risk Preferences under Prospect Theory?" OSF. December 12. osf.io/6cd9n.

budgetary concerns were revised from the design of the treatment and the control of Mani et al. (2013a). [11]

1.4.1.1 Financial concerns : hard condition vs. easy condition

This partly follows the priming in study 1 of Mani et al. (2013a). Scenario 1 and 2 are the replication of scenario 1 and 2 of Mani et al. (2013a), but with additional scenario on the reduction in net worth and additional instruction to calculate the amount of decrease in income in scenario 1[12]. Moreover, the magnitude for percentage of the reduction in income and the increase in unexpected expenses are higher than the original priming by Mani et al. (2013a). These aim to make the financial obligations more salient. Scenario 3 and 4 replicate the idea of increase in expenses in scenario 3 and 4 in Mani et al. (2013a), but changes the frames from broken car to emergency medical expenses and from broken refrigerator to broken cellphone and personal computer. These changes is to lower the possibility that randomly chosen subjects might not own car or refrigerator which would unnecessarily reduce the intensity of treatment. Another mild difference from Mani et al. (2013a)'s priming is that we state explicity that these financial events happen unexpectedly. In addition, words count here is 205 more words than Mani et al. (2013a)'s. For our financial hard priming and financial easy priming, each has 570 words. The following four scenarios of financial priming were presented to each participant in random order. The first figures in each

[11] According to psychology literature(Lench et al., 2011) on emotion elicitation, this method falls into the category of using imagination as emotion elicitation technique, in which participants are asked to read scenarios and imagine themselves in such situation. At the same time, the content of such scenario is primed. Imagination is found to be emotion elicitation method that is as effective as film or real-life experiences.

[12] Some numbers in the priming follows 'Poverty and Cognitive Function: Pre-analysis plan by Justin Abraham, Alexis Grigorieff, Johannes Haushofer, Christopher Roth', August 13, 2015. Accessed March 11, 2019. https://www.socialscienceregistry.org/docs/analysisplan/287/document

scenario are for hard conditions, the second figures (in parentheses), for easy conditions

- Scenario 1a: The economy is going through difficult times. Imagine a scenario in which you receive a 20% (5%) cut in your income[total amount of your earnings][13] for at least 6 months, without prior notice. Approximate how much this reduction in income will be in dollars, and keep this figure in your mind as you consider: given your situation, would you be able to maintain your lifestyle? meet financial commitments? If not, what changes would you need to make? Would this new financial situation affect your housing? leisure? travel plans?
- Scenario 1b: Now imagine instead a scenario in which you have an unexpected 15% (2%) reduction of your net worth. Net worth means everything you own of significance [all your assets] minus what you owe in debts. Net worth is a measure of your financial health because it basically says what you would have left if you sold all of your assets to pay off all your debts.[14] Approximate how much a 15% (2%) reduction in your net worth would be in dollars, and keep this in your mind as you consider: given your situation, would you be able to maintain your lifestyle? meet financial commitments? If not, what changes would you need to make? Would this change in your financial situation affect your housing? leisure? travel plans ? career plans?
- Scenario 2: Suppose that an unforeseen non-medical event costs you an

[13]Wording is from Current Population Survey(CPS)'s questionnaire on family income, by U.S. Census Bureau.

[14]The definition of an individual's net worth is adapted from https://www.investopedia.com/terms/n/networth.asp. Accessed May 10, 2019, and from https://www.thesimpledollar.com/how-to-calculate-your-net-worth/, Accessed May 26, https://www.investopedia.com/terms/n/networth.asp . Accessed May 10, 2019.

immediate $3,000 ($200)[15]. Such events are, for example, house repairs, car damage not covered by an insurance company, family or friend in serious distress, urgent travel expenses, etc. Please write down one such possible event you have in mind. Could you come up with that amount of money on short notice? How would you go about this? Would this cause you long-lasting financial hardship? Would it require you to make sacrifices that could have long-term consequences? If so, what are they?

- Scenario 3: Imagine you have to pay an unplanned and necessary medical expense that amounts to $2,500 ($150) . Your health insurance will cover 10% of the cost. To pay the rest, you need to decide between the following options:

  1. Pay the full amount of $2,250 ($135) in cash. Would this require liquidating your long-term savings, or selling your assets?
  2. Take out a personal loan to pay for the medical bill and pay back the loan in monthly installments. Typically, a loan would require monthly payments of approximately $250 ($15) per month for 12 months, which would amount to about $3,000 ($180) in total. Please name possible sources for such a loan, including, for example, a bank or credit card, a personal loan lender.
  3. Borrow money from family, friends, or an acquaintance.
  4. Delay the medically necessary treatment and its expense. [Of course, this option leaves open the possibility of the condition worsening and leading to greater health costs in the long run.] How would you go

[15] If an individual has annual income $50,000(which is approximately about median household income in many towns in upstate New York), $3,000 is around 70% of monthly income. This is about two times of median housing rent in Ithaca, New York. Source of median housing rent is from https://www.nerdwallet.com/cost-of-living-calculator/compare/rochester-ny-vs-ithaca-ny, accessed May 10, 2019.

about making this decision? Considering all these options, would it be an easy or a difficult decision for you to make? [16]

- Scenario 4: Imagine that you didn't expect to replace your personal computer, but now you must. The model you plan to buy offers two payment options: (a.) You can pay the full amount in cash, which will cost $799 ($299). (b.) You can choose a 12-month installment plan of $80 ($30) per month, which would amount to a total of $960 ($360). Which financing option would you opt for? Would you have the necessary cash on hand? Would the interest be worth paying?

1.4.1.2 Nonfinancial concerns: hard condition vs. easy condition

The objective of having this treatment is to see if there is any difference between the financial frame and nonfinancial frame. That is, if we compare the outcome variables between each financial condition to each nonfinancial condition, we should have the combining effect of both change in cognitive load from changing in the demanding content, and change in the framing from nonfinancial to financial framing. However, given that the increases in cognitive load within each frame might be approximately the same, comparing the effect of having higher financial concerns to nonfinancial ones should capture the financial framing effect. This usage of nonfinancial control is in the same spirit as Lichand and Mani (2016)'s design of control group, in which subjects

[16] For the hard condition, the amount is approximately consistent to having silver-metal health insurance plan, in which deductible for individual is $2,500. The plan is such as MVP Premier Plus HDHP Silver 3 (Ref:the link, Accessed May 10, 2019). For the easy condition, the amount is consistent with outpatient facility fee of platinum-metal health insurance plan. The plan is such as Excellus Platinum Select NS INN Dep25 (Ref: The link. Accessed May 10, 2019).

were primed by concern relating to local soap operas on television. [17]The idea is that this control priming should not make subjects systematically concern about their financial matters, but should be important enough to make them worried and have something to think about that might tax bandwidth too. Importantly, these events must happen exogenously to have a parallel situation of exogenous financial shocks. In the following priming, individuals need to react to unexpected occurring events or react to unexpected warnings of imminent or happening events. This should put subjects in the reactive cognitive control process, the same process presumed to be triggered in financial priming. The nonfinancial priming was designed to avoid thoughts about mortality risks, by giving emotional distance to the imagined threats. In an attempt to avoid triggering financial concerns, we limit the number of the most important things subjects have to think about in response of the events. The number of words used in the priming is designed to be as close as that in the priming of financial concerns as much as possible (570 words for financial condition, 539 words for nonfinancial hard condition, and 541 words for nonfinancial easy condition). The presence of numbers is to expose subjects in similar amount of maths as in financial condition. In the following scenarios, individuals need to react to occurring events or to warnings of imminent or happening events. Events that happen with higher intensities are for hard conditions. The hard conditions are stated first, the easy conditions are in parentheses.

[17]In Lichand and Mani (2016), the control group was primed by messages such as "Please tell us to what extent you have been following the prime-time soap opera this year and tell us why."; "Please tell us to what extent soap operas matter for farmers in Ceará" ; "Please tell us what you think the impacts of soap operas are on viewers."

Mani et al. (2013a) also had nonfinancial conditions which had two levels of numbers. This was to see whether math anxiety was also a reason for their effect, besides financial concern. However, the situations that were primed to subjects might be hard to imagine that they could really happen. Accordingly, this might be the reason why there was no statistical significant effect found.

- Scenario 1: Suppose an unexpected severe snow- or thunderstorm hits your area (a neighboring area). More than 20% (about 5%) of all the facilities in your area are affected and need to be shut down. About 79% (1%) of your town's area has a power outage lasting 48 to 72 hours. During a power outage, you may be left without lights, cell phone communication, and heating/air conditioning.[18] According to USFDA, a refrigerator can keep food cold for about 4 hours if it is unopened. A full freezer will keep the temperature for approximately 48 hours.[19] During this situation, most supermarkets and restaurants (some restaurants) are closed. It is difficult to commute in(into) and out of town. How would you best respond to this event? Please write down the first four things you think you would do during and after the storm. What would you do if you encounter a power outage?
- Scenario 2: Floods are the most common natural disaster in the United States.[20] A flood warning is normally issued by the National Weather Service when a large area of flooding is currently in progress.[21] Suppose that you didn't expect a flood warning, but now it is issued for your area (a neighboring area). The average water height can reach 6.5 feet (0.5 feet) or about 2 meters (15 centimeters). Usually, flooding may last a week or more.[22] It can cause casualties and injuries, wash out road surfaces, disrupt transportation, cut essential services, and destroy property. Physical

[18]https://www.getprepared.gc.ca/cnt/rsrcs/pblctns/pwrtgs-wtd/index-en.aspx, accessed June 23, 2019
https://www.techwalla.com/articles/do-cell-phones-work-in-power-outages, accessed June 23, 2019
[19]https://www.fda.gov/food/buy-store-serve-safe-food/food-and-water-safety-during-power-outages-and-floods, accessed June 18, 2019
[20]https://www.ready.gov/floods, accessed June 18, 2019.
[21]https://www.weather.gov/safety/flood-watch-warning, accessed Jul 1, 2019
[22]https://www.weather.gov/pbz/floods, accessed June 18, 2019.

recovery from flood damage to both public and private properties can be slow and may take more than 6 months (1 month). Please list the three most important things you think you would do in response to a flood warning for your area (your neighboring area) ![23]

- Scenario 3: Earthquakes are unpredictable. However, with the help of artificial intelligence, an increasing number of scientists believe we can eventually have quicker and more precise early warning systems.[24] Imagine that a credible earthquake early warning is issued for your town (neighboring towns). Within 10 minutes, the town(s) will be hit by an earthquake with magnitude 6.9 (3.6) on the Richter scale, followed by a 5.29 (2.6) magnitude temblor. With earthquake-resistant buildings, approximately 15% (2%) of public and private buildings, including your town's infrastructure (neighboring towns' buildings) have a 30% (0.89%) probability of slight to moderate damage. This means shear cracks in non-structural and structural walls could occur.[25] How would you react to the warning? Please list the first three things you would do. Do you know what to do to stay safe during an earthquake?

- Scenario 4: Suppose there is a surprise public announcement of a new governmental health policy to cope with nationwide obesity. Dietary guideline is issued to advise people to limit their added sugar to less than 3% (9%) of their daily calorie consumption.[26] For a person who consumes

[23]The text used here comes from Department of Fire and Emergency Services, Government of Western Australia. "Prepare for flood." Accessed May 24, 2018. https://www.dfes.wa.gov.au/safetyinformation/flood/Pages/prepareforflooding.aspx. Language on flood warning comes from National Warning Services. Accessed Mar 12, 2019. https://forecast.weather.gov/wwamap/wwatxtget.php?cwa=usa&wwa=flood%20warning

[24]https://www.nytimes.com/2018/10/26/technology/earthquake-predictions-artificial-intelligence.html, accessed June 18, 2019.

http://seismo.berkeley.edu/research/eew_basics.html, accessed June 18, 2019.

[25]The damage scale is from Okada&Takai(1999).

[26]The percent for easy condition was set to be less than the 2015-2020 dietary guideline for

2,000 calories a day, the recommended added sugar intake is about 60 (180) calories per day or 15 (45) grams. This is about 4 (11) teaspoons a day.[27] The government also sets rules to ensure that mass-produced foods meet nutritional standard to reduce daily sugar. Please list two mass-produced foods (one food) that you like, and usually eat, and say whether these foods would be affected by this policy. To meet the dietary guideline, please name four foods (one food) high in added sugar that you might want to restrict from your diet. Would you like this policy? How would it affect your daily diet?[28]

1.4.2 Measuring cognitive function and affect

Three traditionally identified components of human mind are cognition, affect and conation(Hilgard, 1980). Here, we measure the first two entities that allow us to know and to feel.

1.4.2.1 Measuring cognitive function

Cognition[29] is all forms of knowledge and awareness, and encompasses many types of cognitive processes, such as perceiving, reasoning, and problem solving. To be aware, perceive and comprehend ideas, cognitive functions, which

Americans and what are recommended American Heart Association.

[27]https://www.today.com/health/4-rules-added-sugars-how-calculate-your-daily-limit-t34731, accessed June 21, 2019.

[28]The idea of this scenario comes from Sitwell, William. "Bring back rationing: Is it time we declared war on the modern British diet?." *The Telegraph*, May 29, 2016. Accessed May 24, 2018. https://www.telegraph.co.uk/health-fitness/nutrition/bring-back-rationing-is-it-time-we-declared-war-on-the-modern-br/.

[29]Cognition.(n.d.). In *APA Dictionary of Psychology*, Retrieved January 24, 2019, from https://dictionary.apa.org/cognition

are multifaceted and latent, are in use. Dean et al. (2017) suggested many facets of cognitive functions could affect (and be affected by) economic decision making, especially in the context of poverty. These include attention, inhibitory control, memory, cognitive flexibility, intelligence, and planning.

In this paper, we are interested in measuring parts of cognitive functions that could contribute to the relative strength between deliberative and affective process, concurrently happening when individuals are trying to make risky economic decisions. The most important feature of such cognitive functions is that their capacities should be limited. In the len of economics, individuals, hence, maximize utility not only subjecting to tangible resources, but also to cognitive resources. In other words, our bandwidth, the brain capabilities to think and decide, is scarce(Schilbach et al., 2016). This is in line with an argument that cognitive processes happening in prefrontal cortex, such as executive functions, have limited capacity(Miller and Cohen, 2001). This is possibly the reason why unrelated competing cognitive demand, such as cognitive load from forcing to memorize digits, could have an impact on the power of deliberative process, and accordingly, decisions at hand, as suggested in Loewenstein et al. (2015). Such competing cognitive demand that we aim to measure has two sources. The first one is from the finding of Mani et al. (2013a) that financial concerns impose cognitive load and hamper cognitive capacity. The other source is nonfinancial concerns, which might impose different kind of restriction on the bandwidth.[30]

The key component of bandwidth is executive functions(EFs; executive control or cognitive control)(Schilbach et al., 2016). Executive functions can be thought of as a collection of top-down mental processes needed when individ-

[30]There are various ways researchers can 'load up' cognitive load, such as using distracting task(Benjamin et al., 2013), asking participants to explain the reasons for their decisions(Benjamin et al., 2013), digit-memorization task(Deck and Jahedi, 2015), etc.

ual has to concentrate, allocate attention, inhibit automatic actions, work with information, and to plan toward internal goals, in the situation where using intuitions through hardwired pathways in the brain is not sufficient(Miller and Cohen, 2001,Diamond, 2013, Inzlicht et al., 2015, Schilbach et al., 2016). Cognitive psychologists generally agree that there are three core EFs: inhibitory control, working memory, and cognitive flexibility. From these basic EFs, higher-order EFs such as reasoning and problem solving are possible. These are subcomponents of EFs that are in line with fluid intelligence. Looking at inhibitory control, it is complex attention that helps determine how much a person can control emotions and win internal predispositions. Cognitive tests used to measure inhibitory control are such as Hearts and Flowers Task(Dots Task), Eriksen Flanker Task, Classic Stroop tasks, Spatial Stroop Task. These tasks ask subjects to inhibit wrong responses that are prepotent (Diamond, 2013). As for working memory(WM), it is the capacity to hold and work with information in mind. WM can help us relate information that is no longer present with what comes later. Working memory is used when updating new information into plan, contemplating alternatives, and reasoning(Diamond, 2013). Working memory capacity can be thought of as a trait and a state variable, and is strongly related to fluid intelligence. It can be related to depression, life stress, sleep deprivation and fatigue (Kane et al., 2004, Conway et al., 2005, Engle, 2010, Jarosz and Wiley, 2012). Backward-digit span, Corsi Block test that requires subjects to reorder the blocks, N-Back task, and Complex span(also called WM span task, including Counting span by Case et al. (1982), Reading span by Daneman and Carpenter (1980), Operation span by Turner and Engle (1989))[31] can be used to measure working memory.

[31] According to Diamond (2013), Complex span and N-Back task seem to require more than working memory and should be called EF measures.

Another important aspect of measuring cognitive ability in our context is to use Cognitive Reflection Test(CRT) developed by Frederick (2005). Subsequently, Stanovich (2009), Ackerman (2014), Baron et al. (2015), Toplak et al. (2014), Primi et al. (2016), and Thomson and Oppenheimer (2016) provided more CRT-type questions[32]. An attractive feature of CRT questions is that incorrect and intuitive answers, system I's answers, are primed and must be overridden by system II's thinking process (Kahneman and Frederick, 2002). Because the likelihood to get the wrong answers corresponds to the likelihood that system 1 is in used more than system 2, CRT evaluates the tendency toward miserly processing. Moreover, the predictive power of CRT for 'rational' thinking process is independent of intelligence, executive functionings, and thinking dispositions (Toplak et al., 2011). This means that CRT might measure facet of cognitive abilities other than fluid intelligence. CRT were used by Andersson et al. (2016), Gerhardt et al. (2016), Park (2016), Jimenez et al. (2018) to measure intuition inhibition and cognitive reflection.

Past research on relation between cognitive function and risk preferences and on relation between income(or poverty mindset) and cognitive function has used different cognitive tests to measure cognitive abilities in different categorizations. For example, such cognitive tests are the Wechsler Adult Intelligence Scale(WAIS)(to measure a person's global capacity to act purposefully); Raven's Progressive Matrices(to nonverbally measure fluid intelligence[33], used by Andersson et al. (2016)); the Hit 15 games(to test the ability to plan, used by Burks et al. (2009)); a quantitative literacy (to test numeracy skill, used by Burks et al. (2009)); a Symbol Digit Modalities test(to measure mental speed, used by Lang

[32]Sirota and Juanchich (2018) suggested using multiple choice version of CRT.

[33]the capacity to think logically and solve problems in novel situations independent of acquired knowledge(Raven and Raven (2003)), i.e. eductive ability

et al. (2007), Dohmen et al. (2010)); a word fluency test(used by Dohmen et al. (2010)); verbal and numeracy standardized test scores and school grades (used by Benjamin et al. (2013)); Wechsler's (1981) Digit-Symbol Substitution test(to test fluid cognitive abilities, used by Dohmen et al. (2010), Pachur et al. (2017)); Wechsler's word fluency test (used by Dohmen et al. (2010)); Spot-the-Word vocabulary test(to test crystallized abilities, used by Pachur et al. (2017)); general numeracy scale(to measure the understanding of probabilities and percentages, used by Lipkus et al. (2001), Pachur et al. (2017)).

For research that is closely related to our experimental design, cognitive tests to measure executive functions are as follows. Mani et al. (2013a) used Heart and Flower Task, a numeric version of traditional Stroop task, and Raven's progressive matrices. For Lichand and Mani (2016), executive function tasks included forward digit span, Stroop task, and with no IQ test. Carvalho et al. (2016) employed the Flanker task, the numerical Stroop task, memory game Simon made by Milton Bradley, Cognition reflection test, one question to measure the gambler's fallacy, as well as measures of fluid and crystallized intelligence. In the similar fashion, Spears (2011), Graves (2015), Dalton et al. (2016) measured cognition by using Raven's Standard Progressive Matrices, and a numeric Stroop Test. Destin and Svoboda (2018) also used Stroop color-naming words task to assess the influence of financial burden on cognitive functioning.

In this paper, color-naming Stroop task will be used to measure inhibitory control, and adapted version of CRT will be used to measure miserly processing. The choice of which tests to perform was made considering time constraint in an online experiment. Stroop task was selected because it should render us a key measure of "cognition", given a short amount of experiment time, with-

out taxing cognition too much by itself. In terms of implementation, Stroop task instruction is easy to comprehend and the task is easy to perform in an online platform. Additionally, CRT was selected because it is a test constructed within a framework of two-systems thinking which ties tightly to the theoretical framework underpinning this study. The specific design of Stroop task and CRT questions are provided in subsection 1.7.4.1.

1.4.2.2 Measuring affect

Given that emotion and cognition are intertwined[34], emotion, both by itself and by interaction with cognition, plays crucial role in decision making (Simon, 1967, 1990; Lerner et al., 2015). After subjects are primed with hypothetical events, it might be possible that these primings trigger changes in emotions, which later might contribute to change in decisions under risk. To capture such changes in emotions from priming, we use a combination of self-reported adjective rating scales.

Since literature on affect and emotions is vast and still growing, we scope the concept of affect and emotion to be measured to the one that is in Loewenstein et al. (2015)'s Dual Process theory and that is related to the design of our experimental manipulation. Loewenstein et al. (2015) focused on immediate emotions, experienced at the moment of decision and possibly unrelated to such decision. Under classical rationality, immediate emotions should not alter how people make choices at hand, because they are not results from such choices. Affect here carries action tendencies, and as stated in the paper, the affective

[34]For example, motivational intensity in emotions might be inversely related to cognitive scope. Desire, anger and fear which are emotions with high motivational intensity might narrow cognitive scope. In contrast, satisfaction or some forms of sadness which are emotions with low motivational intensity might broaden cognitive scope (Harmon-Jones et al., 2017).

motivation for money is a representation of underlying models with multiple types of affects, such as hunger, greed, and fear. Our manipulation, asking subjects to imagine themselves in a situation[35], is in line with manipulations[36] that aim at the vividness of stimuli, the ability to have mental images of experiences. This vividness is a factor of the intensity of affective motivation. In this paper, we aim to capture this intensity of affective motivation for money from the priming of financial concerns and nonfinancial concerns. Importantly, our main measures of affect are not aimed to register the direct change in the feeling of hope to win lotteries which is pleasurable anticipation evoked by such lotteries. Rather, such hope should be recognized in the estimated probability weighting function, given that we interpret the overweighting of small probabilities as disproportionate hope and fear as in Rottenstreich and Hsee (2001).

In this paper, the following scales will be used to measure transient state-dependent fluctuations in affect(short-lived affective states which might happen as situational responses)[37].

- International-PANAS-Short Form (Thompson, 2007, abbreviated as I-PANAS-SF), including low-arousal positive affect(LAPA) as suggested by McManus et al. (2018) and the adjective list from PANAS-X(Watson and Clark (1999)) in Jovality subscale(happy), in Fatigue subscale(sleepy, tired, sluggish), and in Sadness subscale(downhearted), are used to measure affect from dimensionality perspective. The I-PANAS-SF is derived from the Positive and Negative Affect Schedule (PANAS), under copyright of

[35] According to Lench et al. (2011), effective emotion elicitation can be by using films, pictures, music or imagination. When we use imagined events, specific cognitive content is likely primed.

[36] Such manipulation is such as the work by Lerner and Keltner (2000). In similar spirit, Conte et al. (2018) investigated how temporary emotional states, experimentally induced by film clips, affect risk preferences.

[37] Rather than trait affect which is a relatively more stable individual difference.

Watson et al. (1988)

- Financial stress scale by Heo et al. (2017), part of which is overlapped with financial anxiety scale(FAS) by Archuleta et al. (2013) who adapted the scale from GAD-7(Generalized Anxiety Disorder-7), as well as Financial Worries Scale proposed in Archuleta et al. (2013), are used to measure localized anxiety[38] from discrete-emotion perspective.

The rationale behind our choice of scales has threefold as suggested in Ekkekakis (2013). That is, firstly, we should decide which construct among core affect, mood, or emotion to target. Secondly, we have to confine ourselves to specific theoretical model used to explain the chosen construct. Lastly, appropriate measures within selected theoretical model of chosen construct are selected based on psychometric information(e.g. validity, reliability) and practice technicality(the length of measure).

Even though there is no theoretical fine line to differentiate (core) affect, mood, and emotion (Ekkekakis (2013)), our design of experimental manipulation to induce some patterns of cognitive appraisal should lead to change in emotions. As indicated in Ekkekakis (2013) and Crispim et al. (2015), there are theoretical links from manipulation of environment to cognitive appraisal then to emotions. This might stem from Russell (1980)'s circumplex model of affect which proposes that affect is an interpreted stimulus. It would be a reasonable hypothesis that change in affect is embedded within emotion. According to Ekkekakis (2013), other possible reason to support that our target construct is not mood is that the time course of mood lasts for hours to days or longer. In order to argue that mood changes, the length of assessment protocal must be

[38] I appreciate the kind advice and discussion on affect measurement with Prof. Leaf Van Boven from the University of Colorado at Boulder.

long enough. This is an aspect that we would not be able to capture with our experimental design.

By the content of our primings, we cannot anticipate whether any specific emotion, except anxiety, will happen. Accordingly, the investigative scopes are both dimensional[39] models of emotions and discrete model of emotions[40], focusing on anxiety emotions. This mixture of usage is in accordance with the reason provided in Quigley et al. (2014) that, for the sake of discriminant validity, it might be better to measure both the emotion of interest (financial anxiety in our case) and closely related emotions.

The Positive and Negative Affect Schedule(PANAS)[41] is a quasi-independent measure of positive and negative affect, developed by Watson et al., 1988. Affects in PANAS are selected from orthogonal-rotated two dimensional model of affective valence and perceived activation(Russell, 1980,Watson and Tellegen, 1985). According to Watson et al. (1988), by construction, variations in positive and negative affect are constrained to be largely independent of one another. This means that both positive and negative emotions , in PANAS scale, can be simultaneously experienced.

According to Tran (2013), PANAS scale can be used to measure state affect, or emotional responses to events, among healthy volunteers and mainly in experimental contexts. Watson et al. (1988) showed that PANAS is useful for studying in intraindividual mood fluctuation. Fluctuation in negative affect, but not in positive affect, was strongly correlated with within-subject variations in perceived stress. Positive affect also varied through out the day. According to tri-

[39]Dimensions are such as valence and arousal(Watson, 2000)

[40]which views emotions as discrete entities (Ekman and Davidson, 1994).

[41]Positive affect and negative affect was called positive activation and negative activation later to reflect the combination of valence and activation dimensions.

partite theory(Clark and Watson, 1991), high negative affect is correlated with being anxious or depressed. Rossi and Pourtois (2012) argued that PANAS is a reliable measure to capture rapid state-dependent variations in anxiety. PANAS has been widely used. For example, it is used by Ifcher and Zarghamee (2011) to measure the success of mood inducement, by Vogt (2018) to study the effect of induced emotion, used by Haushofer et al. (2013) to measure the effect of income shock on psychological state.

Crawford and Henry (2004) suggested that items' covariance in PANAS scale indicated redundancy among such items. Accordingly, Thompson (2007) developed the short form of PANAS, i.e. I-PANAS-SF (International-PANAS-Short Form). This scale contains 10 items and was built under the objective to incorporate as much the content of the original PANAS as possible, with the least redundancy and ambiguity. Thompson (2007) showed that the I-PANAS-SF exhibited reliability, cross-sample and temporal stability, and convergent and criterion-related validity. I-PANAS-SF has been used by many papers such as Moneta et al. (2012), Thompson and Prendergast (2015), Darrat et al. (2016), Benham and Charak (2018), and Deaves et al. (2018).

The main disadvantage of PANAS is that the items in the schedule were selected to represent only the high activation of affect dimensions. In other words, all low-activation states were treated as if they are non-affective. The pleasant(e.g. calmness, serenity) or unpleasant(e.g. tiredness , fatigue) low-activation states are excluded(Watson and Clark, 1997). To compensate for this disadvantage, low-arousal positive affect (LAPA), following McManus et al., 2018, is included in our measurement of affect. These additional words can be found on the low-arousal positive quadrant in the circumplex model of affect

(Russell (1980); Watson et al. (1988)), as well as in PANAS-X(Watson and Clark, 1999) serenity subscale.

The second disadvantage of using PANAS is that, according to Harmon-Jones et al. (2016), null effects are often reported when PANAS is used to measure responses to experimental manipulation. However, a null effect might be because of the failure of self-report measure to capture change in emotion. With this reason, scale to measure financial anxiety, which falls into discrete emotion perspectives, is also used. This is because it can be hypothesized that there are relationships among anxiety, depression, stress and economic hardship(net worth)(Hayhoe et al., 2012, Viseu et al., 2018). The content of financial stress scale by Heo et al. (2017) seems to be able to encompass financial anxiety, as in Archuleta et al. (2013) who developed their scale of GAD-7(General Anxiety Disorder scale by American Psychiatric Association. However, unlike Fünfgeld and Wang (2009), Hayhoe et al. (2012), Shapiro and Burchell (2012) and Archuleta et al. (2013), Heo et al. (2017)'s scale does not cover questions that might be considered as financial habits, personal finance preferences, mental symptoms that happen in a period of time, or procedure that might subliminally prime subjects itself(like Dot-Probe paradigm to measure financial anxiety in Shapiro and Burchell (2012)).

The measurement of affect, mood, and emotion has progressed. Still, there has much work to be done before we can fully measure affect construct as it actually is. Ekkekakis (2013), Quigley et al. (2014), and Harmon-Jones et al. (2016) emphasized the caution of using adjective rating scale to measure affect. The erroneous conclusion that there was no change in affect when in fact there was, or vice versa could happen. Emotions that happened because of experi-

mental manipulation and the registration of such mental construction onto chosen measures can be different because of many reasons. A set of complex processes, linking emotion to adjective ratings, includes ability to translate raw experiences into words that can be consciously communicated, knowledge of the emotion words , individual differences in emotional granularity, etc. One way to move forward from adjective rating scale is to use a state-of-the-art software that measures emotions using physiological cues, such as the work by Jimenez (2017) who found that images of poverty generate a negative emotional valence. However, with the limitation of our online experimental design, the traditional measurement is still used in this paper. The specific affects asked in this study is discussed in more details in subsection 1.7.4.1.

1.4.3 Elicitation of probability weighting, loss aversion and standard risk aversion parameters

The goal of this subsection is to discuss how to infer decision-makers' unobserved risk preferences by observing their choices over a set of experimental decision problems. We are interested in three dimensions of risk preferences: probability weighting function, loss aversion and standard risk aversion. These key features captured by Prospect theory(Kahneman and Tversky, 1979a) are thought to quantify psychological processes that explains how subjects value outcomes and weigh probabilities, accordingly their risk taking behaviors(Nilsson et al., 2011).

One key ingredient of this paper is the component that allows us to study how people perceive extremely small probabilities with positive rare event with

extremely large outcome magnitude. In the attempt to study such event, we cannot use experimental lotteries because of budget limit, credibility of experimenter, and the norm of no-deception in economics experiment. To solve these problems, we contribute to the literature by resorting to using real lottery tickets, which offer credible extremely small chance to win real jackpot prize and other prizes with much more larger stakes than what experimental lotteries can offer.

1.4.3.1 Identification of Prospect-theory parameters

As noted in Barseghyan et al. (2018), data with the right type of variation is needed in order to identify structural parameters that a researcher is interested in. According to their result 1, to identify rank-dependent expected utility which is equivalent to cumulative prospect theory in gain domain, it is suffice to observe households choosing between three options of insurance in the field. However, with simpler environment of lab experiment where we can design the decision set for subjects, Zeisberger et al. (2012) showed that we need two binary lotteries with two different probabilities of getting a non-zero prize in order to identify one probability weighting parameter and one standard risk aversion parameter, since one level of CE can be result of many combination of risk aversion and probability weighting parameter. For example, we need at least two pure gain lotteries $(x_1, p_1; 0, 1 - p_1)$ and $(x_1, p_2; 0, 1 - p_2)$ to point identify power function of value function and one-parameter probability weighting function. If we have three sources of risk preferences, including standard risk aversion, the sensitivity in probability and degree of optimism, we need at least one additional CE in order to point identify all three parameters. One among

these CEs should involve two non-zero outcomes. For example, we need at least three pure gain lotteries: $(x_1, p_1; 0, 1 - p_1)$, $(x_1, p_2; 0, 1 - p_2)$, and $(x_2, p_1; x_1, 1 - p_1)$. We then can simultaneously solve for each parameter as a function of CE, outcome magnitudes, and probabilities. For the coefficient of loss aversion, Bruhin et al. (2010) and Harrison and Swarthout (2016) emphasized the importance of having mixed lottery to identify the coefficient.

Accordingly, this paper will use following combination of types of lotteries in order to identify the probability weighting parameters, standard risk aversion parameter, and loss aversion parameter.

(a.) Binary outcome lottery: This will mainly come from Bruhin et al. (2010) with the addition of mixed lotteries, in order to be able to estimate loss aversion parameter. We will assume that probability weighting functions for gain and loss lotteries are the same. Similarly, we will also assume that the risk-aversion parameters are the same for the two frames.

(b.) Real binary outcome lottery: We include the real lottery ticket for two reasons. The first reason is the possibility of having stake effect(Markowitz, 1952; Scholten and Read, 2014; Bouchouicha and Vieider, 2017;Fehr-Duda et al., 2010). Regarding to this, the experimental literature hasn't addressed such issue with real extremely high positive outcome and low expected value, like real lottery ticket, in the laboratory setting. Secondly, literatures regarding the probability weighting hasn't been clear toward how people weigh rare events, like the wining of first prize. At the same time, we have seen prevalent behavior like the purchase of lottery even though these tickets have lower expected values than their market prices(the expected value of Powerball ticket is \$0.46 and that of Mega millions is \$0.38, while their market prices are equal to \$2). This

probability weighting of extremely rare event of wining the jackpot might be the area where dual process theory can help explain the real behavior in the market. With these reasons in mind, we can use binary real lottery ticket, such as Mega millions with "*Just the Jackpot(JtJ)*" option with market price equal to $3 for two Easy Pick play. This option to play Mega millions came out as in October 2017. The full list of binary outcome lottery tickets is below.

1.4.3.2 Design of experimental lottery choice task

There are several ways to elicit Prospect theory preferences, differing in terms of varied parameters, representation, framing etc.(Zeisberger et al., 2012). The design of decision set used in experiment will affect the quality of parameter estimates(Broomell and Bhatia, 2014), and we have to tradeoff between noise, exactness and simplicity, when choosing between methods(Csermely and Rabas, 2016). Various important aspects to be considered are whether to use parametric(Stott, 2006; Harrison and Rutström, 2009), semiparametric(Etchart-Vincent, 2004; Barseghyan et al., 2013) or nonparametric methods(Abdellaoui, 2000; Abdellaoui et al., 2005, 2007,?); whether to elicit parameters simultaneously or to use chained elicitation methods; whether to use hierarchical Bayesian parameter estimation(Nilsson et al., 2011) or single-subject maximum likelihood estimation(for example, Fehr-Duda et al. 2006; Harrison and Rutström 2009; Glöckner and Pachur 2012; Zeisberger et al. 2012)or pooled group-level maximum likelihood estimation(for example, Gerhardt et al. 2016; Bouchouicha and Vieider 2017; Bougherara et al. 2017); whether to aim for point estimates or interval estimates; and whether to use paired gambles or single gamble in each choice. Additionally, the discriminability of parameters depends on the design of de-

cision set which can be differed in terms of, for example, the total number of choices elicited from each individual, the method used to design it, the outcome domain, the nominal outcome scale, and the realized incentive scale(Broomell and Bhatia, 2014).

This paper will employ parametric pooled group-level maximum likelihood estimation to get at the average treatment effect on risk preferences. 'Chained' elicitation methods are not used here because varying cognitive load in experiment might exacerbate measurement error and error propagation, the issue specific to chained method (Blavatskyy, 2006; Erner et al., 2013). This might unnecessarily complicate the elicitation. Additionally, assuming parametric structure in the elicitation should enable us to quantify the change in risk preference easier than using nonparametric method.

We will elicit certainty equivalent of pure gain and mixed gambles using multiple price list. The list of gambles is adapted from Harbaugh et al. (2002) and Fehr-Duda et al. 2006(which is the same decision set as Bruhin et al. 2010) by adding mixed gamble. For real lottery tickets, we will also elicit certainty equivalence, given that full information on all odds and prizes is provided. However, market prices of the lottery tickets will not be presented to reduce the possibility of arbitrage behavior and concentration of switching point at market price.

Following are the list of 15 experimental lotteries, comprising of 13 pure gain lotteries and 2 mixed lotteries, that will be used in the experiment. Consider lottery $L(x_1, p; x_2)$, outcome x_1 occurs with probability p and x_2 with probability $1 - p$. $x_1, x_2 > 0$ for pure gain lotteries and $x_1 > 0, x_2 < 0$ for mixed lotteries.

This set of lotteries were designed with the following logic in mind. To elicit

Table 1.1: Experimental lotteries

p %	x_1	x_2
1	4	0
1	12	0
1	24	4
10	6	2
25	4	0
50	4	0
50	6	2
50	12	0
50	24	4
50	4	$-L_1$
50	6	$-L_2$
75	4	0
90	6	2
95	12	0
99	4	0

probability weighting, we vary probability p, holding outcome x_1 constant. To elicit risk aversion, we vary magnitude of outcome x_1, holding p constant. To have more precision in eliciting utility function, we need two-outcome gambles which have non-zero lower outcome. This logic can also be observed by the design of gamble set by Gonzalez and Wu (1999). Probability weighting function and standard risk aversion parameter are elicited from certainty equivalents of this combination of pure gain lotteries.

To elicit the coefficient of loss aversion, the loss amounts L_1 and L_2 will be offered as varied prices in the multiple price list[42]. That is, we will find the amount of loss L_j^* , i.e. loss equivalent, such that subject is indifferent between gamble $(G_j, 1/2; L_j^*) \sim 0$, where $G_j^* = 4, 6,\ j = 1, 2$.

Multiple price list with twenty sure outcomes, logarithmically spaced with

[42]Eliciting loss equivalence has been used by Abdellaoui et al. (2008), Kemel and Paraschiv (2018), Vieider et al. (2019).

values spanning the extreme payouts of the lottery, will be used to elicit certainty equivalent for each pure gain lotteries. For loss equivalent, the loss amount is varied instead. Single switching is enforced to prevent inconsistency. More details on the format of experimental lottery choice task are provided in appendix D of chapter 1.

1.4.3.3 Design of New York lottery choice task

Additionally, to study the impact of scarcity mindset on real world gambling behavior and the weighting of probability of extremely rare event of winning the first prize, we elicit certainty equivalence of New York lotteries with the provision of information on all odds and prizes. Market prices of lottery tickets will not be displayed because, firstly, market price is already public information, and secondly, showing ticket price might bias subject's evaluation of the ticket from its true value.

The New York drawing games that we will use are as follows. There are all in all 15 lottery tickets.

For Win 4, box play and combination play have matched odds. For combination play, higher price is for higher probability to win the same amount $2,500. For box play, ticket prices for each way are the same, but higher prize is traded off by lower odds. Notably, the actual prize of Megamillions JtJ is minimum of US$40 millions and rollover when each drawing is without a jackpot winner. This amount was changed to US$20M in April 2020 due to COVID19 situation but this change was after our study was completed.

For these NY lotteries, we elicit certainty equivalent with multiple price list

Table 1.2: New York lotteries

Name of NY ticket	Price of ticket	Winning prize (US$)	Odds
Win 4, combination play, 4 way	$2	2,500	1/2,500
Win 4, combination play, 6 way	$3	2,500	1/1,667
Win 4, combination play, 12 way	$6	2,500	1/833
Win 4, box play, 4 way	$1	1,200	1/2,500
Win 4, box play, 6 way	$1	800	1/1,667
Win 4, box play, 12 way	$1	400	1/833
Win 4, box play, 24 way	$1	200	1/417
Win 4, front pair	$1	50	1/100
Win 4, straight play	$1	5,000	1/10,000
Numbers, combination, 3 way	$1.5	250	1/333
Numbers, combination, 6 way	$3	250	1/167
Numbers, straight play	$0.5	250	1/1,000
Numbers, box play, 3 way	$0.5	80	1/333
Numbers, box play, 6 way	$0.5	40	1/167
Megamillions Just-the-Jackpot	$3	40 millions	1/302,575,350

with price ranging from zero to three or five times of ticket market price. Single switching is also enforced.

More details on the format of New York lottery choice task are also provided in appendix D of chapter 1.

1.4.4 Sample size, Experimental setting, and Timeline of experiment,

1.4.4.1 Sample size

To get a benchmark, according to table 3 from power analysis by Fritz and Mackinnon (2007) for partially mediated model, sample size necessary for 80% power with effect size 0.26[43] of treatment status on mediator and effect size 0.26 of me-

[43]This is the approximately in the middle between small and medium effect size.

diator on dependent variable ranges from 148 to 224 subjects, depending on different types of tests of mediation. For medium effect size of treatment status on mediator and medium effect size of mediator on dependent variable, the necessary sample size ranges from 71 to 118 subjects. For large effect size of treatment status on mediator and large effect size of mediator on dependent variable, the necessary sample size ranges from 34 to 53 subjects.

This study aims to achieve 80% power at effect size 0.26. Since we have 4 conditions, target sample size is 448. It turned out that we can collect data for 584 subjects with 146 subjects in each experimental condition. However, at this size, we might still be underpowered because priming manipulation might have relatively small effect sizes(Lench et al., 2011, Quigley et al., 2014).

1.4.4.2 Online sample through Qualtrics research service

There are now many platforms that can facilitate online experiment and online subject recruitment. Among these platforms, Qualtrics is a panel aggregator in online panel industry, who can provide survey-participant uniqueness, stratification by demographics, randomization, flexibility in asking PIIs, and access to hard-to-reach participants.

Potential survey participants, majority of whom work as survey respondent as a secondary job, were sent an email invitation informing them about the expected length of the survey and incentives. The invitation email indicated that the survey is for the research purpose only, and didn't contain specific details about the content of the survey.

To stratify, demographic qualifications on income and gender were set as soft

quota when Qualtrics leveraged its panel partner's survey router in order to allocates willing respondents to the survey. All processes related to the routers are said to be completely randomized without prioritization or weighting to avoid selection bias caused by invitation wording, survey topic, or reward offering. All participants had unique identifiers generated by Qualtrics Panels. This identifiers are used to prevent duplication.

1.4.4.3 Incentive structure

The compensation comprises two parts:

1. Fixed participation fee: This will be paid through Qualtrics. Qualtrics' cost per complete for maximum length of survey at 40 minutes was $13. Participants will get 60%-80% of the cost depending on the panel Qualtrics ends up using. The panelists will be compensated in the form of "survey cash" that could be converted into monetary compensation. Participants will know how much they will earn before they take the survey. This fixed participation fee will be paid after panelists' responses are reviewed and within approximately 1-2 weeks out of the field.
2. Varying compensation determined by participants' lottery choices. Depending in both their choices and chances(Random Lottery Incentive Method), participants can either get money or lottery tickets. For the money, the maximum participants can earn is $27. The minimum is $3. On average, they can earn $6.4. There is 1 in 12 chance to earn more than $13, 1 in 33 to earn more than $18, and 1 in 70 chance to earn more than $23. For the lottery tickets, possible tickets they can get are Win4, Numbers, Megamillions JtJ. The compensation will be paid after their responses

are reviewed and their choices are randomly chosen to be implemented. The money will be transferred through PayPal. This is paid on the rolling basis as soon as the answers is received and reviewed.

For the varying compensation, it amounted to US$9.6 per hour, which is a little bit below minimum wage in NY state at $11.8 an hour.[44]

1.4.4.4 Timeline of experiment

This study is between-subject design. Expected time including instruction and payment is approximately 40 mins(15 mins for elicitation task, 12 mins for priming (580 words at reading speed of 48 wpm), 3 mins for socioeconomics questions, 5 mins for cognition and affect tasks, 5 mins for consent, and for instructions). The survey was done using Cornell Qualtrics platform. Timeline of experiment is as follows.

1. Informed consent
2. Instruction
3. Priming (subjects were randomized into one of four conditions.)
4. Risk preference elicitation (experimental lottery decision) (with randomized order for each lottery)
5. Risk preference elicitation (real lottery decision) (with randomized order for each lottery)
6. Cognitive tests (with randomized question order)
7. Affect measurement (with randomized question order)

[44]Information on minimum wage can be retrieved here.

8. Socio-economic questionnaire

Fixed participation fee was later paid after answers were reviewed. Incentivized payment that involves real lotteries were settled and sent out via PayPal and mail.

1.5 Data

To participate, participants must be 22 years or older. Importantly, each participant must live within New York state. This is because New York lotteries can only be sent within state. Additionally, due to limitation on Stroop task in this study, participant must work on the survey on laptop or computer, and not on mobile phone, iPad, or tablet. 85% of the final sample were stratified by gender and income range. The soft income quota used is an even balance of people from each household income segment of: US$0 - $25K, $25K- $50K, $50K- $75K, $75K-$100K, $100K- $150K, $150K-$200K, and $200K+. Soft gender quota was about 50% female, 50% male of the whole final sample.

After about 13 weeks in the field (from 23 December 2019 to 20 March 2020), the online data collection was completed. Out of 4,246 recorded response, 584 subjects qualified, finished, and passed criteria on attention checks. This is about 13.75% completion rate. The rate is computed using pool of participant from any state who viewed the consent form of the study, as the sample. Those who were not rejected from the final sample were those who passed at least 3 out of 5 attention checks and provided no gibberish answers in the priming section. Participants, who were qualified, completed the study, but didn't pass the criterion on attention checks, were rejected from the final sample.

Looking at the quality of data, 38.5% of the 584 subjects passed all 5 attention checks, 39.5% for 4 attention checks, and 22% passed 3 attention checks. About 43% of the sample passed both of the attention checks in the lottery choice section. In terms of realized final payment for lottery choice task, averagely each participant received US$6.32, additional to what they received from their online panel.

Each subject was randomly assigned into one out of four conditions. Each condition has 146 subjects. Collected data on demographics shows that there are about equal proportion of subjects with observed characteristics in each condition. Balance test is presented in part 1.7 below.

1.6 Econometric Analysis

1.6.1 Structural estimation for risk-preference parameters

The heart of our experiment is to observe risk-taking behavior of each individual $i \in \{1, ..., I\}$, who needs to choose between pure gain lottery and some sure amounts of money, or choose whether to accept mixed lotteries or not. The gambles are indexed by $g \in \{1, ..., G\}$. We aim to learn the underlying latent risk preferences that help determine the observed risky-choice behavior. From twenty-eight pure-gain lotteries, our main data used to elicit probability weighting function and the curvature of value function, is observed certainty equivalent, the sure amount of money that gives the same value as the value of prospect. From two mixed lotteries, main data to elicit loss aversion is observed loss equivalent, the amount of loss giving value that equally offsets the

value from gain in a prospect. With underlying assumed risk preferences and the equality conditions arisen from switching preferred option in multiple price list, we can derive modeled equivalent as a function of parameters of Prospect theory. The parameters are estimated by maximizing the likelihood that observed data comes from the modeled equivalents.

Our estimation strategy is similar to that used in Zeisberger et al. (2012) and Bouchouicha and Vieider (2017). This is consistent with that used by Bruhin et al. (2010) and Fehr-Duda et al. (2010), but without estimating the finite mixture of different types of risk preferences. This is because finite mixture model is not directly related to our hypotheses. The finite mixture model assigns each subject into different estimated types, either EUT-type or Prospect-theory type. On the contrary, our hypotheses posit that, for every subject, behavior results from both system 1 (Prospect theory) and system 2 (Expected utility theory). It is about the relative strength between these two systems that we would like to discover, as a result of cognitive load from the financial priming. If we can reject the null hypothesis that the financial primings has no causal effects on the level of overweighting of small probabilities, the level of underweighting of large probabilities, or loss aversion, then the hypothesis that financial priming has no influence over relative strengths between the two systems should also be rejected.

Now consider following model for a two-outcome pure gain lottery $\mathcal{G}_g = (x_{1g}, p_g; x_{2g})$, where $x_{1g} > x_{2g}$, and , $x_{1g}, x_{2g} \geq 0$. The certainty equivalent $\hat{ce}_{ig}$ is defined by the decision model:

$$v_i(\hat{ce}_{ig}) = \pi_i(p_g)v_i(x_{1g}) + \pi_i(1 - p_g)v_i(x_{2g})$$

$$v_i(x) := \begin{cases} x^{\alpha_i} & , x \geq 0 \\ -\lambda_i(-x)^{\alpha_i} & , x < 0 \end{cases}$$

That is, the certainty equivalent for each individual and each lottery is the sure amount of money that makes an individual indifferent between accepting the sure thing and accepting the lottery. It is defined by:

$$\hat{ce}_{ig} = v_i^{-1}\left(\pi_i(p_g)v_i(x_{1g}) + \pi_i(1-p_g)v_i(x_{2g})\right). \tag{1.9}$$

Domain specific value function is concave if $\alpha_i < 1$, convex if $\alpha_i > 1$, or linear if $\alpha_i = 1$.

The probability weighting function is as proposed by Goldstein and Einhorn (1987) and Lattimore et al. (1992). This was also used by Gonzalez and Wu (1999) and Bruhin et al. (2010), and takes the form of:

$$\pi_i(p) = \frac{\delta_i p^{\gamma_i}}{\delta_i p^{\gamma_i} + (1-p)^{\gamma_i}}; \delta_i \geq 0, \gamma_i \geq 0$$

Parameter δ_i governs the elevation of the curve, while γ_i governs its slope. The smaller the value of γ_i, the more curved the weighting function $\pi_i(p)$, that is, the weighting function will be flatter in the range of medium probabilities, and steeper near the ends. γ_i reflects the responsiveness to changes in probability and the direction of inflection of the weighting function.

The value of γ_i majorly determines whether there is the overweighting or underweighting of small probabilities. The less the parameter γ_i is, the more small probabilities are overweighted. At $\delta_i = 0.5$, if $\gamma_i > 1$, there will be no overweighting of small probabilities.

For the parameter δ_i, the higher the level of δ_i is, the larger the range of probabilities where the subject overweighs is, and the higher level of overweighting for a given probability p is. As pointed out by Lattimore et al. (1992), if $\delta_i < 1$, the probability p is downweighted. This might indicate a pessimistic view of the outcome occurring, and $\delta_i > 1$ indicates an optimistic view of the outcome occurring. At $\gamma_i = 0.5$ and p^* where $\pi(p^*) = p^*$, $p^* = 0.5$ if $\delta_i = 1$; $p^* < 0.5$ if $\delta_i < 1$; $p^* > 0.5$ if $\delta_i > 1$. Individual heterogeneity can be accommodated well by this specification(Wu et al., 2004). To note, for all values of δ_i and γ_i, $\pi(0) = 0$ and $\pi(1) = 1$.

Using two-parameter probability weighting function instead of one allows the case of more overweighting of small probability without more underweighting of large probabilities. This scenario can occur because of the fact that not only the inflection point of probability weighting function can rotate, but also the whole function can be elevated.

For mixed prospects with gain and loss $\mathcal{M}_g = (g_g, p_g; l_g)$, where $g_g > 0, l_g < 0$, we varied l_g, the amount of loss, keeping the gain constant, for each gamble and each multiple price list. We are interested in loss equivalent $\hat{l}_{ig}$, the amount of loss that makes each subject indifferent between betting on the mixed prospect and rejecting such prospect and staying with the status quo of zero amount of money. In other words, the loss equivalent $\hat{l}_{ig}$ is the amount such that $(g_g, p_g; \hat{l}_{ig}) \sim 0$.

Accordingly, for mixed prospects, we have that: $v(0) = \pi(p_g)v(g_g) + \pi(1 - p_g)v(\hat{l}_{ig})$. With $p_g = 0.5$, $\pi(p_g) = \pi(1 - p_g)$. Together with $v(0) = 0$, the loss equivalent can be written as:

$$\hat{l}_{ig} = v^{-1}(v(g_g)). \tag{1.10}$$

Under our previous assumptions on functional forms, we have that modeled certainty equivalent and loss equivalent can be written as[45]:

$$\hat{ce}_{ig} = \left(\frac{\delta_i p_g^{\gamma_i}}{\delta_i p_g^{\gamma_i} + (1-p_g)^{\gamma_i}} x_{1g}^{\alpha_i} + \frac{\delta_i (1-p_g)^{\gamma_i}}{\delta_i (1-p_g)^{\gamma_i} + p_g^{\gamma_i}} x_{2g}^{\alpha_i} \right)^{1/\alpha_i}. \tag{1.11}$$

$$\hat{l}_{ig} = -\frac{g_g}{\lambda_i^{1/\alpha_i}} \tag{1.12}$$

.

For individual i, gamble g, let $\hat{d}_{ig}$ be the modeled equivalent, either certainty equivalent $\hat{ce}_{ig}$ or loss equivalent $\hat{l}_{ig}$ [46], of individual i and gamble g. $\hat{d}_{ig}$ is a function of $\{\alpha_i, \delta_i, \gamma_i, \lambda_i\}$, given underlying model that we will estimate and test. Our data is in the form of elicited equivalent d_{ig}, i.e. the observed equivalent. We can write the observed equivalent d_{ig} as the modeled certainty equivalent $\hat{d}_{ig}$ plus error ϵ_{ig}, that is:

$$d_{ig} = \hat{d}_{ig} + \epsilon_{ig}.$$

Sources of error are such as carelessness, hurrying, or inattentiveness (Hey

[45]If we use logarithmic value function instead $v(x) := \begin{cases} ln(\alpha_i + x) & , x \geq 0 \\ -\lambda_i ln(\alpha_i - x) & , x < 0 \end{cases}$, we will have that the certainty equivalent and the loss equivalent take the following forms: $\hat{ce}_{ig} = exp\left\{ \frac{\delta_i p_g^{\gamma_i}}{\delta_i p_g^{\gamma_i} + (1-p_g)^{\gamma_i}} ln(\alpha_i + x_{1g}) + \frac{\delta_i (1-p_g)^{\gamma_i}}{\delta_i (1-p_g)^{\gamma_i} + p_g^{\gamma_i}} ln(\alpha_i + x_{2g}) \right\} - \alpha_i$, $\hat{l}_{ig} = \alpha_i - exp\left\{ \frac{ln(\alpha_i + g_g)}{\lambda_i} \right\}$.

If we use probability weighting function by Prelec (1998) $\pi(p) = e^{-(-lnp)^{\gamma}}$, the certainty equivalent will take the form of: $\hat{ce}_{ig} = \left(e^{-(-lnp_g)^{\gamma_i}} x_{1g}^{\alpha_i} + e^{-(-ln(1-p_g))^{\gamma_i}} x_{2g}^{\alpha_i} \right)^{1/\alpha_i}$, and the loss equivalent will be $\hat{l}_{ig} = -\frac{g_g}{\lambda_i^{1/\alpha_i}}$.

[46]To note, the elicited loss equivalent is negative.

and Orme, 1994, Bruhin et al., 2010). We assume that such errors ϵ_{ig} are independently normally distributed, and add white noise to the modeled behavior.

$$\epsilon_{ig} \sim N(0, \sigma_{ig}^2),$$

$$\sigma_{ig} = \begin{cases} \xi_i(x_{1g} - x_{2g}) & , for\ L(x_{1g}, p_g; x_{2g}) \\ \xi_i(max\, l_g - min\, l_g) & , for\ L(g_g, p_g; l_g) \end{cases}.$$

Following Bruhin et al. (2010), ξ_i denotes an individual specific parameter, and captures heterogeneity at individual level such as knowledge and attention span that might affect the decision making.

For G elicited equivalents, the log-likelihood function for each subject i is thus given as:

$$\mathscr{L}_i = \sum_{g=1}^{G} \left[log \left(\frac{1}{\sqrt{2\pi}\sigma_{ig}} exp \left(-\frac{1}{2} \left(\frac{d_{ig} - \hat{d}_{ig}(\alpha_i, \delta_i, \gamma_i, \lambda_i)}{\sigma_{ig}} \right)^2 \right) \right) \right] \tag{1.13}$$

We let individual parameters $\psi_i = \{\alpha_i, \gamma_i, \delta_i, \lambda_i, \xi_i\}$ depend on treatment dummy and observable individual characteristics. Specifically, $\psi_i = \psi_0 + \psi_1 T_i + \psi_{2j} X_{ij}$, where $j = 1, ..., J$ for each characteristics X_j, and T_i is dummy variable for experimental condition assigned to subject i.

Summing over all individuals I, we obtain the aggregate log-likelihood function:

$$\mathscr{L}(\Psi; ce, le, \mathcal{G}, \mathcal{M}) = \sum_{i=1}^{I} \sum_{g=1}^{G} \left[log \left(\frac{1}{\sqrt{2\pi}\sigma_{ig}} exp \left(-\frac{1}{2} \left(\frac{d_{ig} - \hat{d}_{i,g}(\alpha_i, \delta_i, \gamma_i, \lambda_i)}{\sigma_{ig}} \right)^2 \right) \right) \right] \tag{1.14}$$

,where vector $\Psi = \left(\psi_0, \psi_1, \psi_{2j}\right)$ is all parameters to be estimated. ce is all certainty equivalent data. le is all loss equivalent data. $\mathcal{G}$ is the set of information from all pure-gain gambles. $\mathcal{M}$ is the set of information from all mixed gambles.

Integrating all these equations together, we will have that the detailed log-likelihood function[47] is, for example, as following:

$$\mathscr{L}(\Psi; ce, le, \mathcal{G}, \mathcal{M})$$
$$= \sum_{i=1}^{I} \sum_{g=1}^{G} \left[log \left(\frac{1}{\sigma_{ig}} \phi \left(\frac{\mathcal{I}_{\mathcal{G}} \left[ce_{ig} - \left(\frac{\delta_i p_g^{\gamma_i}}{\delta_i p_g^{\gamma_i} + (1-p_g)^{\gamma_i}} x_{1g}^{\alpha_i} + \frac{\delta_i (1-p_g)^{\gamma_i}}{\delta_i (1-p_g)^{\gamma_i} + p_g^{\gamma_i}} x_{2g}^{\alpha_i} \right)^{1/\alpha_i} \right] + \mathcal{I}_{\mathcal{M}} \left[l_{ig} + \frac{g_g}{\lambda_i^{1/\alpha_i}} \right]}{\sigma_{ig}} \right) \right) \right] \tag{1.15}$$

, where $\delta_i = \delta_0 + \delta_1 T_i + \delta_{2j} X_{ij}$; $\gamma_i = \gamma_0 + \gamma_1 T_i + \gamma_{2j} X_{ij}$; $\lambda_i = \lambda_0 + \lambda_1 T_i + \lambda_{2j} X_{ij}$; $\alpha_i = \alpha_0 + \alpha_1 T_i + \alpha_{2j} X_{ij}$; $\mathcal{I}_{\mathcal{G}}$ and $\mathcal{I}_{\mathcal{M}}$ are indicator functions for pure-gain and mixed gamble, respectively. That is, each individual parameter is a linear combination of conditions and other observed characteristics.

According to Bouchouicha and Vieider (2017), $(\alpha_i, \beta_i, \gamma_i, \delta_i, \xi_i)$ are estimated using maximum likelihood estimation. The loglikelihood can be maximized by optimization algorithm such as BHHH, BFGS, or NR.

[47] We use certainty equivalent and loss equivalent data, instead of treating each price list as a pair of choice, because all of the information for each multiple price list is summed up in the equivalent.

1.6.2 Average Treatment Effects and Mediation Analysis

Our goal is to estimate how the probability weighting function $w_i(p)$, hence δ_i and γ_i, as well as the degree of loss aversion λ_i, change with the scarcity mindset and to see if cognitive ability and affect are mediators. In other words, we are interested in the following linear combinations.

In the following equations, let $RP_i = \{\delta_i, \gamma_i, \lambda_i\}$. Total effects of treatment statuses on elicited risk preferences are captured by equation 1.16 to 1.20. Each equation is with condition dummy with different bases.

$$RP_i = \tau_{0fhfe} + \tau_{1fhfe} fhfe_i \tag{1.16}$$

,where $fhfe_i = \begin{cases} 1 & , if\ subject\ is\ in\ financial\ hard\ condition \\ 0 & , if\ subject\ is\ in\ financial\ easy\ condition \end{cases}$

$$RP_i = \tau_{0fhnfh} + \tau_{1fhnfh} fhnfh_i \tag{1.17}$$

,where $fhnfh_i = \begin{cases} 1 & , if\ subject\ is\ in\ financial\ hard\ condition \\ 0 & , if\ subject\ is\ in\ nonfinancial\ hard\ condition \end{cases}$

$$RP_i = \tau_{0fhnfe} + \tau_{1fhnfe} fhnfe_i \tag{1.18}$$

,where $fhnfe_i = \begin{cases} 1 & , if\ subject\ is\ in\ financial\ hard\ condition \\ 0 & , if\ subject\ is\ in\ nonfinancial\ easy\ condition \end{cases}$

$$RP_i = \tau_{0nfhnfe} + \tau_{1nfhnfe} nfhnfe_i \tag{1.19}$$

,where $nfhnfe_i = \begin{cases} 1 & , if\ subject\ is\ in\ nonfinancial\ hard\ condition \\ 0 & , if\ subject\ is\ in\ nonfinancial\ easy\ condition \end{cases}$

$$RP_i = \tau_{0f} + \tau_{1f} f_i \tag{1.20}$$

,where $f_i = \begin{cases} 1 & , if\ subject\ is\ in\ financial\ condition \\ 0 & , if\ subject\ is\ in\ nonfinancial\ condition \end{cases}$

$\hat{\tau}_{1fhfe}, \hat{\tau}_{1fhnfh}, \hat{\tau}_{1fhnfe}$ are the estimated total average treatment effect of being assigned to financial hard priming condition on risk preferences, compared to financial easy priming condition, nonfinancial hard priming, and nonfinancial easy priming, respectively. "Total", here, is the average treatment effect before controlling for mediators. Thus, these estimated coefficients include both direct and indirect effect of the priming. $\hat{\tau}_{1fhfe}$ captures the effect of intended higher intensity of financial concerns, while $\hat{\tau}_{1fhnfh}$ and $\hat{\tau}_{1fhnfe}$ capture both concern effect and framing effect. This is because the former compares the primings with different intention-to-treat cognitive load in the same financial frame, while the latter should include the effect of cognitive load from more intensified intention-to-treat content and the effect of being primed in different frames.

$\hat{\tau}_{1nfhnfe}$ is the estimated total average treatment effect of being primed with nonfinancial hard situation on risk preferences, compared to nonfinancial easy condition.

$\hat{\tau}_{1fhfe} - \hat{\tau}_{1nfhnfe}$ tells us how changes in risk preferences from financial priming are different from changes in risk preferences from nonfinancial priming. In other words, $\hat{\tau}_{1fhfe} - \hat{\tau}_{1nfhnfe}$ captures average framing effect on risk preferences. That is, given equal intended concerns, $\hat{\tau}_{1fhfe} - \hat{\tau}_{1nfhnfe}$ should tell us whether the

financial framing of the concerns matter. As for $\hat{\tau}_{1f}$, this average treatment effect captures both the effect of financial worries against nonfinancial worries and of the framing effect, without differentiating the intended intensity of concerns. These total average treatment effects are estimated by maximum likelihood estimation of loglikelihood function in equation 1.15.

The effects of treatment statuses on mediators M_i, which are cognitive capacity (C_i) and affect (A_i), are captured by equation (1.21) to (1.25).

$$M_i = \eta_{0fhfe} + \eta_{1fhfe} fhfe_i + \epsilon_i \tag{1.21}$$

$$M_i = \eta_{0fhnfh} + \eta_{1fhnfh} fhnfh_i + \epsilon_i \tag{1.22}$$

$$M_i = \eta_{0fhnfe} + \eta_{1fhnfe} fhnfe_i + \epsilon_i \tag{1.23}$$

$$M_i = \eta_{0nfhnfe} + \eta_{1nfhnfe} nfhnfe_i + \epsilon_i \tag{1.24}$$

$$M_i = \eta_{0nfhnfe} + \eta_{1nfhnfe} f_i + \epsilon_i \tag{1.25}$$

The average treatment effects of treatment statuses on cognition or affect for each specification can be interpreted similarly to the above cases in equation 1.16 to 1.20, except now are looking at the mediators as dependent variables. $\hat{\eta}_{1fhnfe}$ or $\hat{\eta}_{1fhnfh}$ are in line with Lichand and Mani (2020)'s estimation of the effect of

priming on cognition. The estimation of these average treatment effects is done via OLS estimation with robust standard error.

The direct average treatment effects of treatment statuses on elicited risk preferences and the effects of mediator on elicited risk preferences, which constitute indirect effect, are captured in equation 1.26 to 1.30.

$$RP_i = \beta_{0fhfe} + \beta_{1fhfe} fhfe_i + \beta_{2fhfe} M_i \tag{1.26}$$

$$RP_i = \beta_{0fhnfh} + \beta_{1fhnfh} fhnfh_i + \beta_{2fhnfh} M_i \tag{1.27}$$

$$RP_i = \beta_{0fhnfe} + \beta_{1fhnfe} fhnfe_i + \beta_{2fhnfe} M_i \tag{1.28}$$

$$RP_i = \beta_{0nfhnfe} + \beta_{1nfhnfe} nfhnfe_i + \beta_{2nfhnfe} M_i \tag{1.29}$$

$$RP_i = \beta_{0f} + \beta_{1f} f_i + \beta_{2f} M_i \tag{1.30}$$

β_{1fhfe}, β_{1fhnfh}, β_{1fhnfe}, are the direct average treatment effect of having financial hard priming on risk preferences, controlling for cognitive capacity and affect, compared to financial easy priming, nonfinancial hard and easy priming, respectively. $\beta_{1nfhnfe}$ is the direct effect when comparing nonfinancial hard to nonfinancial easy priming, β_{1f} is for the case of comparing financial to nonfinancial condition. β_{1fhfe}, β_{1fhnfh}, β_{1fhnfe}, $\beta_{2nfhnfe}$, β_{2f} are the effects of mediators

on risk preference, given level of financial concerns, for each group of comparison. Equation 1.26 to 1.30 are estimated by maximum likelihood estimation with the loglikelihood as in equation 1.15.

To test whether there is any mediated average treatment effect, we can test whether the total average treatment effect is equal to the direct average treatment effect. If it can be rejected that the difference between the total and the direct effect is equal to zero, as stated in Fritz and Mackinnon (2007), this could be hypothesized that the total effect is partly mediated. The difference between the total and the direct effects can be estimated by using Seemingly Unrelated Regression to calculate covariance between the estimators.

1.7 Results and Discussion

1.7.1 Balance Test and Manipulation Check

Balance test

Comparing between financial and nonfinancial condition, between financial hard and easy condition, between nonfinancial hard and easy condition, and between financial hard and nonfinancial hard condition, subjects have no statistically significant differences in average characteristics, at 5% level of significance. This is true for all characteristics, except equivalent income, annual household income divided by the square root of household size. According to equivalent income, subjects in financial condition happened to be approximately richer than those in nonfinancial condition. Additionally, subjects in financial hard condition has higher annual household income and higher equivalent income than those in nonfinancial easy condition. Balance tests[48] are shown in table 1.3 to 1.7 below.

Our subjects resided within New York state. Forty nine percent of all subjects were male. According to the descriptive statistics shown in Appendix A of Chapter 1, all subjects were between 22 to 85 years old , and averagely 49 years old. Majority were with Bachelor's degree. Averagely, the household size was 2.6 and households earned mean annual household income about US$ 74,000. However, the median annual household income was in the bracket of US$60,000 to US$70,000[49]. This is in alignment with median household income

[48]Balance tables were constructed by Chiapello (2018).

[49]The income data was collected in 14 brackets, starting from less than $20K to more than 200K. Midpoints of each bracket were used to approximate household income for each house-

in New York state between 2014 and 2018[50]. Additionally, in this aspect, subjects in our study are similar to the subjects studied in Mani et al., 2013a. To reflect the tightness of household budget constraint as well as economies of scale in consumption within a family, annual household income is adjusted by dividing by the square root of household size(Buhmann et al., 1988). With this equivalence scale, mean and median equivalent annual household income were US$48,000 and US$38,000, respectively. Based on this equivalent income and 2020 U.S. poverty guidelines 2020[51], 11% of the sample should be considered as the poor. About 38% of the sample were "unemployed". That is, they were either unable to work, student, homemaker, retired, or unemployed. Moreover, around 42% of the subjects received social security, supplemental security income, public assistance, welfare payment from welfare office, or unemployment compensation.

To give a rough picture of financial struggles some subjects might be encountering, 21% of the sample received benefits from the Food Stamp program, SNAP, WIC, or food banks. 31% were in debt, in any form of credit card debt, medical debts, payday loans, student loans, auto loans, business loan, personal loan, installment loan, or loans from relatives owed by members of household. Furthermore, about 40% were in some forms of financial hardship such as inability to pay bills, overdrawing bank account, pawning, skipping meals, or taking out payday loan. In light of subjective well-being, the subjects had mean financial satisfaction lower than mean life satisfaction.

Because the main task of this study dealt with lottery choices, questions measuring basic understanding of probability were also asked, and we have that 70% of the subjects can answer all such questions correctly. In addition, lotto

hold who indicated that the household's income fell into the bracket.

[50]https://www.census.gov/quickfacts/NY, retrieved June 28, 2020

[51]https://aspe.hhs.gov/poverty-guidelines, retrieved June 28, 2020

buying behavior was gauged from the question asking how often subjects buy lotto in a year. From the answer to this question, we have that averagely subjects in this experiment buy about 14 lottery tickets in a year. Moreover, about half of the sample could recall that they had ever won a lottery ticket.

Table 1.3: Balance table(Financial vs. Nonfinancial conditions)

Characteristics	Nonfinancial condition	Financial condition	Difference
Male	0.452	0.521	0.068
	(0.499)	(0.500)	(0.041)
Age	48.565	48.524	-0.041
	(15.139)	(14.910)	(1.243)
Education level	4.185	4.353	0.168
	(1.515)	(1.536)	(0.126)
Household size	2.675	2.568	-0.106
	(1.377)	(1.367)	(0.114)
Annual household income	70.146	77.654	7.509
	(49.803)	(53.040)	(4.258)
Equivalent income	44.533	50.565	6.032*
	(31.631)	(33.784)	(2.708)
Unemployed	0.408	0.356	-0.051
	(0.492)	(0.480)	(0.040)
Welfare recipient	0.435	0.404	-0.031
	(0.497)	(0.492)	(0.041)
Food aid recipient	0.199	0.219	0.021
	(0.400)	(0.414)	(0.034)
Debtor	0.277	0.336	0.058
	(0.448)	(0.473)	(0.038)
In financial hardship	0.421	0.384	-0.038
	(0.495)	(0.487)	(0.041)
Life satisfaction	3.771	3.860	0.089
	(1.105)	(1.114)	(0.092)
Prob Know	0.695	0.712	0.017
	(0.461)	(0.453)	(0.038)
Lotto bought	14.781	13.962	-0.818
	(18.733)	(18.544)	(1.543)
Win lotto	0.483	0.524	0.041
	(0.501)	(0.500)	(0.041)
Insured	0.575	0.527	-0.048
	(0.495)	(0.500)	(0.041)
Health insured	0.935	0.921	-0.014
	(0.247)	(0.270)	(0.021)
Observations	292	292	584

Note: "Difference" is referred to difference in mean, and is equal to the coefficient of treatment dummy of OLS regression with characteristics as dependent variable. Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$

Table 1.4: Balance table(Financial hard vs. Financial easy conditions)

Characteristics	Financial easy condition	Financial hard condition	Difference
Male	0.521	0.521	0.000
	(0.501)	(0.501)	(0.059)
Age	47.411	49.637	2.226
	(13.844)	(15.874)	(1.743)
Education level	4.315	4.390	0.075
	(1.561)	(1.515)	(0.180)
Household size	2.630	2.507	-0.123
	(1.276)	(1.454)	(0.160)
Annual household income	75.993	79.315	3.322
	(53.535)	(52.673)	(6.216)
Equivalent income	47.989	53.141	5.153
	(32.498)	(34.945)	(3.949)
Unemployed	0.356	0.356	-0.000
	(0.481)	(0.481)	(0.056)
Welfare recipient	0.349	0.459	0.110
	(0.478)	(0.500)	(0.057)
Food aid recipient	0.219	0.219	0.000
	(0.415)	(0.415)	(0.049)
Debtor	0.322	0.349	0.027
	(0.469)	(0.478)	(0.055)
In financial hardship	0.377	0.390	0.014
	(0.486)	(0.490)	(0.057)
Life satisfaction	3.918	3.801	-0.116
	(1.117)	(1.112)	(0.130)
Prob Know	0.740	0.685	-0.055
	(0.440)	(0.466)	(0.053)
Lotto bought	14.110	13.815	-0.295
	(18.890)	(18.255)	(2.174)
Win lotto	0.479	0.568	0.089
	(0.501)	(0.497)	(0.058)
Insured	0.493	0.562	0.068
	(0.502)	(0.498)	(0.058)
Health insured	0.918	0.925	0.007
	(0.276)	(0.265)	(0.032)
Observations	146	146	292

Note: "Difference" is referred to difference in mean, and is equal to the coefficient of treatment dummy of OLS regression with characteristics as dependent variable. Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$

Table 1.5: Balance table(Nonfinancial hard vs. Nonfinancial easy conditions)

Characteristics	Nonfinancial easy condition	Nonfinancial hard condition	Difference
Male	0.411	0.493	0.082
	(0.494)	(0.502)	(0.058)
Age	48.445	48.685	0.240
	(14.800)	(15.522)	(1.775)
Education level	4.233	4.137	-0.096
	(1.453)	(1.578)	(0.178)
Household size	2.685	2.664	-0.021
	(1.470)	(1.283)	(0.161)
Annual household income	66.832	73.459	6.627
	(44.394)	(54.634)	(5.826)
Equivalent income	42.331	46.735	4.404
	(26.999)	(35.626)	(3.699)
Unemployed	0.411	0.404	-0.007
	(0.494)	(0.492)	(0.058)
Welfare recipient	0.425	0.445	0.021
	(0.496)	(0.499)	(0.058)
Food aid recipient	0.205	0.192	-0.014
	(0.405)	(0.395)	(0.047)
Debtor	0.247	0.308	0.062
	(0.433)	(0.463)	(0.052)
In financial hardship	0.411	0.432	0.021
	(0.494)	(0.497)	(0.058)
Life satisfaction	3.726	3.815	0.089
	(1.136)	(1.076)	(0.130)
Prob Know	0.705	0.685	-0.021
	(0.457)	(0.466)	(0.054)
Lotto bought	15.630	13.932	-1.699
	(19.383)	(18.087)	(2.194)
Win lotto	0.452	0.514	0.062
	(0.499)	(0.502)	(0.059)
Insured	0.541	0.610	0.068
	(0.500)	(0.490)	(0.058)
Health insured	0.918	0.952	0.034
	(0.276)	(0.214)	(0.029)
Observations	146	146	292

Note: "Difference" is referred to difference in mean, and is equal to the coefficient of treatment dummy of OLS regression with characteristics as dependent variable. Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$

Table 1.6: Balance table(Financial hard vs. Nonfinancial hard conditions)

Characteristics	Nonfinancial hard condition	Financial hard condition	Difference
Male	0.493	0.521	0.027
	(0.502)	(0.501)	(0.059)
Age	48.685	49.637	0.952
	(15.522)	(15.874)	(1.837)
Education level	4.137	4.390	0.253
	(1.578)	(1.515)	(0.181)
Household size	2.664	2.507	-0.158
	(1.283)	(1.454)	(0.160)
Annual household income	73.459	79.315	5.856
	(54.634)	(52.673)	(6.281)
Equivalent income	46.735	53.141	6.407
	(35.626)	(34.945)	(4.130)
Unemployed	0.404	0.356	-0.048
	(0.492)	(0.481)	(0.057)
Welfare recipient	0.445	0.459	0.014
	(0.499)	(0.500)	(0.058)
Food aid recipient	0.192	0.219	0.027
	(0.395)	(0.415)	(0.047)
Debtor	0.308	0.349	0.041
	(0.463)	(0.478)	(0.055)
In financial hardship	0.432	0.390	-0.041
	(0.497)	(0.490)	(0.058)
Life satisfaction	3.815	3.801	-0.014
	(1.076)	(1.112)	(0.128)
Prob Know	0.685	0.685	-0.000
	(0.466)	(0.466)	(0.055)
Lotto bought	13.932	13.815	-0.116
	(18.087)	(18.255)	(2.127)
Win lotto	0.514	0.568	0.055
	(0.502)	(0.497)	(0.058)
Insured	0.610	0.562	-0.048
	(0.490)	(0.498)	(0.058)
Health insured	0.952	0.925	-0.027
	(0.214)	(0.265)	(0.028)
Observations	146	146	292

Note: "Difference" is referred to difference in mean, and is equal to the coefficient of treatment dummy of OLS regression with characteristics as dependent variable. Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$

Table 1.7: Balance table(Financial hard vs. Nonfinancial easy conditions)

Characteristics	Nonfinancial easy condition	Financial hard condition	Difference
Male	0.411	0.521	0.110
	(0.494)	(0.501)	(0.058)
Age	48.445	49.637	1.192
	(14.800)	(15.874)	(1.796)
Education level	4.233	4.390	0.158
	(1.453)	(1.515)	(0.174)
Household size	2.685	2.507	-0.178
	(1.470)	(1.454)	(0.171)
Annual household income	66.832	79.315	12.483*
	(44.394)	(52.673)	(5.701)
Equivalent income	42.331	53.141	10.810**
	(26.999)	(34.945)	(3.655)
Unemployed	0.411	0.356	-0.055
	(0.494)	(0.481)	(0.057)
Welfare recipient	0.425	0.459	0.034
	(0.496)	(0.500)	(0.058)
Food aid recipient	0.205	0.219	0.014
	(0.405)	(0.415)	(0.048)
Debtor	0.247	0.349	0.103
	(0.433)	(0.478)	(0.053)
In financial hardship	0.411	0.390	-0.021
	(0.494)	(0.490)	(0.058)
Life satisfaction	3.726	3.801	0.075
	(1.136)	(1.112)	(0.132)
Prob Know	0.705	0.685	-0.021
	(0.457)	(0.466)	(0.054)
Lotto bought	15.630	13.815	-1.815
	(19.383)	(18.255)	(2.204)
Win lotto	0.452	0.568	0.116*
	(0.499)	(0.497)	(0.058)
Insured	0.541	0.562	0.021
	(0.500)	(0.498)	(0.058)
Health insured	0.918	0.925	0.007
	(0.276)	(0.265)	(0.032)
Observations	146	146	292

Note: "Difference" is referred to difference in mean, and is equal to the coefficient of treatment dummy of OLS regression with characteristics as dependent variable. Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$

Does the priming increase financial worries?

Financial worries were measured both right after the priming and after the lottery choice task. As a manipulation check, whether the priming increase immediate financial worries right after the priming is examined by ordered probit estimation. In table 1.8 to 1.11 below, "fh (stands for financial hard) vs. fe (stands for financial easy)" column presents the estimation result based on subsample of 292 subjects in financial condition; "nfh (stands for nonfinancial hard) vs. nfe (stands for nonfinancial easy)" is based on 292 subjects in nonfinancial condition; and "f (stands for financial) vs. nf (stands for nonfinancial)" is based on all subjects. Subjects were asked to indicate to what extent they agree with how they currently feel worried about their financial situation(table 1.9), about having enough money to make ends meet(table 1.10), and about not being able to find money in case they really need it(table 1.11). The scores from these three questions were summed up as "financial worries after priming" which is the dependent variable in the estimation in table 1.8. Reported standard errors are robust standard error. "In financial hard condition" indicates a dummy variable equal to one if a subject was assigned into financial hard condition. "In nonfinancial hard condition" indicates a dummy variable equal to one if a subject was assigned into nonfinancial hard condition. "In financial condition" indicates a dummy variable equal to one if a subject was assigned into financial condition, either hard or easy version.

It is found that the priming didn't affect all subjects equally, in terms of financial worries. As expected, subjects in nonfinancial hard condition didn't feel more financially worried than subjects in nonfinancial easy condition. In fact, based on all 584 subjects, subjects on financial condition didn't feel more

financial worried than those in nonfinancial condition. This is also the case for subjects in financial hard condition, compared to nonfinancial hard or nonfinancial easy condition. However, it was found that, comparing with subjects in financial easy condition, thinking about scenarios offered in financial hard priming did make subjects more financial worried about their financial situation and about making ends meet. This is shown by the correlation between being in financial hard condition and latent financial worries being statistically significant at 5% significance level, in table 1.9, 1.10, and 1.11. Although subjects in financial hard condition statistically significantly felt more financial worried than those in financial easy condition, they were not more worried than those in nonfinancial hard or easy condition. These are shown in table 1.13 and 1.14. Nonetheless, for subjects who were poor according to 2020 U.S. poverty guideline, asking them financial hard questions rendered them to be more worried than when they needed to think about nonfinancial hard questions. Shown in table 1.12, these effects are estimated as the mean increase in financial worry from being in financial hard condition plus the estimated effect of being poor under financial hard priming. Notably, subjects in financial easy condition didn't feel more financially worried than those in nonfinancial condition, even for the poor. As a side note, those who were in financial hardship did have statistically significantly higher financial worries in all of their subcategories and all experimental condition, compared to those who were not in financial hardship.

For "fh vs. fe" subsample and "f vs. nf" sample, higher equivalent income relates with lower latent financial worries, though this is not true when considering nonfinancial hard against nonfinancial easy condition. Moreover, the older subjects were, the more worried they felt about their financial situations and about no emergency cash. Interestingly, those who had outstanding debt

seems to feel less financial worried about their financial situation and about having no emergency cash. Unsurprisingly, subjects who indicated that they were in some forms of financial hardship feel more financially worried. Notably, in nonfinancial condition in which subjects were primed with the thoughts of natural disasters, subjects who had fire, hazard, or flood insurance on their property they were living in felts less financial worried.

Table 1.8: Does the priming increase financial worries after priming?

Financial Worries after priming	fh vs.fe	nfh vs.nfe	f vs.nf
In financial hard condition	0.297*		
	(0.125)		
In nonfinancial hard condition		-0.0647	
		(0.125)	
In financial condition			-0.0228
			(0.0869)
Equivalent income	-0.0254**	-0.0103	-0.0158**
	(0.00793)	(0.00663)	(0.00504)
Equivalent income^2	0.000105	-0.0000277	0.0000334
	(0.0000547)	(0.0000420)	(0.0000340)
Male	-0.0854	-0.0297	-0.0865
	(0.130)	(0.127)	(0.0893)
Age	0.0674*	0.0513	0.0515*
	(0.0290)	(0.0321)	(0.0216)
Age^2	-0.000725*	-0.000519	-0.000553*
	(0.000290)	(0.000333)	(0.000220)
Education level	0.0649	-0.0868	-0.0126
	(0.0498)	(0.0460)	(0.0341)
Unemployed	0.333	-0.196	0.0226
	(0.198)	(0.199)	(0.135)
Welfare recipient	-0.247	-0.00629	-0.0658
	(0.188)	(0.171)	(0.124)
Debtor	-0.297*	-0.214	-0.254*
	(0.140)	(0.148)	(0.101)
In financial hardship	0.959***	0.973***	0.957***
	(0.141)	(0.158)	(0.105)
Insured	-0.0938	-0.301*	-0.173
	(0.131)	(0.148)	(0.0961)
Health insured	-0.434	0.158	-0.132
	(0.270)	(0.244)	(0.184)
Observations	292	292	584

Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$ *** for $p < 0.001$

Table 1.9: Does the priming increase worries about financial situation?

Worries about financial situation	fh vs.fe	nfh vs.nfe	f vs.nf
In financial hard condition	0.300*		
	(0.129)		
In nonfinancial hard condition		-0.0597	
		(0.130)	
In financial condition			-0.0420
			(0.0894)
Equivalent income	-0.0211**	-0.00872	-0.0135**
	(0.00804)	(0.00715)	(0.00516)
Equivalent income^2	0.0000760	-0.0000376	0.0000199
	(0.0000573)	(0.0000462)	(0.0000352)
Male	-0.0524	-0.0598	-0.0849
	(0.132)	(0.133)	(0.0918)
Age	0.0788**	0.0475	0.0559**
	(0.0281)	(0.0332)	(0.0215)
Age^2	-0.000805**	-0.000492	-0.000586**
	(0.000281)	(0.000345)	(0.000219)
Education level	0.0777	-0.0851	-0.00316
	(0.0508)	(0.0476)	(0.0346)
Unemployed	0.335	-0.118	0.0674
	(0.209)	(0.207)	(0.138)
Welfare recipient	-0.272	0.00881	-0.0818
	(0.216)	(0.178)	(0.134)
Debtor	-0.313*	-0.436**	-0.349***
	(0.141)	(0.159)	(0.104)
In financial hardship	0.914***	0.836***	0.875***
	(0.144)	(0.161)	(0.107)
Insured	-0.0201	-0.376*	-0.163
	(0.141)	(0.155)	(0.101)
Health insured	-0.390	0.125	-0.112
	(0.253)	(0.284)	(0.187)
Observations	292	292	584

Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$ *** for $p < 0.001$

Table 1.10: Does the priming increase worries about making ends meet?

Worries about making ends meet	fh vs.fe	nfh vs.nfe	f vs.nf
In financial hard condition	0.311*		
	(0.135)		
In nonfinancial hard condition		-0.0350	
		(0.129)	
In financial condition			-0.00130
			(0.0891)
Equivalent income	-0.0270**	-0.0107	-0.0168***
	(0.00826)	(0.00641)	(0.00504)
Equivalent income^2	0.000118*	-0.0000152	0.0000458
	(0.0000571)	(0.0000396)	(0.0000341)
Male	-0.0109	-0.0173	-0.0422
	(0.133)	(0.135)	(0.0921)
Age	0.0476	0.0478	0.0402
	(0.0304)	(0.0338)	(0.0227)
Age^2	-0.000524	-0.000474	-0.000434
	(0.000305)	(0.000351)	(0.000231)
Education level	0.0636	-0.0758	-0.00824
	(0.0503)	(0.0463)	(0.0341)
Unemployed	0.267	-0.215	-0.0155
	(0.200)	(0.208)	(0.140)
Welfare recipient	-0.279	0.0710	-0.0503
	(0.199)	(0.177)	(0.132)
Debtor	-0.243	-0.166	-0.194
	(0.148)	(0.150)	(0.103)
In financial hardship	0.927***	0.949***	0.934***
	(0.152)	(0.162)	(0.111)
Insured	-0.0316	-0.357*	-0.157
	(0.137)	(0.155)	(0.100)
Health insured	-0.349	-0.00754	-0.156
	(0.281)	(0.266)	(0.192)
Observations	292	292	584

Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$ *** for $p < 0.001$

Table 1.11: Does the priming increase worries about no emergency cash?

Worries about no emergency cash	fh vs.fe	nfh vs.nfe	f vs.nf
In financial hard condition	0.250		
	(0.129)		
In nonfinancial hard condition		-0.157	
		(0.130)	
In financial condition			-0.0533
			(0.0908)
Equivalent income	-0.0271***	-0.0103	-0.0161**
	(0.00806)	(0.00670)	(0.00508)
Equivalent income^2	0.000118*	-0.0000228	0.0000365
	(0.0000543)	(0.0000427)	(0.0000335)
Male	-0.168	-0.0323	-0.127
	(0.137)	(0.130)	(0.0934)
Age	0.0765*	0.0438	0.0536*
	(0.0304)	(0.0326)	(0.0223)
Age^2	-0.000840**	-0.000436	-0.000580*
	(0.000306)	(0.000336)	(0.000226)
Education level	0.0558	-0.0963*	-0.0218
	(0.0523)	(0.0474)	(0.0354)
Unemployed	0.351	-0.218	0.0126
	(0.212)	(0.194)	(0.137)
Welfare recipient	-0.190	-0.138	-0.0979
	(0.198)	(0.180)	(0.129)
Debtor	-0.297*	-0.0988	-0.219*
	(0.144)	(0.149)	(0.103)
In financial hardship	0.894***	1.014***	0.940***
	(0.148)	(0.160)	(0.108)
Insured	-0.216	-0.175	-0.187
	(0.136)	(0.150)	(0.0988)
Health insured	-0.397	0.382	-0.0326
	(0.292)	(0.232)	(0.192)
Observations	292	292	584

Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$ *** for $p < 0.001$

Table 1.12: Does the priming, moderated by being federal poor, increase financial worries?

	(1)	(2)	(3)
	financial worry	making ends meet	no emergency cash
$\hat{\theta}_1 + \hat{\theta}_2$	0.785+	0.939*	0.715+
	(0.407)	(0.476)	(0.416)
Observations	292	292	292

Standard errors in parentheses, + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

The total score of three categories of financial worries is dependent variable in model (1), Score for "worry about having enough money to make ends meet" for model (2), Score for "worry about no emergency cash" is dependent variable for model (3).

All estimations are based on financial hard condition (fh) and nonfinancial hard condition(nfh). $poorfederal$ is a dummy variable equal to 1 for subject who was poor according to 2020 U.S. Federalpoverty guideline.

In all estimations, the ordered probit estimation is used. The underlying score is estimated as a linear combination of: $\theta_0 + \theta_1 fh_i + \theta_2 fh_i \times poorfederal_i + x_i'\theta_4$, where x_i is a column vector of demographic variables.

Table 1.13: Does the priming increase nancial worries? (fh vs. nfh)

	FWORRY	FWORRY1	FWORRY2	FWORRY3
In financial hard condition	0.180	0.155	0.177	0.171
	(0.126)	(0.129)	(0.129)	(0.132)
Equivalent income	-0.0118	-0.00916	-0.00901	-0.0171*
	(0.00667)	(0.00687)	(0.00681)	(0.00688)
Equivalent income^2	0.00000307	-0.00000640	-0.00000598	0.0000302
	(0.0000416)	(0.0000425)	(0.0000415)	(0.0000417)
Male	-0.0789	-0.0715	-0.0563	-0.106
	(0.128)	(0.131)	(0.130)	(0.132)
Age	0.0545	0.0579*	0.0401	0.0708*
	(0.0294)	(0.0283)	(0.0316)	(0.0304)
Age^2	-0.000576*	-0.000604*	-0.000443	-0.000740*
	(0.000293)	(0.000281)	(0.000315)	(0.000307)
Education level	-0.0412	-0.0315	-0.0382	-0.0459
	(0.0517)	(0.0516)	(0.0520)	(0.0542)
Unemployed	0.216	0.262	0.138	0.243
	(0.192)	(0.196)	(0.193)	(0.197)
Welfare recipient	-0.214	-0.254	-0.101	-0.290
	(0.179)	(0.189)	(0.187)	(0.182)
Debtor	-0.200	-0.226	-0.121	-0.241
	(0.142)	(0.145)	(0.144)	(0.147)
In financial hardship	0.995***	0.958***	0.968***	0.978***
	(0.155)	(0.155)	(0.169)	(0.160)
Insured	0.00325	-0.00691	-0.0320	0.0429
	(0.142)	(0.149)	(0.148)	(0.146)
Health insured	0.127	0.175	0.133	0.137
	(0.247)	(0.253)	(0.279)	(0.253)
Observations	292	292	292	292

Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$ *** for $p < 0.001$
Note: FWORRY is "Financial Worries after priming"; FWORRY1 is "Worries about nancial situation"; FWORRY2 is "Worries about making ends meet"; FWORRY3 is "Worries about no emergency cash".

Table 1.14: Does the priming increase nancial worries? (fh vs. nfe)

	FWORRY	FWORRY1	FWORRY2	FWORRY3
In financial hard condition	0.0512	0.0229	0.0788	-0.0346
	(0.124)	(0.127)	(0.129)	(0.129)
Equivalent income	-0.0219**	-0.0198*	-0.0235**	-0.0180*
	(0.00803)	(0.00813)	(0.00776)	(0.00817)
Equivalent income^2	0.0000934	0.0000889	0.000104	0.0000640
	(0.0000560)	(0.0000565)	(0.0000537)	(0.0000557)
Male	-0.110	-0.0736	-0.0371	-0.166
	(0.123)	(0.129)	(0.127)	(0.130)
Age	0.0160	0.0260	0.00239	0.0290
	(0.0310)	(0.0318)	(0.0316)	(0.0325)
Age^2	-0.000215	-0.000291	-0.0000490	-0.000397
	(0.000317)	(0.000323)	(0.000322)	(0.000333)
Education level	-0.0309	-0.0124	-0.00878	-0.0627
	(0.0492)	(0.0491)	(0.0498)	(0.0507)
Unemployed	0.130	0.250	-0.0100	0.131
	(0.193)	(0.199)	(0.210)	(0.194)
Welfare recipient	-0.189	-0.260	-0.120	-0.195
	(0.175)	(0.194)	(0.192)	(0.175)
Debtor	-0.203	-0.329*	-0.138	-0.152
	(0.140)	(0.145)	(0.143)	(0.142)
In financial hardship	1.017***	0.972***	0.983***	0.918***
	(0.151)	(0.161)	(0.162)	(0.152)
Insured	-0.0293	-0.0326	-0.0451	-0.0711
	(0.138)	(0.147)	(0.148)	(0.138)
Health insured	-0.0444	0.00669	-0.133	0.122
	(0.265)	(0.280)	(0.292)	(0.252)
Observations	292	292	292	292

Standard errors in parentheses, * for $p < 0.05$ ** for $p < 0.01$ *** for $p < 0.001$

Note: FWORRY is "Financial Worries after priming"; FWORRY1 is "Worries about nancial situation"; FWORRY2 is "Worries about making ends meet"; FWORRY3 is "Worries about no emergency cash".

1.7.2 The effect of priming on risk preferences(Average Treatment Effect)

In this section, we analyze the effect of priming on risk preferences, which are shown in the following tables, from table 1.15 to table 1.21. First, the estimation of the effect of priming by MLE, assuming homoskedasticity in error variance with respect to gamble is discussed in subsection 1.7.2.1. Next, in subsection 1.7.2.2, we allow for heteroskedasticity in error variance with respect to gamble in the estimation. From our econometrics framework in subsection 1.6.2, the dummy variables $fhfe_i$, $fhnfh_i$, $fhnfe_i$, $nfhnfe_i$, f_i are now denoted by "financial hard", consistent with the column "fh vs. fe"; "financial hard", consistent with the column "fh vs. nfh"; "financial hard", consistent with the column "fh vs. nfe"; "nonfinancial hard", consistent with the column "nfh vs. nfe"; and "financial", consistent with the column "f vs. nf", respectively.

1.7.2.1 The effect of priming by MLE: Homoskedasticity in error variance with respect to gamble

Our main outcome data is lottery choice. In each lottery, the multiple price list spans from five times of each lottery's market price down to zero for New York lotteries, and from the high outcome to zero, including the low outcome, for the experimental lotteries.

When a subject chooses not to switch at all and is willing to accept no money rather than receiving lottery with positive expected value, such behavior is not conforming to rationality as measured by expected utility theory or expected value theory. We firstly coded this behavior with the one who chooses to switch

at the lowest possible positive amount of sure money in the price list.

For experimental lotteries, one who chooses to accept lotteries even being offered the sure amount equal to the high outcome in the gamble doesn't conform with the rationality as well. We firstly coded this as the one who switches at the first row.

For those who switch at row 0 for NY lotteries, they are conformed with rationality as the maximum price offered in the price list is not equal to the non-zero winning prize of NY lotteries.

In the following, the order of switching row is used to calculate certainty equivalent that will be used in the estimation of risk preference parameters.

In this subsection, we assume that variance of error doesn't depend on gamble characteristics. In this case, the error variance is only individually specific. This individual heterogeneity allows us to capture heterogeneity in individual factors determining lottery choices. That is, we assume that:

$$\epsilon_i \sim N(0, \sigma_i^2), \sigma_i = \xi_i$$

Based on 584 subjects, maximum likelihood estimation is used in order to estimate average treatment effects. For probability weighting function and standard risk aversion, the results, from estimation (1) in table 1.15 and 1.16, show that there is no statistical difference within either financial condition or nonfinancial condition. Based on the lottery choices of 292 subjects on experimental lotteries and NUMBERS lotteries in financial condition, probability weighting (δ, γ) and standard risk aversion(α) of those who were in financial hard condition are not statistically different from those who were in financial easy condi-

tion, at 5% significant level. This is also the case when we consider nonfinancial hard condition against nonfinancial easy condition. However, if we look at loss aversion(λ), financial hard priming causes subject to be more statistically significantly loss averse, comparing to the subjects in financial easy condition.

In a bigger picture, as shown in estimation (2) in table 1.16, the financial framing in which subjects were primed with financial concerns, regardless of the intended intensity of the concerns, has statistically significant effects on probability weighting (δ) and loss aversion(λ), compared to all of those who were in nonfinancial condition(either hard or easy). Those who were in financial frame have higher degree of overweighting of small probabilities (but they don't seem to behave much differently when we consider the underweighting of large probabilities). This is shown by the observation that the treatment effect on probability weighting is driven by the change in elevation of the curve(δ), rather than by the change in parameter γ that governs the responsiveness to change in probability. Averagely, subjects in nonfinancial condition have estimated loss aversion parameter λ equal to 1.305, while subjects in financial condition, interestingly, have slightly lower loss aversion at 1.24.

This pattern of result is originated from the fact that, comparing to nonfinancial hard or easy condition, financial hard priming makes subject have more elevated probability weighting function, that is higher δ, as shown in column (2), (3), and (4) in table 1.15. Although subjects in financial hard condition are more loss averse than those in financial easy condition, as shown in column (1) of table 1.15, subject in financial easy condition were less loss averse than those in nonfinancial conditions, at 5% and 1% level of significance, as shown in estimation (1), (2), and (3) in table 1.17.

Importantly to note is that WIN4 and Megamillions Just the Jackpot were excluded from these estimations because convergences were not achieved or there were flat regions of the likelihood functions when the certainty equivalents of these lotteries were included. Accordingly, these results, with homogeneity in error variance with respect to gamble, were based on fifteen experimental lotteries and five New York NUMBERS lotteries, which have larger probabilities than WIN4 and Megamillions.[52]

[52]In this subsection, separated estimating equations were used when comparing between different groups, however, same results can be achieved with one estimation with all dummy variables for all conditions.

Table 1.15: The effect of priming on risk preferences

	(1) fh vs fe	(2) fh vs nfh	(3) fh vs nfe	(4) fh vs nf
delta				
financial hard	0.0516	0.136*	0.112^{+}	0.124*
	(0.0593)	(0.0636)	(0.0625)	(0.0541)
cons	1.502***	1.417***	1.441***	1.429***
	(0.0404)	(0.0464)	(0.0449)	(0.0323)
gamma				
financial hard	0.0106	-0.0245	-0.0204	-0.0224
	(0.0272)	(0.0294)	(0.0292)	(0.0252)
cons	0.325***	0.361***	0.356***	0.358***
	(0.0181)	(0.0213)	(0.0210)	(0.0150)
alpha				
financial hard	0.00340	-0.0449	-0.0318	-0.0383
	(0.0323)	(0.0361)	(0.0353)	(0.0302)
cons	0.447***	0.496***	0.482***	0.489***
	(0.0221)	(0.0274)	(0.0263)	(0.0190)
lambda				
financial hard	0.0568^{+}	-0.0436	-0.0244	-0.0338
	(0.0336)	(0.0414)	(0.0392)	(0.0341)
cons	1.214***	1.315***	1.296***	1.305***
	(0.0206)	(0.0317)	(0.0289)	(0.0214)
Observations	5840	5840	5840	8760

Standard errors in parentheses

This table presents the effect of financial hard priming, compared to:

,for fh vs fe, to financial easy priming.

,for fh vs nfh, to nonfinancial hard priming.

,for fh vs nfe, to nonfinancial easy priming.

,for fh vs nf, to nonfinancial priming.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.16: The effect of priming on risk preferences

	(1) nfh vs nfe		(2) f vs nf	
delta				
nonfinancial hard	-0.0237	(0.0646)		
financial			0.0975*	(0.0437)
cons	1.441***	(0.0449)	1.429***	(0.0323)
gamma				
nonfinancial hard	0.00409	(0.0299)		
financial			-0.0280	(0.0202)
cons	0.356***	(0.0210)	0.359***	(0.0150)
alpha				
nonfinancial hard	0.0132	(0.0380)		
financial			-0.0403	(0.0249)
cons	0.482***	(0.0263)	0.489***	(0.0190)
lambda				
nonfinancial hard	0.0191	(0.0429)		
financial			-0.0636*	(0.0271)
cons	1.296***	(0.0289)	1.305***	(0.0214)
Observations	5840		11680	

Standard errors in parentheses
nfh vs. nfe presents the effect of nonfinancial hard priming,
,compared to nonfinancial easy priming.
f vs nf presents the effect of financial priming,
,compared to nonfinancial priming.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.17: The effect of priming on risk preferences

	(1) fe vs nfh	(2) fe vs nfe	(3) fe vs nf
delta			
financial easy	0.0845	0.0608	0.0725
	(0.0616)	(0.0604)	(0.0517)
cons	1.417***	1.441***	1.429***
	(0.0464)	(0.0449)	(0.0323)
gamma			
financial easy	-0.0351	-0.0310	-0.0330
	(0.0280)	(0.0277)	(0.0235)
cons	0.361***	0.356***	0.359***
	(0.0213)	(0.0210)	(0.0150)
alpha			
financial easy	-0.0483	-0.0352	-0.0417
	(0.0352)	(0.0343)	(0.0291)
cons	0.496***	0.482***	0.489***
	(0.0274)	(0.0263)	(0.0190)
lambda			
financial easy	-0.100**	-0.0813*	-0.0906**
	(0.0378)	(0.0355)	(0.0297)
cons	1.315***	1.296***	1.305***
	(0.0317)	(0.0289)	(0.0214)
Observations	5840	5840	8760

Standard errors in parentheses

This table presents the effect of financial easy priming,

,for fe vs nfh, compared to nonfinancial hard priming.

,for fe vs nfe, compared to nonfinancial easy priming.

,for fe vs nf, to nonfinancial priming.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.7.2.2 The effect of priming by MLE: Heteroskedasticity in error variance with respect to gamble

Now we assume that variance of error term depends on gamble characteristics. In this case, the error variance is not only individually specific, but also gamble specific. We are allowing the error variance to vary proportionally to the lottery range in each multiple price list. This approach is used in Bruhin et al. (2010), and is similar to that in Wilcox (2011). This heteroskedasticity says that the standard deviation of evaluative noise depends on the context in which individual needs to decide. The context for each lottery in our study is the range of each multiple price list. That is, we assume that:

$$\epsilon_{ig} \sim N(0, \sigma_{ig}^2),$$

$$\sigma_{ig} = \begin{cases} \xi_i(x_{1g} - x_{2g}) & , for\ L(x_{1g}, p_g; x_{2g}) \\ \xi_i(max\, l_g - min\, l_g) & , for\ L(g_g, p_g; l_g) \end{cases}.$$

With two sources of heteroskedasticity in error variance, the probability weighting functions and the coefficient of loss aversion, based on all lotteries including experimental and New York lotteries, can be estimated. The probability weighting functions of those in financial and nonfinancial conditions, based on experimental lotteries(denoted EL) and all lotteries(denoted ALL), are shown below in figure 1.1.

Based on experimental lotteries, there are statistically significant differences, in the elevation parameter δ and the sensitivity parameter γ, between subjects who were primed with financial concerns and those with nonfinancial concerns. The δ in financial frame is higher than that in nonfinancial frame by $\hat{\delta}_1 = 0.18$

with p-value 0.07, and the γ is lower with $\hat{\gamma}_1 = -0.04$, with p-value=0.004. The financial priming made subjects more overweighed small probabilities, as well as medium and large probabilities.

Based on all lotteries, including experimental and NY lotteries, the δ in financial frame is higher than that in nonfinancial frame by $\hat{\delta}_1 = 0.14$ with p-value 0.048[53].

In both cases, the average treatment effects in loss aversion λ and standard risk aversion parameter α are not statistically significant.

Based on experimental lotteries, there is overweighting of probabilities that are smaller than 0.53 and 0.57, and underweighting of probabilities larger than 0.53 and 0.57, in nonfinancial condition and financial condition respectively. This pattern is strikingly different when we include lottery choices for NY lotteries into consideration. By including lottery-choice behavior for NY lotteries and imposing that such behavior must be the same for behavior for experimental lotteries, for example imposing that $\delta_{0,ExpLotto} = \delta_{0,NYlotto}$, we have that there is overweighting of probabilities smaller than 0.91 and 0.93 for nonfinancial and financial condition, respectively. That is, the inclusion of NY lotteries expands the range of objective probabilities that is overweighted. This might be the case that the high amount of overweighting of small probabilities at the level of real lottery tickets inflates the level of overweighting of medium and large probabilities as well.

[53] All p-values are calculated from robust standard errors.

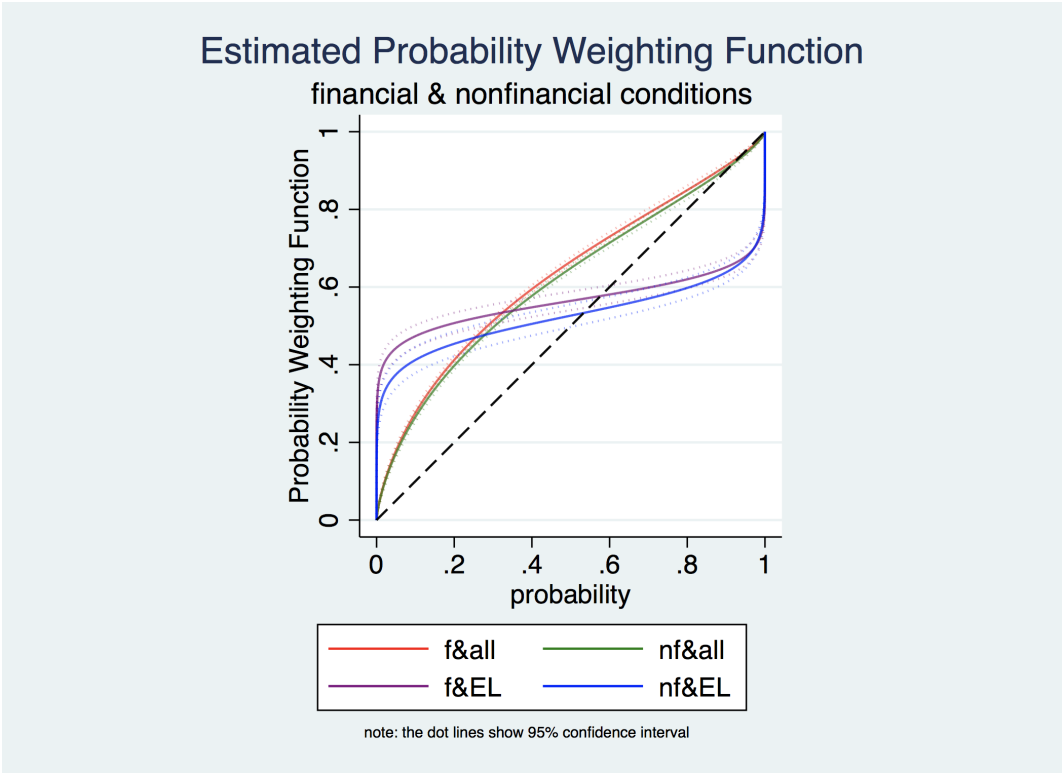

Figure 1.1: Probability weighting function in financial vs. nonfinancial condition (Heteroskedasticity in error variance with respect to gamble)

Note: "f" stands for financial condition; "nf" stands for nonfinancial condition; EL stands for experimental lotteries; "all" includes experimental and NY lotteries.

Looking into more details of average treatment effects between groups within and across financial and nonfinancial condition, it is found that the average treatment effects for nonfinancial hard condition, compared to nonfinancial easy condition are not statistically significant. In other words, the level of thinking one needs to engage in nonfinancial hard condition didn't make any change on one's risk preferences, compared to those in nonfinancial easy condition.

The effect of financial priming on probability weighting function, compared to nonfinancial condition originates from subjects both in financial hard condition and in financial easy condition. Those in financial hard condition has more elevated probability weighting function than those in nonfinancial hard condi-

tion with $\hat{\delta}_1 = 0.245\,(p < 0.05), \hat{\gamma}_1 = 0.059\,(p < 0.10)$, based on all lotteries, and with $\hat{\gamma}_1 = -0.045\,(p < 0.05)$ based on experimental lotteries. Almost similar patterns were found when comparing financial easy against nonfinancial hard or nonfinancial easy condition.

Additionally, the bigger picture masks difference in loss aversion between groups. Whereas there is no statistically significant difference in loss aversion between financial and nonfinancial condition, those who were primed with financial hard scenarios were more loss averse than those with financial easy scenario. That is, from estimation (2) in table 1.18, the coefficient of loss aversion was estimated at 1.44 for financial-easy subjects and at 1.61 for financial-hard subjects. Those in nonfinancial hard and easy conditions also were more loss averse than those in financial easy condition.

Exploring the average treatment effects on the curvature of value function, which indicates standard risk aversion, risk neutrality, or risk loving, no statistical significant effect is found. For experimental lotteries, subjects are risk-loving with $\hat{\alpha}$ about 1.55 to 1.69, while if all certainty equivalents from all lotteries were used, subjects are risk averse with $\hat{\alpha}$ about 0.85 to 0.89. Subjects in different priming conditions don't show any statistically significant difference in this standard component of risk preferences.

This section provides the answer to the main research question. In a nutshell, it is found that spending a short period of time thinking about financial problems causes subject to have higher degree of the overweighting of small probabilities (as well as medium probabilities for all lotteries, plus large probabilities for New York lotteries), compared to thinking about nonfinancial problems. Moreover, thinking about financial problems in different intensity, in terms of

intended perceived tightness of budget constraint, leads to different levels of loss aversion. This is shown by subjects primed with financial hard scenarios being more loss averse than subjects primed with financial easy scenarios. This points out to the situation that the risk preferences are malleable and can be affected by occupied thoughts.

To see whether and to what extent the effects depend on probability weighting functional form, robust analysis with Prelec's probability weighting function is presented in Appendix B of Chapter 1.

Table 1.18: The effect of priming on risk preferences

	(1) fh vs.fe EL	(2) fh vs.fe All	(3) fh vs.nfh EL	(4) fh vs.nfh All	(5) fh vs.nfe EL	(6) fh vs.nfe All
delta						
financial hard	-0.0165	0.0487	0.203	0.245*	0.145	0.0916
	(0.142)	(0.113)	(0.144)	(0.105)	(0.151)	(0.111)
cons	1.303***	1.970***	1.083***	1.773***	1.142***	1.927***
	(0.0961)	(0.0739)	(0.0986)	(0.0612)	(0.109)	(0.0714)
gamma						
financial hard	-0.00343	0.0512	-0.0446*	0.0591+	-0.0460*	0.0150
	(0.0199)	(0.0352)	(0.0218)	(0.0355)	(0.0216)	(0.0355)
cons	0.168***	0.729***	0.209***	0.721***	0.210***	0.765***
	(0.0132)	(0.0227)	(0.0160)	(0.0231)	(0.0157)	(0.0231)
alpha						
financial hard	0.0638	0.0568	0.0612	0.0568	-0.0728	0.0130
	(0.167)	(0.0396)	(0.181)	(0.0402)	(0.193)	(0.0401)
cons	1.548***	0.846***	1.551***	0.846***	1.685***	0.890***
	(0.110)	(0.0255)	(0.129)	(0.0265)	(0.146)	(0.0262)
lambda						
financial hard	0.400	0.173*	0.00449	0.0216	-0.112	0.00479
	(0.250)	(0.0729)	(0.304)	(0.0822)	(0.323)	(0.0822)
cons	1.959***	1.444***	2.354***	1.595***	2.471***	1.612***
	(0.133)	(0.0414)	(0.218)	(0.0563)	(0.244)	(0.0562)
Observations	4380	8760	4380	8760	4380	8760

Standard errors in parentheses

EL means the estimation is based on only 15 experimental lotteries.

All is based on all 30 lotteries.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.19: The effect of priming on risk preferences

	(1) fe vs.nfh EL	(2) fe vs.nfh All	(3) fe vs.nfe EL	(4) fe vs.nfe All
delta				
financial easy	0.220	0.196*	0.162	0.0428
	(0.138)	(0.0960)	(0.145)	(0.103)
cons	1.083***	1.773***	1.142***	1.927***
	(0.0986)	(0.0613)	(0.109)	(0.0714)
gamma				
financial easy	-0.0412*	0.00790	-0.0425*	-0.0363
	(0.0208)	(0.0324)	(0.0206)	(0.0324)
cons	0.209***	0.721***	0.210***	0.765***
	(0.0160)	(0.0231)	(0.0157)	(0.0231)
alpha				
financial easy	-0.00275	-0.0000406	-0.137	-0.0438
	(0.170)	(0.0368)	(0.182)	(0.0366)
cons	1.551***	0.846***	1.685***	0.890***
	(0.129)	(0.0265)	(0.146)	(0.0262)
lambda				
financial easy	-0.396	-0.151*	-0.512+	-0.168*
	(0.255)	(0.0699)	(0.278)	(0.0698)
cons	2.354***	1.595***	2.470***	1.612***
	(0.218)	(0.0563)	(0.244)	(0.0562)
Observations	4380	8760	4380	8760

Standard errors in parentheses

EL means the estimation is based on only 15 experimental lotteries.

All is based on all 30 lotteries.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.20: The effect of priming on risk preferences

	(1) fh vs.nf EL	(2) fh vs.nf All	(3) fe vs.nf EL	(4) fe vs.nf All
delta				
financial hard	0.175	0.172^{+}		
	(0.128)	(0.0971)		
financial easy			0.192	0.123
			(0.121)	(0.0874)
cons	1.111***	1.846***	1.111***	1.846***
	(0.0733)	(0.0467)	(0.0733)	(0.0467)
gamma				
financial hard	-0.0452*	0.0371		
	(0.0186)	(0.0315)		
financial easy			-0.0417*	-0.0142
			(0.0174)	(0.0280)
cons	0.210***	0.743***	0.210***	0.743***
	(0.0112)	(0.0163)	(0.0112)	(0.0163)
alpha				
financial hard	-0.00391	0.0347		
	(0.159)	(0.0356)		
financial easy			-0.0678	-0.0221
			(0.146)	(0.0316)
cons	1.616***	0.868***	1.616***	0.868***
	(0.0971)	(0.0187)	(0.0970)	(0.0187)
lambda				
financial hard	-0.0515	0.0129		
	(0.267)	(0.0720)		
financial easy			-0.452*	-0.160**
			(0.210)	(0.0575)
cons	2.410***	1.604***	2.410***	1.604***
	(0.163)	(0.0398)	(0.163)	(0.0398)
Observations	6570	13140	6570	13140

Standard errors in parentheses

EL means the estimation is based on only 15 experimental lotteries.

All is based on all 30 lotteries.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.21: The effect of priming on risk preferences

	(1) nfh vs.nfe EL	(2) nfh vs.nfe All	(3) f vs.nf EL	(4) f vs.nf All
delta				
nonfinancial hard	-0.0583	-0.153		
	(0.147)	(0.0941)		
financial			0.184^{+}	0.144^{*}
			(0.102)	(0.0729)
cons	1.142^{***}	1.927^{***}	1.111^{***}	1.846^{***}
	(0.109)	(0.0714)	(0.0733)	(0.0467)
gamma				
nonfinancial hard	-0.00136	-0.0442		
	(0.0225)	(0.0326)		
financial			-0.0435^{**}	0.00956
			(0.0150)	(0.0239)
cons	0.210^{***}	0.765^{***}	0.210^{***}	0.743^{***}
	(0.0157)	(0.0231)	(0.0112)	(0.0163)
alpha				
nonfinancial hard	-0.134	-0.0438		
	(0.195)	(0.0373)		
financial			-0.0368	0.00421
			(0.128)	(0.0271)
cons	1.685^{***}	0.890^{***}	1.616^{***}	0.868^{***}
	(0.146)	(0.0262)	(0.0971)	(0.0187)
lambda				
nonfinancial hard	-0.116	-0.0168		
	(0.327)	(0.0795)		
financial			-0.269	-0.0814
			(0.201)	(0.0531)
cons	2.471^{***}	1.612^{***}	2.410^{***}	1.604^{***}
	(0.244)	(0.0562)	(0.163)	(0.0398)
Observations	4380	8760	8760	17520

Standard errors in parentheses

EL means the estimation is based on only 15 experimental lotteries.

All is based on all 30 lotteries.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.7.3 Average Treatment Effects by Poverty status

Does financial priming affect risk preferences of the poor and the rich differently? Do the poor have different risk preferences when they faced seemingly harder financial problems? This question can be answered by including levels of income of each subject into the analysis. We continue the analysis in this subsection with heteroskedasticity with respect to individual and to gamble.

The following graphs are the results when we let individual parameters $\psi_i = \{\alpha_i, \gamma_i, \delta_i, \lambda_i, \xi_i\}$ depend on (a.) treatment dummy T_i (dummy f_i whether one was in financial condition vs. nonfinancial condition; or dummy fh_i whether one was in financial hard condition vs. other conditions); , (b.) dummy $poor_i$ whether one is the "poor" or not, (c.) the interaction between treatment status and "poverty" status, and (d.) three dummies whether the lotteries are NUMBERS, WIN4, or MGM JtJ. Specifically, we let

$$\psi_i = \psi_0 + \psi_1 T_i + \psi_2 poor_i + \psi_3 (T_i \times poor_i) + \psi_4 numbers + \psi_5 win4 + \psi_6 mgm.$$

Subjects are divided into the "poor" and the "rich", and there can be many criteria one could use to draw the line who is "poor" and who is "rich". No matter which line we draw, it would be a simplification of how complicated the reality of poverty situation actually is. In this section, the poverty status is determined by three standards. Firstly, those with annual total household income less than or equal to the median household income of the sample are regarded as the "poor". Accordingly, subjects who have annual household income at most US$60,000 to US$69,999, which is $5,000 to $5,833 per month, are the "poor". This dummy variable is denoted by $poor_i$. Secondly, instead of annual household income, a subject is considered "poor" if she has her equivalent

Table 1.22: Percentage of "poor" subjects by condition

Each group has 146 subjects.	fe	fh	nfe	nfh
% "poor" by annual household income	54	50	58	62
% "poor" by equivalent income	52	43	52	53
% "poor" by being in financial hardship	38	39	41	43
% poor by federal guideline	10	8	14	10

income[54] less than or equal to median equivalent income of the sample which is equal to US$38,000, annually. In this case, the dummy variable $poor_{equi\,inc,i}$ equal to 1 indicates that the subject is "poor". Thirdly, a subject is classified as "poor" if one or more of the following events happened to her over the past 12 month from the survey date, because of a shortage of money. These events are not being able to pay electricity, gas, telephone bills, car registration, car insurance on time, not being able to meet all of essential expenses such as mortgage, rent payments, important medical care, not being able to go to hospital when needed to see a doctor, pawning, or selling something, overdrawing bank accounts, skipping meals, not being able to heat home, seeking assistance from welfare, seeking financial help from friends or family, and taking out a loan from a payday lender or any loan provider. If one or more of these happened, dummy variable $hardship_i$ is equal to 1, indicating the "poor" status.

The table 1.22 shows percentage of subjects in each experimental condition that are regarded as "poor" according to each criterion mentioned above. These criteria divide subjects in the sample into group with the size of 40% to 60% of total number of subjects in each condition. Note to mention is that about 8-14% of subjects in each condition were actually poor according to federal guideline.

[54]household income divided by the square root of household size

The interaction effect of financial hard priming and being poor

Table 1.23 to 1.28 show the estimation results when comparing financial hard condition to financial easy condition, nonfinancial hard condition, and nonfinancial easy condition, and for each of poverty status dummy[55].

Based on poverty status using equivalent income[56], the interaction effects of being "poor" and being financially hard primed on the elevation of probability weighting function are positive and statistically significant with p-value less than 0.001, comparing to financial easy condition, nonfinancial easy condition, and nonfinancial hard condition. This means that being poor and financially hard primed cause subjects to more overweigh (small) probabilities. Similar pattern is found for the case of being poor based on annual household income, when comparing financial hard priming to financial easy or to nonfinancial easy priming. In addition, comparing to subjects in financial easy, subjects who were in financial hardship and primed with financially hard scenarios also had statistically significant higher level of overweighting. Such statistical significant interaction effects on δ ranges from 0.719 to 1.564. It seems that the elevation of probability weighting function is the main channel through which the interaction of priming and poverty status affects probability weighting function. However, there is also a statistically significant, at 5% level of significance, increase in the level of probability insensitivity when we consider the interaction effect between being financially hard primed and being in financial hardship, comparing to those in financial easy condition and not in financial hardship.

[55]The maximum likelihood estimation for financial hard condition against nonfinancial hard condition with $poor_i$ is not achieved.

[56]Although the report of the main results here are based on using dummy variable identifying above or below median split of equivalent income measures, using continuous equivalent income yield largely the same pattern of effects.

For loss aversion, the effect of priming, taking into account the role of poverty status, is seemingly less notable. This is because, largely, subjects across groups didn't have statistically significant difference in the coefficient of loss aversion. The groups that have such significant difference is between subjects not in financial hardship under financial easy priming and subjects under both financial hardship and financial hard priming. Being under two pressures of financial hard condition and financial hardship cause subjects to be more loss averse with increase in the coefficient of loss aversion by 0.58 ($s.e.$ = 0.23, p = 0.014), comparing to under no such pressures.

Apart from the probability weighting and loss aversion, it is found that being primed with financial hard scenarios and being poor, either based on household income or equivalent income, generally lead subjects to be more risk-loving, given that rich subjects in financial easy condition are already risk-loving. This interaction effect on parameter α ranges from 0.296 to 0.405.

Two further questions can be asked regarding how financial priming affect the probability judgement and loss aversion of the poor. These are what the poverty effect conditional on receiving financial hard priming and what financial priming effect conditional on being poor would be.

Poverty effect conditional on receiving financial hard priming

For the first effect, it essentially asks, under the same financial hard condition, how risk preferences of the poor are, comparing to the rich. We can answer this question by looking at $\hat{\psi}_2 + \hat{\psi}_3$. This is denoted by $poverty\,status + fh \times poverty\,status$ in the tables. This amounts to the difference of the coefficients

of the "poor" under financial hard priming and the "rich" also under financial hard priming. $\hat{\delta}_2+\hat{\delta}_3$ are statistical significant different for all estimations, except when considering hardship as poverty status. The estimated effects range from 0.716 to 0.944, with $p < 0.001$. Comparing between financial hard and financial easy priming, the poor under financial hard priming also have lower level of γ than the rich by 0.032 ($\hat{\gamma}_2 + \hat{\gamma}_3 = -0.032$), at $p < 0.10$.

Financial hard priming effect conditional on being poor

The second question of interest is about how risk preferences of the poor change when thinking about financial hard situation, comparing to financial easy situation or even nonfinancial situations. This is equal to understanding the linear combination of coefficients: $\hat{\psi}_1 + \hat{\psi}_3$, denoted by $fh + fh \times poverty\ status$ in the tables. This effect comes from the difference of the coefficients of the "poor" under financial hard priming and the "poor" under reference priming, either financial easy(fe), nonfinancial hard(nfh), or nonfinancial easy(nfe). In a pretty similar pattern in the first question, the elevation of the probability weighting function: $\hat{\delta}_1 + \hat{\delta}_3$ is the part of risk preference showing the statistical significant difference of financial hard priming for the poor. Across different reference conditions, for the poor by criteria of annual household income and equivalent income, the increases in elevation of probability weighting function are in the range of 0.603 to 0.884, with $p < 0.001$. The effect for subjects in financial hardship in financial hard condition, comparing to when in nonfinancial hard condition is equal to an increase in δ by 0.361, with $p < 0.001$. Apart from the effect through δ, the financial hard priming effect also goes through changes in γ. Comparing to nonfinancial priming, the "poor" have lower level of γ by the magnitude of

0.055 to 0.082, with $p < 0.10$.

With these two effects, it might be the case that financial worries cause the poor to have higher level of overweighting of probabilities, both comparing to themselves in lower level of worries and comparing to the rich who are with the same level of worries.

Notably, to both questions, there is no statistically significant effect in loss aversion. This adds to the picture that, based on our data, the effect of financial priming on risk preferences, moderated by poverty status, mainly works through probability weighting function, and majorly through the elevation of probability weighting function.

Besides the analysis of the main effects on probability weighting function and loss aversion that this paper is interested in, it is found that there also exist marginal changes in standard risk-loving. Poverty effects on the level of risk loving, conditional on receiving financial hard priming, are statistically significantly positive, ranging between 0.195 to 0.304. Additionally, financial hard priming effect on the level of standard risk loving, conditional on being poor(either based on household income or equivalent income), is statistically significantly positive and is equal to 0.127, using nonfinancial easy priming as a reference group. That the existence of marginal effect on standard risk aversion cannot be explained by the underpinning model of dual-process theory opens a room for future empirical investigation and for future development of the underlying theoretical framework.

One last point in this subsection is about the shape of probability weighting functions of different lottery types. This helps us to have better understanding

Table 1.23: The effect of priming on risk preferences(moderated by being "poor")

	(1) fh vs. fe		(2) fh vs. nfe	
delta				
cons	1.640***	(0.108)	1.155***	(0.096)
fh	-0.726***	(0.099)	-0.124	(0.097)
poor	-0.620***	(0.102)	-0.011	(0.095)
fh × poor	1.564***	(0.152)	0.727***	(0.154)
numbers	4.933**	(1.721)	69322.377***	(61.621)
win4	4.271**	(1.326)	157208.527***	(17.614)
mgm	-0.654^{+}	(0.364)	-0.932***	(0.181)
gamma				
cons	0.146***	(0.016)	0.195***	(0.023)
fh	0.044*	(0.020)	-0.029	(0.030)
poor	0.033	(0.026)	0.026	(0.031)
fh × poor	-0.065^{+}	(0.038)	-0.026	(0.042)
numbers	0.183***	(0.053)	6.479***	(0.361)
win4	1.075***	(0.136)	8.399***	(0.513)
mgm	4.397	(3.526)	18.734*	(8.474)
alpha				
cons	1.588***	(0.083)	1.728***	(0.103)
fh	0.044^{+}	(0.026)	-0.278***	(0.067)
poor	0.039	(0.034)	-0.100	(0.063)
fh × poor	-0.077	(0.054)	0.405***	(0.091)
numbers	-1.406***	(0.108)	5.326***	(0.534)
win4	-0.302^{+}	(0.165)	7.363***	(0.670)
mgm	3.985	(4.338)	21.451*	(10.331)
lambda				
cons	1.917***	(0.144)	2.404***	(0.255)
fh	0.574*	(0.253)	-0.154	(0.291)
poor	0.180	(0.205)	0.079	(0.307)
fh × poor	-0.431	(0.354)	0.101	(0.425)
N	8760		8760	

Standard errors in parentheses

fh is a dummy variable, equal to 1 if in financial hard condition.

fh vs. fe means the effect of financial hard priming, compared to financial easy priming.

fh vs. nfe means the effect of financial hard priming, compared to nonfinancial easy priming.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.24: The effect of priming on risk preferences(moderated marginal effect)

	(1) fh vs. fe	(2) fh vs. nfe
δ		
fh + fh × poor	0.838***	0.603***
	(0.113)	(0.121)
poor + fh × poor	0.944***	0.716***
	(0.111)	(0.118)
γ		
fh + fh × poor	-0.020	-0.055+
	(0.024)	(0.030)
poor + fh × poor	-0.032+	0.000
	(0.019)	(0.029)
α		
fh + fh × poor	-0.033	0.127*
	(0.031)	(0.060)
poor + fh × poor	-0.038	0.304***
	(0.024)	(0.063)
λ		
fh + fh × poor	0.144	-0.053
	(0.247)	(0.309)
poor + fh × poor	-0.250	0.180
	(0.285)	(0.292)
N	8760	8760

Table 1.25: The effect of priming on risk preferences(moderated by "$\text{poor}_{\text{equi inc}}$")

	(1) fh vs. fe		(2) fh vs. nfh		(3) fh vs. nfe	
delta						
cons	1.242***	(0.094)	1.067***	(0.088)	1.148***	(0.092)
fh	-0.173+	(0.091)	-0.003	(0.085)	-0.126	(0.088)
$\text{poor}_{\text{equi inc}}$	0.026	(0.100)	-0.046	(0.087)	-0.004	(0.093)
fh × $\text{poor}_{\text{equi inc}}$	0.827***	(0.165)	0.887***	(0.158)	0.853***	(0.161)
numbers	179249.802***	(41.335)	225587.287***	(35.304)	141843.141***	(42.844)
win4	168566.815***	(6.887)	410618.897***	(7.996)	81263.826***	(37.316)
mgm	-0.693	(0.792)	2281.919***	(142.010)	-0.854**	(0.305)
gamma						
cons	0.167***	(0.020)	0.200***	(0.023)	0.191***	(0.022)
fh	0.010	(0.028)	-0.023	(0.030)	-0.013	(0.029)
$\text{poor}_{\text{equi inc}}$	0.003	(0.027)	0.021	(0.032)	0.037	(0.030)
fh × $\text{poor}_{\text{equi inc}}$	-0.029	(0.040)	-0.048	(0.044)	-0.064	(0.043)
numbers	6.821***	(0.345)	7.128***	(0.403)	6.941***	(0.390)
win4	8.398***	(0.496)	9.335***	(0.601)	7.920***	(0.484)
mgm	16.058+	(9.269)	11.551*	(5.137)	17.811*	(8.662)
alpha						
cons	1.666***	(0.091)	1.659***	(0.098)	1.763***	(0.102)
fh	-0.215***	(0.060)	-0.202**	(0.064)	-0.236***	(0.062)
$\text{poor}_{\text{equi inc}}$	-0.095+	(0.057)	-0.080	(0.065)	-0.166**	(0.063)
fh × $\text{poor}_{\text{equi inc}}$	0.298***	(0.084)	0.296**	(0.093)	0.361***	(0.090)
numbers	5.662***	(0.513)	6.028***	(0.594)	5.813***	(0.576)
win4	7.415***	(0.649)	8.465***	(0.782)	6.852***	(0.633)
mgm	18.218	(11.344)	12.206+	(6.267)	20.305+	(10.569)
lambda						
cons	1.974***	(0.156)	2.731***	(0.316)	2.404***	(0.241)
fh	0.282	(0.223)	-0.467	(0.331)	-0.049	(0.283)
$\text{poor}_{\text{equi inc}}$	0.082	(0.209)	-0.507	(0.335)	0.097	(0.307)
fh × $\text{poor}_{\text{equi inc}}$	-0.067	(0.347)	0.535	(0.436)	-0.103	(0.430)
N	8760		8760		8760	

Standard errors in parentheses
fh is a dummy variable, equal to 1 if in financial hard condition.
$\text{poor}_{\text{equi inc}}$ is equal to 1 if having equivalent income less than median equivalent income.
fh vs. fe means the effect of financial hard priming, compared to financial easy priming.
fh vs. nfh means the effect of financial hard priming, compared to nonfinancial hard priming.
fh vs. nfe means the effect of financial hard priming, compared to nonfinancial easy priming.
+$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 1.26: The effect of priming on risk preferences(moderated marginal effect)

	(1) fh vs. fe	(2) fh vs. nfh	(3) fh vs. nfe
δ			
fh + fh $\times$ $\text{poor}_{\text{equi inc}}$	0.654***	0.884***	0.727***
	(0.139)	(0.133)	(0.136)
$\text{poor}_{\text{equi inc}}$ + fh $\times$ $\text{poor}_{\text{equi inc}}$	0.853***	0.841***	0.849***
	(0.131)	(0.132)	(0.130)
γ			
fh + fh $\times$ $\text{poor}_{\text{equi inc}}$	-0.019	-0.071*	-0.077*
	(0.029)	(0.032)	(0.031)
$\text{poor}_{\text{equi inc}}$ + fh $\times$ $\text{poor}_{\text{equi inc}}$	-0.026	-0.027	-0.027
	(0.029)	(0.029)	(0.030)
α			
fh + fh $\times$ $\text{poor}_{\text{equi inc}}$	0.083	0.094	0.126*
	(0.060)	(0.065)	(0.064)
$\text{poor}_{\text{equi inc}}$ + fh $\times$ $\text{poor}_{\text{equi inc}}$	0.203***	0.216**	0.195**
	(0.061)	(0.067)	(0.062)
λ			
fh + fh $\times$ $\text{poor}_{\text{equi inc}}$	0.215	0.068	-0.152
	(0.267)	(0.284)	(0.322)
$\text{poor}_{\text{equi inc}}$ + fh $\times$ $\text{poor}_{\text{equi inc}}$	0.015	0.028	-0.006
	(0.276)	(0.282)	(0.299)
N	8760	8760	8760

Table 1.27: The effect of priming on risk preferences(moderated by "hardship")

	(1) fh vs. fe		(2) fh vs. nfh		(3) fh vs. nfe	
delta						
cons	1.566***	(0.177)	1.045***	(0.082)	1.111***	(0.084)
fh	-0.300	(0.214)	0.245**	(0.082)	0.150^{+}	(0.082)
hardship	-0.613***	(0.136)	-0.022	(0.081)	0.088	(0.088)
fh × hardship	0.719***	(0.151)	0.116	(0.131)	-0.008	(0.135)
numbers	7.504	(4.666)	2702.507***	(600.537)	2.827***	(0.405)
win4	4.387**	(1.393)	19.800	(19.958)	12.549	(7.930)
mgm	2.311	(76.867)	-0.191	(1.016)	-0.156	(1.006)
gamma						
cons	0.153***	(0.019)	0.223***	(0.022)	0.199***	(0.021)
fh	0.026	(0.044)	-0.050^{+}	(0.029)	-0.018	(0.031)
hardship	0.029^{+}	(0.016)	-0.026	(0.032)	0.023	(0.031)
fh × hardship	-0.053*	(0.023)	-0.001	(0.043)	-0.064	(0.047)
numbers	0.139**	(0.050)	4.505***	(0.295)	0.306***	(0.089)
win4	1.085***	(0.142)	2.046**	(0.675)	1.696***	(0.380)
mgm	1.163	(8.448)	2.087	(1.559)	0.336	(0.544)
alpha						
cons	1.567***	(0.082)	1.651***	(0.098)	1.661***	(0.098)
fh	0.016	(0.032)	-0.095*	(0.041)	-0.030	(0.041)
hardship	0.021	(0.016)	-0.053	(0.045)	0.027	(0.040)
fh × hardship	-0.036	(0.032)	0.051	(0.064)	-0.072	(0.057)
numbers	-1.445***	(0.117)	3.293***	(0.417)	-1.217***	(0.150)
win4	-0.259	(0.164)	0.764	(0.711)	0.332	(0.405)
mgm	-0.040	(11.662)	1.179	(1.925)	-1.011	(0.703)
lambda						
cons	1.679***	(0.100)	2.649***	(0.282)	2.440***	(0.226)
fh	0.677**	(0.208)	-0.327	(0.300)	-0.022	(0.269)
hardship	1.053***	(0.306)	-0.410	(0.310)	0.031	(0.307)
fh × hardship	-1.155**	(0.414)	0.325	(0.413)	-0.175	(0.421)
N	8760		8760		8760	

Standard errors in parentheses

fh is a dummy variable, equal to 1 if in financial hard condition.

hardship is equal to 1 if subject is in one or more forms of hardship.

fh vs. fe means the effect of financial hard priming, compared to financial easy priming.

fh vs. nfh means the effect of financial hard priming, compared to nonfinancial hard priming.

fh vs. nfe means the effect of financial hard priming, compared to nonfinancial easy priming.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.28: The effect of priming on risk preferences(moderated marginal effect)

	(1) fh vs. fe	(2) fh vs. nfh	(3) fh vs. nfe
δ			
fh + fh × hardship	0.419	0.361***	0.142
	(0.276)	(0.102)	(0.106)
hardship + fh × hardship	0.106	0.095	0.080
	(0.194)	(0.102)	(0.104)
γ			
fh + fh × hardship	-0.027	-0.051	-0.082*
	(0.036)	(0.032)	(0.033)
hardship + fh × hardship	-0.024	-0.027	-0.040
	(0.021)	(0.029)	(0.033)
α			
fh + fh × hardship	-0.020	-0.044	-0.102*
	(0.018)	(0.048)	(0.041)
hardship + fh × hardship	-0.015	-0.002	-0.045
	(0.021)	(0.042)	(0.038)
λ			
fh + fh × hardship	-0.478	-0.002	-0.197
	(0.351)	(0.283)	(0.325)
hardship + fh × hardship	-0.102	-0.085	-0.144
	(0.276)	(0.273)	(0.288)
N	8760	8760	8760

of the effect of being occupied with financial thoughts on real lottery choices, with extremely small probabilities. From our specification of the econometrics model in this subsection, the statistical significant and insignificant effects discussed above hold true for all lottery types. However, because of the strikingly differences in the shape of probability weighting function between experimental lottery(EL) and NY lotteries(NYL), the overall effect of priming seems to vary, depending on the type of lotteries. Below are estimated probability weighting functions of subjects in financial hard and easy conditions, for experimental lotteries, NUMBERS, WIN4, and Megamillions JtJ. These graphs are based on poverty status using annual household income, and these following patterns are similar whether we are talking about the poor based on annual household income, on equivalent income, or on hardship criteria. The graphs for the later two categories are shown in Appendix C of Chapter 1.

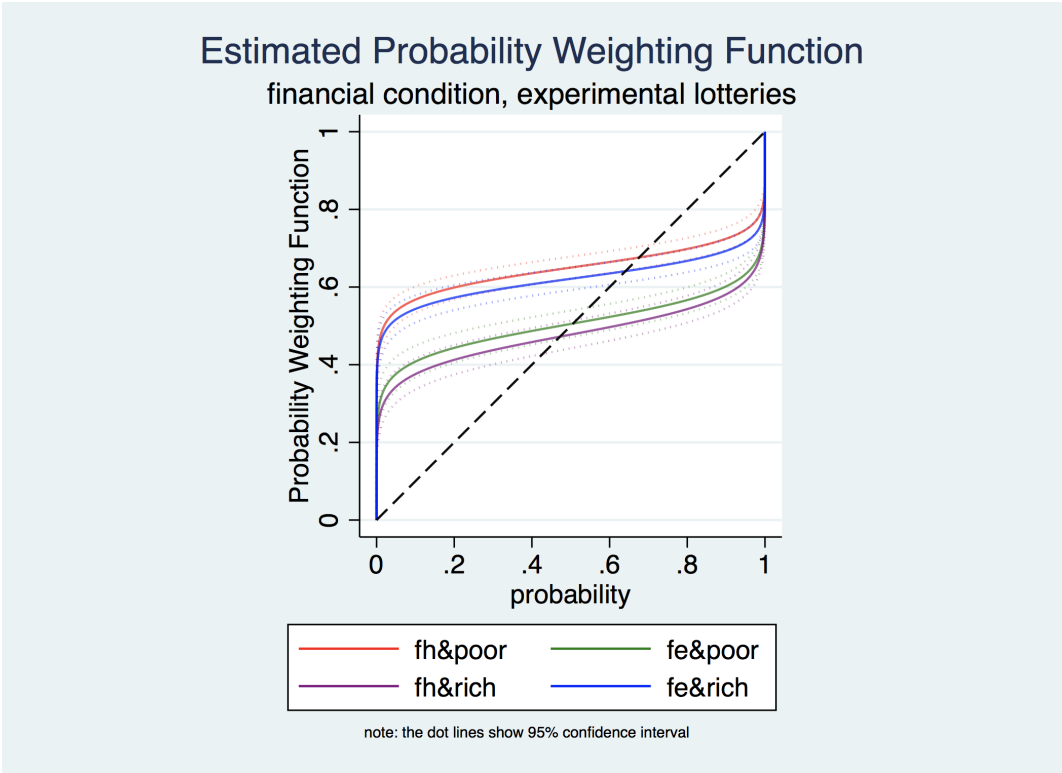

Figure 1.2: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich: Experimental lotteries

Note: "fh" stands for financial hard condition, and "fe" stands for financial easy condition.

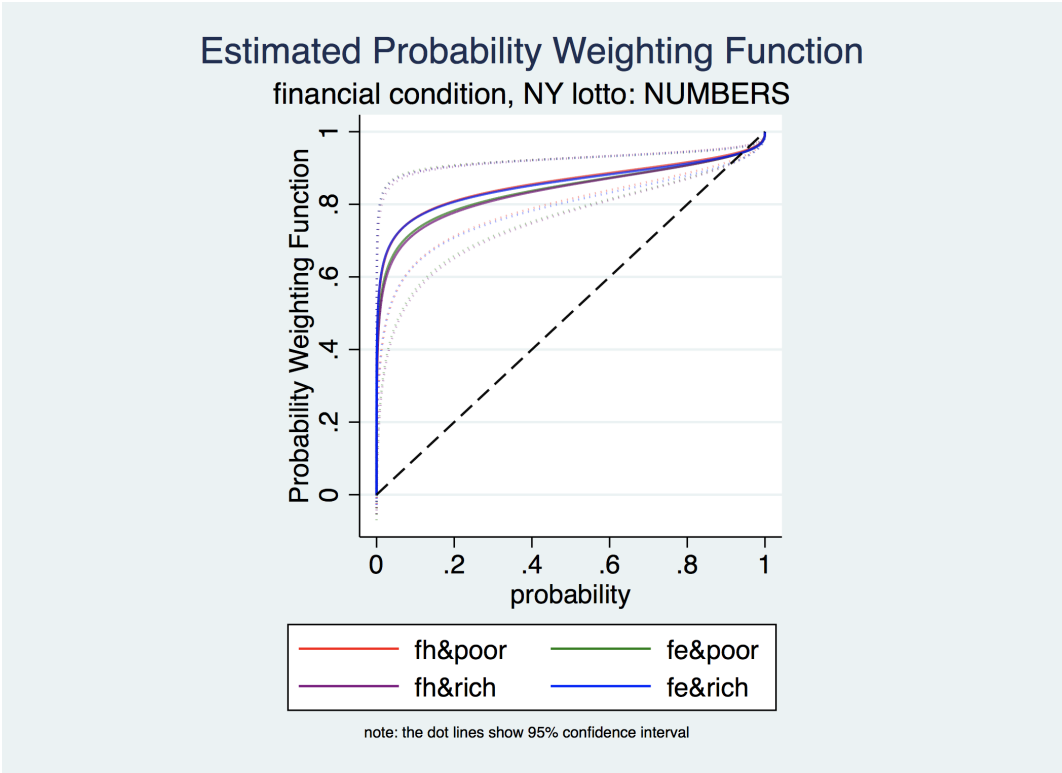

Figure 1.3: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich: NUMBERS

Note: "fh" stands for financial hard condition, and "fe" stands for financial easy condition.

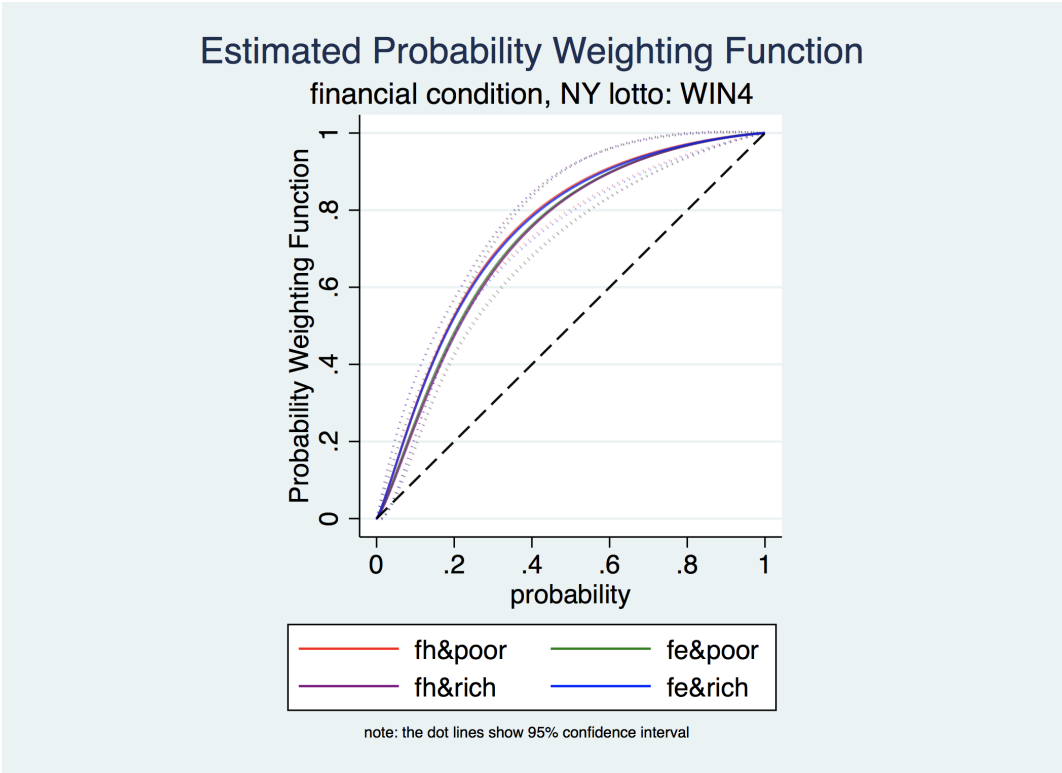

Figure 1.4: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich: WIN4

Note: "fh" stands for financial hard condition, and "fe" stands for financial easy condition.

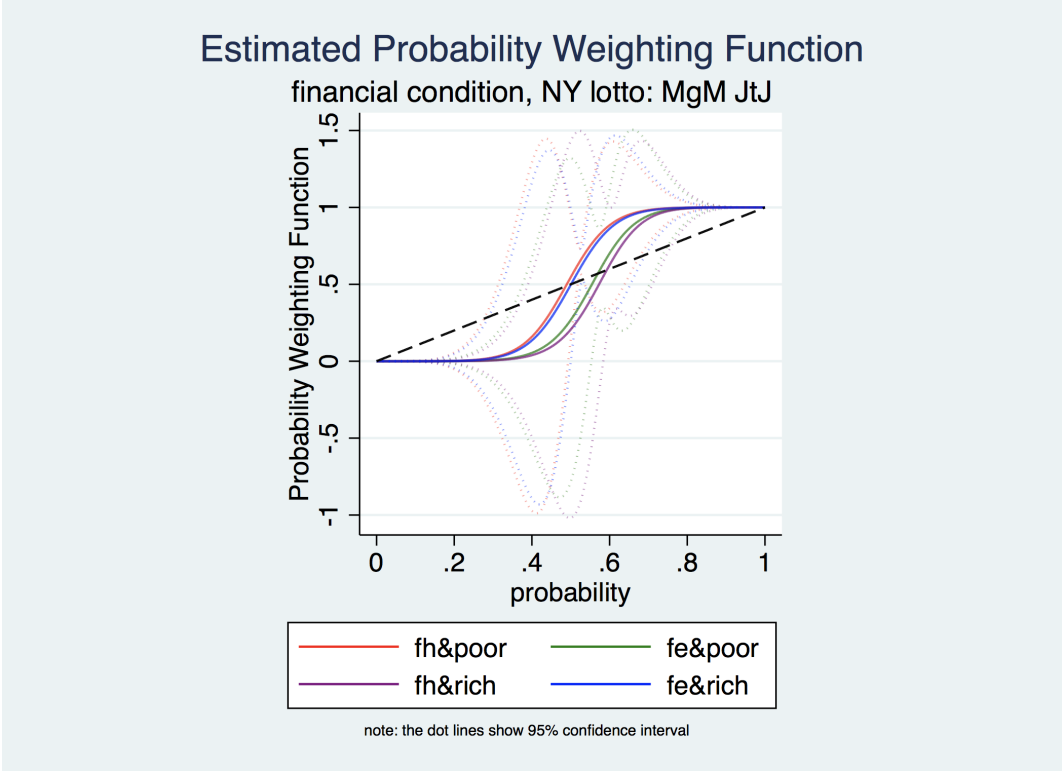

Figure 1.5: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich: MGM JtJ

Note: "fh" stands for financial hard condition, and "fe" stands for financial easy condition.

From the graphs, the probability weighting functions based on experimental lotteries, NUMBERS, WIN4, and MGM JtJ take different shapes. Those based on experimental lotteries take inverse-s shape; those on NUMBERS exhibit high degree of overweighting of all probabilities less than 0.95; those on WIN4 exhibit no range of probability with underweighting; finally, those based on Megamillion-just-the-jackpot exhibit s-shape with zero weight for small probabilities and weight equal to one for large probabilities. This different patterns of probability weighting function might be due to different underlying processes on how people evaluate probabilities. One possible explanation might be that experimental lotteries and each type of New York lotteries could be related to different levels of affective reactions (affect-rich and affect-poor outcomes were

studied in Rottenstreich and Hsee (2001)). Playing New York lotteries might have a higher chance to cause more vivid mental images than betting on experimental lotteries. Based on NUMBERS and WIN4, individuals seem to be willing to take the gambles no matter how small or large the probabilities of winning are. For Megamillions JtJ, the s-shape is consistent with the experience-induced probability weighting function as suggested in, for example, Hertwig et al. (2004) and Iwaki and Osaki (2010). The underweighting of small probabilities in regular s-shape might be due to the situation that subjects have noticed how rare it is to win Megamillion JtJ, hence give the weight of winning equal to zero, despite affect-rich multimillion outcome.

Because of the fact that different lottery type deals with different probability weighting function, the overall shape obscures the pattern of average treatment effects as moderated by poverty status as discussed above for NY lotteries. From the graphs, we can see clearly that there is statistically difference in the elevation of probability weighting between the poor in financial hard priming and in financial easy priming. However, because of the shape of probability weighting function for NY lotteries, we cannot say firmly that such effect partakes in how people really weigh probabilities in a particular way specific to real lotteries with extremely small probabilities.

Financial condition vs. Nonfinancial condition

Table 1.29 and 1.30 present the effects when we consider financial versus nonfinancial condition. When using all sample (584 subjects with 17,520 certainty equivalents), we cannot differentiate the probability weightings based on NUMBERS, WIN4, MGM JtJ against each other. We have that probability weightings based on NY lotteries(NYL) are s-shaped, while those based on experimental lotteries(EL) are inverse-s shape. While both type of probability weighting exhibit high level of overweighting, when it comes to small probabilities, subjects overweigh them for experimental lotteries, but give zero weight for NY lotteries. All probability weighting functions for each group are shown in the figures below.

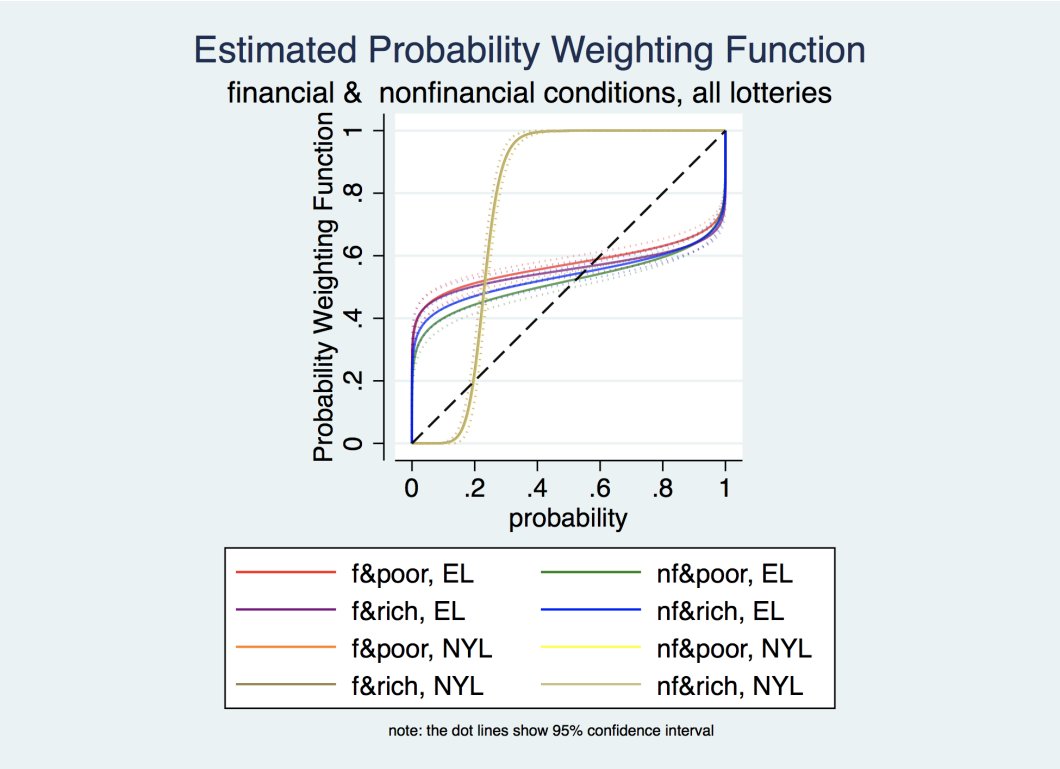

Figure 1.6: Probability weighting function for financial vs. nonfinancial condition and for poor vs. rich based on income

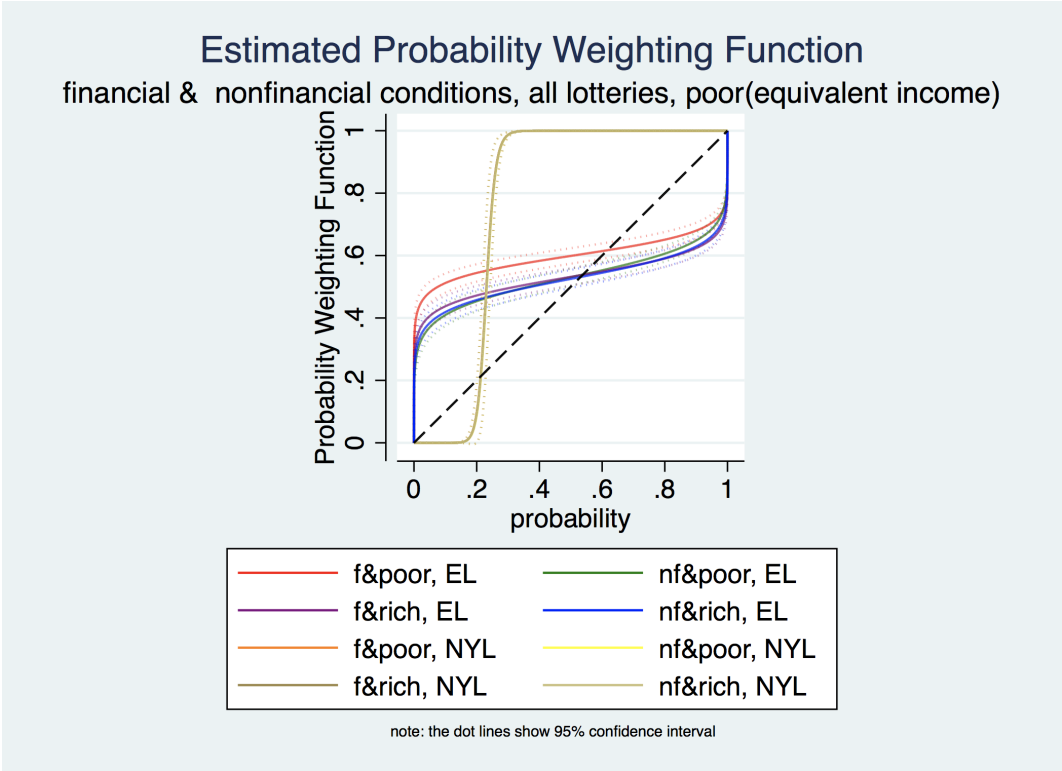

Figure 1.7: Probability weighting function for financial vs. nonfinancial condition and for poor vs. rich based on equivalent income

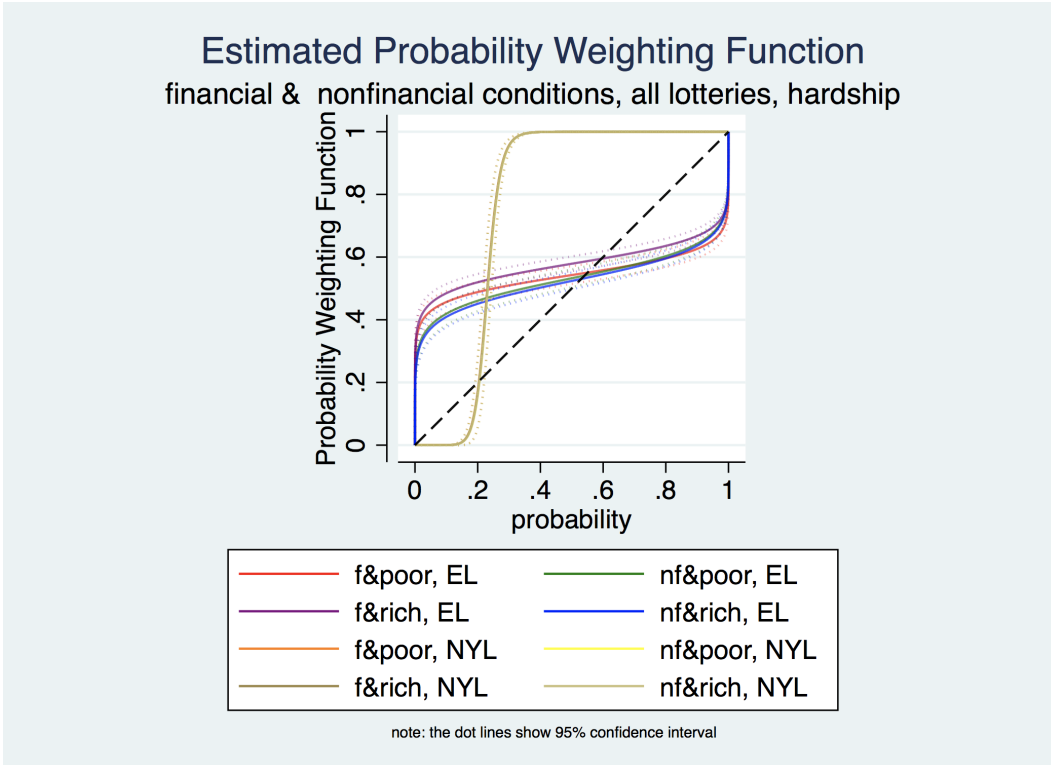

Figure 1.8: Probability weighting function for financial vs. nonfinancial condition and for poor vs. rich based on hardship indicator

Based on annual household income, the poor gives more weight to probabilities when they were primed with financial concerns, than when with nonfinancial concerns. The estimated effects are $\hat{\delta}_1 + \hat{\delta}_3 = 0.26, p = 0.000$, and $\hat{\gamma}_1 + \hat{\gamma}_3 = -0.044, p = 0.029$. Based on equivalent income, the estimated effects are $\hat{\delta}_1 + \hat{\delta}_3 = 0.36, p = 0.000$, and $\hat{\gamma}_1 + \hat{\gamma}_3 = -0.062, p = 0.003$. That is, the poor who were in financial condition were more optimistic when evaluating probabilities and less sensitive in change in probability. Conditional on being poor based on equivalent income, financial priming also increases the elevation of probability weighting function with $\hat{\delta}_2 + \hat{\delta}_3 = 0.36, p = 0.003$, compared to nonfinancial priming. This pattern is different if we consider poverty status by being in financial hardship. Although those who were in financial hard-

ship became less sensitive to change in probability when primed with financial scenario($\hat{\gamma}_1 + \hat{\gamma}_3 = -0.051$, $p = 0.023$), they were less optimistic, comparing to one without any financial hardships $\hat{\delta}_2 + \hat{\delta}_3 = -0.19$, $p = 0.072$.

Another important aspect to note is that financial worries didn't cause statistically significant difference in loss aversion. The poor are not more loss-averse, when are under financial pressure and when compared to the rich under the same financial pressure. This is true except when we consider the effect of being in financial hardship and being financial primed on loss aversion. Compared to subjects who were not in financial hardship, subjects who were in financial troubles had higher coefficient of loss aversion by $\hat{\lambda}_2 + \hat{\lambda}_3 = -0.378$, $p = 0.05$

Notably, all results are with standard risk seeking($\hat{\alpha}_i > 0$), instead of standard risk aversion.

Table 1.29: Moderated effect of priming on risk preferences (financial vs. nonfinancial condition)

	poor		$poor_{equi\ inc}$		hardship	
delta						
cons	1.164***	(0.067)	1.106***	(0.065)	1.100***	(0.060)
f	0.090	(0.069)	0.030	(0.068)	0.274***	(0.065)
poor	-0.080	(0.064)				
$poor_{equi\ inc}$			0.024	(0.069)		
hardship					0.039	(0.066)
f × poor	0.168+	(0.095)				
f × $poor_{equi\ inc}$			0.333**	(0.105)		
f × hardship					-0.227*	(0.097)
NY Lotto	3090.760***	(153.346)	2305254.552***	(2.179)	34394.362***	(4.475)
gamma						
cons	0.194***	(0.017)	0.195***	(0.016)	0.211***	(0.015)
f	-0.038+	(0.022)	-0.022	(0.021)	-0.038+	(0.020)
poor	0.026	(0.022)				
$poor_{equi\ inc}$			0.028	(0.022)		
hardship					-0.003	(0.022)
f × poor	-0.006	(0.030)				
f × $poor_{equi\ inc}$			-0.039	(0.030)		
f × hardship					-0.012	(0.030)
NY Lotto	6.505***	(0.227)	12.026***	(0.403)	8.522***	(0.292)
alpha						
cons	1.655***	(0.069)	1.713***	(0.074)	1.625***	(0.069)
f	-0.126**	(0.041)	-0.162**	(0.057)	-0.004	(0.042)
poor	-0.071+	(0.041)				
$poor_{equi\ inc}$			-0.201***	(0.059)		
hardship					-0.040	(0.048)
f × poor	0.167**	(0.056)				
f × $poor_{equi\ inc}$			0.290***	(0.081)		
f × hardship					-0.064	(0.066)
NY Lotto	5.813***	(0.305)	11.919***	(0.536)	8.048***	(0.391)
lambda						
cons	2.531***	(0.205)	2.565***	(0.199)	2.496***	(0.174)
f	-0.432*	(0.217)	-0.432*	(0.214)	-0.489**	(0.182)
poor	-0.205	(0.224)				
$poor_{equi\ inc}$			-0.305	(0.223)		
hardship					-0.217	(0.210)
f × poor	0.284	(0.280)				
f × $poor_{equi\ inc}$			0.353	(0.284)		
f × hardship					0.595*	(0.287)
N	17520		17520		17520	

s.e. in parentheses; + $p < 0.10$, $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$; f is equal to 1 if in financial condition.

Table 1.30: The effect of priming on risk preferences(moderated marginal effect)

	(1) P = poor	(2) P = $poor_{equi\ inc}$	(3) P = hardship
δ			
f + f × P	0.258***	0.362***	0.047
	(0.066)	(0.080)	(0.072)
P + f × P	0.088	0.357***	-0.188**
	(0.070)	(0.079)	(0.072)
γ			
f + f × P	-0.044*	-0.062**	-0.051*
	(0.020)	(0.021)	(0.022)
P + f × P	0.021	-0.012	-0.016
	(0.020)	(0.020)	(0.020)
α			
f + f × P	0.041	0.129*	-0.068
	(0.038)	(0.058)	(0.051)
P + f × P	0.095*	0.089	-0.104*
	(0.038)	(0.056)	(0.045)
λ			
f + f × P	-0.148	-0.079	0.106
	(0.178)	(0.189)	(0.220)
P + f × P	0.079	0.048	0.378+
	(0.168)	(0.177)	(0.193)
N	17520	17520	17520

1.7.4 Mediation Analysis: The Role of Cognition and Affect

There can be many possible channels through which financial hard priming change risk preferences. The two possible channels, cognition and emotion, explored here in this paper are suggested by Dual Process theory. Mediation analysis of the effect of financial hard priming and the mediated moderation of such effect by poverty status are presented in subsection 1.7.4.2 below.

1.7.4.1 Cognition and affect data

In the color-naming task, the Stroop effect (Stroop, 1935) measures multiple cognitive functions including the ability to inhibit cognitive interference occurring when naming ink color and reading color-word, as well as, attention, processing speed, cognitive flexibility, and working memory. Our Stroop task consists of 28 trials which include 12 trials in congruent conditions(same color and color-word) and 12 trials in incongruent condition(different color and color word), plus the first 4 trails for practice trials. The practice trials are all congruent. The Stroop task was designed on lab.js (Henninger et al., 2019) and hosted on https://www.netlify.com/ (at https://naughty-curie-807d8b.netlify.app).

For each trial, lab.js collects duration (reaction time), color shown, and color-word shown. The last two can be used to calculate measurement of accuracy.

Different scoring methods can be used to measure the Stroop effect. The Stroop effect, i.e. Stroop interference score, in this paper is calculated as the difference in mean reaction time(RT) between incongruent and congruent trials, and the difference in number of correct responses(accuracy) between incongruent and congruent trials. The later inhibitory ability measure was used in Knight

and Heinrich (2017), MacLeod (1991). In other words, the Stroop interference is measured by:

(i.) $SI_{RTdiff} = RT_I - RT_C$, where RT_I is mean reaction time over all trials in incongruent condition, and RT_C is mean reaction time over all trials in congruent;

(ii) $SI_{ACdiff} = AC_I - AC_C$, where AC_I is number of correct responses out of all trials in incongruent condition, and AC_C is number of correct responses out of all trials in congruent condition.

Besides reaction time and percentage of correct responses, the data of cognitive reflection test(CRT) is also used as one of the measures for cognition. CRT data can range from 0 to 3, for how many CRT questions each subject can answer correctly[57].

For affect data, positive affect[58] score ranges from 5 to 25, with higher score for higher level of positive feelings at the current moment in the experiment. Negative affect[59] score can also range from 5 to 25, with higher score for higher level of negative feelings. LAPA[60] score is composed of only six low-arousal positive affects, hence it ranges from 6 to 30. Higher LAPA score relates to higher level of the feelings of calm, peace, being relaxed, being secured, safe, and content. Financial worries[61] are captured with scale 5 to 25. The higher the

[57]CRT questions are: (1.) Soup and salad cost $5.50 in total. The soup costs a dollar more than the salad. How much does the salad cost? (correct answer: 2.25, decoy answer: 4.5) (2.) Ann's father has a total of five daughters: Lala, Lele, Lili, Lolo, and _____ . What is the name of the fifth daughter? (correct answer: Ann, decoy answer: Lulu) (3.) A farmer had 15 sheep. All but 8 died. How many are left? (correct answer: 8, decoy answer: 7).

[58]Positive affect, here, includes active, attentive, alert, determined, and inspired.

[59]Negative affect includes upset, hostile, ashamed, afraid, and nervous.

[60]Low-Arousal Positive Affect (LAPA) includes calm, peaceful, relaxed, secure, safe, and content.

[61]Subjects were asked to describe how they CURRENTLY feel and indicate to what extent they agree with the following sentences: (1.) I am very worried about my financial situation. (2.) I am very worried about having enough money to make ends meet. (3.) I am very worried about not being able to find money in case I really need it. (4.) I feel emotionally drained because

financial worries are, the higher the score is.

1.7.4.2 Mediated moderation analysis of the effect of financial hard priming moderated by poverty status

Based on the causal steps of mediation analysis by Baron and Kenny (1986), three parts of estimations and hypothesis testings are involved. First, the total effect of financial hard priming on risk preferences is estimated to establish that there are effects that may be mediated. This is done in the previous sections. Second, we need to answer if the priming actually causes cognition and affect to change. Third, how changes in cognition and affect correlate with changes in risk preferences are estimated, controlling for treatment dummy. This helps us separate out the direct effect of financial hard priming from the mediated effect. The model without mediators, in the first step, and with mediators, in the third step, are estimated individually via maximum likelihood. For the second step, ordered probit is used for all ordinal affect data and CRT data. Simple OLS regression is used to find the effect on Stroop interference measures(SI_{RTdiff} and SI_{ACdiff}) in cross sectional analysis. However, since each subject performed 28 trials on Stroop task, random effect panel analysis can be used to estimated the effect of financial hard priming on log of reaction time ($log(dur)$) of each trial, and random effect probit can also be used with dummy whether subject answered correctly(cor) as dependent variable[62]. For the estimation of the effect

of my financial situation. (5.) I feel frustrated because of my financial situation.

[62]These panel estimation control for congruent-incongruent conditions by including a dummy *congruent* equal to one if the trial is congruent. Moreover, if reaction time is shorter than 300 millisecond or longer than each subject's average over all trials by two standard deviation. When considering the effect of priming on log of reaction time, only trials with correct answers are included in the analysis. Importantly to note regarding accuracy, total number of correct answers across all stroop trials, and across congruent trial, and across incongruent trial, seem to show ceiling effect. Median of total number of correct answer across all trials is 25 (out

of the priming on mediators, the full set of demographics collected are included as controls variables in an attempt to control for any unobserved heterogeneity.

To sum up, in order to establish mediation through cognition and affect, we need to have: 1.) statistically significant total effects of financial hard priming on risk preferences from the first step; 2.) statistically significant effects of financial hard priming on cognition and emotion; 3.) statistically significant effects of cognition and/or affect on risk preferences; finally, 4.) statistically significant indirect/mediated effect. To test whether there is statistically significant indirect or mediated effect, the robust variance-covariance matrix of estimators, with the between-model covariance, is reestimated using seemingly unrelated estimation of the individual estimation of total effect from the first step and that with indirect and direct effect from step 3. This is to test for the mediation based on the difference-in-coefficient method. Importantly to note, since the prediction of dual process theory focuses on the role of cognition and affect on the overweighting of small probabilities, the underweighting of large probabilities, and loss aversion, only three components of the estimation results relating to, δ, γ, and λ will be presented and discussed in the following results.

An array of estimations and hypothesis testings were done and the null hypothesis of no mediating effects of financial hard priming cannot be rejected. To explain the mechanism why financial hard priming changes risk preferences, we cannot establish any mediating channels through change in cognition and

of 28 trials); that across all incongruent trials is 10 (out of 12 trials); that across all congruent trials is 15 (out of 16 trials) when including practice trials, and 12 (out of 12 trials) when excluding practice trials. However, the Stroop interference measure SI_{ACdiff} doesn't seem to have the ceiling effect. Its statistics are: median equal to -10.4, mean -26, standard deviation 36.19, maximum 25 and minimum -100. This might be due to the fact that the total number of correct answer in incongruent trial is more disperse (with standard deviation equal to 4.4 trials) than in congruent trial (with standard deviation equal to 1.5 trials). Moreover, the random effect probit, using dummy variable for correctness for each trial, might also help with the issue of ceiling effect.

emotion. However, without much precision, it is found that the hypothesis of there is no mediating effect through change in cognition for the effect of financial hard priming moderated by being poor on the elevation of probability weighting function can be rejected.

Applying the causal steps by Baron and Kenny (1986) and the idea of mediating moderation by Muller et al. (2005), the intuition for mediating moderation in our case is that if marginal effect of financial hard priming which depends on the interaction effect between being primed and being poor ($fh + fh \times poor_{equi\,inc}$ in tables) statistically significantly changes when controlling for the effect of mediators on risk preferences, then the mediating effect can be established. This is given that (a.) the total marginal effect of financial hard priming moderated by poverty status, (b.) marginal effect of financial hard priming moderated by poverty status on mediators, and (c.) the effect of mediators on risk preferences are all statistically significant. This allows us to have a better understanding whether changes in cognition and emotion are underlying the moderation effect.

With the indicator of being poor based on equivalent income, $poor_{equi\,inc}$, as a moderator, total effects of financial hard priming on elicited risk preferences are captured by equation 1.31.

$$RP_i = \tau_0 + \tau_1 fh_i + \tau_2 poor_{equi\,inc,i} + \tau_3 fh_i \times poor_{equi\,inc,i} \tag{1.31}$$

$\hat{\tau}_1 + \hat{\tau}_3$ is the estimated total marginal treatment effect of having harder financial concerns, moderated by being poor, on risk preferences.

If we let M_i^* be the (latent) variable corresponding to each observed mediator

M_i, we have that

$$M_i^* = \eta_0 + \eta_1 fh_i + \eta_2 poor_{equi\,inc,i} + \eta_3 fh_i \times poor_{equi\,inc,i} + \eta_4 X_i + \epsilon_i \tag{1.32}$$

The direct marginal effects of financial hard priming on elicited risk preferences and the effects of mediator on elicited risk preferences are captured in equation (1.33).

$$RP_i = \beta_0 + \beta_1 fh_i + \beta_2 poor_{equi\,inc,i} + \beta_3 fh_i \times poor_{equi\,inc,i} + \beta_4 M_i \tag{1.33}$$

Mediated moderation can be established if (1.) $H_o : \tau_1 + \tau_3 = 0$; (2.) $H_o : \eta_1 + \eta_3 = 0$; (3.) $H_o : \beta_4 = 0$; and (4.) $H_o : (\tau_1 + \tau_3) - (\beta_1 + \beta_3) = 0$ can all be rejected. Figure 1.9 below illustrates mediated moderation, total, direct and indirect marginal effect.

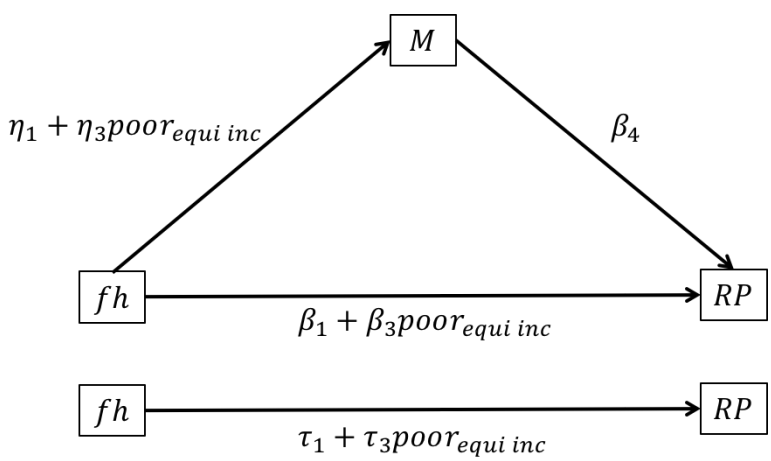

Figure 1.9: Mediated Moderation

It is found that comparing to nonfinancial easy priming, financial hard priming moderated by being poor statistically significantly deters cognition in terms of reduced accuracy in responses for Stroop task. Both OLS regression of SI_{ACdiff} and random-effect probit panel estimation of correctness indicator(cor) for each trial on a full factorial of financial hard priming and being poor yield negative marginal effect of financial hard priming with $p = 0.055$ and $p = 0.103$, respectively. The results are shown in table 1.36 with related main estimation in table 1.34 and table 1.35.[63] However, in this specification, there is no statistically significant marginal effect on log of reaction time ($log(dur)$) or SI_{RTdiff}, or CRT score. There is also no statistically significant marginal effect of financial hard priming, given that subjects are poor, on positive affect, negative affect, low-arousal positive affect, or on financial worries.

Interestingly to note are some correlations between cognition and demographics. It seems to be the case that the older spent longer to react to stimuli in stoop task. Education positively correlates with accuracy of stroop trial and negatively correlate with cognitive misery measured by CRT score. Additionally, those in financial hardship also had longer duration time in stroop task, indicating of the reduction in cognitive capacity. There are also highly statistically significant positive correlation between negative affect and financial hardship indicator. The same pattern also goes for financial worries.

Turning to the effect of control variables on risk preferences, SI_{RTdiff}, CRT

[63]By considering the full factorial of condition and poor dummy as independent variables, i.e. the independent variables are condition dummy, poor dummy, and their interaction, this is in the same spirit as the estimation in Mani et al. (2013a). However, while we use stroop interference or dummy for correctness as dependent variable, Mani et al. (2013a) used total accuracy across all trials and later divided into congruent trial and incongruent trial in Mani et al. (2013b)'s response (table 2 in the paper) to comments by Wicherts and Scholten (2013). The main effect from Mani et al. (2013a) was the statistically significant interaction effect of condition dummy and poor dummy. In our study, such interaction effects are not statistically significant, while the marginal moderated effects of financial hard priming are.

score, positive affect and negative affect negatively impact both δ and γ. These control variables would have been mediators if financial hard priming statistically changed them. The only mediator that can explain why financial hard priming change the level of optimism in probabilities is Stroop effect as measured by accuracy. We have that the lower number of trials subjects got them right, the lower cognitive capacity subjects have, and the higher the level of the overweighting of probabilities. In other words, more cognitive load leads to higher level of probability overweighting (The coefficient for SI_{ACdiff} is -0.00267, with p = 0.074).

Now that we have established that there is a possibility of mediated moderating relationship from financial hard priming on risk preferences, the next step is to see if such effect causes statistically significant difference in total marginal effect and direct marginal effect. The null hypothesis of $H_o : (\tau_1+\tau_3)-(\beta_1+\beta_3) = 0$ can be rejected with $p < 0.05$. The mediated moderation effect is equal to 0.457 with $s.e.$ = 0.184. That is, the total marginal effect of financial hard priming on δ is more than the direct one by 0.457.

Putting all pieces together, it might be the case that, comparing to nonfinancial easy priming, financial hard priming taxes more cognitive capacity as shown by reduction in accuracy. This taxed cognition in turn renders subjects to have higher level of overweighting of probabilities through higher elevation of the function (higher δ). This effect is moderated by being poor based on equivalent income. This points out to one of the two categories of factors in dual process theory. Here in this sample and in this particular specification, only change in cognition matters, given all of the effect that might not be captured due to measurement error. The moderation of the financial hard priming

effect by poverty status is mediated by change in cognition, but not the change in affect. There is also no mediating effect found for the case of γ which governs the insensitivity to probability, whereas, for loss aversion, there is no statistical significant total marginal effect of financial hard priming to be mediated.

Table 1.31: The effect of financial hard priming on risk preferences by poverty status with and without mediators, in the case of financial hard priming (fh) against nonfinancial easy priming(nfe)

	fh vs. nfe, no mediators		fh vs. nfe, with mediators	
delta				
cons	1.670***	(0.0971)	2.798***	(0.392)
fh	-0.286**	(0.110)	-0.362***	(0.101)
$poor_{equi\ inc}$	-0.143	(0.116)	-0.259*	(0.111)
fh × $poor_{equi\ inc}$	1.199***	(0.261)	0.818***	(0.238)
win4mgm	0.783***	(0.236)	0.491**	(0.161)
SI_{RTdiff}			-0.0000822*	(0.0000398)
SI_{ACdiff}			-0.00267++	(0.00149)
CRT score			-0.169***	(0.0386)
Positive affect			-0.0337*	(0.0146)
Negative affect			-0.0380***	(0.00858)
Financial worries			0.00601	(0.00805)
LAPA			0.00471	(0.00975)
gamma				
cons	0.705***	(0.0363)	1.033***	(0.148)
fh	-0.119*	(0.0479)	-0.119**	(0.0432)
$poor_{equi\ inc}$	-0.0322	(0.0483)	-0.0258	(0.0448)
fh × $poor_{equi\ inc}$	0.347***	(0.0791)	0.213*	(0.0857)
win4mgm	0.429***	(0.0998)	0.287***	(0.0705)
SI_{RTdiff}			-0.0000708***	(0.0000150)
SI_{ACdiff}			-0.000436	(0.000522)
CRT score			-0.0282++	(0.0161)
Positive affect			-0.0121*	(0.00569)
Negative affect			-0.0147***	(0.00351)
Financial worries			-0.00265	(0.00355)
LAPA			0.00545	(0.00491)
lambda				
cons	1.585***	(0.0798)	2.074***	(0.270)
fh	-0.0436	(0.104)	-0.0437	(0.0942)
$poor_{equi\ inc}$	0.0629	(0.115)	0.0406	(0.118)
fh × $poor_{equi\ inc}$	0.153	(0.183)	0.0888	(0.185)
SI_{RTdiff}			-0.0000794*	(0.0000311)
SI_{ACdiff}			0.000806	(0.00113)
CRT score			-0.00863	(0.0429)
Positive affect			-0.0159	(0.0138)
Negative affect			-0.0231***	(0.00660)
Financial worries			-0.000337	(0.00725)
LAPA			0.00305	(0.00955)
Observations	8760		8760	

s.e. in parentheses; $+p < 0.20$, $++p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 1.32: Mediated moderation of the effects of financial hard priming on risk preferences(δ), in the case of financial hard priming (fh) against nonfinancial easy priming(nfe)

	fh vs. nfe
Total marginal effect of fh	
$\delta_{\text{fh, total}}+\delta_{\text{fh} \times \text{poor}_{\text{equi inc}}, \text{total}}$	0.913***
	(0.228)
Direct marginal effect of fh	
$\delta_{\text{fh, direct}}+\delta_{\text{fh} \times \text{poor}_{\text{equi inc}}, \text{direct}}$	0.456++
	(0.260)
Mediated moderation effect	
Total effect - Direct effect	0.457*
	(0.184)
N	8760

Table 1.33: The effect of financial hard priming on affect, moderated by poverty status, in the case of financial hard priming (fh) against nonfinancial easy priming(nfe)

	Positive Affect	Negative Affect	Financial Worries	LAPA
In financial hard condition	-0.039	-0.038	0.159	0.006
	(0.174)	(0.213)	(0.181)	(0.164)
$\text{poor}_{\text{equi inc}}$	-0.129	-0.271+	0.583**	-0.077
	(0.183)	(0.195)	(0.183)	(0.172)
$\text{fh} \times \text{poor}_{\text{equi inc}}$	0.270	0.276	-0.108	0.054
	(0.262)	(0.262)	(0.254)	(0.257)
Male	0.295**	0.051	-0.143	0.304*
	(0.112)	(0.133)	(0.129)	(0.132)
Age	-0.008	-0.017	0.007	-0.037
	(0.029)	(0.029)	(0.034)	(0.030)
Age^2	0.000	0.000	-0.000	0.000+
	(0.000)	(0.000)	(0.000)	(0.000)
Education level	0.153**	0.091++	-0.041	0.109*
	(0.053)	(0.050)	(0.053)	(0.056)
Unemployed	-0.104	0.041	0.083	0.071
	(0.159)	(0.190)	(0.182)	(0.183)
Welfare recipient	0.389*	-0.211	0.000	0.072
	(0.178)	(0.195)	(0.195)	(0.171)
Debtor	0.074	-0.196	-0.383*	0.079
	(0.139)	(0.157)	(0.151)	(0.144)
In financial hardship	0.021	0.733***	0.953***	-0.251++
	(0.144)	(0.150)	(0.169)	(0.145)
Insured	0.109	-0.064	-0.107	0.052
	(0.122)	(0.149)	(0.134)	(0.132)
Health insured	0.347	-0.038	0.154	0.366
	(0.314)	(0.225)	(0.258)	(0.296)
Observations	292	292	292	292

Standard errors in parentheses are obtained by bootstrap estimation. + for $p < 0.20$ ++ for $p < 0.10$ * for $p < 0.05$ ** for $p < 0.01$ *** for $p < 0.001$
All estimations are estimated by ordered probit.

Table 1.34: The effect of financial hard priming on cognition, moderated by poverty status, in the case of financial hard priming (fh) against nonfinancial easy priming(nfe)

	(1)		(2)	
	SI_{RTdiff}		SI_{ACdiff}	
	OLS		OLS	
Constant	276.456	(560.516)	-26.343	(23.058)
fh	-58.119	(135.431)	-3.953	(6.572)
$poor_{equi\ inc}$	-81.049	(137.029)	12.672*	(5.782)
fh × $poor_{equi\ inc}$	-138.240	(215.307)	-6.698	(8.478)
Male	-168.415^{+}	(103.248)	-3.423	(4.291)
Age	6.037	(23.886)	-0.094	(0.943)
agesq	-0.094	(0.258)	-0.004	(0.010)
Education level	4.936	(38.269)	2.463^{+}	(1.576)
Unemployed	-83.219	(129.952)	-5.855	(5.952)
Welfare recipient	335.628*	(147.069)	12.350*	(5.765)
Debtor	-29.459	(138.418)	-2.001	(5.026)
In financial hardship	-96.303	(134.188)	-2.137	(4.690)
Insured	-137.332	(113.669)	-0.894	(4.567)
Health insured	-133.063	(202.623)	3.774	(7.566)
Observations	292		292	

Standard errors in parentheses

Standard errors are bootstrapped.

$^{+}$ $p < 0.20$, $^{++}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.35: The effect of financial hard priming on cognition, moderated by poverty status, in the case of financial hard priming (fh) against nonfinancial easy priming(nfe)

	(1) log(dur) xtreg		(2) cor xtprobit		(3) CRT oprobit	
Constant	6.657***	(0.173)	0.526	(1.017)		
fh	-0.028	(0.045)	-0.254	(0.287)	0.010	(0.178)
$\text{poor}_{\text{equi inc}}$	0.030	(0.050)	0.537^{++}	(0.305)	-0.003	(0.226)
fh × $\text{poor}_{\text{equi inc}}$	0.028	(0.064)	-0.205	(0.400)	-0.043	(0.284)
Male	0.067*	(0.031)	0.016	(0.201)	-0.026	(0.146)
Age	0.013*	(0.007)	0.009	(0.040)	-0.011	(0.033)
agesq	-0.000	(0.000)	-0.000	(0.000)	0.000	(0.000)
Education level	0.008	(0.012)	0.112^{+}	(0.072)	0.093^{++}	(0.054)
Unemployed	-0.070^{++}	(0.037)	-0.339	(0.290)	0.083	(0.193)
Welfare recipient	0.029	(0.038)	0.493^{++}	(0.283)	-0.132	(0.173)
Debtor	-0.028	(0.039)	-0.244	(0.234)	-0.128	(0.154)
In financial hardship	0.047^{+}	(0.036)	-0.060	(0.233)	-0.112	(0.161)
Insured	-0.041	(0.033)	-0.051	(0.217)	0.054	(0.148)
Health insured	0.040	(0.054)	0.522^{+}	(0.354)	0.126	(0.236)
congruent	-0.195***	(0.010)	2.614***	(0.218)		
Observations	6757		7758		292	

Standard errors in parentheses
Standard errors are bootstrapped for ordered probit(oprobit).
Standard errors are clustered at subject-level for random-effect GLS(xtreg) and random-effect probit(xtprobit).
$^{+}$ $p < 0.20$, $^{++}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.36: Marginal effect of financial hard priming on mediators, in the case of financial hard priming (fh) against nonfinancial easy priming(nfe)

	fh vs. nfe
Cor(=1 if correct)	
fh + fh × $\text{poor}_{\text{equi inc}}$	-0.459+
	(0.282)
$\text{SI}_{\text{ac\_diff}}$	
fh + fh × $\text{poor}_{\text{equi inc}}$	-10.651++
	(5.660)

1.7.5 Further considerations on estimation

1.7.5.1 Robust standard error vs. Cluster robust standard error

To take into account for different types of standard error, robust Eicker-Huber-White sandwich standard error, clustered robust Liang-Zeger sandwich estimator, and bootstrap standard error are estimated. For all types of standard error, the estimated coefficients and the pattern of p-values are the same, except the model with clustered robust standard error.

If we consider individuals as clusters, we might suspect that errors are independent across clusters, i.e. across individuals, but correlates within clusters for different CEs elicited for each individual. We then might use cluster robust standard error(, i.e. heteroskedastic- and cluster- robust standard error) at the level of individual, instead of robust standard error (,i.e. heteroskedastic-robust standard error). We pursued the guidance from Cameron and Miller (2016) on clustering in nonlinear model in a population-averaged approach. This is to estimate the model in the absence of clustering, then also estimate cluster-robust standard errors. After clustering error by each individual, our main effect of the interaction between being in financial hard condition and income on risk preference (the elevation of probability weighting function) is still statistically significant at 5% level of significance. However, the financial priming effect on risk preferences become statistically insignificant. Additionally, there is no statistical significant mediated effects by measures of cognition and emotion

However, there are issues on using cluster-robust standard error that we need to consider. Firstly, Cameron and Miller (2016) show that the cluster-robust variance inflation factor is increasing in (1.) the within-cluster correlation

of the regressor (2.) the within-cluster correlation of the error (3.) the number of observations in each cluster. Since each observation for each individual corresponds to the same treatment status assigned to each individual, the cluster robust s.e. will be inflated by perfect correlation of treatment status between each observation of CE within each individual. Secondly, as Abadie et al. (2017) have established, even though clustering will mostly matter by conservatively increasing standard error, to cluster or not to cluster depends rather on sampling design, experimental design and heterogeneity in treatment effect with respect to clusters. Our setting corresponds to the situation that no clustering is needed as suggested by Abadie et al. (2017). This is because, there is neither sampling clustering, nor assignment clustering at individual level and at lottery-type level. Our assignment of treatment does not vary systematically with individuals in the sample, because individuals are randomly assigned into one of the four conditions. Importantly, assignment of lottery choice tasks also does not vary systematically with individuals because every individual have to do the same set of tasks on lotteries with different characteristics on randomized order. Additionally, we assume constant treatment effect across individuals, and have no intention to claim external validity of the results. In the case that there is heterogeneity in treatment effect with respect to lottery types, it is captured by lottery-type fixed effect. The treatment effect for each lottery type is still homogenous across sampling unit, i.e. across individual. Most importantly, we have captured heterogeneity at individual level such as knowledge and attention span that might affect each lottery choice through individual- and gamble- specific error variance.

Intuitively, clustering is necessary when each observation within a cluster does not provide new independent information of the treatment effect. In this

study, if we view individual as cluster with many observations of elicited CEs for each individual, each elicited CE corresponds to different lotteries with either different probabilities or different outcomes. Hence, it might not be wrong to assume that each observation of elicited CE provides independent piece of information on risk preferences. In fact, it is this pattern emerging from these pieces of information that we would like to capture into the risk preference estimation. Accordingly, the robust standard error that assumes no clustering at individual level is argued to be appropriated.

1.7.5.2 What explains risk-loving behavior

In all previous analyses, we have tried to tackle the factors explaining observed risk loving behavior by jointly estimating probability weighting function and the curvature of value function together. In other words, we have estimated δ's, γ's, and α's together by maximum likelihood estimation without any restrictions on any parameters. An issue might be whether we can truly differentiate the estimated overweighting of probabilities from standard risk-loving behavior. Considering on this issue, we further explore the case in which:

(a.) linear probability weighting (,i.e. no probability weighting) is assumed among experimental lotteries with constant objective probability at 0.5, but with varying magnitudes of the outcomes. In this case, only certainty equivalents of experimental lotteries $(\$4, 0.5; 0, 0.5)$, $(\$6, 0.5; 2, 0.5)$, $(\$12, 0.5; 0, 0.5)$, $(\$24, 0.5; 4, 0.5)$, $(\$4, 0.5; -L, 0.5)$, $(\$6, 0.5; -L, 0.5)$ were included in the maximum likelihood estimation.

(b.) risk neutrality (, i.e. the value function is linear) is assumed among ex-

perimental lotteries with varying objective probabilities, but with constant magnitude of outcome at \$4. In this case, only certainty equivalents of experimental lotteries $(\$4, 0.01; 0, 0.99)$, $(\$4, 0.25; 0, 0.75)$, $(\$4, 0.50; 0, 0.50)$, $(\$4, 0.50; -L, 0.50)$, $(\$4, 0.75; 0, 0.25)$, $(\$4, 0.99; 0, 0.01)$ were included in the maximum likelihood estimation.

Comparing the results in (a.) to the previous results with all experimental lotteries and no restriction on parameter δ or γ, we have that the estimated α's are pretty stable at around 1.7, consistent to the value function being convex expressing risk-loving.

Comparing the results in (b.) to the previous results all experimental lotteries and no restriction on parameter α, we also have that the estimated γ's are pretty stable at around 0.18. However, the estimated δ in (b.) inflates and is higher than the previous results.

From these results, they suggest that, when jointly estimated without any restrictions on parameter values, $\hat{\delta}$'s shouldn't pick up the part of risk loving behavior that can be explained by value function's curvature α. On the contrary, if we restrict to the case of risk neutrality (linear value function), the risk-loving behavior that once was captured into $\hat{\alpha}$ should be instead embedded into $\hat{\delta}$, which could inflate the level of overweighting of probabilities.

1.8 Conclusion, Limitations, and Further research

This study has provided novel evidence that latent risk preferences, specifically probability weighting function and loss aversion, can be changed due to a brief exposure to induced thoughts about uncertain financial situations. In addition, the channel through which these changes occur might be through cognitive capacity that controls the relative strength of the deliberative process over the affective process. That null effects were not found is in support of the idea that risk preferences are malleable.

Triggered financial concerns are found to lead to a higher level of overweighting of probabilities when compared to nonfinancial thoughts, and to cause more loss aversion when compared to triggered financial concerns with less intensity. The treatment effect of the financial priming on the degree of optimism in probability weight is found to depend on whether participants had lower equivalent income than the median in the sample or not. Moreover, the indirect treatment effect works through deterred cognitive capacity as manifested by lower accuracy in the Stroop task. The statistically significant effect of this induced scarcity mindset, moderated by income, on reduced cognitive performance is in the same line with the findings in Mani et al. (2013a) and Lichand and Mani (2020). By investigating further on the whole chain from financial worries to risk preferences, through cognitive and affective channels, we have provided empirical evidence to a framework on various ways taxed bandwidth and poverty can possibly reinforce each other(Dean et al., 2017; Haushofer and Fehr, 2014; Schilbach et al., 2016). This evidence also supports the usually assuming role of two-systems thinking in understanding the psychology of poverty and economic decision-making, and for a possible applica-

tion of a proposed model of Dual Process theory by Loewenstein et al. (2015).

This paper does not find a statistically significant treatment effect of nonfinancial hard priming, compared to nonfinancial easy priming, on risk preferences. Two cases can be considered as possible explanations. First, the intended intensity between the two conditions was not successfully manipulated. Alternatively, the null effect of the nonfinancial frame would suggest that only the financial frame matters in changing the risk preferences. This limitation of the study is worth further investigation. This is because, in the dual-process theory, any equal cognitive load should alter risk preferences equally and in the same way, regardless of framing that renders such load. However, suppose the latter case of the null effect cannot actually be rejected statistically. In that case, it might mean that the financial concerns on uncertainty in income, central to the poor's psychological life, have their own unique way of impeding cognitive function, changing affective states, and shaping risk preferences.

Many aspects that can be improved in future work are as follows. Firstly, this study elicited risk preferences from experimental lotteries and NY lotteries, which were also presented in multiple price lists. It would be a further contribution to the literature if, after the priming, risk preferences can be elicited from risky choices in real life that are rich enough to elicit probability weighting, both in the gain and loss domain, and loss aversion. Notably, our probability weighting function is elicited from pure gain lotteries only. The weighting function might appear to take a different shape if we consider pure loss lotteries. The effect of financial priming on probability weighting in the loss domain might also take on different pattern. Secondly, in this study, exposure to financial worries was brief, and there is evidence that people already in some forms

of economic hardship might be differently responsive to new financial situations they need to think through. On this front, the study that helps tackle the causal effect of lengthened poverty experiences, or adverse asset shocks, to the stability of risk preferences across time and contexts, would help shed more light on how poverty perpetuates itself. Thirdly, this study used self-reported measures of affect without having more rigorous measures of stress, like cortisol level. Further research could proceed by combining medical measures like stress hormone(Haushofer et al., 2013) to increase measured emotional reaction accuracy. Finally, it is shown in this paper that risky choices based on New York Lotteries yield different patterns of probability weighting function than experimental lotteries. Further analysis that can be done to understand underlying mechanisms behind choices dealing with real lotteries would help explain the poor's economic behavior in lottery buying. Additionally, due to the limited experimental budget, the multiple price lists for NY lottery tickets were limited to the highest prices at three or five times of each ticket's market price. Accordingly, the true level of certainty equivalent might be censored. Future studies focusing on the mechanism behind the probability weighting from real lotteries could find a suitable way to approach such censoring.

This study highlights the situation that financial worries partake in taxing limited mental reserves and altering how people weigh probabilities and how people are averse to loss. Combining policies that help people under financial strains knowingly give linear weighting to probabilities or be less loss-averse while easing cognitive load should be beneficial to the poor who have smaller room for errors.

CHAPTER 2

THE EFFECT OF THE SALIENCE OF FLOOD EXPERIENCES ON SUBJECTIVE PROBABILITY OF MEGA FLOOD

Abstract

This paper revisits the old question of how people form subjective beliefs of extreme events by studying beliefs on the occurrence of a natural disaster, floods. We try to answer whether the salience of flood shocks encountered by rice farmers in Cambodia affects their subjective beliefs on the probability of extreme flood events. This is done by exploiting variation in memory of flood experiences. The key identification strategy hinges upon the stratification in key observables in sampling design done by Chantarat et al. (2019) and the steady pattern of flood experiences to largely resemble to flood experience in year 2011. We mostly found no recency effect of the occurrence of floods on the subjective belief of the event of megaflood. However, it was found that shocks that are more salient, in terms of the extremeness of flood loss, make farmers have a higher subjective probability of extreme flood events. This indicates the role of availability heuristics (Tversky and Kahneman, 1974) and the salience theory of choice under risk(Bordalo et al., 2012).

2.1 Introduction

Since the seminal work by Malmendier and Nagel (2011), a vast literature has tried to study the role of experiences of shocks in changing risk-taking behavior. The contribution of this paper is to explore how Cambodian rice farmers who have mixed experiences of floods with different levels of salience form their observed beliefs over the probability of extreme flood events (megafloods).

Many facets of risk-taking behaviors have been explored as a result of different paths of shock experiences. Malmendier and Nagel (2011) examined willingness to take financial risk, stock and bond market participation, and fraction of liquid asset invested in stocks. In the same essence, Gallagher (2014), Zaleskiewicz et al. (2002), and Browne and Hoyt (2000) observed insurance take-up behavior, while Dessaint and Matray (2017) look at corporate cash holding. According to Kahneman and Tversky (1979a), risk attitudes, hence risk-taking behavior, are the results of the interplay between risk aversion over gains and losses, and the weighting and the estimation of subjective probabilities. In this regard, rather than inferring update in beliefs from changes in behavior, we directly focus on individuals' subjective beliefs of the probability of extreme flood events, a unique data obtained from the study by Chantarat et al. (2015) and Chantarat et al. (2019)[1]. By considering the variation of experiences from retrospective past flood shocks that occurred in the year 2013, 2011, and backward until 2001, we hope to answer whether the salience of experiences of flood shocks encountered by rice farmers affect their subjective belief of probability of megaflood. In other words, the question is whether flood shocks that are

[1]I am extremely grateful for the kind help from Dr. Sommarat Chantarat in sharing the unique data set on "household response to natural disasters: the case of flood 2011 and 2013 in Cambodia".

more salient to the farmers make them a have higher subjective probability of future extreme flood events. This should allow us to learn more about the role of availability heuristics(Tversky and Kahneman, 1973, 1974) in the over-or under-estimation of small probabilities. This directly ties to the challenge posed by Barberis (2013) on the misestimation of the subjective probability of rare and extreme events. In addition, this is also in line with the salience theory of choice under uncertainty by Bordalo et al. (2012), which proposes that people over-weight subjective probability of the state that is more salient than other states of the world. A better understanding of the mechanisms driving the subjective probabilities for rare floods after experiencing adverse flood shocks is vital to learning about downstream behaviors under uncertainty and long-term risk management design.

2.2 Literature Review

Literature has helped us to understand that there must be learning from experiences both in the context of experiences from natural disasters and from the other kinds of shocks, such as macroeconomic shocks. Resulting behaviors from learning that has been studied comes in many forms, such as purchases in insurance, liquidity holding, timing or amount of risky investment, or subjective probability of the occurrence of disaster or loss. Chantarat et al. (2015) and Chantarat et al. (2019) studied the impacts of the 2011 megaflood on risk aversion, impatience, altruism, trust, subjective expectations, safety net perceptions, and related behaviors among the Cambodian rice-farming households. The paper used the 2011 megaflood as a natural experiment, creating variations in flood exposures across sampled villages and households. Controlling for being

in flood prone area, the size of flood in subjective expectation, and households' characteristics, the OLS estimation(table 9 in Chantarat et al. (2019)) of indicator for flood, either at household level or village level, on subjective probability for floods revealed a pattern of updated beliefs. Floods seemed to have little impact to subjective belief for probability to occur mild flood, while having relatively bigger impact on the subjective belief for megaflood. Living in flooded villages or being a flooded household related with higher subjective probability of having a megaflood, for those who were not living in the flood-prone area. Those who lived in a flood-prone area already had a higher subjective expectation for megaflood and experience the megaflood in 2011 had a very small impact on their expectation.

Deryugina (2013) estimated how local temperature fluctuations influenced individuals' belief about global warming. The paper found that some features of the updating process are consistent with rational updating. Also, the paper found strong evidence for representativeness, and some evidence for availability heuristics. As Just (2008) surveyed, Zaleskiewicz et al. (2002) found that more flood insurance was purchased when individuals had recent memories of disasters. The level of insurance decreased to the normal level after some period of time. The memory of floods in distant areas also could influence the purchase of flood insurance. Similarly, Browne and Hoyt (2000) also found the recency effect toward the purchase of insurance, but personal involvement exacerbated the effect. As a consequence, those who had been personally affected by a disaster were very likely to over-invest in insurance. Menapace et al. (2012) studied whether heuristics- the availability, the representativeness, and biased assimilation- were used to form the perception of hazards from climate change among 195 farmers in Trentino, Italy in the year 2011. The hazards included

crop disease(powdery mildew or apple dieback) and hail. The heuristics were detected by comparing the patterns of the effects of crop loss experiences or of hail trend observation on the perception of risks between climate change believers and non-believers. In addition, Gallagher (2014) found that insurance take-up was most consistent with a Bayesian learning model that allowed for forgetting or incomplete information about past floods. By using flexible event study framework, the paper examined how flood risk beliefs changed after floods using an 18-year community-level dataset on flooding and the purchase of flood insurance. The change in the number of insurance policies per capita was used as a measure of changing homeowner beliefs over the expectation of a future flood, specifically, expected probability of a future flood. A flexible event study was used to estimate the causal effect of large regional floods on insurance take-up for hit and neighboring homeowners. It was found that there was an immediate rise in the fraction of homeowners covered by flood insurance in flooded communities. The effect peaked at 9 percent and then began to steadily decline. The jump combined with the quick decline to baseline levels suggested that homeowners were not incorporating all available information. The study points toward a learning model that allows homeowners to weigh recent floods more heavily than earlier floods (Camerer and Ho, 1999; Malmendier and Nagel, 2011). The data was also consistent with Availability Bias, a nonlearning model interpretation (Kahneman et al., 1982). Moreover, Turner et al. (2014) looked at 384 individuals in Pakistan to study the impact of prior loss experiences from severe 2010 flood on willingness to purchase insurance. The paper found that flood-affected individuals demanded more insurance and personal losses and observations of others' losses were significant determinants of demand, controlling for location-specific flood propensity, pre-

flood mitigation, post-flood assistance. The paper also pointed out to the determinants that could affect change in risk aversion after natural disaster that had not been explored. Such determinants were such as memories of past events, expectations of outside assistance, and individual loss and mitigation behaviors. Furthermore, Kousky and Shabman (2015) discussed ways in which ones can use mental shortcuts to form beliefs of probability of flooding. Consistent to the availability heuristic, higher salience and imaginability of future flood among people who were in major-flood locations could cause higher evaluation of flooding possibilities. Time since and losses from being flooded could determine the extent to which the role of availability heuristics matters. To the contrary of the availability heuristics, gambler's fallacy could bring down the estimation of flood probability. Related, Dessaint and Matray (2017) studied the effect of the occurrence of hurricane toward the distortion between subjective and objective risk, through change in the amount of corporate cash holdings. The paper focused at the saliency of hurricane by considering the difference in distance of firms' locations from hurricane zone. Sudden shock to perceived liquidity risk cause managers in hurricane area express more concerns about hurricane risk, but this perceived risk decreased and the bias disappeared as time goes by. Lastly, Kala (2019) studied how learning from Monsoon signal affected optimal planting time with the assumption that farmers were ambiguity averse. Kala (2019) used data from ICRISAT(2005-2012) and rainfall data from CPC Morphing Technique (CMORPH) from 2003-2012. Kala (2019) developed a general framework which accommodated two critical aspects of learning: varying underlying state and ambiguity about the distribution of the monsoon onset signal. She found that when considering the monsoon onset signal and the optimal planting time farmers showed concerns for the worst-case scenario. Apart

from above observational studies, Cai and Song (2017) used lab-in-the-field experiment to study whether hypothetical experience on disaster affected weather insurance adoption. It was founded that there was recency effect. That is, a greater number of hypothetical disasters in latter rounds of the game increased the perceived probability of disaster. In addition, the experience directly determined insurance demand, and its effect didn't pass through change in perception of insurance benefit, change in risk attitudes, or changes in perceived probability of future disaster.

Besides literature in natural disaster and climate change context, Malmendier and Nagel (2011) examined how past stock market returns affect investment portfolio purchasing decisions and found that recent return experiences had larger effect. The paper also discussed possible channels including an increase in the stock market return expected over the next 12 months and the return respondents expected to earn on their portfolios over the next 12 months. They did not fully disentangle the effect of change in belief from change in risk preference. Additionally, they considered weighting scheme that might not capture nonlinear effect of extreme event. In the same essence, Malmendier and Nagel (2016) used adaptive learning model to study expectation updating when experiencing inflation shocks. The experiences carried more weight on expectation than other historical data. What Malmendier and Nagel (2016) did in addition to Malmendier and Nagel (2011) was to use expectation data to isolate the experience-induced changes in belief from the experience-induced changes in risk preference.

Related to the study about shocks, especially natural disasters, is the study of how subjective probability of rare and extreme events is formed, or be de-

termined. Slovic et al. (1977) experimentally studied why subjects bought less insurance against low-probability high-loss events and suggested that convex utility over losses or threshold of subjective probability might be the possible answers. In addition, the study also found gambler's fallacy, that is, if hazard just happened in previous rounds, subjects would believe that it was unlikely to repeat soon. Burns et al. (2011) and Barberis (2013) discuss the weighting (and estimation) of the probability of tail events and point out to the challenges in identifying the rigorous explanation for such over- or under- estimation and over- or under- weighting. One explanation for the overweighting of probability for each state is offered by Bordalo et al. (2012), as well as by Gennaioli and Shleifer (2010). These papers fit into the bigger picture that all the information available to decision makers is not fully taken into account. Instead, only information their minds focus on is overemphasized. Decision makers overweigh the subjective probability of the states that draw their attention and neglect states that do not. Bordalo et al. (2012) focus on the salience of lottery payoffs and distorted decision weight, when considering choice under uncertainty. In this paper, the salience of lottery payoff is defined as the extremeness of difference in percentage terms from the payoffs of other available lotteries in the same state of the world. The state that is more salient will be given higher subjective probability.

2.3 Data

The data used in this paper is from Chantarat et al. (2019), which is cross-sectional data surveyed in year 2014 in four key rice-growing provinces in Cambodia: Prey Veng, Kampong Thom, Banteay Meanchey and Battambang. According to Chantarat et al. (2019), 2011 major flood event was focused when designing sampling strategy, and was the main source of variation in flood experiences. Flood experiences are in the terms of being directly and severely hit by flood or not. Those who are considered as flooded households in Chantarat et al. (2019) had areas covered with floodwater for more than 15 days and experienced rice production damage. Endogeneity of flood exposure in 2011 was resolved by stratifying by key heterogeneities: wealth, geophysical and production system, distance from major drainage, exposure to land conflict, location upstream(Plain Zone) and downstream(Tonle Sap zone), and being in flood prone and less prone area at the commune level. For each stratum, flooded and non-flooded households were chosen randomly. Being flood prone is based on World Food Program's historical data of flood events. Commune that is considered flood-prone is the one that experienced at least three extended floods in 10 years. At the household level, a household is prone to floods if at least 2 floods experience in the past 5 years were reported. As shown in table 2.1, the sample covers rice farmers in 4 provinces (which are equal to 16 communes) 32 rice-growing villages (16 villages severely flooded) 256 rice-farming households (8 households per village).

Parts of the data that are key to this study are as followed. The first part is retrospective question that asked about severe shocks that affect rice production. Such shocks include megaflood 2011 and 2013 as well as other past shocks

Table 2.1: Sampled households by province

Sampled households	All	Prey Veng	Kampong Thom	Banteay Meanchey	Battambang
Total villages	32	8	8	8	8
Flooded villages	16	4	4	4	4
Total households	256	64	64	64	64
Flooded households	172	29	53	46	44

Source: Table 1 in Chantarat et al. (2019)

Table 2.2: megaflood experiences across households (% of total number of households)

	Flooded in 2013		
Flooded in 2011	No	Yes	Total
No	10.9	16.4	27.3
Yes	21.5	51.2	72.7
Total	32.4	67.6	100

and the timing of shocks. Table 2.2 and 2.3, show variation in experiences of flood in 2011 and 2013, in both the occurrence aspect and the loss aspect. We have that 45% of households experienced rice income loss from megaflood in 2011 and 2013 and 69% of households experienced same intensity of flood effect from both flood events.

Apart from this, serious shocks that affected households' rice production over the past 10 years between 2004-2014 are drought, 12%, flood, 49%, insect, 14%, pest, 17%, disease, 7%, and other, 1%, of all incidences that ever have happened to all households. These serious shocks affect households at both same and different timings.

Secondly, subjective belief on the probability of extreme flood is at the heart of analyses in this paper. Chantarat et al. (2019) asked each respondent to assign probability of flood events in the next 10 years. This is done by using 10 coins as

Table 2.3: Loss experiences in 2011 and 2013 (% of total number of households)

	Affected by flood in year 2013?				
Affected by flood in year 2011?	No	Rice income loss	Asset loss	Both	Total
No	9	2	1	3	15
Rice income loss	7	45	2	3	57
Asset loss	0	1	2	0	4
Both	4	6	1	13	24
Total	21	55	6	19	100

visual aid to express probabilistic concept and asked each respondent to place the coins in front of each of the three flood events (no flood, mild flood, and megaflood), where the number of the coins he/she put would reflect the likelihood he/she thought each event would happen in the coming 10-year period. The questionnaire contains pictures of flood in exhaustive scenarios, as shown in figure 2.1.

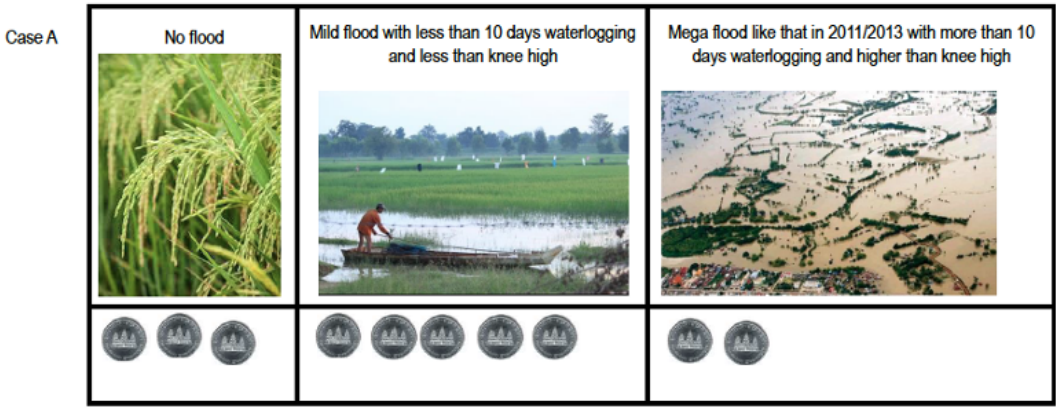

Figure 2.1: Subjective probability on each flood scenario in questionnaire surveyed by Chantarat et al. (2019)

2.4 Nature of Flood Shocks and Subjective Probability

Two most recent flood events were large in scale. From table 2.4 and 2.5, they indicate that, even for households who are not flood prone, 12-18 % of them were flooded in 2011 and 2013. However, majority of households who were flooded are in flood prone area. At household level, household was prone to floods if they reported with at least 2 floods experience in the past 5 years. Moreover, when such a megaflood happens, there is the possibility of having general equilibrium effect. That is, there have households who haven't experienced floods directly but reported that they were affected by floods by having income or asset losses. This is shown in table 2.6 and 2.7 below. Moreover, given being flooded, the higher fraction of households experienced rice income losses due to floods, comparing to experiencing asset loss from flood.

Table 2.4: megaflood experiences in 2011 and being floodprone (% of total number of households)

	Floodprone		
Flooded in 2011	No	Yes	Total
No	22.6	4.7	27.3
Yes	18.8	53.9	72.7
Total	41.4	58.6	100

Table 2.5: megaflood experiences in 2013 and being floodprone(% of total number of households)

	Floodprone		
Flooded in 2013	No	Yes	Total
No	28.9	3.5	32.4
Yes	12.5	55.1	67.6
Total	41.4	58.6	100

To capture variation of experiences of shocks households encountered, we

Table 2.6: The effect of flood in 2011(% of total number of households)

	Flooded in 2011		
Affected by flood 2011	No	Yes	Total
No	13.7	1.2	14.8
Rice income loss	11.3	46.5	57.8
Asset loss	0.4	3.1	3.5
Both	2.0	21.9	23.8
Total	27.3	72.7	100

Table 2.7: The effect of flood in 2013(% of total number of households)

	Flooded in 2013		
Affected by flood 2013	No	Yes	Total
No	18.9	2.0	20.9
Rice income loss	9.8	44.9	54.7
Asset loss	0.4	5.5	5.9
Both	2.8	15.7	18.5
Total	31.9	68.1	100

can firstly take a look at how many times flood shocks have been happening, how much damage these shocks caused, and when they happened.

According to figure 2.2, majority of households experienced 1-2 serious flood shocks that affect rice production. And, from figure 2.5, most of serious flood experiences happened within 5 years, dating back from 2013. According to figure 2.3, about 60% of households have average income loss from floods less than 2,000,000 KHR(Cambodian Reil) which is approximately equal to 485 USD (exchange rate = 4,130 KHR/USD). In addition, when flood shocks happened, around 60% of households have the average magnitude smaller than current rice income farmer can earn as shown in figure 2.4. Nonetheless, a nonnegligible number of households encountered losses that is more than their rice income.

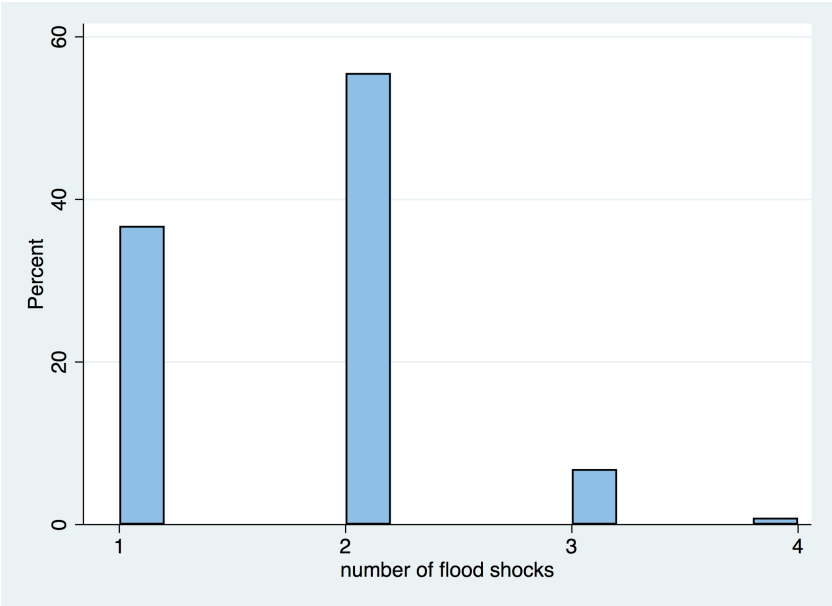

Figure 2.2: Number of flood shocks households experienced in the past 10 years

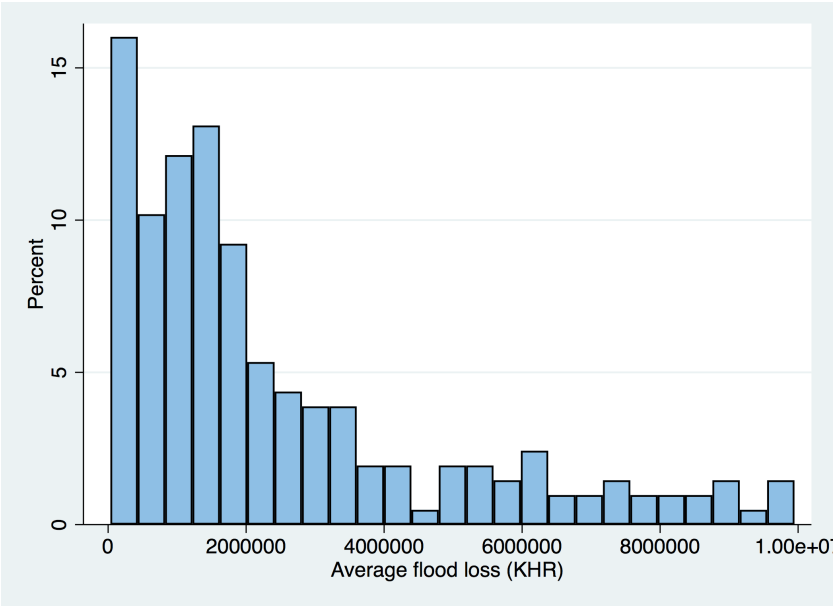

Figure 2.3: Average loss of flood shocks households experienced in the past 10 years

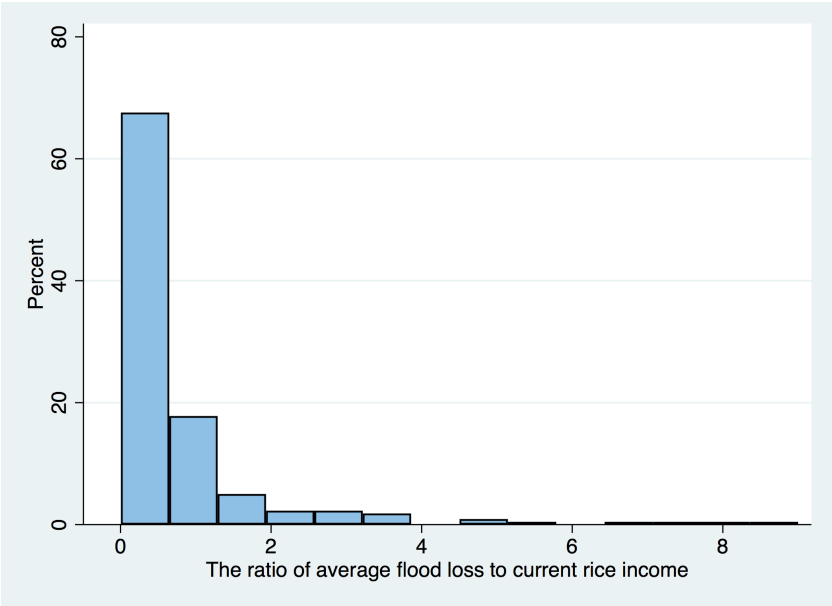

Figure 2.4: The ratio of average flood loss to current rice income

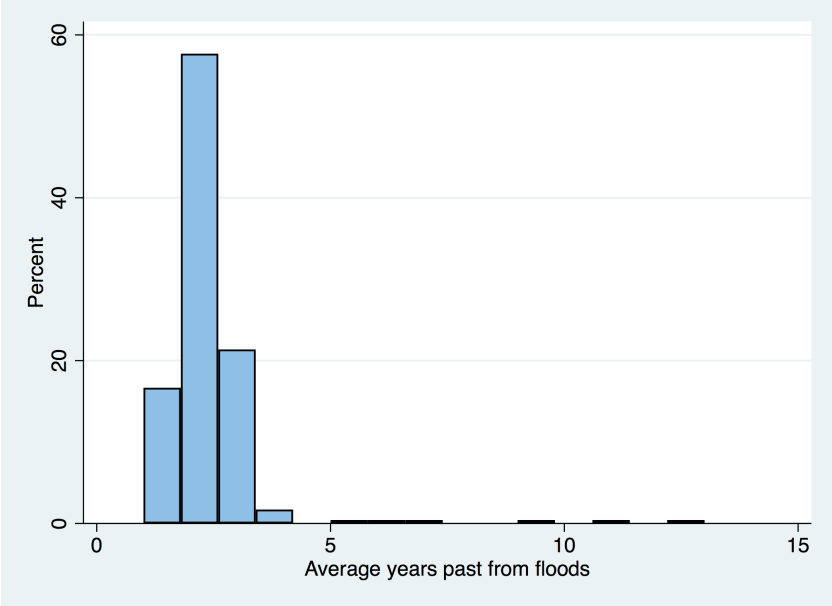

Figure 2.5: Average time distance from the present day

Figure 2.6 to 2.9 show distribution of subjective belief of having megaflood. In figure 2.6, it belongs to households who experienced no flood both in 2011 and 2013. In figure 2.7, it is for those who were flooded in 2011 and were not

flooded in 2013, figure 2.8 for the vice versa, and figure 2.9 for the ones who were flooded in both years. It seems that the distribution of the belief of having megaflood slightly move to the right when considering the households with more vivid experiences of floods (with more recent or both floods).

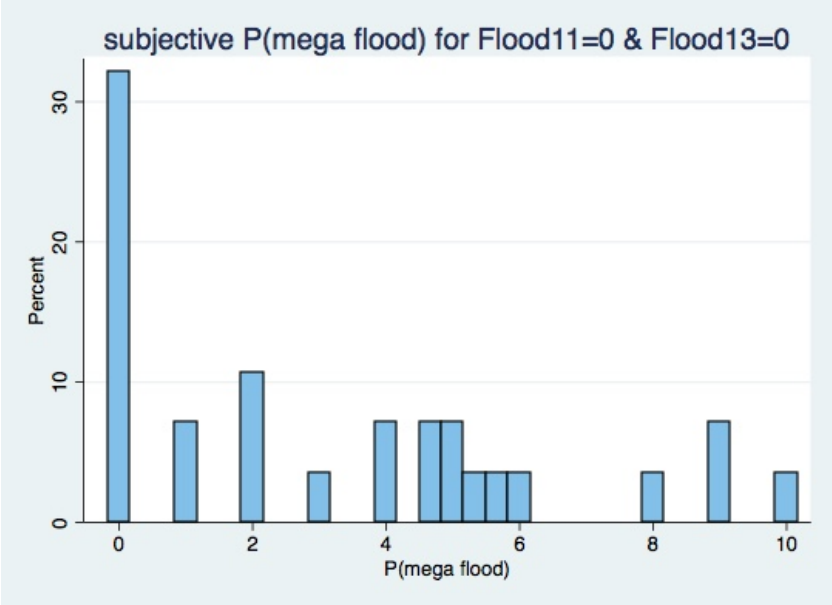

Figure 2.6: Subjective belief of probability of having megaflood among households who didn't experience flood in 2011 and 2013

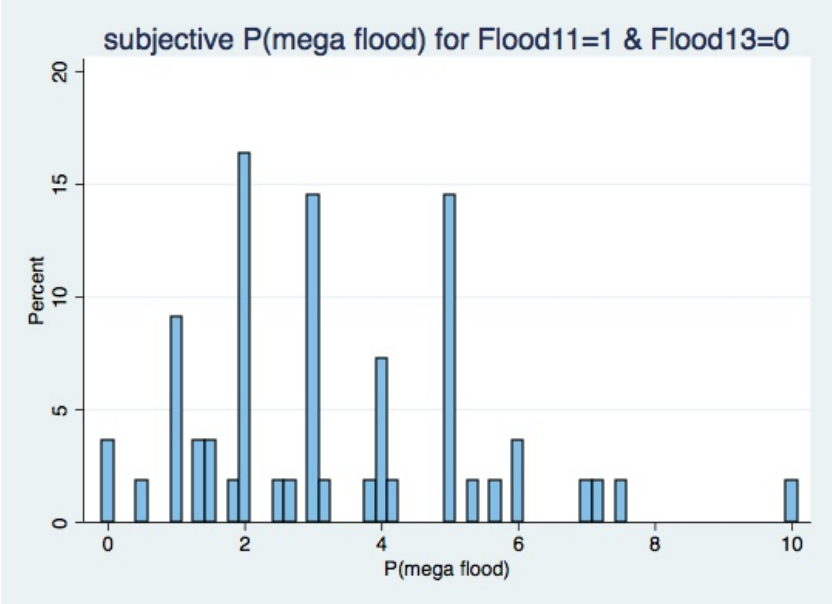

Figure 2.7: Subjective belief of probability of having megaflood among households who experienced flood in 2011

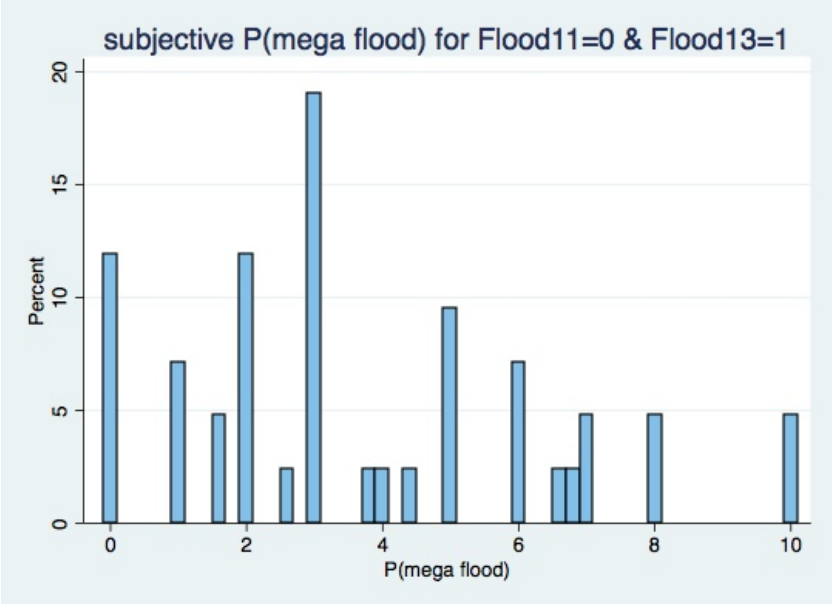

Figure 2.8: Subjective belief of probability of having megaflood among households who experienced flood in 2013

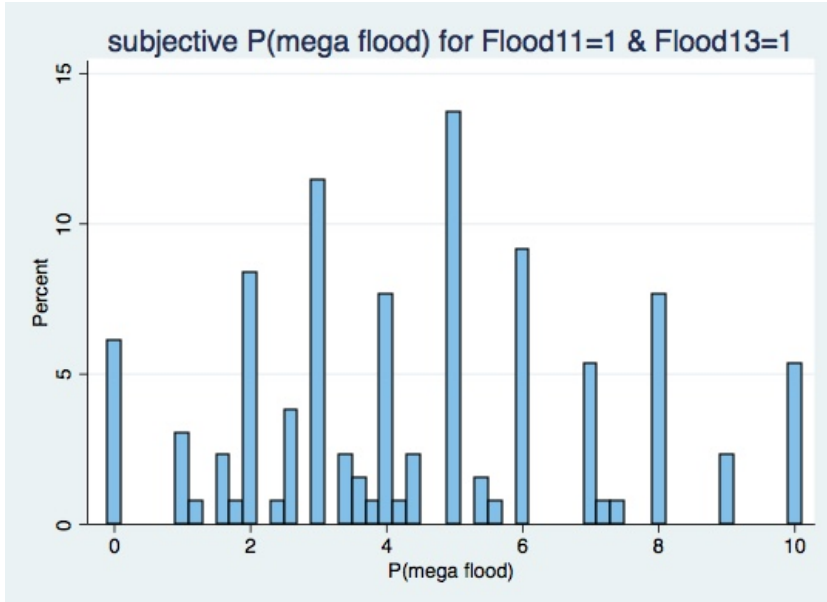

Figure 2.9: Subjective belief of probability of having megaflood among households who experienced flood in 2011 and 2013

2.5 Methodology

The reduced-form model that we will use to identify the effect of salience of flood experiences toward the subjective probability of megaflood is as followed:

$$P(mega\ flood)_{iv} = \alpha + S_{iv}\beta + X_{iv}\gamma + \eta_v + \epsilon_{iv} \tag{2.1}$$

,where $S_{iv}\beta$ is the specification that we will be testing for a pattern of coefficients that could reflect the relationship between salience of experiences of household i in village v and subjective probability. X_{iv} is a vector of household characteristics, and η_v is village fixed effect to control for unobserved heterogeneities at village level. Among other things, village fixed effect should capture location specific objective probability of flood.

Salience is a concept prevalent in many contexts, spanning from neuroscience, psychology to behavioral economics. Tversky and Kahneman (1974) mention salience as a factor contributing to biases in probability judgement due to the retrievability of instances. Taylor and Thompson (1982) defined salience as: "Salience refers to the phenomenon that when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments."

To capture the salience of flood shocks encountered by households in this study, we will consider some proxies for salience as follows.

Specification A

First, given that floods in 2011 and 2013 can be considered as megafloods in terms of number of affected households, if flood in 2013 has statistically significant and larger effect than flood in 2011, this could be regarded as a form of recency effect. The same idea applies for rice income losses[2] from year 2013 and year 2011. That is, $S_{iv}\beta$ is:

$$S_{iv}\beta = \beta_1 Flood2013_{iv} + \beta_2 Flood2011_{iv} \tag{2.2}$$

,where $Flood2013_{iv}$ and $Flood2011_{iv}$ are dummy variables whether household i in village v was flooded in 2013 and 2011 or not. To be specific, these variables indicate whether household experienced flood that affected rice production and there existed crop income loss incurred. The hypothesis to be tested in this case is:

[2]Loss in this study is measured by expected income minus actual income.

$H_o : |\beta_1| = |\beta_2|$ vs. $H_a : |\beta_1| > |\beta_2|$

That is, the null hypothesis says that, regardless of the direction of the effect, the timing of flood experiences has no different effect toward the subjective probability. In other words, flood shocks in different years have the effect with the same magnitude. This should be related to the case of Bayesian updating, in which prior information and more recent information have the same weight in the updating process. As for the alternative hypothesis, we are trying to see whether data strongly supports the recency effect or not. Moreover, we can consider salience in aspect of loss incurred to households as well as the timing of losses. That is,

$$S_{iv}\beta = \beta_1 Loss2013_{iv} + \beta_2 Loss2011_{iv} \tag{2.3}$$

,where $Loss2013_{iv}$ and $Loss2011_{iv}$ are losses from flood in year 2013 and 2011 of household i in village v respectively. In this specification, we should have that the higher the loss, the more salient it should be. And, we can test whether households with more salient flood experience have higher subjective probability or not. Moreover, we can test whether the timing of loss renders the recency effect or not. Hence, the hypothesis to be tested in this case are:

$H_o : \beta_1 = 0$ vs. $H_a : \beta_1 > 0$;

$H_o : \beta_2 = 0$ vs. $H_a : \beta_2 > 0$;

$H_o : |\beta_1| = |\beta_2|$ vs. $H_a : |\beta_1| > |\beta_2|$

In addition, we should also examine whether the effect of timing of flood would still show the same pattern when we control for the size of losses. That

is, another specification that we can explore is:

$$S_{iv}\beta = \beta_1 Flood2013_{iv} + \beta_2 Flood2011_{iv} + \beta_3 Loss2013_{iv} + \beta_4 Loss2011_{iv} \tag{2.4}$$

Moreover, we can also expand the series of dummies for flood experiences and of losses incurred to include the situation happened in year 2001 to 2010, and year 2012.

Specification B

Recency effect might also be observed from higher marginal effect given to the number of shocks occurred recently, comparing with that given to the number of shocks occurred previously(Cai and Song, 2017). The same should also go for gross losses happened recently versus those happened before. In this exercise, we will try the most recent year and all other later years in 12-years experiences to observe this recency effect. This should allow us to observe whether recency effect, if exists, is strong enough when we contrast the most recent experience against all past experiences, instead of against experience only from year 2011. In this case, $S_{iv}\beta$ is:

$$S_{iv}\beta = \beta_1 Flood2013_{iv} + \beta_2 CFreq_{iv} \tag{2.5}$$

$$S_{iv}\beta = \beta_1 Loss2013_{iv} + \beta_2 CLoss_{iv} \tag{2.6}$$

, where $CFreq_{iv}$ is the number of all previous flood shocks of individual i in village v, and $CLoss_{iv}$ is cumulative losses from previous flood shocks of individual

i in village v. The hypothesis to be tested in this case is also:

$H_o : |\beta_1| = |\beta_2|$ vs. $H_a : |\beta_1| > |\beta_2|$

Specification C

Apart from observing pattern of coefficients above, we can also try to capture salience through some proxies such as the number of flood shocks ever happened to each households, and average income losses from all flood experiences. It is imaginable that the higher the number of flood shocks households ever experienced, the more salient these shocks should be in one's mind. This should also be true for the case of gross losses incurred. In this case, $S_{iv}\beta$ is:

$$S_{iv}\beta = \beta_1 SalienceProxy_{iv} \tag{2.7}$$

The hypothesis to be tested is:

$H_o : \beta_1 = 0$ vs. $H_a : \beta_1 > 0$

Apart from the salience proxy in previous aspects, by the underlying idea offered in Bordalo et al. (2012) on the salience of lottery payoff, we can look at the salience of loss when there was megaflood (such as in year 2011, and year 2013). We can construct salience measure as the deviation of loss occurred from reference point. Possible reference points are such as the average of losses from all past shocks, the minimum loss ever happened. This should capture how standing out flood in 2013 should be from average past shocks, in terms of amount of rice income loss. That is,

$$S_{iv}^{a13} = Loss2013_{iv} - AverageLoss_{iv} \tag{2.8}$$

$$S_{iv}^{m13} = Loss2013_{iv} - MinLoss_{iv} \tag{2.9}$$

,where $AverageLoss_{iv}$ is average crop income loss due to flood shocks, and $MinLoss_{iv}$ is the minimum loss from past flood shocks of household i in village v. Crop income loss due to shock was calculated from expected income minus actual income. The average is calculated by dividing gross flood loss by number of flood shocks household could ever recall back in the past 10 years.

X_{iv} is a vector of characteristics of household i, village v, which includes gender, experience in rice farming, education, ratio of rice income to total income, whether drought has ever occurred, average income losses from all other kinds of shocks, number of all other serious shocks ever happened to households in the past 10 years.

The key concern in studying the causal effect of salience of experiences on subjective probability is that such experiences might be endogenous. The identification strategy for this study hinges upon the stratification by key heterogeneities, used by Chantarat et al. (2019). Flood 2011 was the focus when the sample was stratified and we might expect the selection on observable assumption to fail when consider experiences other than megaflood in 2011. However, experiences of floods will be mostly driven by megafloods in year 2013 and 2011. That is, we have that 92.31 percent of households experienced 1 to 2 flood shocks. 76.4 percent and 71 percent of those households were flooded in 2011 and 2013, respectively. Importantly, 71% of those who were flooded in 2011, which is equal to 51% of overall households, were flooded again in 2013.

2.6 Result

2.6.1 Balance test

Table 2.8 to 2.10, show the balance test among covariates X_{iv} and salience measures S_{iv}. Each reported figure in the tables is from OLS regression of each characteristics on each (composition of) salience measure. Subjects with different flood experiences, and different level of salience measures, are similar in terms of gender, age, education, the length in doing rice farming(rice experiences), the classification to be in Cambodian ID poor program(ID poor), the importance of rice income to total income (ratio of rice income to total income), and experiences with droughts(number of drought). However, they usually are different in terms of household size, wealth level(log of wealth), number of all other shocks than flood ever happened to households, and gross losses from all other shocks. This shows that the balance in characteristics originated from 2011 sampling still largely holds for other years' experiences.

Table 2.8: Balance test (1)

	Gender	Age	Education	Rice Experience
$Flood2013$	0.0211	-1.445	-0.151	-0.708
	(0.29)	(-0.79)	(-1.02)	(-0.40)
$Flood2012$	-0.096	3.015	0.0641	3.414
	(-0.97)	(1.2)	(0.31)	(1.41)
$Flood2011$	0.00323	-0.401	-0.074	1.002
	(0.05)	(-0.22)	(-0.52)	(0.6)
$Flood2001-2010$	-0.096	3.015	0.0641	3.414
	(-0.97)	(1.2)	(0.31)	(1.41)
$Loss2013$	-2.60E-09	6.78E-09	7.13E-10	1.68E-10
	(-1.20)	(0.12)	(0.16)	(0.00)
$Loss2012$	-1.22E-08	0.000000631	6.69E-09	0.000000738
	(-0.49)	(1.00)	(0.13)	(1.21)
$Loss2011$	-1.56E-09	-2.08E-08	2.25E-09	-1.90E-08
	(-1.06)	(-0.56)	(0.74)	(-0.53)
$Loss2001-2010$	-1.21E-08	0.000000579	2.62E-08	0.000000188
	(-1.00)	(1.89)	(1.05)	(0.63)
No.of flood 2001-2012	-0.0342	0.893	0.133	1.92
	(-0.55)	(0.57)	(1.06)	(1.27)
Average losses from floods	-2.37E-09	1.00E-09	2.16E-09	-1.64E-08
	(-1.35)	(0.02)	(0.6)	(-0.38)
S_{iv}^{a13}	5.99E-09	3.12E-08	-1.53E-08	0.000000149
	(1.13)	(0.23)	(-1.41)	(1.15)
S_{iv}^{a12}	2.30E-09	2.16E-09	-2.12E-09	2.00E-08
	(1.31)	(0.05)	(-0.59)	(0.46)
S_{iv}^{a11}	1.34E-09	-0.000000295*	1.01E-08	-0.000000104
	(0.25)	(-2.15)	(0.9)	(-0.78)
S_{iv}^{m13}	9.87E-09	-0.000000176	-8.50E-09	8.58E-08
	(1.42)	(-0.99)	(-0.59)	(0.5)
S_{iv}^{m12}	3.42E-09	-1.88E-08	-1.47E-09	1.36E-08
	(1.59)	(-0.34)	(-0.33)	(0.26)
S_{iv}^{m11}	3.91E-10	-0.000000163	7.87E-09	-7.78E-08
	(0.12)	(-1.93)	(1.15)	(-0.95)

Note: the estimated coefficient of regressing characteristics on each salience measure composition is presented. t statistics in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.9: Balance test (2)

	Household size	ID poor	Ratio of rice income to total income	Log of Wealth
$Flood2013$	-0.232	-0.155	-0.0434	0.249
	(-0.78)	(-1.66)	(-1.80)	(1.63)
$Flood2012$	-0.0496	0.118	0.00458	0.215
	(-0.12)	(0.91)	(0.14)	(1.02)
$Flood2011$	0.560*	-0.0631	-0.0344	-0.00328
	(2.03)	(-0.68)	(-1.54)	(-0.02)
$Flood2001-2010$	-0.0496	0.118	0.00458	0.215
	(-0.12)	(0.91)	(0.14)	(1.02)
$Loss2013$	2.50e-08**	-4.10E-09	-3.27E-10	1.75e-08***
	(2.84)	(-1.45)	(-0.45)	(3.92)
$Loss2012$	-0.000000113	1.41E-08	7.53E-09	9.89E-08
	(-1.10)	(0.44)	(0.90)	(1.88)
$Loss2011$	1.84e-08**	-2.24E-09	1.19E-10	1.24e-08***
	(3.1)	(-1.17)	(0.24)	(4.10)
$Loss2001-2010$	-3.98E-09	-7.08E-09	2.59E-09	2.79E-08
	(-0.08)	(-0.45)	(0.63)	(1.09)
No.of flood 2001-2012	0.32	0.0883	-0.00749	0.0725
	(1.26)	(1.1)	(-0.36)	(0.55)
Average losses from floods	2.21e-08**	-3.33E-09	1.86E-10	1.70e-08***
	(3.11)	(-1.46)	(0.31)	(4.75)
S_{iv}^{a13}	-5.11e-08*	5.73E-09	-3.62e-09*	-4.94e-08***
	(-2.37)	(0.83)	(-2.04)	(-4.58)
S_{iv}^{a12}	-2.26e-08**	3.39E-09	-1.48E-10	-1.64e-08***
	(-3.18)	(1.48)	(-0.25)	(-4.59)
S_{iv}^{a11}	4.14E-08	1.18E-09	-1.53E-10	7.15E-09
	(1.85)	(0.17)	(-0.08)	(0.62)
S_{iv}^{m13}	-4.10E-08	-3.20E-10	-5.36e-09*	-2.75E-08
	(-1.44)	(-0.04)	(-2.31)	(-1.87)
S_{iv}^{m12}	-2.95e-08***	4.11E-09	-1.37E-10	-1.92e-08***
	(-3.39)	(1.47)	(-0.19)	(-4.35)
S_{iv}^{m11}	2.62E-08	-1.90E-09	1.46E-10	1.59e-08*
	(1.92)	(-0.44)	(0.13)	(2.27)

Note: the estimated coefficient of regressing characteristics on each salience measure composition is presented. t statistics in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.10: Balance test (3)

	No.of droughts	Whether drought ever occured	No. of all other shocks except flood	Gross losses from all other shocks
$Flood2013$	-0.0231	-0.021	-0.500**	-3525373.8*
	(-0.30)	(-0.33)	(-3.31)	(-2.34)
$Flood2012$	-0.0166	0.0222	-0.00798	-622325.1
	(-0.14)	(0.23)	(-0.04)	(-0.26)
$Flood2011$	0.0604	0.0513	-0.0192	441823.4
	(0.74)	(0.76)	(-0.12)	(0.28)
$Flood2001-2010$	-0.0166	0.0222	-0.00798	-622325.1
	(-0.14)	(0.23)	(-0.04)	(-0.26)
$Loss2013$	-2.31E-09	-1.90E-09	-5.30E-09	0.209***
	(-0.90)	(-0.91)	(-1.14)	(4.2)
$Loss2012$	7.01E-09	1.27E-08	5.93E-08	0.992
	(0.24)	(0.53)	(1.11)	(1.69)
$Loss2011$	-7.03E-10	-5.49E-10	-6.12E-10	0.167***
	(-0.40)	(-0.39)	(-0.19)	(5.03)
$Loss2001-2010$	-3.69E-09	-4.45E-09	1.35E-08	-0.0208
	(-0.26)	(-0.38)	(0.52)	(-0.07)
No.of flood 2001-2012	0.0429	0.0419	0.017	-334134
	(0.59)	(0.70)	(0.13)	(-0.23)
Average losses from floods	-1.20E-09	-9.58E-10	-1.02E-09	0.234***
	(-0.58)	(-0.56)	(-0.27)	(6.03)
S_{iv}^{a13}	-2.86E-09	-2.64E-09	-2.22e-08*	-0.877***
	(-0.46)	(-0.52)	(-1.97)	(-7.85)
S_{iv}^{a12}	1.23E-09	1.02E-10	1.31E-09	-0.229***
	(0.59)	(0.60)	(0.35)	(-5.87)
S_{iv}^{a11}	1.89E-09	1.64E-10	1.39E-09	0.046
	(0.29)	(0.31)	(0.12)	(0.36)
S_{iv}^{m13}	-4.69E-09	-3.33E-09	-3.88e-08**	-0.958***
	(-0.57)	(-0.50)	(-2.64)	(-6.27)
S_{iv}^{m12}	1.88E-09	1.65E-10	1.93E-09	-0.290***
	(0.74)	(0.79)	(0.42)	(-6.11)
S_{iv}^{m11}	7.60E-10	8.92E-11	4.09E-10	0.144
	(0.19)	(0.28)	(0.06)	(1.84)

Note: the estimated coefficient of regressing characteristics on each salience measure composition is presented. t statistics in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

2.6.2 Does the salience of flood experiences change subjective probability of having megaflood?

To answer whether experience of a flood event that is more salient cause people to have higher subjective probability of extreme flood event in the future, we firstly, run OLS regression of subjective probability of megaflood on various salience measures, controlling for unbalanced characteristics from the balance test for each specification. That is, equation 2.1 is estimated with the results shown in table 2.12 to 2.16. Then, we control for all possible characteristics that might be related to the salience measures and might affect subjective probability of megaflood for each specification in robustness check, shown in table 2.18 to 2.22. Related hypothesis testing[3] is shown in table 2.17 and 2.23. In the following analyses, the salience measure used in each specification is displayed in table 2.11.

In specification A and B (, i.e. specification A.1, A.2, A.3, A.4, A.5, A.6, B.1, and B.2) in table 2.12 to 2.14, we are looking whether there is recency effect, that is, whether the event that is more recent which can be regarded as more salient has higher impact (bigger magnitude) toward the subjective probability. For specification C (,i.e. C.1 to C.8), we test whether higher level of salience as measured by proxies for salience causes subject to have higher level of subjective probability.

From specification A.1 without controlling for the size of losses and A.3 when controlling for size of losses, the flood in 2013 has statistically significant and positive effect, while flood in 2011 has positive lower-in-magnitude

[3]For one-sided tests, the corresponding two-sided Wald test of linear combination of coefficients is performed first. Then, p-value of one-sided t-test is calculated from F-statistics.

effect. However, the 2011 flood effect on subjective probability of megaflood is not statistically significant at 5% level of significance. In specification A.2, rice income losses, both in year 2013 and year 2011, have statistically insignificant effect toward subjective probability.

For all three specifications A.1 to A.3 as shown in table 2.12, we cannot reject the hypotheses that the magnitude of the effects of flood or loss in year 2013 is equal to that of flood and loss in year 2011, at 10% level of significance. In other words, the recency effect cannot be statistically and significantly supported here.

Table 2.11: Salience measures in each specification

Specification	Salience measure $S_{iv}\beta$
A.1	$\beta_1 Flood2013_{iv} + \beta_2 Flood2011_{iv}$
A.2	$\beta_1 Loss2013_{iv} + \beta_2 Loss2011_{iv}$
A.3	$\beta_1 Flood2013_{iv} + \beta_2 Flood2011_{iv} + \beta_3 Loss2013_{iv} + \beta_4 Loss2011_{iv}$
A.4	$\beta_1 Flood2013_{iv} + \beta_2 Flood2012_{iv} + \beta_3 Flood2011_{iv}$
A.5	$\beta_1 Loss2013_{iv} + \beta_2 Loss2012_{iv} + \beta_3 Loss2011_{iv} + \beta_4 Loss01 - 10$
A.6	$\beta_1 Flood2013_{iv} + \beta_2 Flood2012_{iv} + \beta_3 Flood2011_{iv}$ $+\beta_4 Loss2013_{iv} + \beta_5 Loss2012_{iv} + \beta_6 Loss2011_{iv} + \beta_7 Loss01 - 10$
B.1	$\beta_1 Flood2013_{iv} + \beta_2 CFreq_{iv}$
B.2	$\beta_1 Loss2013_{iv} + \beta_2 CLoss_{iv}$
C.1	$\beta_1 CFreqall_{iv}$
C.2	$\beta_1 AverageLoss_{iv}$
C.3	$\beta_1 S_{iv}^{a13}, S_{iv}^{a13} = Loss2013_{iv} - AverageLoss_{iv}$
C.4	$\beta_1 S_{iv}^{a12}, S_{iv}^{a12} = Loss2012_{iv} - AverageLoss_{iv}$
C.5	$\beta_1 S_{iv}^{a11}, S_{iv}^{a11} = Loss2011_{iv} - AverageLoss_{iv}$
C.6	$\beta_1 S_{iv}^{m13}, S_{iv}^{m13} = Loss2013_{iv} - MinLoss_{iv}$
C.7	$\beta_1 S_{iv}^{m12}, S_{iv}^{m12} = Loss2012_{iv} - MinLoss_{iv}$
C.8	$\beta_1 S_{iv}^{m11}, S_{iv}^{m11} = Loss2012_{iv} - MinLoss_{iv}$

In the following analyses, in specification A.3 and A.6, the interaction terms between flood and flood loss are omitted due to colinearlity. Number of flood shocks from 2001 to 2010 is omitted due to colinearity, in A.4 and A.6.
$CFreq_{iv}$ is Number of flood shocks 2001-2012. $CFreqall_{iv}$ includes all flood shocks.
$CLoss_{iv}$ is Gross Losses from flood 2001-2012.
$AverageLoss_{iv}$ is Average income loss from all past floods of household i in village v.

From specification A.4, A.5, and A.6, when also considering experiences of

flood in year 2012 and/or loss in year 2012 and year 2001-2010, the occurrence of flood in year 2012 has no significant effect, while flood losses in year 2012 have positive and statistically significant effect. In addition, there exists statistically significant recency effect when considering the timing of losses between year 2012 versus that in year 2011 ($p-value = 0.028$). This result comes with a surprise as flood in year 2012 was much less severe than in year 2013 and 2011, in terms of number of households affected, and magnitude of losses incurred. That is, only 12% of households were affected by flood in year 2012, while 68% and 73% of households in the sample were affected by flood in year 2011 and 2013, respectively. Moreover, the average magnitude of loss in year 2013 and year 2011 are 13 times and 18 times larger than average loss from flood in year 2012. There is also statistically significant positive effect from the loss from previous floods in year 2001-2010 and in 2012, as shown in specification A.6.

Considering previous experiences of floods in terms of number of floods ever happened to households from year 2001 to year 2012 in specification B.1, there are positive and significant effect of flood experience in year 2013, while positive but insignificant effect, with less magnitude, from all previous experiences. However, we are unable to reject the hypothesis that the magnitude of the effect from the occurrence of flood in year 2013 is equal to that of the number of flood shocks in year 2001-2012.

In spite of the fact that the recency effect cannot be mostly and strongly supported by the data, we find that the higher measure of salience of flood, in terms of overall number of flood shocks ever experienced and the extremeness of flood loss, the more probable subjects judge megaflood can occur again in the future. This is shown by the positive and significant effect of salience measures in spec-

ification C.1, C.3, C.4, C.6, and C.7 in table 2.14 to 2.16, together with related hypothesis testing in table 2.17.

The pattern of statistical significance for coefficients for each specification is robust with respect to the inclusion of other covariates that might be related to the salience measure and subjective probability, as shown in consistent pattern between coefficients in table 2.17 and table 2.23.

All in all, we have mixed results. Even though the pattern of effects is suggestive of recency effect, "salience" as measure by the timing of the occurrence of flood shocks, mostly, has no statistically significant effects toward subjective probability. However, the more salient flood experiences households have encountered, in terms of the extremeness of incurred losses and in terms of the overall number of flood shocks, cause them to think that the megaflood is more likely to happen in the future.

This result might help add to the understanding of the result found by Chantarat et al. (2019) by focusing on possible mechanisms why the occurrence of flood could cause household to adjust upward subjective probability of having 2011 megaflood in the next ten years. Moreover, this result might also help explain the finding of Browne and Hoyt (2000) that there is high correlation between the level of flood losses and flood insurance purchase. However, we don't find strong evidence to support recency effect in subjective probability to support the recency effect in terms of flood insurance behavior found in Zaleskiewicz et al. (2002) and Gallagher (2014) in the form of a surge of flood insurance purchase among flooded communities or among households with recent memories of flood.

Regarding the positive effects of 2013 flood on subjective belief of megaflood, if we instead look through the len of the representativeness heuristics, this might be possible if farmers hold belief that floods originate from climate change process like La Niña. With La Niña, subjective belief on the correlation of the occurrence of current megaflood and future megaflood should be positive.

In the aspect of salience measured by extremeness of loss, this is consistent with the case that subjects using availability heuristics in judging subjective probability of rare event(Tversky and Kahneman, 1974), as well as that more salient event receives higher subjective probability (Bordalo et al., 2012).

To note, one side interesting finding from these exercises is that log of wealth has robust negative effect on subjective probability on megaflood. This means that the poorer subjects are, the more likely they think megaflood could occur. This might also help explain risk-averse behavior, apart from what is usually explained by risk preferences.

Table 2.12: Result Table: Specification A

$P(mega\ flood)$	A.1	A.2	A.3
$Flood2013$	0.957*		1.113**
	(0.02)		(0.01)
$Flood2011$	0.795		0.839
	(0.07)		(0.05)
$Loss2013$		2.98E-08	2.20E-08
		(0.21)	(0.30)
$Loss2011$		-2.93E-08	-2.80e-08*
		(0.07)	(0.05)
Log of Wealth		-0.351*	-0.389*
		(0.04)	(0.02)
Household size	0.101	0.12	0.129
	(0.25)	(0.16)	(0.13)
No.of all other shocks except floods	0.0217		0.00402
	(0.89)		(0.98)
Gross losses from all other shocks	-1.65E-08	-2.13E-09	3.79E-09
	(0.16)	(0.85)	(0.74)
Constant	3.529*	10.81***	9.799***
	(0.01)	(0.00)	(0.00)
Village dummy	yes	yes	yes
N	234	234	234

Note: Each specification is estimated by OLS regression with robust standard error. For all specifications, the dependent variables are subjective probability of mega flood. p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.13: Result Table: Specification A(continued)

$P(mega\ flood)$	A.4	A.5	A.6
$Flood2013$	0.974*		1.318**
	(0.02)		(0.00)
$Flood2011$	0.826		0.929*
	(0.06)		(0.03)
$Loss2013$		2.95E-08	1.77E-08
		(0.21)	(0.38)
$Loss2011$		-2.76E-08	-2.41E-08
		(0.08)	(0.08)
$Flood2012$	0.239		-0.572
	(0.66)		(0.35)
$Loss2012$		0.000000255*	0.000000411**
		(0.03)	(0.01)
$Loss01-10$		1.87E-08	7.11e-08*
		(0.40)	(0.01)
Log of Wealth		-0.393*	-0.459**
		(0.02)	(0.00)
Household size	0.101	0.134	0.154
	(0.25)	(0.12)	(0.08)
No.of all other shocks except floods	0.0213		-0.00909
	(0.89)		(0.95)
Gross losses from all other shocks	-1.61E-08	-3.47E-09	2.14E-09
	(0.18)	(0.77)	(0.86)
Constant	3.491*	11.46***	10.67***
	(0.01)	(0.00)	(0.00)
Village dummy	yes	yes	yes
N	234	234	234

Note: Each specification is estimated by OLS regression with robust standard error. For all specifications, the dependent variables are subjective probability of mega flood.
p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.14: Result Table: Specification B and C

$P(mega\ flood)$	B.1	B.2	C.1	C.2
$Flood2013$	1.078**			
	(0.01)			
$Loss2013$		1.77E-08		
		(0.42)		
No. of flood shocks 2001-2012	0.58			
	(0.07)			
Gross Losses from flood 2001-2012		-2.02E-08		
		(0.16)		
No. of all past flood shocks			0.746**	
			(0.01)	
Average income loss from floods				-0.00987
				(0.79)
Log of Wealth		-0.346*		-0.371*
		(0.04)		(0.03)
Household size		0.117		0.114
		(0.17)		(0.19)
No.of all other shocks except floods	0.00546		-0.0222	
	(0.97)		(0.89)	
Gross losses from all other shocks	-1.06E-08	-3.42E-09	-1.15E-08	-6.48E-09
	(0.33)	(0.77)	(0.29)	(0.61)
Constant	3.951**	10.73***	4.148**	11.20***
	(0.00)	(0.00)	(0.00)	0.00
Village dummy	yes	yes	yes	yes
N	234	234	234	228

Note: Each specification is estimated by OLS regression with robust standard error. For all specifications, the dependent variables are subjective probability of mega flood.

p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.15: Result Table: Specification C (continued)

$P(mega\ flood)$	C.3	C.4	C.5
S_{iv}^{a13}	8.3e-08***		
	(0.00)		
S_{iv}^{a12}		1.51e-08**	
		(0.00)	
S_{iv}^{a11}			-1.90E-08
			(0.54)
Log of Wealth	-0.316	-0.333*	
	(0.06)	(0.05)	
Household size	0.122	0.126	0.0879
	(0.15)	(0.15)	(0.30)
No.of all other shocks except floods	-0.0919		
	(0.56)		
Gross losses from all other shocks	1.15E-08	-2.70E-09	
	(0.35)	(0.81)	
Ratio of rice income to total income	0.198		
	(0.83)		
Constant	10.13***	10.49***	5.016***
	(0.00)	(0.00)	(0.00)
Village dummy	yes	yes	yes
N	234	234	234

Note: Each specification is estimated by OLS regression with robust standard error. For all specifications, the dependent variables are subjective probability of mega flood.
p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.16: Result Table: Specification C (continued)

$P(mega\ flood)$	C.6	C.7	C.8
S_{iv}^{m13}	8.81e-08**		
	(0.00)		
S_{iv}^{m12}		1.94e-08**	
		(0.01)	
S_{iv}^{m11}			-1.19E-08
			(0.34)
Log of Wealth		-0.338*	-0.381*
		(0.05)	(0.02)
Household size		0.128	
		(0.14)	
No.of all other shocks except floods	-0.0592		
	(0.71)		
Gross losses from all other shocks	-5.34E-11	-2.00E-09	
	(1.00)	(0.86)	
Ratio of rice income to total income	-0.0796		
	(0.93)		
Constant	5.455***	10.58***	11.73***
	(0.00)	(0.00)	(0.00)
Village dummy	yes	yes	yes
N	234	234	234

Note: Each specification is estimated by OLS regression with robust standard error. For all specifications, the dependent variables are subjective probability of mega flood.
p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.17: p-value for each hypothesis testing for each specification of the main results

H_a :	$\lvert\beta_1\rvert > \lvert\beta_2\rvert$	$\lvert\beta_2\rvert > \lvert\beta_3\rvert$	$\lvert\beta_3\rvert > \lvert\beta_4\rvert$	$\lvert\beta_1\rvert > \lvert\beta_3\rvert$	$\lvert\beta_1\rvert > \lvert\beta_4\rvert$	$\beta_1 > 0$	$\beta_2 > 0$	$\beta_3 > 0$	$\beta_4 > 0$
A.1	0.390								
A.2	0.478					0.105	0.968		
A.3	0.314								
A.4	0.134	0.816		0.400					
A.5	0.971	0.028*	0.379	0.425	0.375	0.103	0.015*	0.962	0.202
A.6	0.164	0.680		0.243					
B.1	0.143								
B.2	0.603								
C.1						0.004*			
C.2						0.604			
C.3						0.0003***			
C.4						0.002**			
C.5						0.728			
C.6						0.001**			
C.7						0.003**			
C.8						0.829			

* $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.18: Robustness check: Specification A

$P(mega\ flood)$	A.1	A.2	A.3
$Flood2013$	1.055*		1.027*
	(0.01)		(0.02)
$Flood2011$	0.671		0.824
	(0.12)		(0.06)
$Loss2013$		2.76E-08	2.44E-08
		(0.27)	(0.27)
$Loss2011$		-2.99E-08	-3.09e-08*
		(0.08)	(0.04)
Age	-0.0247	-0.0318	-0.0281
	(0.14)	(0.07)	(0.10)
Gender	0.251	0.228	0.258
	(0.48)	(0.53)	(0.46)
Education	-0.0669	-0.0739	-0.0464
	(0.73)	(0.71)	(0.82)
Rice experience	0.00419	0.0071	0.00418
	(0.80)	(0.67)	(0.80)
IDpoor	-0.319	-0.416	-0.299
	(0.32)	(0.19)	(0.36)
Ratio of rice income to total income	0.593	0.381	0.642
	(0.49)	(0.67)	(0.46)
Ever experienced drought?	0.0978	0.0315	0.0554
	(0.83)	(0.95)	(0.90)
Log of Wealth	-0.468*	-0.370*	-0.403*
	(0.01)	(0.05)	(0.03)
Household size	0.106	0.119	0.131
	(0.23)	(0.17)	(0.14)
No.of all other shocks except floods	-0.0237	-0.0945	-0.022
	(0.90)	(0.59)	(0.90)
Gross losses from all other shocks	-1.21E-09	1.58E-09	3.94E-09
	(0.93)	(0.89)	(0.73)
Constant	12.33***	12.75***	11.17***
	(0.00)	(0.00)	(0.00)
Village dummy	yes	yes	yes
N	234	234	234

Note: Each specification is estimated by OLS regression with robust standard error. For all specifications, the dependent variables are subjective probability of mega flood. p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.19: Robustness check: Specification A(continued)

$P(mega\ flood)$	A.4	A.5	A.6
$Flood2013$	1.085*		1.247**
	(0.01)		(0.00)
$Flood2011$	0.727		0.928*
	(0.09)		(0.03)
$Loss2013$		2.65E-08	2.05E-08
		(0.27)	(0.33)
$Loss2011$		-2.76E-08	-2.72E-08
		(0.09)	(0.06)
$Flood2012$	0.447		-0.485
	(0.43)		(0.43)
$Loss2012$		0.000000281*	0.000000410**
		(0.02)	(0.00)
$Loss01-10$		3.74E-08	8.54e-08**
		(0.16)	(0.01)
Age	-0.0249	-0.0333	-0.0304
	(0.14)	(0.07)	(0.08)
Gender	0.244	0.205	0.232
	(0.49)	(0.57)	(0.50)
Education	-0.0715	-0.0686	-0.0289
	(0.71)	(0.73)	(0.88)
Rice experience	0.00329	0.00743	0.00528
	(0.84)	(0.66)	(0.75)
IDpoor	-0.343	-0.478	-0.333
	(0.29)	(0.13)	(0.30)
Ratio of rice income to total income	0.604	0.345	0.641
	(0.50)	(0.71)	(0.46)
Ever experienced drought?	0.0852	0.0152	0.0541
	(0.85)	(0.97)	(0.90)
Log of Wealth	-0.482**	-0.427*	-0.487**
	(0.01)	(0.01)	(0.00)
Household size	0.107	0.135	0.157
	(0.23)	(0.12)	(0.08)
No.of all other shocks except floods	-0.0222	-0.111	-0.035
	(0.90)	(0.52)	(0.84)
Gross losses from all other shocks	1.06E-11	1.07E-09	3.05E-09
	(1.00)	(0.93)	(0.80)
Constant	12.54***	13.80***	12.32***
	(0.00)	(0.00)	(0.00)
Village dummy	yes	yes	yes
N	234	234	234

Note: Each specification is estimated by OLS regression with robust standard error. p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.20: Robustness Check: Specification B and C

$P(mega\ flood)$	B.1	B.2	C.1	C.2
$Flood2013$	1.234**			
	(0.00)			
$Loss2013$		1.24E-08		
		(0.59)		
No. of flood shocks 2001-2012	0.710*			
	(0.03)			
Gross Losses from flood 2001-2012		-1.84E-08		
		(0.24)		
No. of all past flood shocks			0.882**	
			(0.00)	
Average income loss from floods				-0.0305
				(0.52)
Age	-0.0273	-0.0303	-0.0282	-0.0244
	(0.10)	(0.08)	(0.09)	(0.16)
Gender	0.269	0.235	0.279	0.189
	(0.45)	(0.52)	(0.44)	(0.62)
Education	-0.0981	-0.0852	-0.129	-0.0817
	(0.61)	(0.67)	(0.49)	(0.68)
Rice experience	0.00266	0.00677	0.00137	0.00709
	(0.87)	(0.68)	(0.93)	(0.67)
IDpoor	-0.389	-0.428	-0.454	-0.486
	(0.23)	(0.18)	(0.15)	(0.12)
Ratio of rice income to total income	0.609	0.351	0.543	-1.245
	(0.51)	(0.69)	(0.56)	(0.68)
Ever experienced drought?	0.125	0.0306	0.0907	0.147
	(0.79)	(0.95)	(0.84)	(0.75)
Log of Wealth	-0.515**	-0.366*	-0.485**	-0.384
	(0.00)	(0.05)	(0.01)	(0.05)
Household size	0.104	0.115	0.0969	0.093
	(0.23)	(0.19)	(0.26)	(0.32)
No.of all other shocks except floods	-0.0241	-0.0996	-0.043	-0.108
	(0.90)	(0.57)	(0.81)	(0.54)
Gross losses from all other shocks	2.69E-09	6.19E-11	8.21E-10	-2.33E-09
	(0.83)	(1.00)	(0.95)	(0.86)
Constant	13.18***	12.68***	13.14***	14.19***
	(0.00)	(0.00)	(0.00)	(0.00)
Village dummy	yes	yes	yes	yes
N	234	234	234	228

Note: Each specification is estimated by OLS regression with robust standard error. p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.21: Robustness Check: Specification C (continued)

$P(mega\ flood)$	C.3	C.4	C.5
S_{iv}^{a13}	8.41e-08***		
	(0.00)		
S_{iv}^{a12}		1.77e-08***	
		(0.00)	
S_{iv}^{a11}			-2.22E-08
			(0.44)
Age	-0.0304	-0.0306	-0.0303
	(0.08)	(0.08)	(0.09)
Gender	0.251	0.241	0.22
	(0.48)	(0.51)	(0.55)
Education	-0.0723	-0.101	-0.0877
	(0.71)	(0.61)	(0.66)
Rice experience	0.00568	0.00646	0.00715
	(0.73)	(0.70)	(0.67)
IDpoor	-0.4	-0.455	-0.433
	(0.21)	(0.15)	(0.17)
Ratio of rice income to total income	0.458	0.314	0.338
	(0.60)	(0.72)	(0.70)
Ever experienced drought?	0.0591	0.0171	0.0393
	(0.90)	(0.97)	(0.93)
Log of Wealth	-0.334	-0.35	-0.407*
	(0.07)	(0.06)	(0.03)
Household size	0.121	0.122	0.106
	(0.16)	(0.16)	(0.22)
No.of all other shocks except floods	-0.099	-0.123	-0.0937
	(0.57)	(0.48)	(0.59)
Gross losses from all other shocks	1.19E-08	2.25E-09	-4.12E-09
	(0.33)	(0.85)	(0.73)
Constant	11.99***	12.51***	13.39***
	(0.00)	(0.00)	(0.00)
Village dummy	yes	yes	yes
N	234	234	234

Note: Each specification is estimated by OLS regression with robust standard error. For all specifications, the dependent variables are subjective probability of mega flood.
p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.22: Robustness Check: Specification C (continued)

$P(mega\ flood)$	C.6	C.7	C.8
S_{iv}^{m13}	8.55e-08**		
	(0.01)		
S_{iv}^{m12}		2.23e-08**	
		(0.00)	
S_{iv}^{m11}			-1.81E-08
			(0.20)
Age	-0.0261	-0.03	-0.0309
	(0.12)	(0.08)	(0.08)
Gender	0.279	0.251	0.216
	(0.44)	(0.49)	(0.55)
Education	-0.0937	-0.106	-0.0854
	(0.63)	(0.59)	(0.67)
Rice experience	0.00492	0.00626	0.00719
	(0.76)	(0.70)	(0.67)
IDpoor	-0.395	-0.458	-0.436
	(0.21)	(0.14)	(0.17)
Ratio of rice income to total income	0.441	0.305	0.34
	(0.61)	(0.73)	(0.70)
Ever experienced drought?	0.0906	0.0157	0.0353
	(0.84)	(0.97)	(0.94)
Log of Wealth	-0.423*	-0.357	-0.389*
	(0.02)	(0.05)	(0.04)
Household size	0.104	0.124	0.108
	(0.23)	(0.16)	(0.21)
No.of all other shocks except floods	-0.0907	-0.127	-0.0965
	(0.60)	(0.47)	(0.58)
Gross losses from all other shocks	9.51E-09	3.09E-09	-3.46E-09
	(0.51)	(0.80)	(0.78)
Constant	13.35***	12.63***	13.11***
	(0.00)	(0.00)	(0.00)
Village dummy	yes	yes	yes
N	234	234	234

Note: Each specification is estimated by OLS regression with robust standard error. For all specifications, the dependent variables are subjective probability of mega flood.
p-values in parentheses, * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 2.23: p-value for each hypothesis testing for each specification of robustness check

H_a :	$\lvert\beta_1\rvert > \lvert\beta_2\rvert$	$\lvert\beta_2\rvert > \lvert\beta_3\rvert$	$\lvert\beta_3\rvert > \lvert\beta_4\rvert$	$\lvert\beta_1\rvert > \lvert\beta_3\rvert$	$\lvert\beta_1\rvert > \lvert\beta_4\rvert$	$\beta_1 > 0$	$\beta_2 > 0$	$\beta_3 > 0$	$\beta_4 > 0$
A.1	0.249								
A.2	0.592					0.133	0.962		
A.3	0.361								
A.4	0.181	0.665		0.266					
A.5	0.980	0.020*	0.625	0.548	0.623	0.137	0.011*	0.955	0.078
A.6	0.157	0.714		0.287					
B.1	0.136								
B.2	0.741								
C.1						0.0009***			
C.2						0.738			
C.3						0.0003***			
C.4						0.0004***			
C.5						0.780			
C.6						0.003**			
C.7						0.0008***			
C.8						0.900			

* $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

2.7 Conclusion

This paper tries to answer whether the salience of flood shocks encountered by rice farmers affects their subjective belief on the probability of extreme flood events by exploiting variation in memory of flood experiences. The key identification strategy hinges upon the stratification in key observables in sampling design done by Chantarat et al. (2019) and the steady pattern of flood experiences to be largely resemble flood experience in the year 2011.

We capture the salience concept with flood experiences' timings, the number of floods that ever occurred to households, and the extremeness of flood loss from a reference point. Although salience, in terms of the timings of flood

events, mainly has no statistically significant effect, it was found that shocks that are more salient, in terms of the extremeness of flood loss, make farmers have a higher subjective probability on extreme flood event.

This should contribute to the understanding of the role of availability heuristics (Tversky and Kahneman, 1973, 1974) and the salience theory of choice under risk (Bordalo et al., 2012) in the over-or under-estimation of small probability, the challenge posed by (Barberis, 2013). The result helps explain the immediate increase in flood insurance take-up found in Browne and Hoyt (2000), but cannot find recency effect of flood experiences on subjective probability to support the flood insurance behavior found in Gallagher (2014). In addition, due to the nature of cross-sectional data on subjective probability, we cannot trace the persistency of existing salience effects.

CHAPTER 3

WHAT MORE CAN REFERENCE-DEPENDENT POVERTY MEASURES TELL US? : APPLICATION TO THAI ECONOMY USING TOWNSEND-THAI PANEL DATA

Abstract

To understand what insight we can learn more from reference-dependent poverty measures as compared to traditional FGT measures, this paper applies the concept of '*equivalent income*' as proposed by Jäntti et al. (2014) to Townsend-Thai household panel data. The results show that poverty headcount and poverty gap are on decreasing trend over the year 2000 to 2011, with prospect-theory-based poverty measures mostly higher than conventional measures. By building in loss aversion into the poverty measures, the economic insecurity of the vulnerable who have had income around the poverty line and have experienced income loss is now reflected in the overall level of reference-dependent poverty. Those who were not classified as poor based on conventional income became one based on equivalent income when they have experienced income loss with a significant enough magnitude. The comparison between the conventional measure and the reference-dependent measure should help us better understand the nature of poverty among people whose incomes are around the poverty line, especially in the aspect of the churning in income versus the persistency of poverty.[1]

[1] I would like to thank Prof. Ravi Kanbur and Prof. Jukka Pirttilä for comments and ideas helping in the development of this paper. All errors in this paper are mine.

3.1 Introduction

It has long been recognized that there are multi-facets to the lives of the poor, many of which cannot be captured by conventional poverty measures. At the same time, increasing empirical evidences (for example, Camerer and Loewenstein, 2004; Kahneman et al., 1990, 1991; Booij et al., 2010; Yesuf and Bluffstone, 2009b; Harrison et al., 2010) have indicated that people measure their economic wellbeing relative to their reference point and that they are loss-averse(Kahneman and Tversky, 1979b). Accordingly, the incorporation of reference dependence and loss aversion into how we measure the deprivation of such wellbeing might be informative both in the aspect of the behavior of the "poor" and for policymaking, especially if people behave according to how they feel and perceive their situations.

One facet that can be emphasized more through this development on poverty measure is the presence of the losers who lose their income and the gainers who gain income as time goes by. This might be particularly important for an economy where there is considerable "churning" around the poverty line (Jäntti et al., 2014), hence economic insecurity among the poor and the vulnerable (Bossert and D'Ambrosio, 2013). The classification of people into "poor" or "nonpoor" based on reference-dependent poverty measure, as developed by Jäntti et al. (2014), should be able to help better target the "poor" who continually struggle with ups and downs in their income. At the same time, the reference-dependent poverty measure should help capture the level of "feeling poor" into how we measure the level of economy-wide poverty.

Apart from having a uniquely long household panel data, Thailand is an in-

teresting case study in studying underlying losers and winners stories covered by poverty reduction's success story. One assertion in Thailand's economic development success over a few past decades is its ability to lift a fraction of people out of extreme poverty. The overall number of Thai people classified as the poor by the designated official poverty line has lessened tremendously (Krongkaew, 2002). In 1988, 65.26% of the Thai population was classified as poor, while in 2014, there were only around 10.53% of the population, which is about 7 million Thai people, still being identified as ones (NESDB, 2014). At the same time, the country has experienced various macroeconomic shocks, many policy experiments, and political crises. Winners and losers have received attention in the policy arena and debate, nonetheless without rigorous understanding and well-studied measures built into how we have measured official the level of poverty in one economy.

To better understand what more reference-dependent poverty measures can tell us, this research's first contribution is to apply the measures proposed in Jäntti et al. (2014) to Thai data with further consideration on the design of reference point. Secondly, this paper will try to compare the designs of two existing reference-dependent poverty measures, i.e., that of Günther and Maier (2014) and of Jäntti et al. (2014), both of which apply the reference-dependent utility from Kőszegi and Rabin (2006). This will be done by answering what the differences in levels and trends of measured poverty for each design are.

3.2 Literature Review

There are two main strands that the literature have tried to incorporate behavioral economics into the way we measure poverty. The first is to incorporate the concept of subjective wellbeing and the second is to incorporate Prospect theory(Kahneman and Tversky, 1979b). This paper embeds itself into the second strand.

Based on the reference-dependent utility function proposed in Kőszegi and Rabin (2006), Jäntti et al. (2014) incorporated the idea of gain-loss utility into poverty and inequality measure and this is done by inventing the concept of "*equivalent income*". Welfare measures were calculated from this defined equivalent income, which tied income level up with loss aversion and diminishing sensitivity. However, Jäntti et al. (2014) didn't incorporate the personal equilibrium concept determining reference point, as proposed in Kőszegi and Rabin (2006), into consideration. In the empirical part of Jäntti et al. (2014), poverty and inequality measures for Russia and Vietnam were calculated using equivalent income and income. Related to the idea suggested by Jäntti et al. (2014), Povel (2015) proposed a measure of exposure to downside risk that used the current standard of living as reference point, enabling the paper to capture all states of the world in which a household is worse off.

In similar spirit to Jäntti et al. (2014), Günther and Maier (2014) employed the concept from Kőszegi and Rabin (2006) into poverty and vulnerability measures by inventing "*perceived*" multi-period poverty and perceived vulnerability. The measures were constructed using reference dependent utility with the previous period income as the reference point and, unlike Jäntti et al. (2014) who applied

to the real world data, were applied to simulated data on consumption path, in order to compare with other measures of poverty and vulnerability at the individual level. In the same arena to Jäntti et al. (2014) and Günther and Maier (2014), Liang (2017) tried to apply prospect theory to theoretically find the optimal level of inequality.

Two major competing concepts for reference-dependent poverty measure that are focused in this paper are those of Jäntti et al. (2014) and Günther and Maier (2014). Jäntti et al. (2014) assumed that each individual derived the actual utility from her actual income by having utility function as proposed in Kőszegi and Rabin (2006) which exhibits reference-dependence, loss aversion and diminishing sensitivity. The equivalent income is the level of income such that individual with conventional risk-averse utility achieves the same level of utility from prospect theory. Based on equivalent income and regular poverty line, FGT-poverty measures can be calculated using regular routine. By doing this, the loss and gain with respect to reference income are captured into equivalent income. The loss(gain) makes individual equivalent income lower(higher) than actual income. As for the poverty rate which takes everyone's income into account, poverty measures should be higher when the presence of losers and the extent of the lost are large enough. Their theoretical framework can be exhibited through following simple scenario of income of a hypothetical person in figure 3.1.

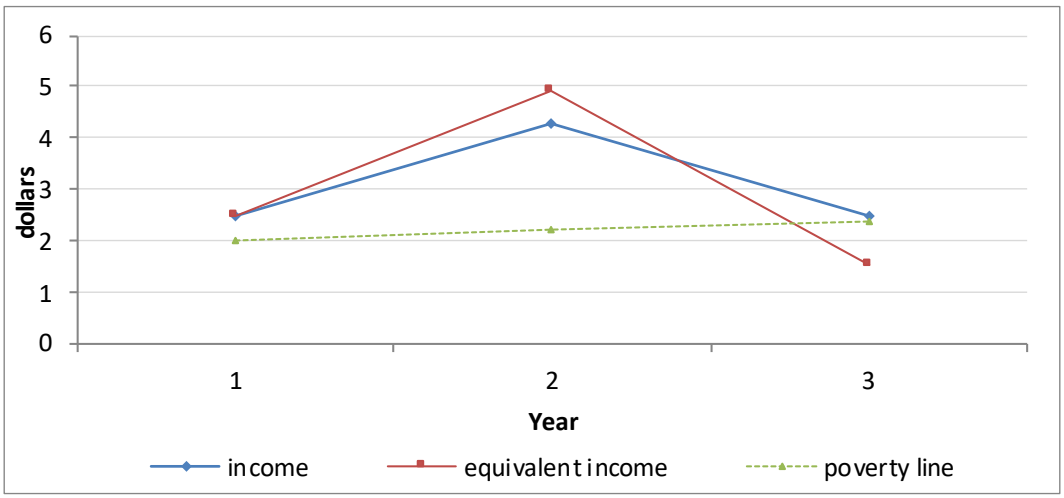

Figure 3.1: Income and Equivalent income

If we use previous period income as the reference point of this person, and we assume that income and equivalent income in period 1 is the same, we will have that time path of equivalent income will be more concave than that of income. Conventional poverty and inequality measures at period 1 and period 3 are the same, while the measures based on equivalent income will not be the same as this person has experienced the fluctuation in income between period 1 and 3.

In order to calculate poverty measure based on Jäntti et al. (2014), we first have to find individual "*equivalent income*" y^*_{it} such that, for income y_{it} of individual i at time t:

$$u(y^*_{it}) = u(y_{it}) + v(y_{it} - \bar{y}_{it}) \tag{3.1}$$

Let $c = y_{it} - \bar{y}_{it}$ and $\bar{y}_{it}$ is reference income. The properties of function $u(.)$, and $v(.)$ are $u' > 0; u'' < 0; v' > 0; v'(-c) > v'(c)$ when $c > 0; v'' > 0$ when $c < 0$, and $v'' < 0$ when $c > 0$.

Equivalent income y^*_{it} , will tell us how much individual needs to have in order to both have utility from her own income and compensate for gain or loss feelings from her current income, relative to her reference point.

Possible choices of reference income are status quo (previous income), the average income, the best year's income, etc.

The parameterization of function $u(\cdot)$ and $v(\cdot)$ employed in Jäntti et al. (2014) and in this present paper is:

$$ln(y^*_{it}) = \begin{cases} ln(y_{it}) + [ln(y_{it}) - ln(y_{it-1})]^{0.5} \; if \; y_{it} \geq y_{it-1} \\ ln(y_{it}) - 2[ln(y_{it-1}) - ln(y_{it})]^{0.5} \; if \; y_{it} < y_{it-1} \end{cases} \tag{3.2}$$

To calculate the poverty measure using equivalent income and regular income, considering an economy of n people, an individual i is considered poor if equivalent income is lower than poverty line z_t. FGT poverty measure(Foster et al., 1984), P^{α}_t, based on equivalent income is:

$$P^{\alpha}_t = \frac{1}{n} \sum_{i=1}^{q} \left(\frac{z_t - y^*_{it}}{z_t} \right)^{\alpha} \tag{3.3}$$

,where $y^*_{it} \leq y^*_{qt} \leq z_t \leq y^*_{nt}$. P^{α}_t is poverty head count at time t when $\alpha = 0$, and is poverty gap at time t when $\alpha = 1$.

For Günther and Maier, 2014, the reference-dependent concept is not incorporated by using equivalent income. Instead, the utility gap in each period's poverty measure is calculated by comparing consumption in that period to being hypothetically lifted to the poverty line in that period. That is, in each pe-

riod t, and given the reference point of previous period consumption x_{it-1}, an individual's perceived per-period poverty $M^1_{it}(\cdot)$ is[2]:

$$M^1_{it}(x_{it}, x_{it-1}, z_t) = N[RU(z_t|x_{it-1}) - RU(x_{it}|x_{it-1})] \tag{3.4}$$

,where $RU(z_t|x_{it-1}) = u(z_t) + \mu(u(z_t) - u(x_{it-1}))$ and $RU(x_{it}|x_{it-1}) = u(x_t) + \mu(u(x_{it}) - u(x_{it-1}))$, and $N = 1/[RU(z_t|z_t) - RU(0|0)] = 1/u(z_t)$, $\mu(\cdot)$ is gain-loss utility.

Another measure of poverty that is suggested by Günther and Maier (2014) is when individual has reference point at poverty line when considering utility she would have had if she consumed at the poverty line.

$$M^2_{it}(x_{it}, x_{it-1}, z_t) = N[RU(z_t|z_t) - RU(x_{it}|x_{it-1})] \tag{3.5}$$

[2]The symbol here is adapted from original version in Günther and Maier (2014) to express the idea that their measure is for individual level.

3.3 Data

This study will use Townsend-Thai annual rural household panel data[3] because it is the only long run panel data available in Thai economy. According to the information provided by the Townsend-Thai project, the survey started in May 1997 before the economic crisis in July 1997. Lop Buri and Chachoengsao, two provinces (Changwats) in the richer central region; and Sisaket and Buriram, the other two provinces on the poorer northeast region were chosen to have at least two levels of variations in terms of levels of regional economic development. Sisaket and Buriram were the third and fourth poorest provinces in the year 2011. These four specific provinces were chosen because one county (Amphoe) in each province has been in the Thai Household Socio-Economic Survey (SES) every years. SES is the survey that Thai national poverty line has been calculated from.

This study will use publicly available 12-years Townsend-Thai annual resurvey rural panel data from 2000 to 2011. Household module is the targeted data set, and there are 900 households in 64 villages in the panel data set. However, if we consider the households whose incomes have been surveyed for every years over 12 years, the balanced panel that we will work with has 678 households.

[3]The Townsend-Thai Project is at http://townsend-thai.mit.edu/. The data archive is at http://dvn.iq.harvard.edu/dvn/dv/rtownsend .

3.4 The Nature of Reference-Dependent Poverty Measure

3.4.1 The Level and Trend of Reference-Dependent Poverty Measure

Based on Jäntti et al. (2014), to calculate equivalent income for the following result in table 3.1, 3.2, and 3.3, the equivalent-income equation (3.2) is employed. That is, the base case of the analysis will use past year income as reference point in each year. The official provincial poverty line is used. Moreover, while poverty head count calculated in this session is based on gross income, poverty line is calculated from the minimum sufficient expenditure point of view. To note, yearly gross household income from Townsend-Thai data is averaged to be monthly individual income, assuming smooth income over seasons. Household income is averaged to be individual income using equivalent scale, following Townsend (1994).

Poverty head count for each province, using income and equivalent income is as shown in figure 3.4 to 3.7 and table 3.1 and 3.2 below. Poverty head count is calculated from the number of poor people classified by their (nominal) income or (nominal) equivalent income below official (nominal) provincial poverty line in each year and each province, over the total number of households in each province. According to income poverty head count, as shown in figure 3.2, for most of the periods considered, Sisaket is the poorest province, followed by Buriram, Lopburi and Chachoengsao. However, according to equivalent income, Lopburi and Chachoengsao alternatively have more poverty rate for different time periods, and, surprisingly, Sisaket is not always the poorest province which is the picture we have from merely looking at income poverty headcount, as shown in figure 3.3. Moreover, for Lopburi, Chachoengsao, and Buri-

ram, since poverty head count calculated using equivalent income is uniformly higher than that calculated from income, this indicates that there are people living nearby poverty line who experience income loss. As for Sisaket, that poverty headcount from income and equivalent income are alternately higher than one another indicates the existence of gainers for year 2000, 2002-2003, and 2007-2008. Although there are episodes of different pattern of relation between level of conventional and prospect-theory based poverty headcount, the trends of both measures are consistent in that poverty head count for Thai economy is on decreasing trend over the years.

In term of poverty gap, the contradicting picture shows up for Sisaket as well. It is not the province with the highest gap over the years if we looks through the len of equivalent income. Unlike poverty head count, poverty gap from equivalent income is higher than that from income for every provinces for all time periods.

From all provinces, our sample has higher poverty headcount than country level between 2000-2009 and higher poverty gap for all time periods.

From table 3.3 panel (a.), there are gainers more than losers for all sampled periods, except year 2005. Average income of losers is less than that of gainers. Average income change of poor losers ranges from -41% to -32%, while that of poor gainer ranges from 8-74%. To note, if we look only at income growth of gainers, it is extremely high, owning to outliers from the non-poor. From table 3.3 panel (b.) among those who experienced income losses, prospect-theory poverty head count is extremely high and ranges between 68% to 88%, while conventional poverty head count is also high and ranges from 21% to 60%. Nonetheless, they are both on the declining trend. Some of the gainers are also

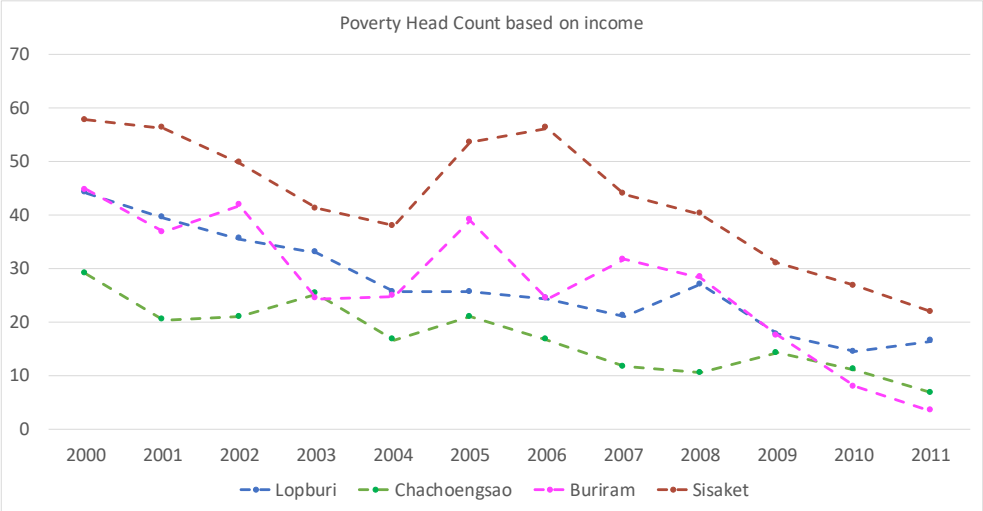

Figure 3.2: Poverty Head Count based on income, all four provinces

poor. For gainers, the poverty head count using income ranges between 7% to 31%. This range is lower when we consider PHC using equivalent income.

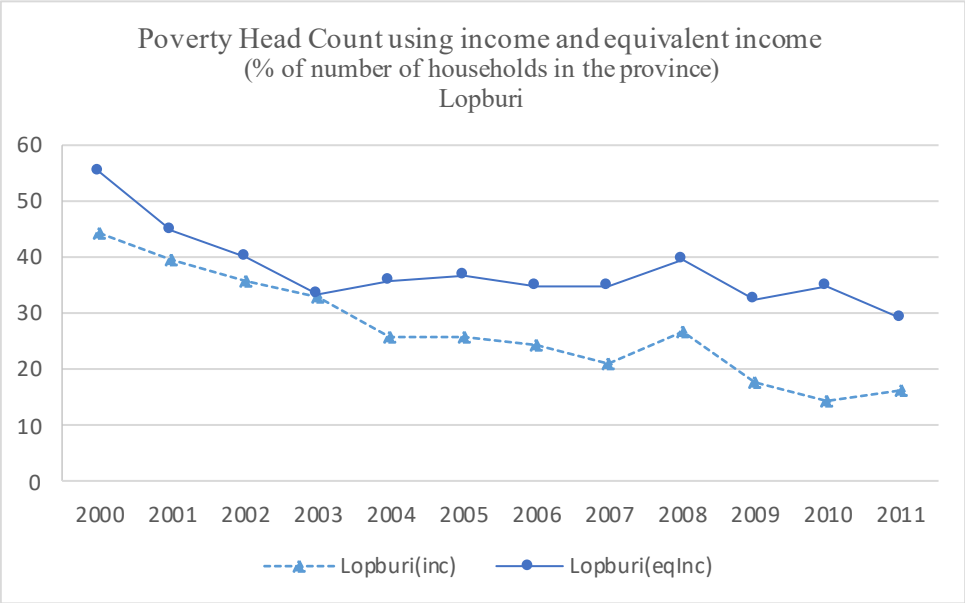

Figure 3.4: Poverty Head Count, Lopburi, 2000-2011

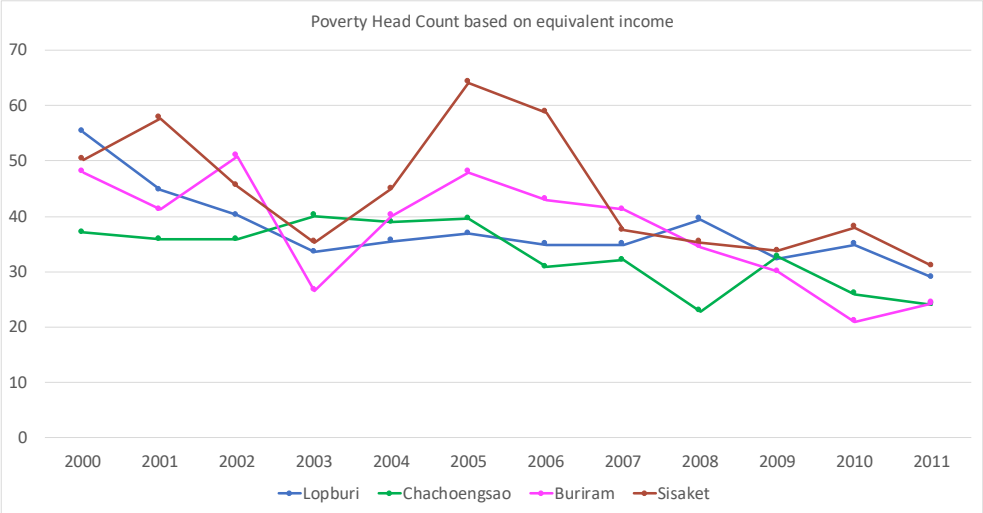

Figure 3.3: Poverty Head Count based on equivalent income, all four provinces

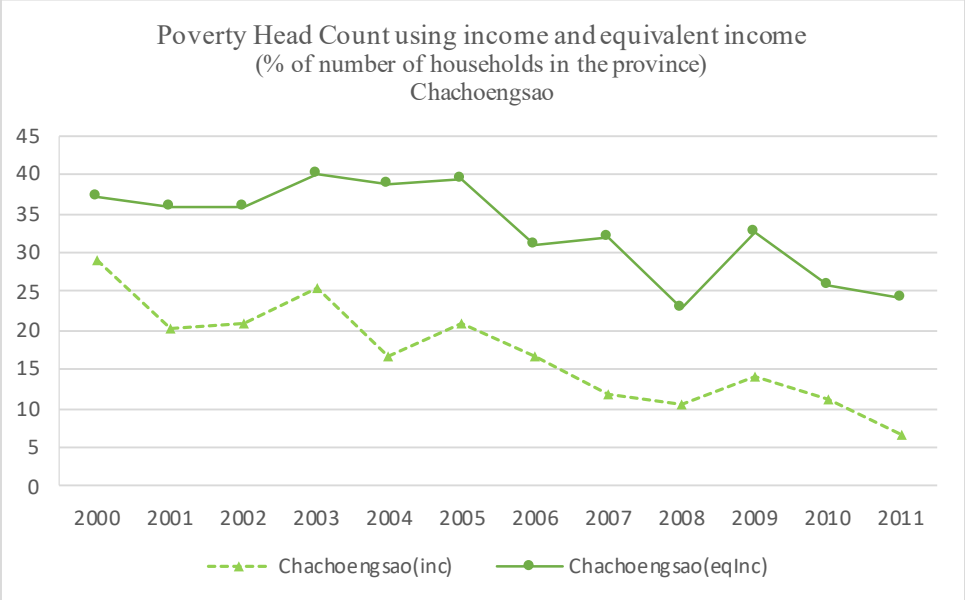

Figure 3.5: Poverty Head Count, Chachoengsao, 2000-2011

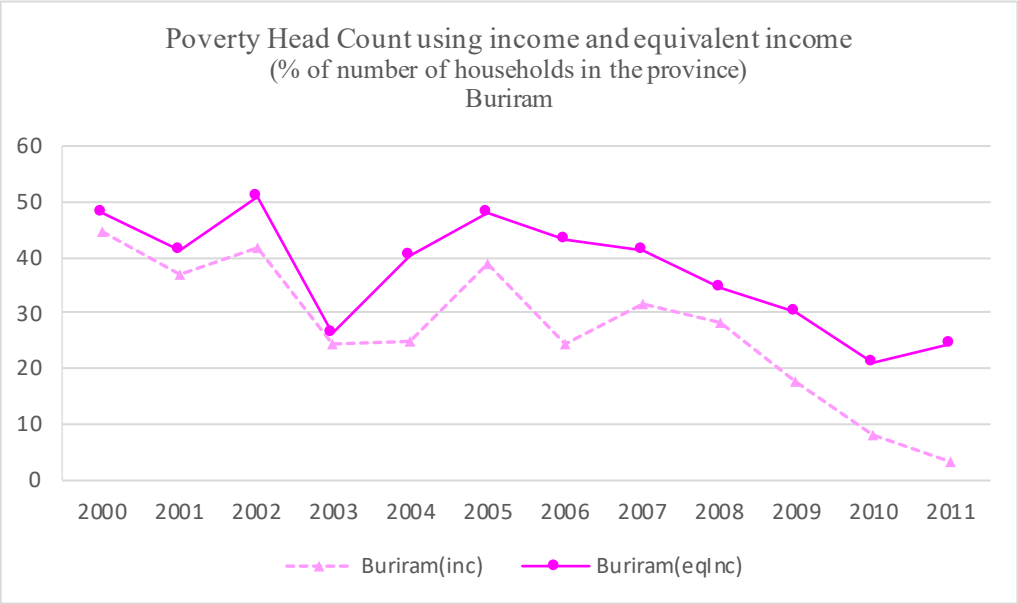

Figure 3.6: Poverty Head Count, Buriram, 2000-2011

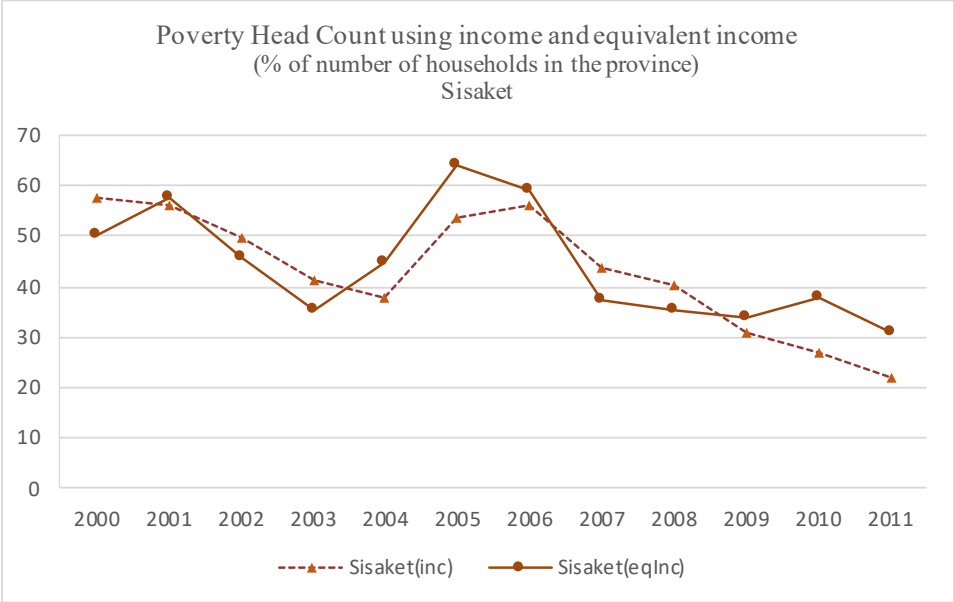

Figure 3.7: Poverty Head Count, Sisaket, 2000-2011

Table 3.1: Poverty head count and poverty gap, using income and equivalent income

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Poverty Head Count (% of number of households in each province in sample)												
Income												
Lopburi	44.08	39.47	35.53	32.89	25.66	25.66	24.34	21.05	26.97	17.76	14.47	16.45
Chachoengsao	29.01	20.37	20.99	25.31	16.67	20.99	16.67	11.73	10.49	14.2	11.11	6.79
Buriram	44.63	36.72	41.81	24.29	24.86	38.98	24.29	31.64	28.25	17.51	7.91	3.39
Sisaket	57.75	56.15	49.73	41.18	37.97	53.48	56.15	43.85	40.11	31.02	26.74	21.93
All	44.4	38.79	37.61	31.12	26.7	35.69	31.27	27.88	26.99	20.5	15.34	12.24
Equivalent Income												
Lopburi	55.26	44.74	40.13	33.55	35.53	36.84	34.87	34.87	39.47	32.24	34.87	28.95
Chachoengsao	37.04	35.8	35.8	40.12	38.89	39.51	30.86	32.1	22.84	32.72	25.93	24.07
Buriram	48.02	41.24	50.85	26.55	40.11	48.02	42.94	41.24	34.46	29.94	20.9	24.29
Sisaket	50.27	57.75	45.45	35.29	44.92	64.17	58.82	37.43	35.29	33.69	37.97	31.02
All	47.64	45.28	43.36	33.78	40.12	47.94	42.63	36.58	33.04	32.15	29.94	27.14
NESDB provincial poverty head count												
Lopburi	40.98	n/a	39.97	n/a	22.15	n/a	19.5	17.38	21.41	20.46	25.38	21.7
Chachoengsao	22.68	n/a	17.33	n/a	14.23	n/a	13.97	8.29	12.51	9.56	12.58	7.95
Buriram	60.3	n/a	56.38	n/a	49.26	n/a	54.53	47.29	42.84	47.18	32.82	33.67
Sisaket	62.13	n/a	62.54	n/a	45.51	n/a	43.19	48.93	54.87	58.73	55.79	35.89
All	42.33	n/a	32.44	n/a	26.76	n/a	21.94	20.04	20.43	17.88	16.37	13.22

Table 3.2: Poverty head count and poverty gap, using income and equivalent income

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Poverty Gap												
					Income							
Lopburi	0.203	0.198	0.152	0.111	0.072	0.082	0.092	0.057	0.078	0.062	0.048	0.05
Chachoengsao	0.106	0.07	0.056	0.075	0.065	0.06	0.054	0.023	0.03	0.034	0.029	0.02
Buriram	0.201	0.135	0.154	0.082	0.078	0.145	0.106	0.108	0.09	0.053	0.015	0.008
Sisaket	0.267	0.238	0.195	0.159	0.156	0.234	0.239	0.156	0.135	0.09	0.074	0.056
All	0.197	0.162	0.141	0.108	0.095	0.135	0.127	0.089	0.085	0.061	0.042	0.033
					Equivalent Income							
Lopburi	0.375	0.303	0.241	0.185	0.184	0.234	0.214	0.215	0.233	0.199	0.207	0.155
Chachoengsao	0.22	0.19	0.197	0.218	0.222	0.239	0.175	0.182	0.124	0.175	0.152	0.13
Buriram	0.324	0.246	0.347	0.159	0.266	0.36	0.278	0.278	0.219	0.176	0.100	0.118
Sisaket	0.338	0.36	0.247	0.203	0.288	0.438	0.422	0.227	0.213	0.204	0.211	0.164
All	0.315	0.277	0.26	0.191	0.243	0.324	0.279	0.227	0.198	0.189	0.167	0.142
NESDB national poverty gap	0.115	n/a	0.078	n/a	0.061	n/a	0.048	0.042	0.04	0.035	0.032	0.024

Table 3.3: Gainers and Losers

(a.) Distribution, average income, and average income change of gainers and losers in the sample

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Distribution of Gainers and Losers (Number and Percentage of the overall sample)												
Gainers (households)	348	387	379	429	356	323	374	398	403	406	408	420
Gainers (%)	51	57	56	63	53	48	55	59	59	60	60	62
Losers (households)	330	291	299	249	322	355	304	280	275	272	270	258
Losers (%)	49	43	44	37	47	52	45	41	41	40	40	38
Average monthly income per person (in baht)												
Gainers	3,862	4,246	3,918	4,142	4,883	6,735	6,476	6,550	6,684	7,870	9,276	9,006
Losers	2,082	2,109	2,660	3,292	3,172	2,677	3,285	4,020	4,713	4,937	5,362	6,858
Average income change over year (%)												
Gainers	123	106	99	97	79	187	125	121	82	95	91	74
Losers	-32	-33	-31	-27	-31	-37	-35	-35	-30	-31	-29	-29
Poor Gainers	74	38	29	32	24	27	20	28	24	17	8	20
Poor Losers	-36	-36	-34	-32	-35	-41	-39	-38	-35	-35	-34	-34

(b.) Poverty head count and poverty gap among gainers and losers

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
based on *income*												
PHC among gainers	30.2	30.7	29.3	25.2	19.1	19.2	17.4	18.6	18.4	13.1	9.1	7.1
PHC among losers	59.4	49.5	48.2	41.4	35.1	50.7	48.4	41.1	39.6	31.6	24.8	20.5
poverty gap among gainers	0.113	0.117	0.099	0.083	0.053	0.06	0.06	0.047	0.049	0.031	0.02	0.017
poverty gap among losers	0.285	0.221	0.196	0.152	0.141	0.204	0.21	0.15	0.139	0.105	0.075	0.06
based on *equivalent income*												
PHC among gainers	12.9	13.4	12.1	9.3	5.1	6.8	8	3.5	4.5	3	2.2	2.1
PHC among losers	84.2	87.6	82.9	75.9	78.9	85.4	85.2	83.6	74.9	75.7	71.9	67.8
poverty gap among gainers	0.035	0.041	0.033	0.026	0.015	0.017	0.024	0.007	0.012	0.006	0.005	0.004
poverty gap among losers	0.609	0.591	0.547	0.475	0.495	0.604	0.591	0.539	0.471	0.462	0.411	0.367

3.4.2 Reference-dependent Poverty Measure and Reference Points

One critical point when embedding the idea of reference dependency into welfare measurement is the issue of reference point. This is because the structure of reference point might determine the pattern of reference dependent welfare measure. Statistics in table 3.1 and 3.3 are based on the idea that individual's own previous period income is one good candidate for reference point because it reflects habit formation and has empirical supports as determinant of individual's wellbeing (Jäntti et al., 2014). Using previous period income as reference point also capture the idea that people compare their wellbeing to the status quo (Günther and Maier, 2014). However, using status quo as reference point might correspond to the situation that decision makers have status quo bias. Kőszegi and Rabin (2006),Kőszegi and Rabin (2007), and Kőszegi and Rabin (2009) suggested endogenized reference point as lagged rational expectation about outcomes. Crawford and Meng (2011) applied Köszegi and Rabin's reference-dependent model and treated reference points as rational expectations which was proxied by natural sample averages. In this paper, two additional structures of reference point will be analyzed. Consider equivalent income equation:

$$ln(y^*_{it}) = \begin{cases} ln(y_{it}) + [ln(y_{it}) - ln(\bar{y}_{it})]^{0.5} \; if \; y_{it} \geq \bar{y}_{it} \\ ln(y_{it}) - 2[ln(\bar{y}_{it}) - ln(y_{it})]^{0.5} \; if \; y_{it} < \bar{y}_{it} \end{cases} \tag{3.6}$$

, where $\bar{y}_{it}$ is reference income. $\bar{y}_{it}$ can take the form of:

Scenario 1(equal weight): $\bar{y}_{it} = \frac{1}{3}\sum_{s=t-3}^{t-1} y_s$, which correspond to the case of rational expectation and perfect Bayesian learner. That is, past incomes in every year have the same weight. Or, another possible form is:

Scenario 2(recency effect): $\bar{y}_{it} = \frac{6}{11}\sum_{s=1}^{3}\frac{1}{s}y_{t-s}$, which is the case of individual showing recency effect, which could be the case of people using representativeness heuristics. Individual tends to use information from nearer past, more than farer past, ignoring prior information. To note, here we assume adhocly that the span of memory is 3 years because it is the shortest length of time that people can encounter fluctuation in income, both ups and downs.

For all four provinces, from figure 3.8 and 3.9 and table 3.4, poverty headcount for the case of having recency effect is more than or equal to the case of equal weight. In some years, poverty headcount based on previous income is more than the other two, and in some years, it is less than the other two. Nonetheless, all three measures both for poverty headcount and poverty gap have the same trends and track one another overtime.

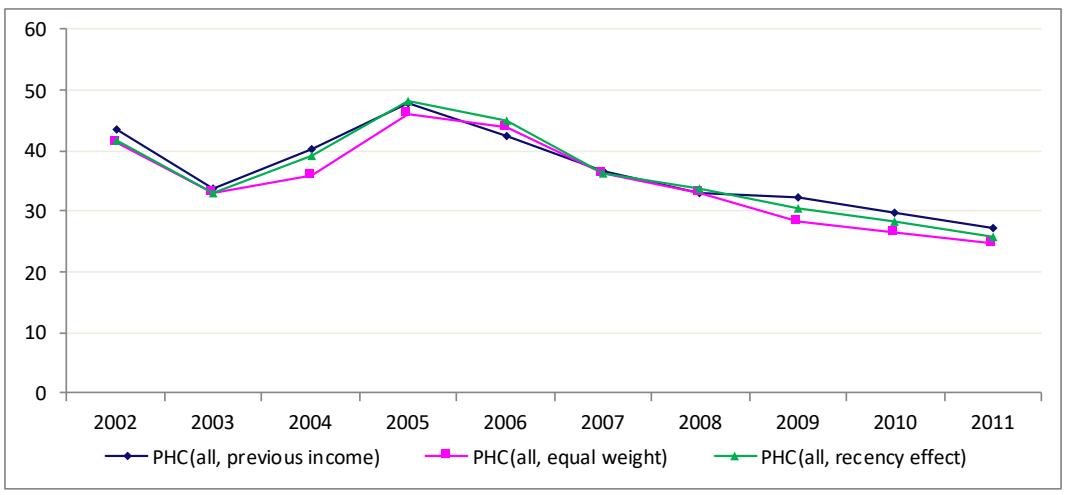

Figure 3.8: Poverty head count and different types of reference points

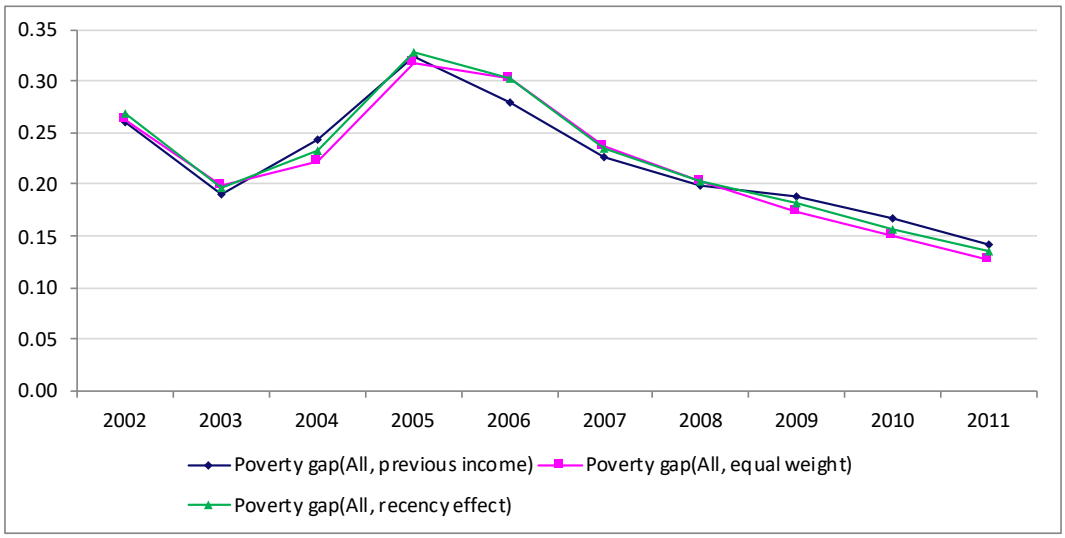

Figure 3.9: Poverty gap and different types of reference points

Table 3.4: Poverty headcount and poverty gap from different types of reference points

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
PHC, reference point with equal weight for each period										
Lopburi	38.82	33.55	32.89	32.24	33.55	31.58	36.18	30.92	33.55	29.61
Chachoengsao	31.48	34.57	38.89	38.89	32.1	28.4	24.07	29.63	26.54	23.46
Buriram	50.85	29.38	35.03	49.15	45.2	39.55	35.59	28.81	16.38	18.08
Sisaket	42.78	34.22	36.9	60.43	61.5	44.39	35.83	25.13	30.48	27.81
All	41.3	32.89	35.99	46.02	43.95	36.43	33.04	28.47	26.55	24.63
PHC, reference point with recency effect										
Lopburi	40.13	32.89	34.87	33.55	34.87	33.55	37.5	28.95	35.53	29.61
Chachoengsao	34.57	35.8	38.89	41.36	35.19	29.63	22.84	31.48	27.78	24.69
Buriram	49.72	29.94	40.68	50.85	42.94	41.24	37.29	31.64	17.51	19.21
Sisaket	41.71	34.22	41.18	63.64	63.1	40.11	37.43	29.95	33.69	29.95
All	41.74	33.19	39.09	48.23	44.84	36.43	33.92	30.53	28.47	25.81
Poverty Gap, reference point with equal weight for each period										
Lopburi	0.257	0.2	0.17	0.197	0.209	0.192	0.223	0.199	0.199	0.16
Chachoengsao	0.17	0.227	0.233	0.235	0.194	0.168	0.136	0.173	0.147	0.131
Buriram	0.353	0.176	0.225	0.364	0.311	0.276	0.244	0.176	0.08	0.068
Sisaket	0.26	0.192	0.251	0.441	0.464	0.297	0.203	0.147	0.177	0.152
All	0.262	0.198	0.222	0.317	0.302	0.237	0.202	0.172	0.15	0.127
Poverty Gap, reference point with recency effect										
Lopburi	0.244	0.191	0.182	0.213	0.215	0.2	0.231	0.196	0.21	0.157
Chachoengsao	0.186	0.225	0.229	0.247	0.191	0.174	0.136	0.177	0.152	0.138
Buriram	0.368	0.176	0.24	0.366	0.298	0.279	0.246	0.182	0.082	0.089
Sisaket	0.262	0.197	0.267	0.456	0.472	0.276	0.201	0.174	0.184	0.161
All	0.268	0.197	0.232	0.328	0.302	0.235	0.204	0.182	0.155	0.136

3.5 Comparing Design of Prospect-theory Based Poverty Measures

To compare the idea behind the construction of poverty measure proposed in Günther and Maier (2014) versus that in Jäntti et al. (2014), we can consider as the following. Günther and Maier (2014) incorporated reference-dependence into Chakravarty (1983)'s utility-based static poverty measure and have $M^1_{it}(x_{it}, x_{it-1}, z_t)$ as in definition 3.4 and make it a measure of multi-period poverty by averaging per-period poverty measure overtime which yields:

$$M^1_i(x_{i2}, x_{i3}, ..., x_{iT}, z_2, ..., z_T, T) = \frac{\sum_{t=1}^{T} M^1_{it}}{T} \tag{3.7}$$

, where $M^1_i(\cdot)$ is an individual-level poverty measure.

Jäntti et al. (2014) worked the idea of reference-dependence into poverty measure through the concept of equivalent income as shown in equation 3.1, 3.2, and 3.3. The nature of measure proposed in Jäntti et al. (2014) is that it is aggregate-level and per-period measure.

To be able to compare these measures at the heart of their differences, we can synchronize all other surrounding differences such as the level of aggregation, the type of welfare indicator (income or expenditure), considered time span, so that we can compare the idea of equivalent income in Jäntti et al. (2014) against utility gap in Günther and Maier (2014). In the following analysis, we focus on poverty measure with previous income as reference point.

To synchronize the surrounding differences, we can consider as follows. For q numbers of poor people out of sample of size n, and T arbitrary time span,

there are five synchronized measures that we can compare. They are:

(a.) Using income y_{it}, instead of consumption x_{it}, we can adapt in Günther and Maier (2014)'s measure to be:

$$\bar{M}^1(y_{i2}, y_{i3}, ..., y_{iT}, z_{p(i)2}, ..., z_{p(i)T}, T, q, n) = \frac{\sum_{i=1}^{q} \sum_{t=1}^{T} M_{it}^1}{nT} \tag{3.8}$$

, where the gain-loss utility function is piecewise linear[4]. Equation 3.8 can be written as:

$$\bar{M}_i^1(\cdot) = \frac{\sum_{i=1}^{q} \sum_{t=1}^{T} [u(z_{p(i)t}) + \mu(u(z_{p(i)t}) - u(y_{it-1}))] - [u(y_{it}) + \mu(u(y_{it}) - u(y_{it-1}))]}{nTu(z_{p(i)t})} \tag{3.9}$$

$$u(y_{it}) + \mu(u(y_{it}) - u(y_{it-1})) = \begin{cases} ln(y_{it}) + [ln(y_{it}) - ln(y_{it-1})]^{0.5} \; if \; y_{it} \geq y_{it-1} \\ ln(y_{it}) - 2[ln(y_{it-1}) - ln(y_{it})]^{0.5} \; if \; y_{it} < y_{it-1} \end{cases} \tag{3.10}$$

, and $z_{p(i)t}$ is poverty line for province p at time t, based on residential location of household i.

(b.) Another measure from Günther and Maier (2014), which consider reference point to be poverty line when considering utility from poverty line.

$$\bar{M}^2(y_{i2}, y_{i3}, ..., y_{iT}, z_{p(i)2}, ..., z_{p(i)T}, T, q, n) = \frac{\sum_{i=1}^{q} \sum_{t=1}^{T} M_{it}^2}{nT} \tag{3.11}$$

, with

$M_{it}^2(y_{it}, y_{it-1}, z_{p(i)t}) = \frac{RU(z_{p(i)t}|z_{p(i)t}) - RU(y_{it}|y_{it-1})}{u(z_{p(i)t})}$, i.e.

[4],i.e. $\mu(y) = \eta y^{0.5}$ if $y \geq 0$ and $\mu(y) = \lambda\eta(-y)^{0.5}$ if $y < 0$, assuming $\eta = 1, \lambda = 2$

$M^2_{it}(y_{it}, y_{it-1}, z_{p(i)t}) = \frac{[u(z_{p(i)t})+\mu(u(z_{p(i)t})-u(z_{p(i)t}))]-[u(y_{it})+\mu(u(y_{it})-u(y_{it-1}))]}{u(z_{p(i)t})}$

$M^2_{it}(y_{it}, y_{it-1}, z_{p(i)t}) = \frac{u(z_{p(i)t})-[u(y_{it})+\mu(u(y_{it})-u(y_{it-1}))]}{u(z_{p(i)t})}$, hence,

$$\bar{M}^2(\cdot) = \frac{\sum_{i=1}^{q}\sum_{t=1}^{T} u(z_{p(i)t}) - [u(y_{it}) + \mu(u(y_{it}) - u(y_{it-1}))]}{nTu(z_{p(i)t})} \tag{3.12}$$

Equation 3.9 and 3.12 are considered together with focus assumption being income less than poverty line in each period.

(c.) As for the measure from Jäntti et al. (2014), we can turn their measure into multi-period measure and have:

$$P^{\alpha}_{*} = \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{q}\left(\frac{z_{p(i)t} - y^{*}_{it}}{z_{p(i)t}}\right)^{\alpha} \tag{3.13}$$

,where $y^{*}_{qt} \leq z_{p(q)t}$ and $\alpha = 1$. $z_{p(i)t}$ is provincial poverty line of individual i at time t who lives in province p.

(d.) One way to synchronize the focus assumption between Jäntti et al. (2014) and Günther and Maier (2014) is to limit attention to the income poor household, not the equivalent-income poor. Hence, another measure to be analyzed is:

$$P^{\alpha} = \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{q}\left(\frac{z_{p(i)t} - y^{*}_{it}}{z_{p(i)t}}\right)^{\alpha} \tag{3.14}$$

,where $y_{qt} \leq z_{p(q)t}$ and $\alpha = 1$

(e.) The last measure to be considered is the standard FGT poverty measure.

The simplest way to synchronize time dimension of the measure is to average per-period measure overtime. That is,

$$P^{\alpha}_{FGT} = \frac{1}{nT} \sum_{t=1}^{T} \sum_{i=1}^{q} \left(\frac{z_{p(i)t} - y_{it}}{z_{p(i)t}} \right)^{\alpha} \tag{3.15}$$

That all time periods are weighted equally is in the same fashion as measure proposed in Calvo and Dercon (2007), which is published in Addison et al. (2009). We have set aside the issue of aggregating across individuals and across time by considering the simplest form of aggregation.

All five poverty measures are shown in figure 3.10 below. To construct these poverty measures, the sample size is 678 households. Household income is adjusted into per-individual income by using equivalent scale following Townsend (1994) which is that, for adult males, 1.0; for adult females, 0.9; for aged 13-18 males, 0.94 ; for aged 13-18 females, 0.83; for aged 7-12, 0.67; for children 4-6, 0.52; for toddlers 1-3, 0.32, and for infants 0.05. Townsend-Thai household panel data from 2000-2011 is used and provincial poverty lines in year 2001, 2003, 2005 are linearly projected from existing poverty lines.

The result shows that P^{α}_{*} has the highest level, followed by P^{α}_{FGT} , $\bar{M}^2$, and by $\bar{M}^1$ accordingly. If we take a closer look at the formulation of P^{α}_{*} and $\bar{M}^2$, we would have that the main difference would be that $\bar{M}^2$ is the utility scale of P^{α}_{*}. However, the difference in the levels also originates from focus assumption. If we experiment with focus assumption by looking at people whose income is below poverty line and calculate poverty gap by looking at their equivalent income, we will have that the level of poverty gap measure for Jäntti et al. (2014) decreases starkly, i.e. from P^{α}_{*} to P^{α}, in figure 3.11. This should indicate that by considering equivalent income, the poverty gap measure picks up the vulnera-

ble who has experienced income loss. However, P^{α} is still higher than Günther and Maier (2014)'s measures.

The higher level might come from using utility scale and income scale. When we consider P^{α}_{*} in details and substitute out the notion of equivalent income. We will have that $y^{*}_{it} = exp\{ln(y_{it}) + \mu(ln(y_{it}) - ln(y_{it-1})\}$, and $P^{\alpha}_{*} = \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{q}(G_{it})^{\alpha}$, where $G_{it} = \frac{z_{p(i)t} - exp\{ln(y_{it}) + \mu(ln(y_{it}) - ln(y_{it-1}))\}}{z_{p(i)t}}$. It appears that $G_{it} > M^{2}_{it}$ as long as:

$$\frac{y_{it}exp\{\mu(ln(y_{it}) - ln(y_{it-1}))\}}{ln(y_{it}) + \mu(ln(y_{it}) - ln(y_{it-1}))} < \frac{z_{p(i)t}}{ln(z_{p(i)t})} \tag{3.16}$$

, which is true as long as $z_{p(i)t} > y_{it}$. In other words, under conventional focus assumption, P^{α}_{*} will be more than $\bar{M}^{2}$.

Moreover, $\bar{M}^{2}$ is less than P^{α}_{FGT} as long as:

$$\frac{\mu(ln(y_{it}) - ln(y_{it-1}))}{y_{it}} > \frac{ln(z_{p(i)t})}{z_{p(i)t}} - \frac{ln(y_{it})}{y_{it}} \tag{3.17}$$

, that is, as long as the ration of gain-loss utility to income is more than the difference between scaling factor of poverty line and of income.

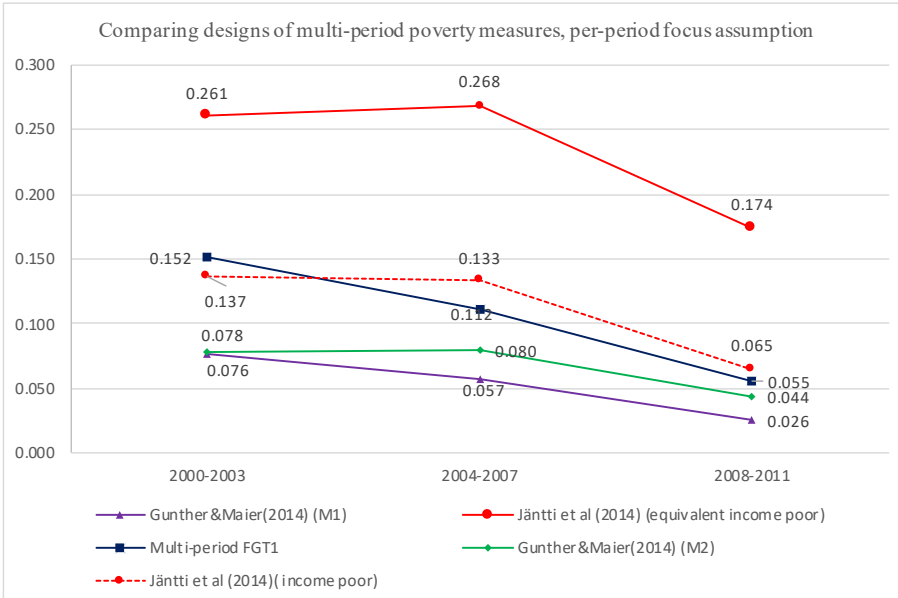

Figure 3.10: Levels and trends of different designs of reference-dependent poverty measures, per-period focus assumption

Another aspect that we can look at when trying to analyze behavior of poverty measure is focus assumption. Earlier, we look at per-period focus assumption, meaning that multi-period poverty rate that is calculated is the average level and doesn't necessarily track the incidence of poverty of the same group of people overtime. We can look at more restrictive focus assumption by focusing on the multi-period poor. The mean of income over all observed time periods T is set equal to poverty line if $\frac{1}{T}\sum_{t=1}^{T} y_{it} > \frac{1}{T}\sum_{t=1}^{T} z_{p(i)t}$ for P^{α}_{FGT}, and if $\frac{1}{T}\sum_{t=1}^{T} y^{*}_{it} > \frac{1}{T}\sum_{t=1}^{T} z_{p(i)t}$ for P^{α}_{*}. And, income of all periods are equalized to the poverty line if $\sum_{t=1}^{T} RU(y_{it}|y_{it-1}) > \sum_{t=1}^{T} RU(z_{p(i)t}|y_{it-1})$ for $\bar{M}^1$, and if $\sum_{t=1}^{T} RU(y_{it}|y_{it-1}) > \sum_{t=1}^{T} RU(z_{p(i)t}|z_{p(i)t})$ for $\bar{M}^2$.

As shown in figure 3.11, what is starkly different from scenario with per-period focus assumption is the reduction in level of P^{α}_{*}. This should be an evidence that gain-loss utility that is embedded in equivalent income makes

equivalent income have higher volatility, comparing to income. Accordingly, less people are categorized as multi-period poor since their equivalent incomes are not chronically below poverty line. The increase in equivalent income due to gain utility can pull up the average of overall period equivalent income.

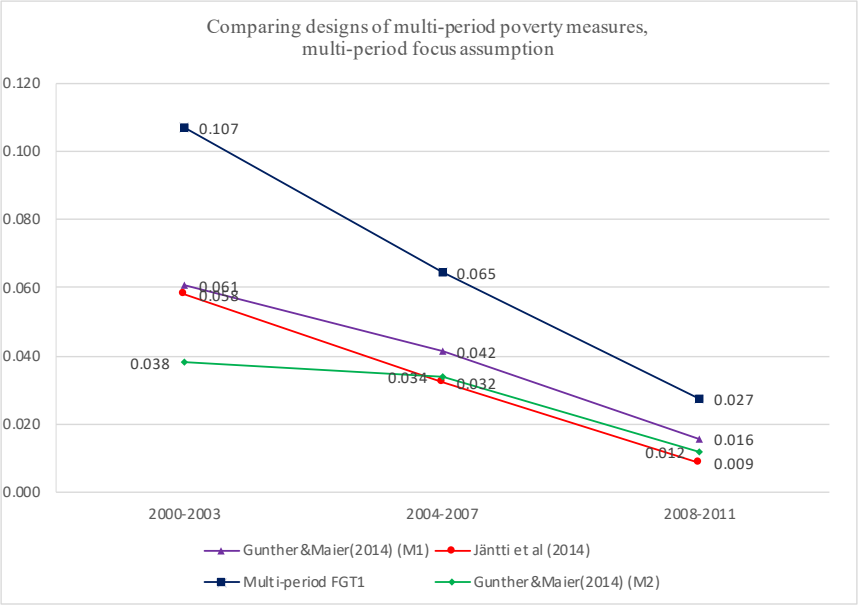

Figure 3.11: Levels and trends of different designs of reference-dependent poverty measures, multi-period focus assumption

3.6 The Nature of Reference-Dependent Inequality Measure

Gini coefficient among households in the sample based on income and equivalent income are shown in figure 3.12 and table 3.5 and 3.6. We have that Gini coefficient calculated using equivalent income is higher than that calculated using income for overall sample, which is also higher than national measure uniformly. This might be due to the fact that equivalent income will naturally have higher spread as it incorporates value of gain and loss into income measure.

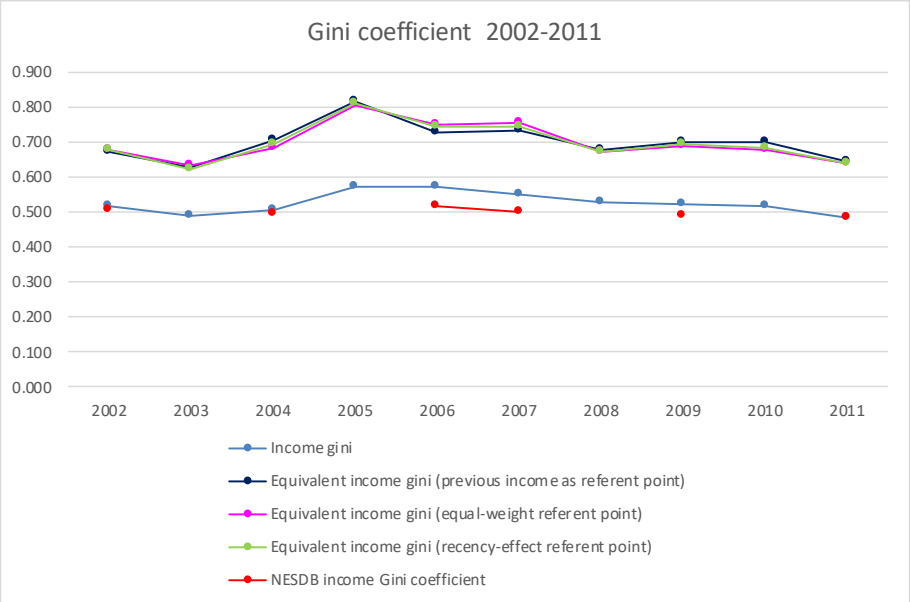

Figure 3.12: Gini Coefficient based on income and equivalent income

Table 3.5: Gini Coefficient using income or equivalent income for each province

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Lopburi												
Income	0.499	0.518	0.529	0.497	0.458	0.475	0.482	0.552	0.486	0.492	0.48	0.477
Equivalent income	0.699	0.662	0.697	0.629	0.593	0.675	0.65	0.796	0.682	0.699	0.672	0.626
Chachoengsao												
Income	0.541	0.545	0.45	0.445	0.492	0.559	0.529	0.511	0.469	0.468	0.522	0.473
Equivalent income	0.745	0.699	0.615	0.613	0.751	0.847	0.691	0.673	0.601	0.656	0.719	0.625
Buriram												
Income	0.482	0.443	0.499	0.468	0.482	0.562	0.574	0.516	0.522	0.54	0.491	0.475
Equivalent income	0.657	0.643	0.709	0.601	0.699	0.763	0.751	0.705	0.689	0.705	0.656	0.671
Sisaket												
Income	0.523	0.525	0.48	0.468	0.526	0.602	0.581	0.518	0.549	0.52	0.464	0.401
Equivalent income	0.687	0.733	0.587	0.622	0.712	0.821	0.756	0.64	0.712	0.693	0.607	0.557
NESDB income gini coefficient												
Central region	0.448	n/a	0.44	n/a	0.432	n/a	0.44	0.418	n/a	0.412	n/a	0.395
Northeastern	0.484	n/a	0.471	n/a	0.454	n/a	0.508	0.483	n/a	0.486	n/a	0.464

Table 3.6: Gini Coefficient using income or equivalent income for all households with different designs of referent points

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Gini Coefficient of households in the sample												
Income												
	0.543	0.551	0.519	0.489	0.503	0.571	0.569	0.551	0.526	0.523	0.518	0.485
Equivalent income (previous income as referent point)												
	0.727	0.713	0.673	0.624	0.703	0.812	0.727	0.729	0.679	0.696	0.697	0.644
Equivalent income (equal-weight referent point)												
	n/a	n/a	0.677	0.63	0.685	0.802	0.748	0.752	0.669	0.688	0.676	0.635
Equivalent income(recency-effect referent point)												
	n/a	n/a	0.678	0.624	0.694	0.809	0.742	0.745	0.67	0.692	0.683	0.638
NESDB income Gini coefficient												
	0.522	n/a	0.508	n/a	0.493	n/a	0.514	0.499	n/a	0.49	n/a	0.484

3.7 Conclusion

In an attempt to learn what insight prospect theory can give when it is incorporated into how we measure poverty and inequality, this paper applies the methodology suggested by Jäntti et al. (2014) to 12 years of Townsend-Thai annual resurvey rural household panel data, between year 2000 to 2011. We calculated poverty and inequality measures using '*equivalent income*,' the level of income at which standard utility is equal to reference-dependent utility, hence capturing loss aversion into the income measure.

The results show that poverty headcount and poverty gap are on a decreasing trend, with prospect-theory-based poverty measures mostly higher than conventional measures. Prospect-theory based inequality is uniformly higher than conventional inequality.

Poverty and inequality measure seems not to be sensitive to different designs of reference point. Additionally, two competing prospect-theory-based poverty measures, that of Jäntti et al. (2014) and of Günther and Maier (2014), are computed and compared. We have that both measures are the same conceptually under some specific restrictions, and that focus assumption is critical to the analysis of the level of poverty. Under conventional focus assumption, Jäntti et al. (2014)'s reference-dependent poverty measure will be more than that of Günther and Maier (2014).

The comparison between the conventional measure and the reference-dependent measure should help us better understand the nature of poverty among people whose incomes are around the poverty line, specifically in the aspect of the churning in income versus the persistency of poverty. The over-

all analysis suggested that, around the poverty line, the churning phenomenon, hence insecurity and vulnerability, might be more salient for the Thai economy than the persistency of poverty, which might only be concentrated at the extreme poverty level.

One insight that can be learned is that the persistency of poverty should reduce the wedge between reference-dependent poverty measures and conventional ones. Another is that the presence of gainers and losers with a higher level of poverty among losers than among gainers should increase the wedge between prospect-theory based inequality and the conventional one.

APPENDIX A

APPENDIX A OF CHAPTER 1

Descriptive statistics

Descriptive statistics for socioeconomic characteristics of subjects are shown below.

Table A.1: Descriptive Statistics

	count	mean	sd	min	max
Male	584	0.49	0.50	0	1
Age	584	48.5	15.0	22	85
Education level	584	4.27	1.53	1	7
Household size	584	2.62	1.37	1	9
Annual household income	584	73.9	51.5	10	200
Equivalent income	584	47.5	32.8	5	200
Unemployed	584	0.38	0.49	0	1
Welfare recipient	584	0.42	0.49	0	1
Food aid recipient	584	0.21	0.41	0	1
Debtor	584	0.31	0.46	0	1
In financial hardship	584	0.40	0.49	0	1
Life satisfaction	584	3.82	1.11	1	5
Prob Know	584	0.70	0.46	0	1
Lotto bought	584	14.4	18.6	0	52
Win lotto	584	0.50	0.50	0	1
Insured	584	0.55	0.50	0	1
Health insured	584	0.93	0.26	0	1

Note: "Prob Know" is a dummy variable equal to 1 if subject answered both questions testing understanding of probability correctly. "Lotto bought" is number of lottery tickets a subject bought in a year. "Win lotto" is a dummy variable equal to 1 if subject used to win lottery ticket. "Insured" is a dummy variable equal to 1 if subject had fire, hazard, or flood insurance on her property at the time of the survey. "Health insured" is a dummy variable equal to 1 if subject covered by any health insurance or health coverage plans at the time of survey.

APPENDIX B

APPENDIX B OF CHAPTER 1

Robust Analysis with Prelec's probability weighting function

What if probability weighting function is not that of Goldstein and Einhorn (1987), $\pi(p) = \frac{\delta_i p^{\gamma_i}}{\delta_i p^{\gamma_i} + (1-p)^{\gamma_i}}; \delta_i \geq 0, \gamma_i \geq 0$, and takes the form of Prelec (1998), $\pi(p) = e^{-(-lnp)^{\gamma_i}}$ (lower γ, more overweighting of small probabilities) instead, how would the effects of financial (hard) priming on risk preferences change? The effect of financial hard priming on parameter γ of Prelec's probability weighting function, α (capturing standard risk aversion), and λ (coefficient of loss aversion), comparing to financial easy priming and nonfinancial easy priming are presented below. We also compare the overall effect of financial priming to nonfinancial priming. Each case is separated into the estimates for experimental lotteries and for all lotteries. The results show that using Prelec's gives similar pattern of effects as using Goldstein and Einhorn's. Those in financial hard priming condition are more loss averse than those in financial easy condition. Comparing to nonfinancial easy priming, financial hard priming makes subject have higher level of overweighting of small probabilities. This is also the case when comparing financial condition vs. nonfinancial condition. The stark difference between these two variation of probability weighting function is the function for New York Lottery. Goldstein and Einhorn's can capture the overweighting of almost all level of probabilities, while Prelec's estimates indicate that the probability weighting function for New York lotteries is almost linear. This makes the inclusion of New York lotteries into the estimation yield almost linear probability weighting function. This point can also be alternatively illus-

trated by including dummy for NY lotto into linear combination of parameters.

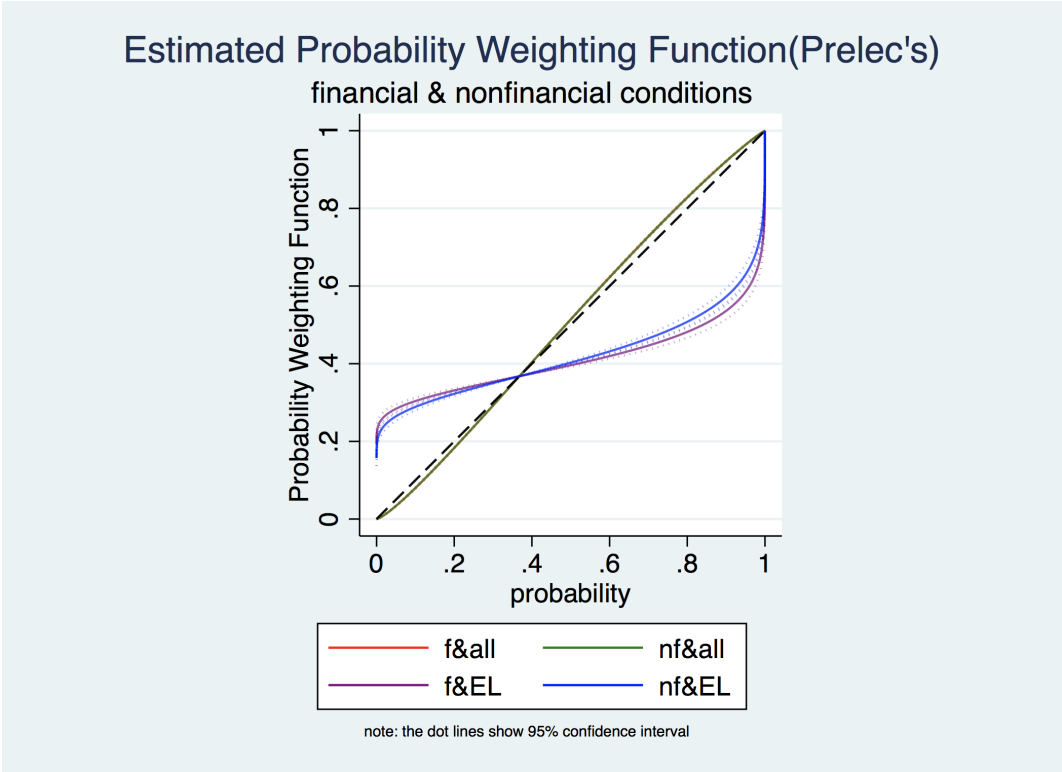

Figure B.1: Prelec's probability weighting function

Table B.1: The effect of priming on risk preferences(Prelec's $\pi(p)$)

	fh vs. fe		fh vs. nfe		f vs. nf	
	EL	All	EL	All	EL	All
gamma						
cons	0.213***	1.117***	0.264***	1.114***	0.260***	1.109***
	(0.0191)	(0.00822)	(0.0209)	(0.00868)	(0.0150)	(0.00553)
financial hard	-0.00669	-0.00493	-0.0576+	-0.00228		
	(0.0291)	(0.0124)	(0.0303)	(0.0127)		
financial					-0.0499*	0.00539
					(0.0209)	(0.00826)
alpha						
cons	2.581***	1.685***	2.399***	1.663***	2.261***	1.645***
	(0.0853)	(0.0297)	(0.0741)	(0.0308)	(0.0496)	(0.0197)
financial hard	0.0783	-0.0292	0.260*	-0.00752		
	(0.122)	(0.0439)	(0.114)	(0.0447)		
financial					0.358***	0.0246
					(0.0785)	(0.0294)
lambda						
cons	3.066***	2.078***	3.623***	2.441***	3.425***	2.449***
	(0.272)	(0.113)	(0.343)	(0.151)	(0.222)	(0.108)
financial hard	1.052*	0.336+	0.495	-0.0276		
	(0.524)	(0.191)	(0.564)	(0.215)		
financial					0.110	-0.212
					(0.332)	(0.143)
N	4380	8760	4380	8760	8760	17520

Standard errors in parentheses, + for $p < 0.10$ * for $p < 0.05$ ** for $p < 0.01$ *** for $p < 0.001$
EL means the estimation is based on only 15 experimental lotteries. All is based on all 30 lotteries.

APPENDIX C

APPENDIX C OF CHAPTER 1

Additional estimated probability weighting functions

Probability weighting functions for financial hard vs. financial easy condition and for poor vs. rich based on equivalent income and hardship are shown below, for experimental lotteries, NUMBERS, WIN4, and MGM JtJ.

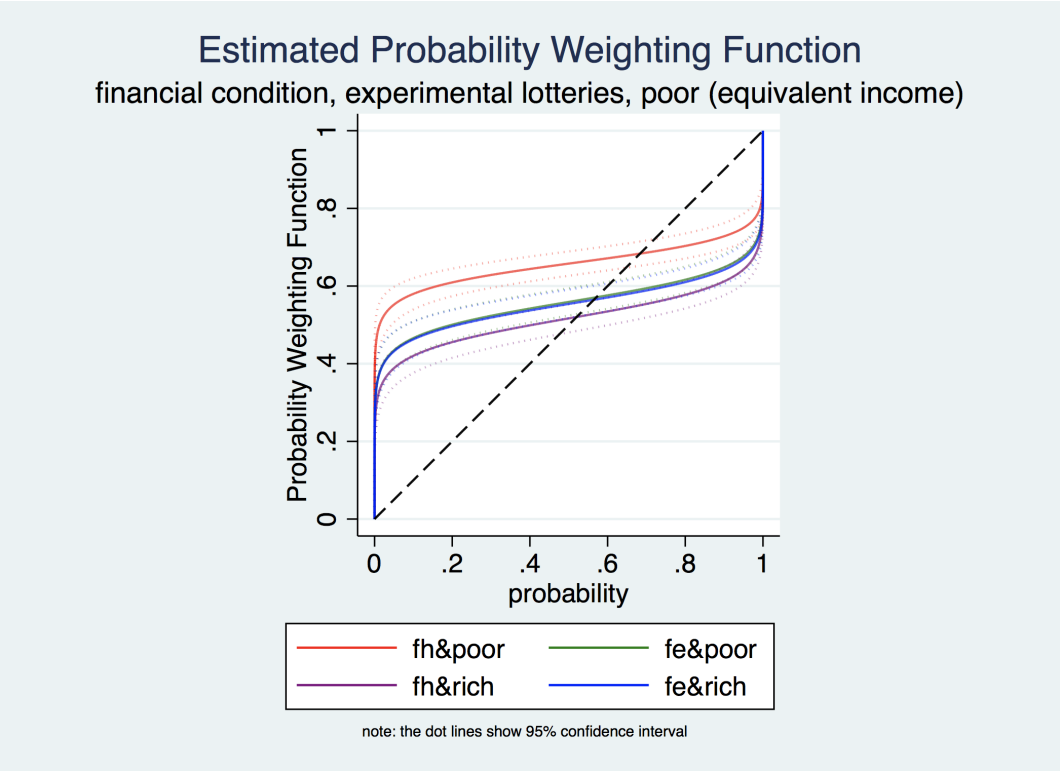

Figure C.1: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich based on equivalent income: Experimental lotteries

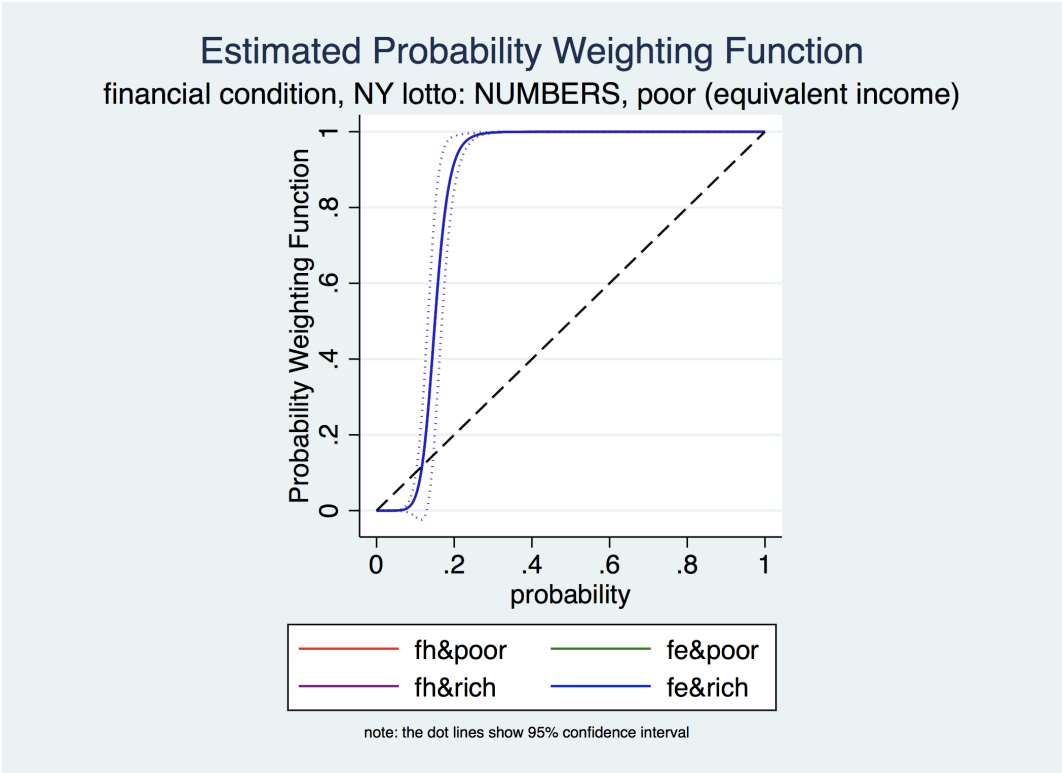

Figure C.2: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich based on equivalent income: NUMBERS

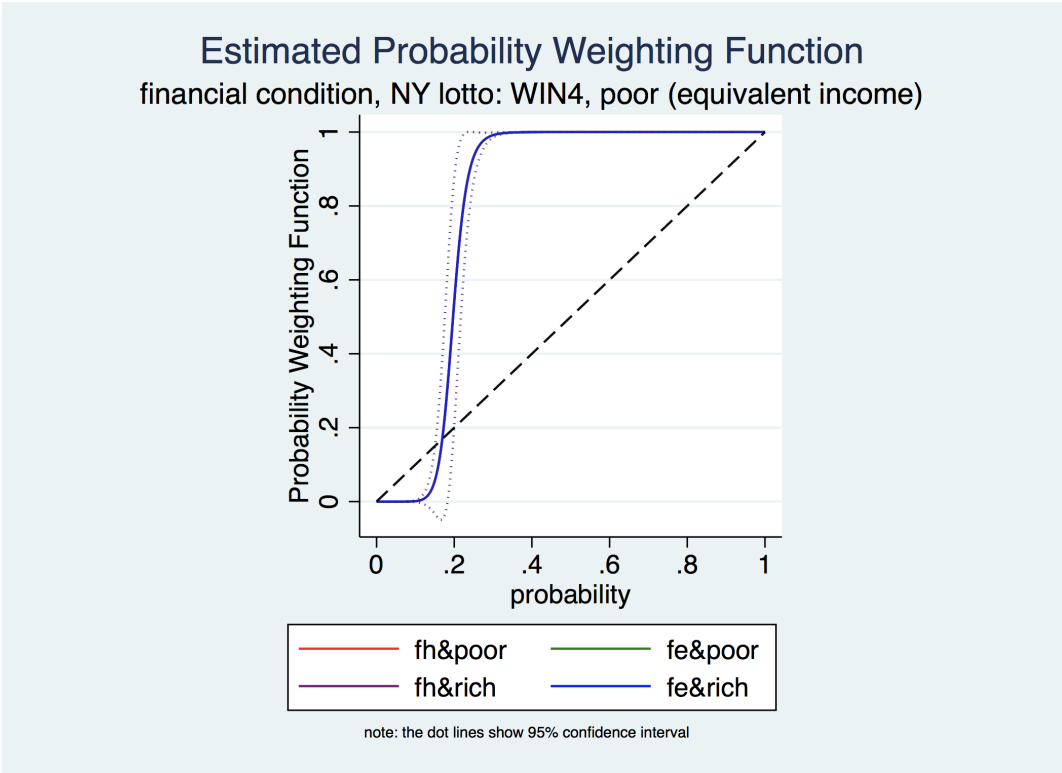

Figure C.3: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich based on equivalent income: WIN4

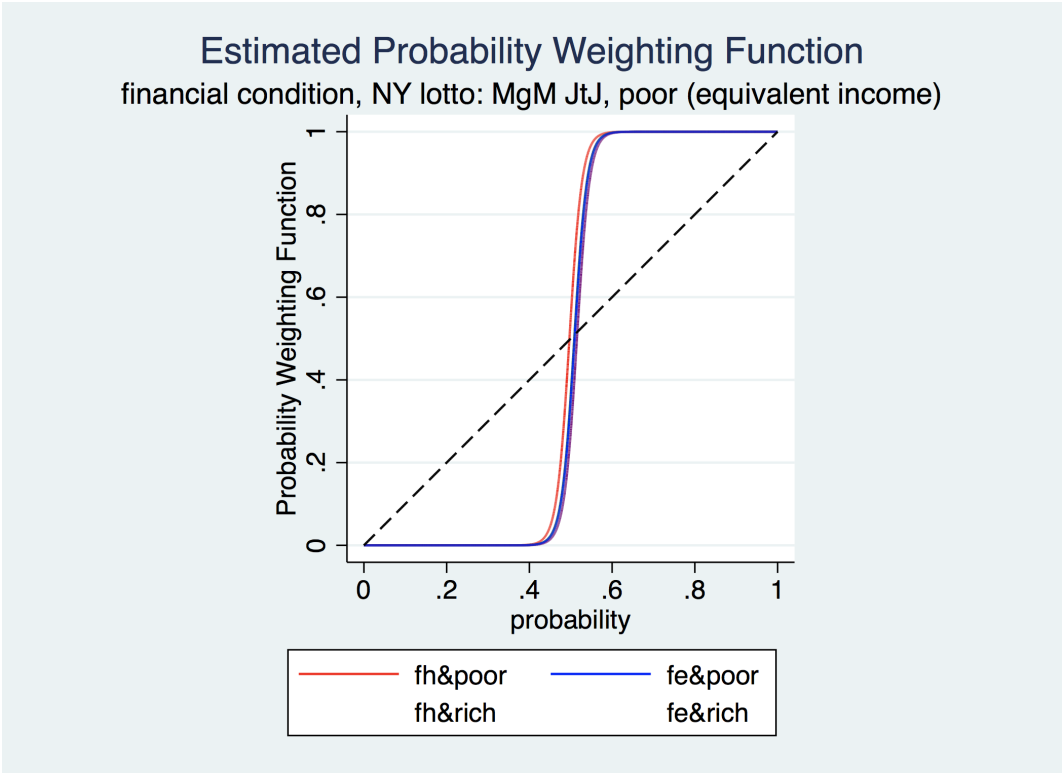

Figure C.4: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich based on equivalent income: MGM JtJ

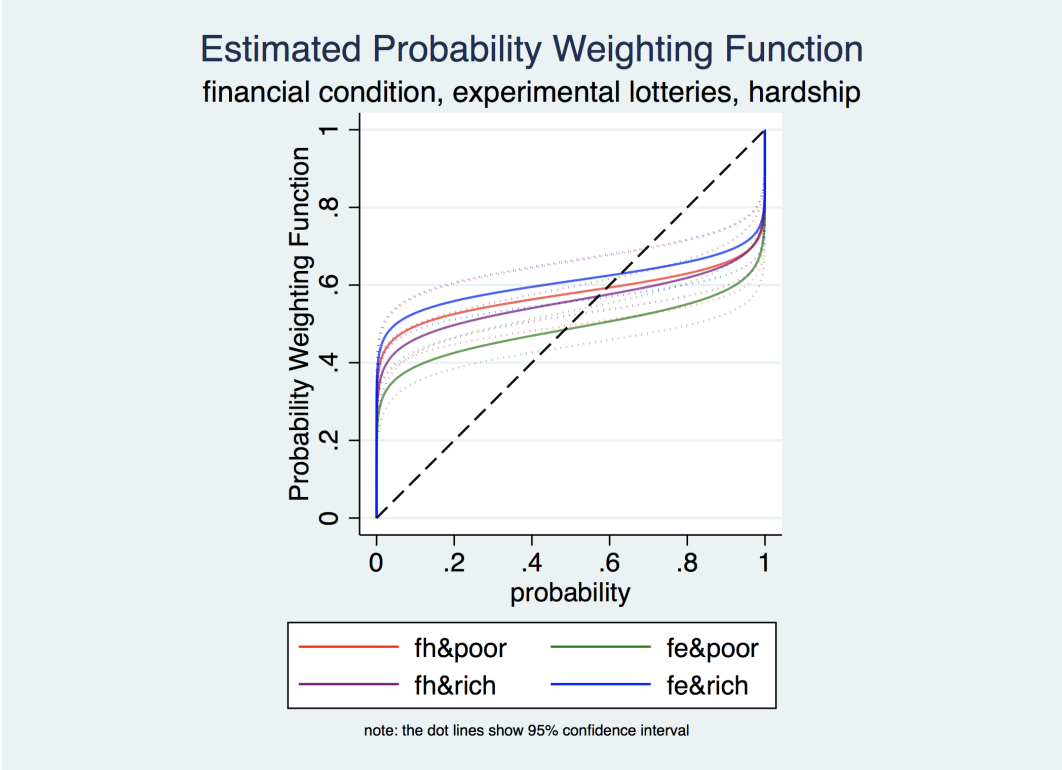

Figure C.5: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich based on hardship indicator: Experimental lotteries

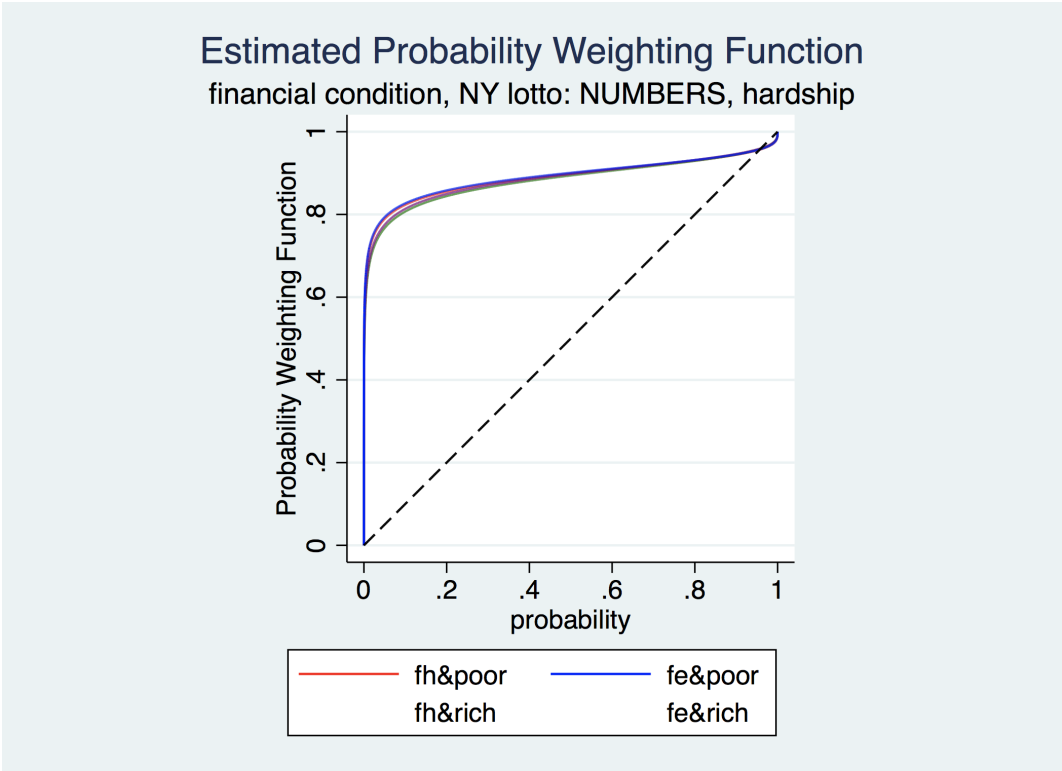

Figure C.6: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich based on hardship indicator: NUMBERS

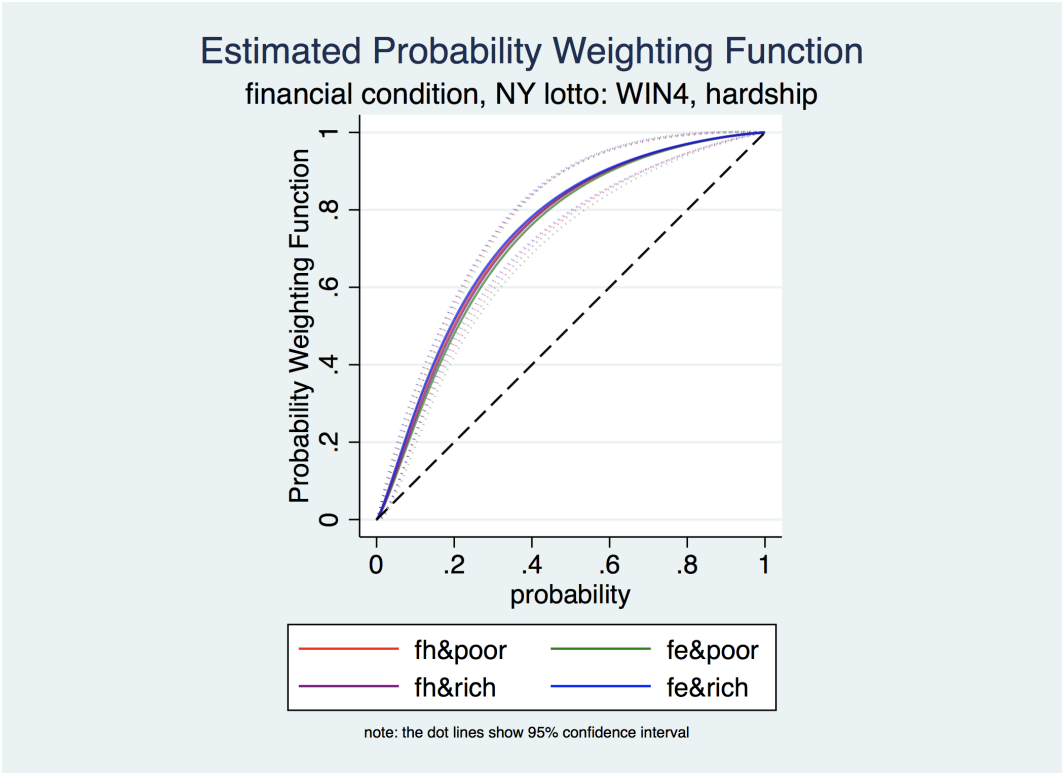

Figure C.7: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich based on hardship indicator: WIN4

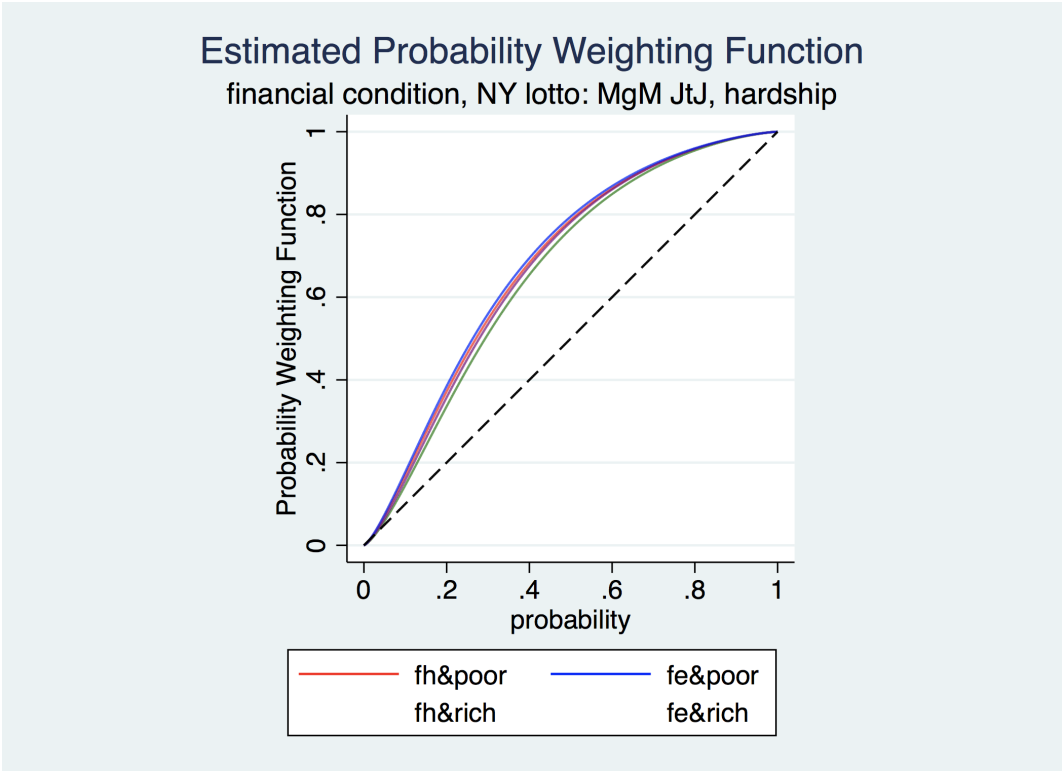

Figure C.8: Probability weighting function for financial hard vs. financial easy condition and for poor vs. rich based on hardship indicator: MGM JtJ

APPENDIX D

APPENDIX D OF CHAPTER 1

Format of Lottery Choice Task

Example of an experimental lottery choice task for ($12, 0.01; 0, 0.99) is shown in figure D.1. This is a shortened version with only nine price lists. The actual choice task contains the price lists with sure money varying down to zero cent. An example of filled multiple price list is shown in D.2. Subjects only need to select one switching point and all selected options are automatically filled. This is in order to save time, to make the choice task less tedious, and to enforce single switching.

For mixed lottery choice tasks, the introduction saying that subject would earn $3 after the survey (figure D.3) was designed to motivate the reference point and to induce loss aversion from the two lotteries with gains and losses. The choice tasks for the two mixed lotteries are different from pure gain lotteries in that the multiple prices are offered by varying the amount of loss, while the sure money stays the same at zero dollar. Figure D.4 shows a shortened version of the choice task for ($2, 0.5; $-L$, 0.5). The actual task varies the amount of loss down to twenty cent.

After all experimental lottery choice tasks were complete, the choice task for New York lotteries was introduced with an example. Firstly, it was emphasized, as in figure D.5, that betting numbers of all New York lotteries would be randomly picked. This was meant to reduce any anticipation about favorite numbers that could happen. Then, an instruction was given for the case of WIN4

24-way Combination ticket(figure D.6). Prize and Odd were informed, but the market price of the ticket wasn't. Twenty-one logarithmically-spaced price list was given.

In the lottery choice task section, two attention checks were embedded, one after all pure-gain lottery choice task (figure D.7) and another after all New York lottery choice task (figure D.8). In the former attention check, figure D.7, the lottery is actually not a lottery because it gave $0 no matter what. In the latter attention check, figure D.8, all sure money is zero hence completely an inferior choice to the New York lottery.

Cornell University

Please consider the following decisions between:

OPTION A:

A gamble offering a 1 in 100 chance to win $12 or $0 otherwise

Chance	Outcome
1 in 100 (i.e. 1%)	$12
99 in 100 (i.e. 99%)	$0

VS.

OPTION B:

The following amounts of sure money

Please indicate the option you prefer by checking the button next to that option.

	OPTION A: PREFER GAMBLE	**OR**	**OPTION B:** PREFER MONEY	
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		○	$12 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		○	$9 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		○	$6.74 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		○	$5.1 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		○	$3.79 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		○	$2.84 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		○	$2.13 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		○	$1.6 for sure

Figure D.1: Experimental lottery ($12, 0.01; 0, 0.99)

Cornell University

Please consider the following decisions between:

OPTION A:

A gamble offering a 1 in 100 chance to win $12 or $0 otherwise

Chance	Outcome
1 in 100 (i.e. 1%)	$12
99 in 100 (i.e. 99%)	$0

VS.

OPTION B:

The following amounts of sure money

Please indicate the option you prefer by checking the button next to that option.

	OPTION A: PREFER GAMBLE	**OR**	**OPTION B:** PREFER MONEY	
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		●	$12 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		●	$9 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		●	$6.74 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		●	$5.1 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		●	$3.79 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	○		●	$2.84 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	●		○	$2.13 for sure
Win $12 with a 1 in 100 chance, or Win $0 with a 99 in 100 chance	●		○	$1.6 for sure

Figure D.2: Experimental lottery ($12, 0.01; 0, 0.99) with selected options

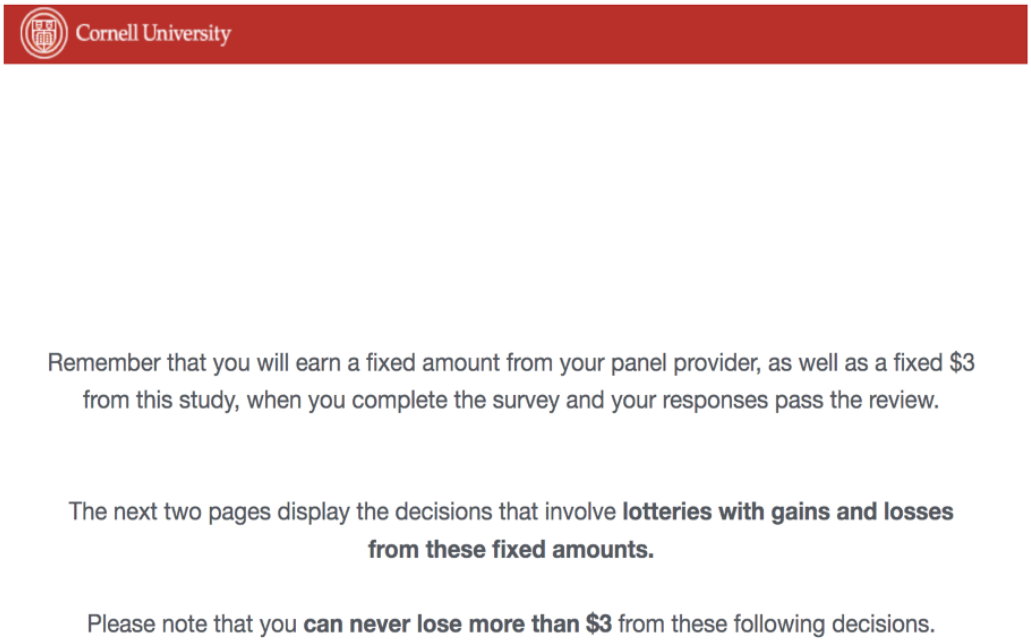

Figure D.3: Introduction of Mixed lottery choice task

Cornell University

Please consider the following decisions between:

OPTION A:

A gamble offering a 1 in 2 chance to **gain $2** and
a 1 in 2 chance to **lose** the following amounts of money

Chance	Outcome
1 in 2 (i.e. 50%)	**gain** $2
1 in 2 (i.e. 50%)	**lose** the following amounts

VS.

OPTION B:

US$0

NOTE that the sure amounts of money in this table are all $0.
This means that you will win nothing and lose nothing when you choose these $0 options.

Please indicate the option you prefer by checking the button next to that option.

	OPTION A: PREFER GAMBLE **(ACCEPT GAMBLE)**	**OR**	**OPTION B:** PREFER MONEY **(REJECT GAMBLE))**	
Gain $2 with a 1 in 2 chance **Lose $3** with a 1 in 2 chance	○		○	$0 for sure
Gain $2 with a 1 in 2 chance **Lose $2.8** with a 1 in 2 chance	○		○	$0 for sure
Gain $2 with a 1 in 2 chance **Lose $2.6** with a 1 in 2 chance	○		○	$0 for sure
Gain $2 with a 1 in 2 chance **Lose $2.4** with a 1 in 2 chance	○		○	$0 for sure
Gain $2 with a 1 in 2 chance **Lose $2.2** with a 1 in 2 chance	○		○	$0 for sure
Gain $2 with a 1 in 2 chance **Lose $2** with a 1 in 2 chance	○		○	$0 for sure
Gain $2 with a 1 in 2 chance **Lose $1.8** with a 1 in 2 chance	○		○	$0 for sure

Figure D.4: Experimental lottery ($2, 0.5; $-L$, 0.5)

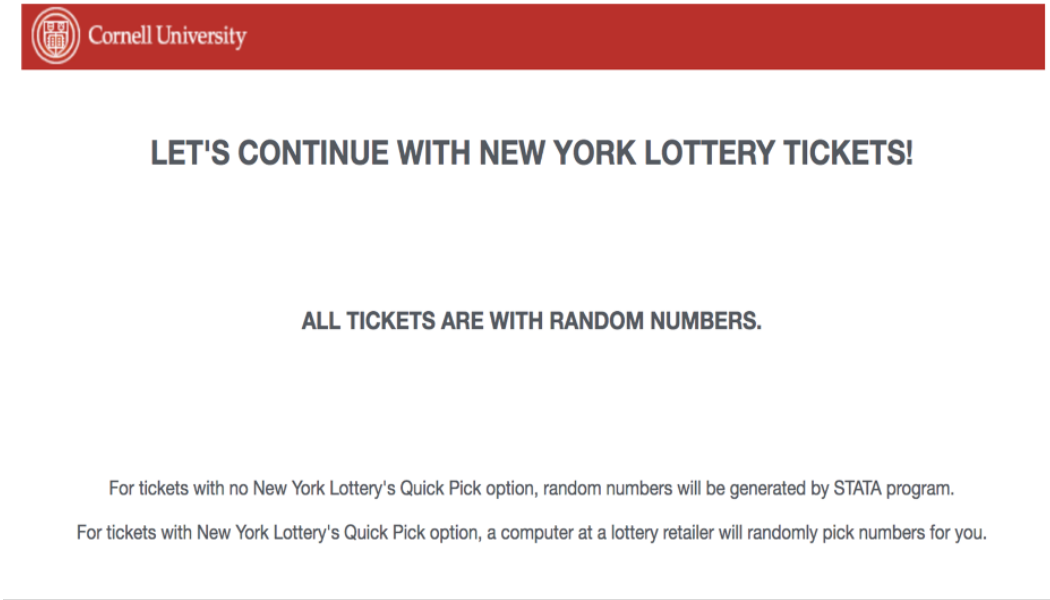

Figure D.5: Introduction of New York lottery choice task

EXAMPLE

This is to illustrate only. You will NOT be paid based on this example.

Please consider the following decisions between:

OPTION A:

One New York WIN4 24-way Combination ticket:

A ticket offering a 1 in 417 chance to win $2,500 or $0 otherwise

New York lottery ticket:	**WIN4**
Wager Type:	**24-WAY COMBINATION**
Prize:	**$2,500**
Odds of Winning:	**1 in 417**
Odds of Not Winning:	**416 in 417**

VS.

OPTION B:

The following amounts of sure money

Please indicate the option you prefer by checking the button next to that option.

Figure D.6: Example choice task for New York WIN4 24-way combination ticket

Cornell University

Please consider the following decisions between:

OPTION A:

A gamble offering a 1 in 2 chance to win $0 or $0 otherwise

Chance	Outcome
1 in 2 (i.e. 50%)	$0
1 in 2 (i.e. 50%)	$0

VS.

OPTION B:

The following amounts of sure money

Please indicate that you prefer the sure money for every choices in this following table (you can select the button next to the option '0¢ for sure') to pass this attention check.

	OPTION A: PREFER GAMBLE	**OR**	**OPTION B:** PREFER MONEY	
Win $0 with a 1 in 2 chance, or Win $0 with a 1 in 2 chance	○		○	$4 for sure
Win $0 with a 1 in 2 chance, or Win $0 with a 1 in 2 chance	○		○	$3.59 for sure
Win $0 with a 1 in 2 chance, or Win $0 with a 1 in 2 chance	○		○	$3.21 for sure
Win $0 with a 1 in 2 chance, or Win $0 with a 1 in 2 chance	○		○	$2.88 for sure
Win $0 with a 1 in 2 chance, or Win $0 with a 1 in 2 chance	○		○	$2.58 for sure
Win $0 with a 1 in 2 chance, or Win $0 with a 1 in 2 chance	○		○	$2.31 for sure
Win $0 with a 1 in 2 chance, or Win $0 with a 1 in 2 chance	○		○	$2.07 for sure

Figure D.7: Attention check in experimental lottery choice task

Cornell University

Please consider the following decisions between:

OPTION A:

One New York WIN4 24-way Combination ticket:

A ticket offering a 1 in 417 chance to win $2,500 or $0 otherwise

New York lottery ticket:	**WIN4**
Wager Type:	**24-WAY COMBINATION**
Prize:	**$2,500**
Odds of Winning:	**1 in 417**
Odds of Not Winning:	**416 in 417**

VS.

OPTION B:

US$0

Please indicate that you prefer the lottery ticket for every decisions in this following table to pass this attention check.

	OPTION A: PREFER TICKET	**OR**	**OPTION B:** PREFER MONEY	
WIN4(24-WAY COMBINATION) Win $2,500 with 1 in 417 chance Win $0 with 416 in 417 chance	○		○	$0 for sure
WIN4(24-WAY COMBINATION) Win $2,500 with 1 in 417 chance Win $0 with 416 in 417 chance	○		○	$0 for sure
WIN4(24-WAY COMBINATION) Win $2,500 with 1 in 417 chance Win $0 with 416 in 417 chance	○		○	$0 for sure

Figure D.8: Attention check in New York lottery choice task

BIBLIOGRAPHY

Abadie, A., S. Athey, G. Imbens, and J. Wooldridge (2017, October). When Should You Adjust Standard Errors for Clustering? *arXiv:1710.02926 [econ, math, stat]*.

Abdellaoui, M. (2000, November). Parameter-Free Elicitation of Utility and Probability Weighting Functions. *Management Science 46*(11), 1497–1512.

Abdellaoui, M., C. Barrios, and P. P. Wakker (2007, May). Reconciling introspective utility with revealed preference: Experimental arguments based on prospect theory. *Journal of Econometrics 138*(1), 356–378.

Abdellaoui, M., H. Bleichrodt, and O. L'Haridon (2008, June). A tractable method to measure utility and loss aversion under prospect theory. *Journal of Risk and Uncertainty 36*(3), 245–266.

Abdellaoui, M., H. Bleichrodt, and C. Paraschiv (2007, October). Loss Aversion Under Prospect Theory: A Parameter-Free Measurement. *Management Science 53*(10), 1659–1674.

Abdellaoui, M., F. Vossmann, and M. Weber (2005). Choice-Based Elicitation and Decomposition of Decision Weights for Gains and Losses under Uncertainty. *Management Science 51*(9), 1384–1399.

Ackerman, R. (2014, June). The diminishing criterion model for metacognitive regulation of time investment. *Journal of Experimental Psychology. General 143*(3), 1349–1368.

Addison, T., D. Hulme, and R. Kanbur (2009, January). *Poverty Dynamics*. Oxford University Press.

Andersson, O., H. J. Holm, J.-R. Tyran, and E. Wengström (2016, October). Risk Aversion Relates to Cognitive Ability: Preferences or Noise? *Journal of the European Economic Association 14*(5), 1129–1154.

Archuleta, K. L., A. Dale, and S. M. Spann (2013). College Students and Financial Distress: Exploring Debt, Financial Satisfaction, and Financial Anxiety. *24*(2), 13.

Ariyabuddhiphongs, V. and N. Chanchalermporn (2007, April). A Test of Social Cognitive Theory Reciprocal and Sequential Effects: Hope, Superstitious Belief and Environmental Factors among Lottery Gamblers in Thailand. *Journal of Gambling Studies 23*(2), 201–214.

Barberis, N. (2013, May). The Psychology of Tail Events: Progress and Challenges. *American Economic Review 103*(3), 611–616.

Baron, J., S. Scott, K. Fincher, and S. Emlen Metz (2015, September). Why does the Cognitive Reflection Test (sometimes) predict utilitarian moral judgment (and other things)? *Journal of Applied Research in Memory and Cognition 4*(3), 265–284.

Baron, R. M. and D. A. Kenny (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology 51*(6), 1173–1182.

Barseghyan, L., F. Molinari, T. O'Donoghue, and J. C. Teitelbaum (2013, October). The Nature of Risk Preferences: Evidence from Insurance Choices. *American Economic Review 103*(6), 2499–2529.

Barseghyan, L., F. Molinari, T. O'Donoghue, and J. C. Teitelbaum (2018). Estimating Risk Preferences in the Field. *Journal of Economic Literature*.

Benham, G. and R. Charak (2018). Stress and sleep remain significant predictors of health after controlling for negative affect. *Stress and Health 0*(0), 1–10.

Benjamin, D. J., S. A. Brown, and J. M. Shapiro (2013, December). Who is 'Behavioral'? Cognitive Ability and Anomalous Preferences. *Journal of the European Economic Association 11*(6), 1231–1255.

Bertrand, M., S. Mullainathan, and E. Shafir (2004). A Behavioral-Economics View of Poverty. *The American Economic Review 94*(2), 419–423.

Binswanger, H. P. (1980, August). Attitudes Toward Risk: Experimental Measurement in Rural India. *American Journal of Agricultural Economics 62*(3), 395–407.

Binswanger, H. P. (1981). Attitudes Toward Risk: Theoretical Implications of an Experiment in Rural India. *The Economic Journal 91*(364), 867–890.

Blalock, G., D. R. Just, and D. H. Simon (2007, July). Hitting the Jackpot or Hitting the Skids: Entertainment, Poverty, and the Demand for State Lotteries. *American Journal of Economics and Sociology 66*(3), 545–570.

Blavatskyy, P. (2006, May). Error Propagation in the Elicitation of Utility and Probability Weighting Functions. *Theory and Decision 60*(2-3), 315–334.

Booij, A. S., B. M. S. van Praag, and G. van de Kuilen (2010, February). A parametric analysis of prospect theory's functionals for the general population. *Theory and Decision 68*(1), 115–148.

Bordalo, P., N. Gennaioli, and A. Shleifer (2012, August). Salience Theory of Choice Under Risk. *The Quarterly Journal of Economics 127*(3), 1243–1285.

Bossert, W. and C. D'Ambrosio (2013). Measuring Economic Insecurity. *International Economic Review 54*(3), 1017–1030.

Bouchouicha, R. and F. M. Vieider (2017, August). Accommodating stake effects under prospect theory. *Journal of Risk and Uncertainty 55*(1), 1–28.

Bougherara, D., X. Gassmann, L. Piet, and A. Reynaud (2017, December). Structural estimation of farmers' risk and ambiguity preferences: A field experiment. *European Review of Agricultural Economics 44*(5), 782–808.

Bowles, S. (1998). Endogenous Preferences: The Cultural Consequences of Markets and Other Economic Institutions. *Journal of Economic Literature 36*(1), 75–111.

Broomell, S. B. and S. Bhatia (2014). Parameter recovery for decision modeling using choice data. *Decision 1*(4), 252–274.

Browne, M. J. and R. E. Hoyt (2000, May). The Demand for Flood Insurance: Empirical Evidence. *Journal of Risk and Uncertainty 20*(3), 291–306.

Bruhin, A., H. Fehr-Duda, and T. Epper (2010, July). Risk and Rationality: Uncovering Heterogeneity in Probability Distortion. *Econometrica 78*(4), 1375–1412.

Buhmann, B., L. Rainwater, G. Schmaus, and T. M. Smeeding (1988). Equivalence Scales, Well-Being, Inequality, and Poverty: Sensitivity Estimates Across Ten Countries Using the Luxembourg Income Study (lis) Database. *Review of Income and Wealth 34*(2), 115–142.

Burks, S. V., J. P. Carpenter, L. Goette, and A. Rustichini (2009, May). Cognitive skills affect economic preferences, strategic behavior, and job attachment. *Proceedings of the National Academy of Sciences 106*(19), 7745–7750.

Burns, Z., A. Chiu, and G. Wu (2011). Overweighting of Small Probabilities. In *Wiley Encyclopedia of Operations Research and Management Science*. American Cancer Society.

Cai, J. and C. Song (2017, January). Do disaster experience and knowledge affect insurance take-up decisions? *Journal of Development Economics 124*, 83–94.

Calvo, C. and S. Dercon (2007, August). Chronic Poverty and All that: The Measurement of Poverty Over Time. Chronic Poverty Research Centre Working Paper No. 89 ID 1646392, Social Science Research Network, Rochester, NY.

Camerer, C. and T. H. Ho (1999). Experience-weighted Attraction Learning in Normal Form Games. *Econometrica 67*(4), 827–874.

Camerer, C. and G. Loewenstein (2004). Behavioural Economics: Past, Present & Future. In C. Camerer, G. Loewenstein, and M. Rabin (Eds.), *Advances in Behavioral Economics*, Volume Roundtable series in behavioral economics. New York: Russell Sage Foundation.

Cameron, A. C. and D. L. Miller (2016, April). Robust Inference with Clustered Data. http://www.taylorfrancis.com/.

Carvalho, L. S., S. Meier, and S. W. Wang (2016, February). Poverty and Economic Decision-Making: Evidence from Changes in Financial Resources at Payday. *American Economic Review 106*(2), 260–284.

Case, R., D. M. Kurland, and J. Goldberg (1982, June). Operational efficiency and the growth of short-term memory span. *Journal of Experimental Child Psychology 33*(3), 386–404.

Chakravarty, S. R. (1983, December). A new index of poverty. *Mathematical Social Sciences 6*(3), 307–313.

Chantarat, S., K. Chheng, K. Minea, S. Oum, K. Samphantharak, and V. Sann (2015). The Effects of Natural Disasters on Households' Preferences and Behaviours: Evidence from Cambodian Rice Farmers After the 2011 Mega Flood. *Disaster Risks, Social Preferences, and Policy Effects: Field Experiments in Selected ASEAN and East Asian Countries ERIA Research Project Report 2013*(34), 47.

Chantarat, S., S. Oum, K. Samphantharak, and V. Sann (2019, August). Natural Disasters, Preferences, and Behaviors: Evidence from the 2011 Mega Flood in Cambodia. *Journal of Asian Economics 63*, 44–74.

Chiapello, M. (2018, November). BALANCETABLE: Stata module to build a balance table and print it in a LaTeX file or an Excel file. Boston College Department of Economics.

Choi, S., S. Kariv, W. Müller, and D. Silverman (2014, June). Who Is (More) Rational? *American Economic Review 104*(6), 1518–1550.

Choi, S., J. Kim, E. Lee, and J. Lee (2018, May). Probability Weighting and Cognitive Ability. Technical Report no121, Institute of Economic Research, Seoul National University.

Clark, L. A. and D. Watson (1991, August). Tripartite model of anxiety and depression: Psychometric evidence and taxonomic implications. *Journal of Abnormal Psychology 100*(3), 316–336.

Conte, A., M. V. Levati, and C. Nardi (2018, April). Risk Preferences and the Role of Emotions. *Economica 85*(338), 305–328.

Conway, A. R. A., M. J. Kane, M. F. Bunting, D. Z. Hambrick, O. Wilhelm, and

R. W. Engle (2005, October). Working memory span tasks: A methodological review and user's guide. *Psychonomic Bulletin & Review 12*(5), 769–786.

Crawford, J. R. and J. D. Henry (2004, September). The Positive and Negative Affect Schedule (PANAS): Construct validity, measurement properties and normative data in a large non-clinical sample. *British Journal of Clinical Psychology 43*(3), 245–265.

Crawford, V. P. and J. Meng (2011, August). New York City Cab Drivers' Labor Supply Revisited: Reference-Dependent Preferences with Rational-Expectations Targets for Hours and Income. *American Economic Review 101*(5), 1912–1932.

Crispim, A. C., L. Amorim, R. M. Cruz, D. Baasch, and R. L. Trevisan (2015). Measurement of Affect: From Theoretical and Instrumental Perspectives. *Psychology Research 5*(2), 96–107.

Csermely, T. and A. Rabas (2016, December). How to reveal people's preferences: Comparing time consistency and predictive power of multiple price list risk elicitation methods. *Journal of Risk and Uncertainty 53*(2-3), 107–136.

Dalton, P. S., N. Nhung, and J. Ruschenpohler (2016). The Right Amount of Income Variability: Evidence from Small Retailers in Vietnam. *DFID working paper, Tilberg university*, 22.

Dalton, P. S., N. Nhung, and J. Rüschenpöhler (2020, August). Worries of the poor: The impact of financial burden on the risk attitudes of micro-entrepreneurs. *Journal of Economic Psychology 79*, 102198.

Daneman, M. and P. A. Carpenter (1980, August). Individual differences in

working memory and reading. *Journal of Verbal Learning and Verbal Behavior 19*(4), 450–466.

Darrat, A. A., M. A. Darrat, and D. Amyx (2016, July). How impulse buying influences compulsive buying: The central role of consumer anxiety and escapism. *Journal of Retailing and Consumer Services 31*, 103–108.

Dean, E. B., F. Schilbach, and H. Schofield (2017). Poverty and Cognitive Function. *Working paper*.

Deaves, R., B. Kluger, and J. Miele (2018, August). An exploratory experimental analysis of path-dependent investment behaviors. *Journal of Economic Psychology 67*, 47–65.

Deck, C. and S. Jahedi (2015, August). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review 78*, 97–119.

Deryugina, T. (2013, May). How do people update? The effects of local weather fluctuations on beliefs about global warming. *Climatic Change 118*(2), 397–416.

Dessaint, O. and A. Matray (2017, October). Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics 126*(1), 97–121.

Destin, M. and R. C. Svoboda (2018, May). Costs on the Mind: The Influence of the Financial Burden of College on Academic Performance and Cognitive Functioning. *Research in Higher Education 59*(3), 302–324.

Diamond, A. (2013, January). Executive Functions. *Annual Review of Psychology 64*(1), 135–168.

Dohmen, T., A. Falk, D. Huffman, and U. Sunde (2010, June). Are Risk Aversion and Impatience Related to Cognitive Ability? *American Economic Review 100*(3), 1238–1260.

Dohmen, T., A. Falk, D. Huffman, and U. Sunde (2018, May). On the Relationship between Cognitive Ability and Risk Preference. *Journal of Economic Perspectives 32*(2), 115–134.

Donkers, B., B. Melenberg, and A. V. Soest (2001, March). Estimating Risk Attitudes using Lotteries: A Large Sample Approach. *Journal of Risk and Uncertainty 22*(2), 165–195.

Duquennois, C. (2019, October). Fictional Money, Real Costs: Impacts of Financial Salience on Disadvantaged Students. *Working paper*.

Eckel, C. C. and P. J. Grossman (2002, July). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and Human Behavior 23*(4), 281–295.

Ekkekakis, P. (2013). *The Measurement of Affect, Mood, and Emotion: A Guide for Health-Behavioral Research*. The Measurement of Affect, Mood, and Emotion: A Guide for Health-Behavioral Research. New York, NY, US: Cambridge University Press.

Ekman, P. and R. J. Davidson (Eds.) (1994). *The Nature of Emotion: Fundamental Questions*. The Nature of Emotion: Fundamental Questions. New York, NY, US: Oxford University Press.

Engle, R. W. (2010). Role of Working-Memory Capacity in Cognitive Control. *Current Anthropology 51*(S1), S17–S26.

Erner, C., A. Klos, and T. Langer (2013, June). Can prospect theory be used to predict an investor's willingness to pay? *Journal of Banking & Finance 37*(6), 1960–1973.

Etchart-Vincent, N. (2004, May). Is Probability Weighting Sensitive to the Magnitude of Consequences? An Experimental Investigation on Losses. *Journal of Risk and Uncertainty 28*(3), 217–235.

Etchart-Vincent, N. (2009, August). Probability weighting and the 'level' and 'spacing' of outcomes: An experimental study over losses. *Journal of Risk and Uncertainty 39*(1), 45–63.

Fehr, E. and L. Goette (2007, March). Do Workers Work More if Wages Are High? Evidence from a Randomized Field Experiment. *American Economic Review 97*(1), 298–317.

Fehr-Duda, H., A. Bruhin, T. Epper, and R. Schubert (2010, April). Rationality on the rise: Why relative risk aversion increases with stake size. *Journal of Risk and Uncertainty 40*(2), 147–180.

Fehr-Duda, H., M. de Gennaro, and R. Schubert (2006, May). Gender, Financial Risk, and Probability Weights. *Theory and Decision 60*(2-3), 283–313.

Foster, J., J. Greer, and E. Thorbecke (1984). A Class of Decomposable Poverty Measures. *Econometrica 52*(3), 761–766.

Frederick, S. (2005, December). Cognitive Reflection and Decision Making. *Journal of Economic Perspectives 19*(4), 25–42.

Freudenreich, H., O. Musshoff, and B. Wiercinski (2017). The Relationship between Farmers' Shock Experiences and their Uncertainty Preferences - Experimental Evidence from Mexico. *Working paper*.

Fritz, M. S. and D. P. Mackinnon (2007, March). Required sample size to detect the mediated effect. *Psychological Science 18*(3), 233–239.

Fünfgeld, B. and M. Wang (2009, February). Attitudes and behaviour in everyday finance: Evidence from Switzerland. *International Journal of Bank Marketing 27*(2), 108–128.

Gallagher, J. (2014, July). Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States. *American Economic Journal: Applied Economics 6*(3), 206–233.

Gennaioli, N. and A. Shleifer (2010, November). What Comes to Mind. *The Quarterly Journal of Economics 125*(4), 1399–1433.

Gerhardt, H., G. P. Biele, H. R. Heekeren, and H. Uhlig (2016, March). Cognitive Load Increases Risk Aversion. Technical Report SFB649DP2016-011, Sonderforschungsbereich 649, Humboldt University, Berlin, Germany.

Glöckner, A. and T. Pachur (2012, April). Cognitive models of risky choice: Parameter stability and predictive accuracy of prospect theory. *Cognition 123*(1), 21–32.

Gneezy, U. and J. Potters (1997). An Experiment on Risk Taking and Evaluation Periods. *The Quarterly Journal of Economics 112*(2), 631–645.

Goldstein, W. M. and H. J. Einhorn (1987). Expression theory and the preference reversal phenomena. *Psychological Review 94*(2), 236–254.

Gonzalez, R. and G. Wu (1999, February). On the Shape of the Probability Weighting Function. *Cognitive Psychology 38*(1), 129–166.

Graves, V. (2015, May). Does Poverty Really Impede Cognitive Function? Experimental Evidence from Tanzanian Fishers. *Master's Theses*.

Guiso, L. and M. Paiella (2008). Risk Aversion, Wealth, and Background Risk. *Journal of the European Economic Association 6*(6), 1109–1150.

Günther, I. and J. K. Maier (2014). Poverty, Vulnerability, and Reference-Dependent Utility. *Review of Income and Wealth 60*(1), 155–181.

Hackman, D. A. and M. J. Farah (2009, February). Socioeconomic status and the developing brain. *Trends in cognitive sciences 13*(2), 65–73.

Haisley, E., R. Mostafa, and G. Loewenstein (2008, July). Subjective relative income and lottery ticket purchases. *Journal of Behavioral Decision Making 21*(3), 283–295.

Harbaugh, W. T., K. Krause, and L. Vesterlund (2002, June). Risk Attitudes of Children and Adults: Choices Over Small and Large Probability Gains and Losses. *Experimental Economics 5*(1), 53–84.

Harmon-Jones, C., B. Bastian, and E. Harmon-Jones (2016, August). The Discrete Emotions Questionnaire: A New Tool for Measuring State Self-Reported Emotions. *PLOS ONE 11*(8), e0159915.

Harmon-Jones, E., C. Harmon-Jones, and E. Summerell (2017, September). On the Importance of Both Dimensional and Discrete Models of Emotion. *Behavioral Sciences 7*(4), 66.

Harrison, G. W., S. J. Humphrey, and A. Verschoor (2010). Choice under Uncertainty: Evidence from Ethiopia, India and Uganda*. *The Economic Journal 120*(543), 80–104.

Harrison, G. W. and E. E. Rutström (2009, June). Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics 12*(2), 133.

Harrison, G. W. and J. T. Swarthout (2016). Cumulative Prospect Theory in the Laboratory: A Reconsideration. *Working paper*, 103.

Haushofer, J. and E. Fehr (2014, May). On the psychology of poverty. *Science 344*(6186), 862–867.

Haushofer, J., D. Schunk, and E. Fehr (2013). Negative Income Shocks Increase Discount Rates. *Working paper*.

Haushofer, J. and J. Shapiro (2016, November). The Short-term Impact of Unconditional Cash Transfers to the Poor: Experimental Evidence from Kenya. *The Quarterly Journal of Economics 131*(4), 1973–2042.

Hayhoe, C. R., S. H. Cho, S. A. DeVaney, S. L. Worthy, J. Kim, and E. Gorham (2012). How Do Distrust and Anxiety Affect Saving Behavior? *Family and Consumer Sciences Research Journal 41*(1), 69–85.

Henninger, F., Y. Shevchenko, U. Mertens, P. J. Kieslich, and B. E. Hilbig (2019, January). Lab.js: A free, open, online study builder.

Heo, W., S. Cho, and P. Lee (2017, September). How Can We Know Our Clients' Financial Stress? SSRN Scholarly Paper ID 3037527, Social Science Research Network, Rochester, NY.

Hertwig, R., G. Barron, E. U. Weber, and I. Erev (2004, August). Decisions from Experience and the Effect of Rare Events in Risky Choice. *Psychological Science 15*(8), 534–539.

Hey, J. D. and C. Orme (1994). Investigating Generalizations of Expected Utility Theory Using Experimental Data. *Econometrica 62*(6), 1291–1326.

Hilgard, E. R. (1980). The trilogy of mind: Cognition, affection, and conation. *Journal of the History of the Behavioral Sciences 16*(2), 107–117.

Ifcher, J. and H. Zarghamee (2011, December). Happiness and Time Preference: The Effect of Positive Affect in a Random-Assignment Experiment. *American Economic Review 101*(7), 3109–3129.

Inzlicht, M., B. D. Bartholow, and J. B. Hirsh (2015, March). Emotional foundations of cognitive control. *Trends in cognitive sciences 19*(3), 126–132.

Iwaki, H. and Y. Osaki (2010, June). Some properties of subjective probabilities induced by optimal expectations. *Finance Research Letters 7*(2), 98–102.

Jäntti, M., R. Kanbur, M. Nyyssölä, and J. Pirttilä (2014). Poverty and Welfare Measurement on the Basis of Prospect Theory. *Review of Income and Wealth 60*(1), 182–205.

Jarosz, A. F. and J. Wiley (2012, September). Why does working memory capacity predict RAPM performance? A possible role of distraction. *Intelligence 40*(5), 427–438.

Jimenez, N., I. Rodriguez-Lara, J.-R. Tyran, and E. Wengström (2018, January). Thinking fast, thinking badly. *Economics Letters 162*, 41–44.

Jimenez, V. G. (2017). On the psychological motives of economic performance. *Tilburg University Dissertation*.

Joy, E. E. (2017, May). For the poor, Does attentional bias or worry explain the relationship between financial stressors and poor cognitive performance?

Kahneman, D. and S. Frederick (2002, July). Representativeness Revisited: Attribute Substitution in Intuitive Judgment. In T. Gilovich, D. Griffin, and D. Kahneman (Eds.), *Heuristics and Biases* (First ed.)., pp. 49–81. Cambridge University Press.

Kahneman, D., J. L. Knetsch, and R. H. Thaler (1990). Experimental Tests of the Endowment Effect and the Coase Theorem. *Journal of Political Economy 98*(6), 1325–1348.

Kahneman, D., J. L. Knetsch, and R. H. Thaler (1991, March). Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias. *Journal of Economic Perspectives 5*(1), 193–206.

Kahneman, D., P. Slovic, and A. Tversky (Eds.) (1982, April). *Judgment under Uncertainty: Heuristics and Biases* (First ed.). Cambridge University Press.

Kahneman, D. and A. Tversky (1979a, March). Prospect Theory: An Analysis of Decision under Risk. *Econometrica 47*(2), 263.

Kahneman, D. and A. Tversky (1979b). Prospect Theory: An Analysis of Decision under Risk. *Econometrica 47*(2), 263–291.

Kala, N. (2019). Learning, Adaptation, and Climate Uncertainty: Evidence from Indian Agriculture. *Working paper*, 52.

Kane, M. J., D. Z. Hambrick, S. W. Tuholski, O. Wilhelm, T. W. Payne, and R. W. Engle (2004, June). The generality of working memory capacity: A latent-variable approach to verbal and visuospatial memory span and reasoning. *Journal of Experimental Psychology. General 133*(2), 189–217.

Kemel, E. and C. Paraschiv (2018, June). Deciding about human lives: An experimental measure of risk attitudes under prospect theory. *Social Choice and Welfare 51*(1), 163–192.

Knight, S. and A. Heinrich (2017, March). Different Measures of Auditory and Visual Stroop Interference and Their Relationship to Speech Intelligibility in Noise. *Frontiers in Psychology 8*.

Kőszegi, B. and M. Rabin (2006, November). A Model of Reference-Dependent Preferences. *The Quarterly Journal of Economics 121*(4), 1133–1165.

Kőszegi, B. and M. Rabin (2007). Reference-Dependent Risk Attitudes. *The American Economic Review 97*(4), 1047–1073.

Kőszegi, B. and M. Rabin (2009, June). Reference-Dependent Consumption Plans. *American Economic Review 99*(3), 909–936.

Kousky, C. and L. Shabman (2015, February). Understanding Flood Risk Decision making: Implications for Flood Risk Communication Program Design. SSRN Scholarly Paper ID 2561374, Social Science Research Network, Rochester, NY.

Krongkaew, M. (2002, April). Alienated Life: Socioeconomic Characteristics of the Ultra Poor in Thailand. *Journal of Asian and African Studies 37*(2), 128–146.

Lang, F., D. Weiss, A. Stocker, and B. von Rosenbladt (2007). Assessing Cognitive Capacities in Computer-Assisted Survey Research: Two Ultra-Short Tests of Intellectual Ability in the German Socio-Economic Panel (SOEP). *Schmollers Jahrbuch : Journal of Applied Social Science Studies / Zeitschrift für Wirtschafts- und Sozialwissenschaften 127*(1), 183–192.

Lattimore, P. K., J. R. Baker, and A. D. Witte (1992, May). The influence of probability on risky choice: A parametric examination. *Journal of Economic Behavior & Organization 17*(3), 377–400.

Lench, H. C., S. A. Flores, and S. W. Bench (2011, September). Discrete emotions predict changes in cognition, judgment, experience, behavior, and physiology: A meta-analysis of experimental emotion elicitations. *Psychological Bulletin 137*(5), 834–855.

Lerner, J. S. and D. Keltner (2000). Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cognition and Emotion 14*(4), 473–493.

Lerner, J. S., Y. Li, P. Valdesolo, and K. S. Kassam (2015). Emotion and Decision Making. *Annual Review of Psychology 66*(1), 799–823.

Liang, C.-Y. (2017, October). Optimal inequality behind the veil of ignorance. *Theory and Decision 83*(3), 431–455.

Lichand, G. and A. Mani (2016). Cognitive Droughts. CAGE Online Working Paper Series, Competitive Advantage in the Global Economy (CAGE).

Lichand, G. and A. Mani (2020, February). Cognitive Droughts. SSRN Scholarly Paper ID 3540149, Social Science Research Network, Rochester, NY.

Lipina, S., S. Segretin, J. Hermida, L. Prats, C. Fracchia, J. L. Camelo, and J. Colombo (2013). Linking childhood poverty and cognition: Environmental mediators of non-verbal executive control in an Argentine sample. *Developmental Science 16*(5), 697–707.

Lipkus, I. M., G. Samsa, and B. K. Rimer (2001, February). General Performance

on a Numeracy Scale among Highly Educated Samples. *Medical Decision Making 21*(1), 37–44.

Loewenstein, G. (2000). Emotions in Economic Theory and Economic Behavior. *The American Economic Review 90*(2), 426–432.

Loewenstein, G. and J. S. Lerner (2003). The role of affect in decision making. In *Handbook of Affective Sciences*, Series in Affective Science, pp. 619–642. New York, NY, US: Oxford University Press.

Loewenstein, G., T. O'Donoghue, and S. Bhatia (2015). Modeling the interplay between affect and deliberation. *Decision 2*(2), 55–81.

Loewenstein, G. F., E. U. Weber, C. K. Hsee, and N. Welch (2001). Risk as feelings. *Psychological Bulletin 127*(2), 267–286.

MacLeod, C. M. (1991). Half a century of research on the Stroop effect: An integrative review. *Psychological Bulletin 109*(2), 163–203.

Malmendier, U. and S. Nagel (2011, February). Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?*. *The Quarterly Journal of Economics 126*(1), 373–416.

Malmendier, U. and S. Nagel (2016, February). Learning from Inflation Experiences. *The Quarterly Journal of Economics 131*(1), 53–87.

Mani, A., S. Mullainathan, E. Shafir, and J. Zhao (2013a, August). Poverty Impedes Cognitive Function. *Science 341*(6149), 976.

Mani, A., S. Mullainathan, E. Shafir, and J. Zhao (2013b, December). Response to Comment on "Poverty Impedes Cognitive Function". *Science 342*(6163), 1169–1169.

Markowitz, H. (1952, April). The Utility of Wealth. *Journal of Political Economy 60*(2), 151–158.

McManus, J. (2014, August). Cognitive Function and Beliefs in Luck in the Consumer Context. SSRN Scholarly Paper ID 2521071, Social Science Research Network, Rochester, NY.

McManus, M. D., J. T. Siegel, and J. Nakamura (2018, August). The predictive power of low-arousal positive affect. *Motivation and Emotion*.

Menapace, L., G. Colson, and R. Raffaelli (2012). Cognitive Heuristics and Farmers' Perceptions of Risks Related to Climate Change. Technical Report 124770, Agricultural and Applied Economics Association.

Mezzacappa, E. (2004). Alerting, Orienting, and Executive Attention: Developmental Properties and Sociodemographic Correlates in an Epidemiological Sample of Young, Urban Children. *Child Development 75*(5), 1373–1386.

Miller, E. K. and J. D. Cohen (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience 24*, 167–202.

Moneta, G. B., A. Vulpe, and J. Rogaten (2012, September). Can positive affect "undo" negative affect? A longitudinal study of affect in studying. *Personality and Individual Differences 53*(4), 448–452.

Mullainathan, S. and E. Shafir (2013, September). *Scarcity: Why Having Too Little Means So Much*. Times Books.

Muller, D., C. M. Judd, and V. Y. Yzerbyt (2005). When moderation is mediated and mediation is moderated. *Journal of Personality and Social Psychology 89*(6), 852–863.

NESDB (2014). Poverty and Inequality Statistics 1988-2014.

Nilsson, H., J. Rieskamp, and E.-J. Wagenmakers (2011, February). Hierarchical Bayesian parameter estimation for cumulative prospect theory. *Journal of Mathematical Psychology 55*(1), 84–93.

Pachur, T., R. Mata, and R. Hertwig (2017, April). Who Dares, Who Errs? Disentangling Cognitive and Motivational Roots of Age Differences in Decisions Under Risk. *Psychological Science 28*(4), 504–518.

Park, N. Y. (2016, April). Domain-specific risk preference and cognitive ability. *Economics Letters 141*, 1–4.

Povel, F. (2015, July). Measuring Exposure to Downside Risk with an Application to Thailand and Vietnam. *World Development 71*, 4–24.

Prelec, D. (1998). The Probability Weighting Function. *Econometrica 66*(3), 497–527.

Primi, C., K. Morsanyi, F. Chiesi, M. A. Donati, and J. Hamilton (2016). The Development and Testing of a New Version of the Cognitive Reflection Test Applying Item Response Theory (IRT). *Journal of Behavioral Decision Making 29*(5), 453–469.

Quigley, K. S., K. A. Lindquist, and L. F. Barrett (2014, February). Inducing and Measuring Emotion and Affect. /core/books/handbook-of-research-methods-in-social-and-personality-psychology/inducing-and-measuring-emotion-and-affect/F4CB49AC001474625EF11E8BE74AD7F1.

Raven, J. and J. Raven (2003). Raven Progressive Matrices. In R. S. McCallum (Ed.), *Handbook of Nonverbal Assessment*, pp. 223–237. Boston, MA: Springer US.

Rieger, M. O., M. Wang, and T. Hens (2017, April). Estimating cumulative prospect theory parameters from an international survey. *Theory and Decision 82*(4), 567–596.

Rossi, V. and G. Pourtois (2012, November). Transient state-dependent fluctuations in anxiety measured using STAI, POMS, PANAS or VAS: A comparative review. *Anxiety, Stress, & Coping 25*(6), 603–645.

Rottenstreich, Y. and C. K. Hsee (2001, May). Money, Kisses, and Electric Shocks: On the Affective Psychology of Risk. *Psychological Science 12*(3), 185–190.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology 39*(6), 1161–1178.

Schilbach, F., H. Schofield, and S. Mullainathan (2016, May). The Psychological Lives of the Poor. *American Economic Review 106*(5), 435–440.

Schneider, P. (2004, November). Why should the poor insure? Theories of decision-making in the context of health insurance. *Health Policy and Planning 19*(6), 349–355.

Scholten, M. and D. Read (2014, February). Prospect theory and the "forgotten" fourfold pattern of risk preferences. *Journal of Risk and Uncertainty 48*(1), 67–83.

Shah, A. K., S. Mullainathan, and E. Shafir (2012, November). Some consequences of having too little. *Science (New York, N.Y.) 338*(6107), 682–685.

Shah, A. K., E. Shafir, and S. Mullainathan (2015, April). Scarcity Frames Value. *Psychological Science 26*(4), 402–412.

Shah, A. K., J. Zhao, S. Mullainathan, and E. Shafir (2018, January). Money in the Mental Lives of the Poor. *Social Cognition 36*(1), 4–19.

Shapiro, G. K. and B. J. Burchell (2012). Measuring financial anxiety. *Journal of Neuroscience, Psychology, and Economics 5*(2), 92–103.

Simon, H. (1990, July). *Reason in Human Affairs*. Stanford University Press.

Simon, H. A. (1967). Motivational and emotional controls of cognition. *Psychological Review 74*(1), 29–39.

Sirota, M. and M. Juanchich (2018, December). Effect of response format on cognitive reflection: Validating a two- and four-option multiple choice question version of the Cognitive Reflection Test. *Behavior Research Methods 50*(6), 2511–2522.

Slovic, P., B. Fischhoff, S. Lichtenstein, B. Corrigan, and B. Combs (1977). Preference for Insuring against Probable Small Losses: Insurance Implications. *The Journal of Risk and Insurance 44*(2), 237–258.

Spears, D. (2011, January). Economic Decision-Making in Poverty Depletes Behavioral Control. *The B.E. Journal of Economic Analysis & Policy 11*(1).

Stanovich, K. E. (2009). Rational and Irrational Thought: The Thinking That IQ Tests Miss. *Scientific American Mind 20*(6), 34–39.

Stott, H. P. (2006, March). Cumulative prospect theory's functional menagerie. *Journal of Risk and Uncertainty 32*(2), 101–130.

Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology 18*(6), 643–662.

Tanaka, T., C. F. Camerer, and Q. Nguyen (2010, March). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review 100*(1), 557–571.

Taylor, S. E. and S. C. Thompson (1982). Stalking the elusive "vividness" effect. *Psychological Review 89*(2), 155–181.

Thompson, E. R. (2007, March). Development and Validation of an Internationally Reliable Short-Form of the Positive and Negative Affect Schedule (PANAS). *Journal of Cross-Cultural Psychology 38*(2), 227–242.

Thompson, E. R. and G. P. Prendergast (2015, April). The influence of trait affect and the five-factor personality model on impulse buying. *Personality and Individual Differences 76*, 216–221.

Thomson, K. S. and D. M. Oppenheimer (2016). Investigating an alternate form of the cognitive reflection test. *Judgment and Decision Making 11*(1), 15.

Toplak, M. E., R. F. West, and K. E. Stanovich (2011, May). The Cognitive Reflection Test as a predictor of performance on heuristics-and-biases tasks. *Memory & Cognition 39*(7), 1275.

Toplak, M. E., R. F. West, and K. E. Stanovich (2014, April). Assessing miserly information processing: An expansion of the Cognitive Reflection Test. *Thinking & Reasoning 20*(2), 147–168.

Townsend, R. M. (1994). Risk and Insurance in Village India. *Econometrica 62*(3), 539–591.

Townsend, R. M. (2009a). Townsend Thai Project Household Annual Resurvey, 2000.

Townsend, R. M. (2009b). Townsend Thai Project Household Annual Resurvey, 2001.

Townsend, R. M. (2009c). Townsend Thai Project Household Annual Resurvey, 2002.

Townsend, R. M. (2009d). Townsend Thai Project Household Annual Resurvey, 2003.

Townsend, R. M. (2009e). Townsend Thai Project Household Annual Resurvey, 2004.

Townsend, R. M. (2009f). Townsend Thai Project Household Annual Resurvey, 2005 (Rural).

Townsend, R. M. (2009g). Townsend Thai Project Household Annual Resurvey, 2006 (Rural).

Townsend, R. M. (2009h). Townsend Thai Project Household Annual Resurvey, 2007 (Rural).

Townsend, R. M. (2011a). Townsend Thai Project Household Annual Resurvey, 2008 (Rural).

Townsend, R. M. (2011b). Townsend Thai Project Household Annual Resurvey, 2009 (Rural).

Townsend, R. M. (2011c). Townsend Thai Project Household Annual Resurvey, 2010 (Rural).

Townsend, R. M. (2013). Townsend Thai Project Household Annual Resurvey, 2011 (Rural).

Tran, V. (2013). Positive Affect Negative Affect Scale (PANAS). In M. D. Gellman and J. R. Turner (Eds.), *Encyclopedia of Behavioral Medicine*, pp. 1508–1509. New York, NY: Springer New York.

Turner, G., F. Said, and U. Afzal (2014, April). Microinsurance Demand After a Rare Flood Event: Evidence From a Field Experiment in Pakistan. *The Geneva Papers on Risk and Insurance - Issues and Practice 39*(2), 201–223.

Turner, M. L. and R. W. Engle (1989, April). Is working memory capacity task dependent? *Journal of Memory and Language 28*(2), 127–154.

Tversky, A. and D. Kahneman (1973, September). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology 5*(2), 207–232.

Tversky, A. and D. Kahneman (1974, September). Judgment under Uncertainty: Heuristics and Biases. *Science 185*(4157), 1124–1131.

Vieider, F. M., P. Martinsson, P. K. Nam, and N. Truong (2019, February). Risk preferences and development revisited. *Theory and Decision 86*(1), 1–21.

Viseu, J., R. Leal, S. N. de Jesus, P. Pinto, P. Pechorro, and E. Greenglass (2018, October). Relationship between economic stress factors and stress, anxiety, and depression: Moderating role of social support. *Psychiatry Research 268*, 102–107.

Vogt, A. S. (2018, April). Induced emotions and economic behavior: An experimental approach.

Watson, D. (2000). *Mood and Temperament*. Mood and Temperament. New York, NY, US: Guilford Press.

Watson, D. and L. A. Clark (1997, April). Measurement and mismeasurement of mood: Recurrent and emergent issues. *Journal of Personality Assessment 68*(2), 267–296.

Watson, D. and L. A. Clark (1999, August). The PANAS-X: Manual for the Positive and Negative Affect Schedule - Expanded Form. *Psychology Publications*.

Watson, D., L. A. Clark, and A. Tellegen (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology 54*(6), 1063–1070.

Watson, D. and A. Tellegen (1985). Toward a consensual structure of mood. *Psychological Bulletin 98*(2), 219–235.

Wicherts, J. M. and A. Z. Scholten (2013, December). Comment on "Poverty Impedes Cognitive Function". *Science 342*(6163), 1169–1169.

Wilcox, N. T. (2011, May). 'Stochastically more risk averse:' A contextual theory of stochastic discrete choice under risk. *Journal of Econometrics 162*(1), 89–104.

Wu, G., J. Zhang, and R. Gonzalez (2004, January). Decision Under Risk. In D. J. Koehler and N. Harvey (Eds.), *Blackwell Handbook of Judgment and Decision Making*, pp. 399–423. Malden, MA, USA: Blackwell Publishing Ltd.

Yesuf, M. and R. A. Bluffstone (2009a, November). Poverty, Risk Aversion, and Path Dependence in Low-Income Countries: Experimental Evidence from Ethiopia. *American Journal of Agricultural Economics 91*(4), 1022–1037.

Yesuf, M. and R. A. Bluffstone (2009b, November). Poverty, Risk Aversion, and Path Dependence in Low-Income Countries: Experimental Evidence from Ethiopia. *American Journal of Agricultural Economics 91*(4), 1022–1037.

Zaleskiewicz, T., Z. Piskorz, and A. Borkowska (2002, December). Fear or money? Decisions on insuring oneself against flood. *Risk Decision and Policy 7*(3), 221–233.

Zeisberger, S., D. Vrecko, and T. Langer (2012, March). Measuring the time stability of Prospect Theory preferences. *Theory and Decision 72*(3), 359–386.