ESSAYS IN BEHAVIORAL AND ENERGY ECONOMICS

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This thesis presents three studies in behavioral and energy economics. The first two use laboratory experiment to show how individuals make decisions under risk and uncertainty. The third study uses a simulation tool to investigate the environmental effect of an institutional change.

Study 1 studies reference dependent behavior under risk using a controlled laboratory experiment and demonstrates the need of probability weighting in explaining the observed behavior. The paper also suggests a behavioral model that explains reference dependence under risk using loss aversion and rank-dependent probability weighting. The behavioral model used in the estimation is flexible enough to accommodate both expected utility theory and prospect theory as special cases.

Study 2 conducts a set of laboratory experiments on a simulated hazard event to understand how individuals allocate resources between private insurance and public good measures to reduce the likelihood of the hazardous event. By inducing negative emotions with distressing video images and very loud unexpected sounds of explosions, we find that fear increases support for both public measures and private insurance in response to the threat. Our findings suggest that people purchase private insurance to address emotional as well as financial concerns even though private insurance may not help to reduce negative emotions associated with the simulated events. We also propose a model using Subjective Expected Utility (SEU) theory to explain the experimental data.

Results imply that limited social resources may not be efficiently allocated between public and private solutions regarding uncertain hazardous events due to emotional responses.

Study 3 uses a detailed simulation tool (E4ST) of the Eastern Interconnect (EI) to identify the environmental effect of RTP in different regions. The simulation uses a detailed network model which contains all high voltage lines in EI. Moreover, it also accommodates different hour types so we are able to simulate consumption pattern changes. Using generator level cost and emission data, we conduct two sets of simulations. The first set simulates consumption change under different demand elasticities while the second set keeps consumption constant and investigates how load variation affects emissions. We reach a similar conclusion as Holland and Mansur (2008) that RTP may lead to high emission levels in some regions but our results explain this conclusion with different reasons.

BIOGRAPHICAL SKETCH

Jubo Yan joined the Charles H. Dyson School of Applied Economics and Management at Cornell University for his PhD study in 2010. Before then, Jubo received a bachelor's degree in Computer Science and a dual degree in Business Administration both from Beijing Normal University in 2005. After college, Jubo continued his study at BNU and received a master's degree in Financial Economics in 2008. Before joining Cornell, Jubo also received another master's degree in Agricultural and Resource Economics from University of Delaware.

Jubo's research interests include behavioral economics, experimental economics, and examining policy related issues. He is particularly interested in individual decision making under risk and uncertainty both theoretically and empirically. Jubo extensively uses laboratory experiments to answer different questions. These questions include how individuals treat known and unknown probabilities; how emotions, framing and contextual factors affect risk attitudes; how to induce cooperative actions through non-monetary incentives to improve efficiency. He also conducts industrial organization experiments to test different market structures especially those in the agricultural markets.

Jubo works on different projects and with many researchers from different fields and institutions. These researchers include economists, psychologists, electrical engineers from universities, government agencies and consulting firms. During his graduate study, Jubo has published articles in journals like *Environmental and Resources Economics* and *Resource and Energy Economics*. He has also presented his research at many professional conferences.

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TABLE OF CONTENTS

Biographical Sketch . . . iii
Acknowledgements . . . iv
Table of Contents . . . vi
List of Tables . . . viii
List of Figures . . . ix

1 Overview 1

2 Reference Dependence under Risk: An Experimental Examination 5
2.1 Introduction . . . 5
2.2 Experimental Design . . . 10
2.2.1 Structure . . . 10
2.2.2 Details . . . 13
2.3 Results . . . 19
2.4 Structural Analysis . . . 26
2.4.1 Expected Utility Theory . . . 27
2.4.2 Loss Aversion and Possible Reference Points . . . 28
2.4.3 Rank Dependent Probability Weighting . . . 31
2.4.4 A Behavioral Model . . . 33
2.4.5 Estimation . . . 36
2.4.6 Validation . . . 41
2.4.7 Robustness and Discussion . . . 46
2.5 Conclusion . . . 50

3 Emotions and Subjective Probabilities: An Example of Terrorism Insurance 55
3.1 Introduction . . . 55
3.1.1 Influence of Emotions . . . 56
3.1.2 Calculations of Risk . . . 56
3.1.3 Previous Field and Experimental Studies . . . 58
3.2 Experimental Design and Procedures . . . 60
3.2.1 Theoretical Framework . . . 60
3.2.2 Experimental Procedure . . . 64
3.3 Results . . . 67
3.4 Possible Explanations . . . 79
3.5 Conclusion . . . 84

4 Is Real-time Pricing Green? A Simulation Study Using Detailed Network Model 87
4.1 Introduction . . . 87
4.2 Conceptual Analysis . . . 89
4.3 The Simulation Model and Data . . . 94

4.4 Results and Discussions 99
4.5 Conclusion 109

A Appendices of Chapter 2 **111**
A.1 Predicted Valuations under DARA Utility Function 111
A.2 Predicted Valuations in Coffee Mug Experiment 113
A.3 Markov Chain of Estimates with Heterogeneity 115
A.4 Visual Basic Application (VBA) Programs 116
A.5 Sample Written Instructions 118

B Appendices of Chapter 3 **123**
B.1 Supplementary figures and tables 123
B.2 Experimental instruction 126

C Appendices of Chapter 4 **129**
C.1 Supplementary Tables 129

LIST OF TABLES

2.1 Reference Points and Possible Outcomes in Each Treatment . . . 14
2.2 Summary of Treatments in Laboratory Experiment 15
2.3 Parameters in Each Part of Lab Experiment 18
2.4 Linear Regression Analysis 25
2.5 Maximum Likelihood (ML) and Markov Chain Monte Carlo (MCMC) Estimates of Parameters in Money Experiment 39
2.6 Maximum Likelihood (ML) and Markov Chain Monte Carlo (MCMC) Estimates of Parameters in Mug Experiment 40
2.7 Model Calibration and Validation 45
2.8 Valuations in Each Money Treatment 52
2.9 Valuations in Each Coffee Mug Treatment 53

3.1 Treatment Design 62
3.2 Votes in Different Treatments 68
3.3 Average Emotions in Different Treatments 71
3.4 Regression Results on Voting Decisions (part A) 74
3.5 Regression Results on Voting and Insurance Decisions (part B) . 75
3.6 Estimated Random Utility Model with Predicted Emotion Data . 82
3.7 Estimated Random Utility Model with Measured Emotion Data . 83

4.1 Electricity Consumption in Each NERC Region in the EI 103
4.2 Electricity Generation in Each NERC Region in the EI 104
4.3 Regionsl LMP ($) in Each NERC Region in EI 108

B.1 Predict Emotions with Linear Model 125

C.1 Emissions in Each NERC Region in EI 129
C.2 Shares of Major Generation Sources 130
C.3 Emissions in Each NERC Region in EI with Load Scaling 131
C.4 Shares of Major Generation Sources with Load Scaling 131

LIST OF FIGURES

2.1 WTAG/WTPG Ratio (of means) under Different Probabilities (money-top; mug-bottom) . . . 21
2.2 Mean (top) and Median (bottom) Valuations from All Money Sessions . . . 22
2.3 Mean (top) and Median (bottom) Valuations from All Coffee Mug Sessions . . . 23
2.4 Model Prediction (top) and Probability Weighting Function (bottom) for Money Experiment . . . 42
2.5 Model Prediction (top) and Probability Weighting Function (bottom) for Mug Experiment . . . 43
2.6 Model Prediction (top) and Probability Weighting Function (bottom) for Money Experiment with Heterogeneity in Consumption Utility of Money . . . 49

3.1 Anger and Fear from All Measurements . . . 70
3.2 Anger and Fear from the First Measurement . . . 70

4.1 Dead Weight Loss Under FRP . . . 90
4.2 A Simple Network with 3 Nodes . . . 90
4.3 Supply and Demand at Node B . . . 91
4.4 The NERC Regions . . . 93
4.5 The Eastern Interconnection(EI) Network . . . 93
4.6 The Reduced Eastern Interconnection(EI) Network . . . 96
4.7 Bin Allocation Criteria . . . 98
4.8 Representative Hours vs. Actual Hours Load . . . 99
4.9 Flat Rate Prices and Real Time Prices . . . 100
4.10 CO_2 Emission Change by Region . . . 105
4.11 NO_X Emission Change by Region . . . 105
4.12 SO_2 Emission Change by Region . . . 106
4.13 CO_2 Emission Change by Region with Load Scaling . . . 106
4.14 NO_X Emission Change by Region with Load Scaling . . . 107
4.15 SO_2 Emission Change by Region with Load Scaling . . . 107

A.1 Markov Chain of Estimates with Heterogeneity . . . 115
A.2 Visual Basic Application (VBA) Programs . . . 116

B.1 Part A Screen-shot . . . 123
B.2 Part B Screen-shot . . . 123
B.3 Post Event Questions Screen-shot . . . 124

CHAPTER 1

OVERVIEW

Adam Smith began his famous work ***The Theory of Moral Sentiments*** with the following paragraph.

> "How selfish soever man may be supposed, there are evidently some principles in his nature, which interest him in the fortunes of others, and render their happiness necessary to him, though he derives nothing from it, except the pleasure of seeing it. Of this kind is pity or compassion, the emotion we feel for the misery of others, when we either see it, or are made to conceive it in a very lively manner. That we often derive sorrow from the sorrows of others, is a matter of fact too obvious to require any instances to prove it; for this sentiment, like all the other original passions of human nature, is by no means confined to the virtuous or the humane, though they perhaps may feel it with the most exquisite sensibility. The greatest ruffian, the most hardened violator of the laws of society, is not altogether without it."

This notion of emotion has long been ignored both intentionally and unintentionally in the neoclassic economic analysis until recently. This does not mean that factors such as emotion are not important in decision making. On the contrary, even the most hardcore neoclassic economists would agree that these factors shape decisions in their own ways. Economics, psychology, sociology, anthropology and many other disciplines each has its own methodology to study human behaviors. Economics, of course, is not superior to other disciplines so it

would be inappropriate to criticize economic theories only because they fail to explain phenomenons observed by psychologists and sociologists (e.g. framing effects, contextual effects, etc..) (Rubinstein, 2006). Economic theories should be judged by their power to explain and predict behaviors *in general* or at the aggregate level. Nonetheless, there are certain aspects of the "homo economicus" that *systematically* deviate from actual behaviors. It is such systematic deviations call the rise of behavioral economics which tries to incorporate intuitions from other disciplines in economic analysis.

Many see behavioral economics as a substitute of mainstream economics. For example, David Levine claimed in his book ***Is Behavioral Economics Doomed?: The Ordinary Versus the Extraordinary*** that the standard to judge behavioral economics is "whether mainstream economics has failed" (Levine, 2012). This is certainty a view shared by some researchers but not by all behavioral economists. The purpose of incorporating psychology intuitions is indeed to build or improve economic theories that can better explain and predict behaviors (Camerer et al., 2004). In this sense, behavioral economics should be viewed as a complement or even part of mainstream economics. There are also methodological debates over behavioral economics arguing that economic models are "as if" models built on revealed preferences so the underlying psychological processes are irrelevant (Gul and Pesendorfer, 2008). From a scientific research point of view, however, the knowledge from other disciplines such as psychology and neuroscience does help to improve the explanatory and prediction power of some economic models (Bernheim and Rangel, 2005, 2009; Camerer et al., 2004).

This thesis presents three studies that employ different methods to study human behaviors. The first two studies use laboratory experiments to empirically test a fundamental theory – expected utility theory. As previously mentioned that showing counter examples to the theory is *not* the purpose of the studies. Rather, various improvements are suggested to make the theory more robust while still portable and tractable. The third study is a simulation study taking an institutional example from energy economics. This study demonstrates that even with the assumption of "homo economicus", economic tools can still be useful in reality.

Chapter 2 studies how individuals make decisions under risks (known probabilities). Expected utility theory has been and is the dominant theory in economics that explains behavior under risk and uncertainty. However, much evidence have shown counter examples to expected utility theory. The first study especially focuses on two concepts – loss aversion and rank dependent probability weighting – to show how they can help to improve the theory.

Chapter 3 uses expected utility theory to explain behavior under uncertainty (unknown probabilities) and focuses on the role of emotions in the decision process. The study first demonstrates evidence that emotions alter economic decisions. It then shows that observed behavior from the laboratory can be rationalized within the framework of expected utility theory.

Chapter 4 compares the environmental effects of different electricity tariff schemes with simulations. The simulation tool features a detailed network model of the eastern interconnection and utilizes generator level cost and emission data. Since real time pricing in the retail market has not been made available in large regions, the simulation study provides a reasonable conterfactual

to policy makers. The study shows that real time pricing does not necessarily lead to less emissions as conventional wisdom claimed.

CHAPTER 2

REFERENCE DEPENDENCE UNDER RISK: AN EXPERIMENTAL EXAMINATION

2.1 Introduction

Economists favor parsimonious theories that can reasonably explain and predict behavior because of their portability and tractability. When explaining and predicting behavior under risk and uncertainty, expected utility theory is considered a parsimonious theory. But it is also not without critics. For example, expected utility theory cannot explain the Allais Paradox (Allais, 1953) and Ellsberg Paradox (Ellsberg, 1961). Because of these and other systematic violations of expected utility theory, the profession has not yet settled on a universal theory that explains and predicts behavior under risk and uncertainty. To resolve the issues that challenge expected utility theory, prospect theory was proposed by Kahneman and Tversky (1979). They argued that utility of a risky prospect is reference dependent and non-linear in probabilities. Since then, many studies including laboratory experiments have been conducted to test these propositions. Most of previous empirical studies in economics have focused on using loss aversion to explain reference dependent behavior (Haigh and List, 2005; Kahneman et al., 1991; Thaler and Tversky, 1997; Tversky and Kahneman, 1991). In recent years, reference-dependent utility model has also been proposed to explain reference dependent behavior and has received much attention (Kszegi, 2009; Kszegi and Rabin, 2006, 2007).

In comparison, economic literature has less emphasized probability weighting. The majority of studies on probability weighting have been conducted by

psychologists (Gonzalez and Wu, 1999; Kilka and Weber, 2000; Wu and Gonzalez, 1996) and relevant economic studies have been focusing on the theoretical aspect. These studies try to relax the linearity constraint on probability in expected utility theory to rationalize empirically observed anomalies (Abdellaoui, 2002; Machina, 2009; Quiggin, 1982, 1987). However, they should not be considered as examinations of probability weighting given the purpose of the studies was to propose a more general version of expected utility theory. Recently, economists have started to investigate the role of probability distortion in explaining observed risk preferences (Barberis and Huang, 2008; Barseghyan et al., 2013a; Snowberg and Wolfers, 2010). The term probability distortion here describes the behavior of *systematic* deviation from objective probabilities in decision making under the framework of expected utility theory. In filed works, researchers usually do not observe the decision makers perceived risks, so it is difficult or even impossible to distinguish probability distortion behavior caused by probability weighting from those caused by systematic risk misperception (Barseghyan et al., 2013b). Laboratory experiments do not suffer from this issue because risk (objective probability) associated with a choice can be made known to subjects. Therefore, observed probability distortion in laboratory experiments can be safely attributed to probability weighting. This study uses a controlled laboratory experiment to examine reference dependent behavior under risk. The structural analysis in the paper extends the aforementioned reference-dependent utility model to explain reference dependent behavior under risk. The analysis also shows that probability weighting plays an important role in successfully extending the reference-dependent utility model.

There is a large body of literature that studies behavior under risk and uncertainty, but most of them can be traced back to (subjective) expected utility

theory (Bernoulli, 1954; Samuelson, 1952; Savage, 1954; Von Neumann and Morgenstern, 1947). As a normative theory, expected utility theory describes how people should behave, but it fails to explain many anomalies including the endowment effect (Thaler, 1980) that can be explained by loss aversion – a concept from prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991, 1992). Prospect theory itself is a descriptive theory and its reference dependent feature is capable to make good explanations and predictions of many real world phenomena. However, unlike expected utility theory, the original prospect theory (Kahneman and Tversky, 1979) did not provide a tractable form that economists can easily test and implement. Later models based on prospect theory tried to quantify the predictions by focusing on loss aversion (**?**). The study of probability weighting, however, falls into a different line of research (Fehr-Duda and Epper, 2012).

The main innovation of this work is to estimate a tractable model with loss aversion *and* probability weighting that explains reference dependent behavior under risk. By eliciting valuations for different risky prospects in both the gain and loss domains, the data allows for identification of an extended version of the reference-dependent utility model derived from previous studies. The loss aversion in the model is represented by a single parameter and the probability weighting function is estimated nonparametrically given the richness of the experimental data. Estimates show that the model fits experimental data well and can also be extended to other applications.

Based on previous experimental studies on the endowment effect (Coursey et al., 1987; Eisenberger and Weber, 1995; Gneezy et al., 2006; Kahneman et al., 1990; Knetsch, 1989, 1995; Knetsch and Sinden, 1984; List, 2004, 2003) under

either certainty or a single probability, I use endowment effect under *different probabilities* to study reference dependent behavior under risk in the current paper. Although loss aversion (Köbberling and Wakker, 2005) is usually considered an explanation for the endowment effect, attempts have been made to extend expected utility theory to explain the phenomenon. For example, a number of researchers (Amiran and Hagen, 2003; Hanemann, 1991, 2003; Weber, 2003) provide theoretical frameworks under which the endowment effect can be explained by the income effect without violating axioms in neoclassic theory. However, their explanation only applies to exogenously determined consumption of a public good. There are also other theoretical models which utilize information asymmetry to explain the observed endowment effect (Dupont and Lee, 2002; Kolstad and Guzman, 1999; Zhao and Kling, 2001, 2007) but, unlike loss aversion, none of them provides a satisfactory yet consistent answer to the question. Hence, loss aversion is at least a convincing explanation of reference dependent behavior under certainty.

The research question in this paper is thus to explain and predict reference dependent behavior under risk with loss aversion and probability weighting. The presented laboratory experiment identifies the roles of both. I elicit bids or offers for either $5 or a coffee mug under risk. Specifically, Willingness To Accept (WTA) and Willingness To Pay (WTP) values in both the gain and loss domains are obtained. Using within subject variation in risk (objective probability) and between subject variation in elicitation mode, I can observe the endowment effect under different probabilities. The contribution of this paper is both theoretical and empirical. On the one hand, this paper demonstrates that a reference dependent model with loss aversion can explain reference dependent behavior under risk when combined with rank dependent probability weighting. On the

other hand, it shows (quantitatively) that the estimated loss aversion and probability weighting are consistent with literature and thus further demonstrates the robustness of the proposed behavioral model. In addition, understanding why discrepancies exist among different valuations (WTA and WTP values for gains and losses) is also critical since consistent preferences are critical for many welfare implications (Grether and Plott, 1979).

Experimental results show significant endowment effect under *all* probabilities and thus not supporting expected utility theory. Following Kszegi and Rabin (2006), I propose using a model in which people receive both consumption utility and gain-loss (reference dependent) utility to fit the experimental data. By imposing a specific structure, I estimate the single loss aversion parameter as well as a nonparametric probability weighting function. The estimated loss aversion parameter is within a reasonable range as suggested by literature and the nonparametric probability weighting function is consistent with an inverse S shaped curve.

The rest of the paper is organized as follows: the next section describes a controlled laboratory experiment which I use to elicit WTA and WTP values for either gains or losses of $5 or a university coffee mug under risk, section three presents the experimental results and conducts a reduced-form analyses to investigate how probability and elicitation mode influence the values for risky prospects. In section four, loss aversion and probability weighting are discussed in details before I explain why they are both necessary to form a tractable model that explains the experimental data. The structural estimation then shows the magnitudes of loss aversion and probability weighting I observed in the experiment. The last section concludes the study and discusses possible future

research directions.

2.2 Experimental Design

The experiment is conducted with the risky prospects of $5 (money experiment) or of a coffee mug with a university logo (mug experiment). In this section, I mostly refer to the money experiment when illustrating the design, but the same design applies to the mug experiment unless otherwise noted.

2.2.1 Structure

A lottery ticket and an insurance policy are used to form different reference points in the gain and loss domains respectively[1]. In all lottery (gain) sessions, subjects are told that they do not own the $5 but they have a chance to win (receive) it; in all insurance (loss) sessions, subjects are told that they own the $5 but they face a possibility to lose it. Considering gains and losses of the $5 and WTA or WTP we have the following four treatments.

1. Willingness To Pay in the Gain Domain (WTPG) is the maximum amount of money that one would be willing to give up for a lottery ticket with a known probability of obtaining $5.
2. Willingness To Accept in the Gain Domain (WTAG) is the minimum

[1]Researchers used different methods in similar experiments (Bateman et al., 1997; Eisenberger and Weber, 1995). In the design of our experiment, we only use these terms to help subjects to understand the questions. More discussion on reference points can be found in later sections of the paper.

amount of money that one would be willing to accept to give up her lottery ticket with a known probability of obtaining $5.

3. Willingness To Pay in the Loss Domain (WTPL) is the maximum amount of money that one would be willing to give up to purchase an insurance policy to fully protect against the loss of the $5 with a known probability.

4. Willingness to Accept in the Loss Domain (WTAL) is the minimum amount of money that one would be willing to accept in return for giving up an insurance policy that fully protects against loss of the $5 with a known probability.

The manipulation of reference points and framing in the experiment presented here is similar to Bateman et al. (1997) although following different naming rules [2]. The novelty of this experimental design is the introduction of systematic risk into valuation process. Also, I use the Becker-DeGroot-Marschak (BDM) mechanism to directly elicit valuations while Bateman et al. conducted their experiments with transactions that exchange one good for another good, as in Knetsch (1989). Other related studies also framed the questions in different ways. For example, Eisenberger and Weber (1995) reports elicited WTA and WTP values for a certain lottery. Specifically, their lottery experiment had four treatments including buying, selling, short buying, and short selling. Their experimental design is essentially the same as Bateman et al. (1997) and this in the manipulation of reference point and valuation methods. In this study, I use different framings (lottery vs. insurance policy) to help subjects to understand the questions.

[2]The WTAG and WTPL here correspond to their Equivalent Gain (EG) and Equivalent Loss (EL) values.

Before diving into the discussion of reference dependence, it is useful to lay out possible gains and losses that subjects face. Since the fixed participation fee is uniform across all treatments, it is irrelevant in the following discussion. In the WTPG sessions, participants were given \$15 to purchase a lottery ticket and in the event of winning the lottery, \$5 was added to their account balance. In the WTAG sessions, participants were given \$10 *and* the lottery ticket which they could sell for cash. In the WTPL sessions, participants were given \$20 and they faced a risk of losing \$5 of it. They were given an opportunity to purchase an insurance policy that protects them from losing the \$5 using the rest \$15. In the WTAL sessions, participants were given \$15 and the insurance policy that they could sell for cash. Let p represent the probability of winning the lottery or the probability a loss. Changes in wealth levels in each treatment are listed below in lottery form. The first lottery in each treatment represents the risky option and the second (degenerate) lottery represents the safe option.

1. WTPG: $(\$20 - WTP_{Gain}, p; \$15 - WTP_{Gain}, 1-p) vs. (\$15, 1)$
2. WTAG: $(\$15, p; \$10, 1-p) vs. (\$10 + WTA_{Gain}, 1)$
3. WTPL: $(\$15, p; \$20, 1-p) vs. (\$20 - WTP_{Loss}, 1)$
4. WTAL: $(\$10 - WTA_{Loss}, p; \$15 + WTA_{Loss}, 1-p) vs. (\$15, 1)$

A direct observation is that if participants always equate the expected value of the risky option and safe option, then the four valuations should be all equal to 5p which is not consistent with the experimental results.

Table 2.1 shows two possible reference points in this experimental design: endowment and status quo. As shown both in laboratory study (**?**) and using

field data (Crawford and Meng, 2011), choice of reference point in analyzing behaviors is largely an empirical question. I shall defer discussion to the structural analysis section where I will show how reference points matter in my specific experimental setting.

2.2.2 Details

All experimental sessions were conducted in a dedicated experimental economics laboratory at a major university in North America. All subjects were recruited from university undergraduate population. Eighteen sessions, including two pilot sessions[3], were conducted. On average, a subject earned a total amount between $15 and $25 (including the value of coffee mug in the case of mug experiment) upon completion of the experiment which took about 40 minutes. Each session consists of 9 parts, only one of which was actually implemented to determine the payment. In order to determine the part implemented, a bingo ball was drawn from a bingo cage having 9 bingo balls numbered 1-9. All subjects were incentivized to reveal their true valuations in all parts since they (and the experimenter) did not know which part would be implemented until the end of the experiment[4]. In all experimental sessions, the order of the 9 parts was randomized to mediate any possible order effect.

[3]Pilot sessions are excluded from analyses due to slight difference in design but including them does alter results. Analyses with all data are available from the author upon request.

[4]To avoid possible confusion, subjects are told to treat each part as a separate experiment but their earnings are determined by only one of the separate experiments.

Table 2.1: Reference Points and Possible Outcomes in Each Treatment

Money – one dimension				
	Reference Point		Possible Outcomes	
	Endowment	Status Quo*		
			Without Lottery	With Lottery
WTPG	x^0	x^0	x^0	$(x^0 + \Delta x - WTP, p; x^0 - WTP, 1-p)$
WTAG	$(x^0 + \Delta x, p; x^0, 1-p)$	x^0	$x^0 + WTA$	$(x^0 + \Delta x, p; x^0, 1-p)$
			With Insurance	Without Insurance
WTPL	$(x^0, p; x^0 + \Delta x, 1-p)$	$x^0 + \Delta x$	$x^0 + \Delta x - WTP$	$(x^0, p; x^0 + \Delta x, 1-p)$
WTAL	$x^0 + \Delta x$	$x^0 + \Delta x$	$x^0 + \Delta x$	$(x^0 + WTA, p; x^0 + \Delta x + WTA, 1-p)$
Coffee Mug – two dimension				
	Reference Point		Possible Outcomes	
	Endowment	Status Quo*		
			Without Lottery	With Lottery
WTPG	$(0, x^0)$	$(0, x^0)$	$(0, x^0)$	$((\bar{m}, x^0 - WTP), p; (0, x^0 - WTP), 1-p)$
WTAG	$((\bar{m}, x^0), p; (0, x^0), 1-p)$	$(0, x^0)$	$(0, x^0 + WTA)$	$((\bar{m}, x^0), p; (0, x^0), 1-p)$
			With Insurance	Without Insurance
WTPL	$((0, x^0), p; (\bar{m}, x^0), 1-p)$	$(\bar{m}, x^0)$	$(\bar{m}, x^0 - WTP)$	$((0, x^0), p; (\bar{m}, x^0), 1-p)$
WTAL	$(\bar{m}, x^0)$	$(\bar{m}, x^0)$	$(\bar{m}, x^0)$	$((0, x^0 + WTA), p; (\bar{m}, x^0 + WTA), 1-p)$

Status quo is defined empirically. That is, people do not feel they own the prize even they possess a lottery ticket and people do not feel they have suffered from a loss even they face risks.

$x^0$is current wealth level;$\Delta x = \$5$is the prize of lottery.$\bar{m}$is intrinsic consumption value of the coffee mug. p is probability of winning the lottery or experiencing the loss. In the money experiment, subjects consider only on dimension while in the mug experiment, subjects consider two dimensions consumption of coffee mug and money.

Once a subject was checked into the lab, he/she was randomly seated at a private desktop computer. All computers had a Visual Basic Application (VBA) program set up and subjects submitted their valuations through the program. Subjects were given sufficient time to read instructions before the experimenter read and explained the instruction with PowerPoint slides. Subjects were encouraged to ask any question either before or during the experiment but were not allowed to communicate with each other. Subjects then submitted their valuations by accepting or rejecting the prices shown on their computer screens for all 9 parts without further direction. After all subjects finished all parts of the experiment, attention was drawn to the experimenter and a bingo ball was drawn by a lab assistant to determine which single part, of the nine parts, was the implemented part for payment. To determine the buying/selling price, a poker chip was drawn with a price listed on it from a bag by a volunteer subject in the room. After the experimenter calculated earnings, subjects were directed to a complete a survey before they were paid.

Table 2.2: Summary of Treatments in Laboratory Experiment

	Treatment	Gain or Loss	Mode	# of Subjects
Money	Lottery-WTP	Gain	Buy	48
	Lottery-WTA	Gain	Sell	48
	Insurance-WTP	Loss	Buy	45
	Insurance-WTA	Loss	Sell	45
Mug	Lottery-WTP	Gain	Buy	41
	Lottery-WTA	Gain	Sell	48
	Insurance-WTP	Loss	Buy	46
	Insurance-WTA	Loss	Sell	47

Table 2.2 shows a summary of all the experimental sessions. In half of the sessions (lottery/gain treatments), subjects were shown the experimental good and were told that they did not yet own it but could have a chance to win it if they were to buy/keep the lottery ticket. Part of the WTPG money instructions reads as follows:

> "This experiment is about how much you value a lottery ticket.…The experiment has 9 parts. You will be given a chance to purchase a lottery ticket in each part. Only one part will be implemented. We will determine which part to implement by drawing one ball from a bingo cage with 9 balls numbered from 1-9 in it. The ticket has a certain probability of winning $5. In part 1, the lottery ticket has a 0% chance to win; in part 2, the lottery ticket has a 1% chance to win; …. in part 8, the lottery ticket has a 99% chance to win; in part 9, the lottery ticket has a 100% chance to win. In each part, we will ask you whether you want to buy the lottery ticket at different prices…"

In the other half of the sessions (insurance/loss treatments), subjects are given an identical experimental good and are told it is theirs to keep although they face a risk of losing it during the experiment. An insurance policy can be bought/kept to protect them from losing the experimental good. Part of the WTPL mug instructions reads as follows:

> "This experiment is about how much you value a Cornell mug. Please look at the mug on your desk. ….The Cornell mug sitting on your desk is yours. The experiment has 9 parts. In each part there

will be a chance (probability) that you will lose your mug. Only one part will be implemented. We will determine which part to implement by drawing one ball from a bingo cage with 9 balls numbered from 1-9 in it. In part 1, there is a 0% chance that you will lose your mug; in part 2, there is a 1% chance that you will lose your mug . . . in part 8, there is a 99% chance that you will lose your mug; in part 9, there is a 100% chance that you will lose your mug. In each part, you have a chance to buy an insurance policy out of your initial $15 participation balance that protects you from losing your mug. We will ask you whether you want to buy the insurance policy at different prices that would protect you against loss of your mug in that part of the experiment . . . "

A full version of experimental instructions can be found in the appendix. Table **??** shows the probabilities in each part. To elicit valuations in each part, I employ a revised version of Becker-DeGroot-Marschak (BDM) mechanism. For each price listed on subjects computer screen[5], subjects either accept or reject that price. After all parts were completed, a poker chip with price on it was randomly drawn by a subject to determine the price of the good. In the WTPG (WTAG) and WTPL (WTAL) sessions, if a subject said yes to the drawn price, he/she pays (receives) that amount and receives (gives up) the lottery ticket or insurance policy. If a subject says no to the drawn price, he/she does not buy (keep) the lottery ticket or insurance policy. To account for possible income effect, subjects in WTPG and WTPL sessions were given $15 at the start of the session as theirs to keep or spend. Subjects in WTAG and WTAL sessions were given $10, in order to make the expected earnings from the experiment similar

[5]See screenshot in appendix.

and more importantly to control for possible income effect. Finally, to implement the randomly determined binding part, two stacks of white and red chips are shown to the subjects to illustrate probabilities. Depending on the probability chosen for implementation, the appropriate number of white and red chips were put into a bag. For example, if part 3 was drawn, the experimenter put 95 white chips and 5 red chips into a bag. One of the subjects then drew a chip out of the bag to determine the outcome. In a gain (lottery) session, if a red chip was drawn, those who held a lottery ticket received the experimental good. In the loss (insurance) session, if a red chip was drawn, those who did NOT hold an insurance policy lost their experimental good.

Table 2.3: Parameters in Each Part of Lab Experiment

Part Number	Probability of Receiving/Losing $5 (Mug)	# of Chips
1	0%	100 white chips and 0 red chip
2	1%	99 white chips and 1 red chip
3	5%	95 white chips and 5 red chips
4	25%	75 white chips and 25 red chips
5	50%	50 white chips and 50 red chips
6	75%	25 white chips and 75 red chips
7	95%	5 white chips and 95 red chips
8	99%	1 white chip and 99 red chips
9	100%	0 white chip and 100 red chips

All treatments have the same parameters in each part. In gain/lottery sessions, drawing a red chip means a gain. In loss/insurance sessions, drawing a red chip means a loss.

2.3 Results

In this section, I report results from the experiment without referring to any specific theory. Table 2.8 at the end summarizes means and medians of valuations in each treatment of the money experiment, while Table 2.9 summarizes the same statistics from the mug experiment. Each column represents valuations under a different probability. Under all probabilities, including certainty, tests show that both WTAG-WTPG and WTPL-WTAL disparities are statistically significant[6] thus supporting endowment effect under all probabilities. A closer examination of Table 2.8 and Table 2.9 reveals that the mean WTAG-WTPG and WTAL-WTPL disparities are approximately constant while the ratios increases when probabilities decrease. In fact, constant absolute disparities are found among the four different values under intermediate probabilities ($0.05 \leq p \leq 0.95$). In the money experiment, the ratio of (mean) WTAG/WTPG is 3.87 at $p = 0.05$, in contrast to a ratio of 1.08 under certainty, while these ratios are 3.62 versus 1.46 in the loss domain. In the mug experiment, the ratio of (mean) WTAG/WTPG is 8.63 at $p = 0.05$ versus 1.60 under certainty while the same ratios are 3.88 versus 1.61 in the loss domain. The ratios under small probabilities are especially high for a private good (Horowitz and McConnell, 2002). The ratios under all probabilities are also shown in Figure 2.1. These evidences therefore indicate a higher level of reference dependent behavior under smaller probabilities in the valuation task.

Mean and median valuations elicited from all sessions are plotted in Figure 2.2 (money) and Figure 2.3 (mug).Means and medians are very similar ex-

[6]Under certainty, in the money experiment, Wilcoxon-Mann-Whitney test results in z=-4.21 with p=0.00 for WTAG-WTPG and z=-5.416 for WTAG-WTPL; in the mug experiment, Wilcoxon-Mann-Whitney test results in z=-3.24 with p=0.00 for WTAG-WTPG and z=-3.22 for WTAL-WTPL.

cept in the WTAL treatment in the money experiment, where, as shown for median values, a majority of subjects do realize they should never bid or offer more than $5 for the lottery ticket or insurance policy. For mediate probabilities, valuations appear to increase at similar rates (lines share the same slope). These parallel lines suggest valuations under risk responds to probability proportionally. That is, all valuations respond to risk changes in the same way. Another noteworthy observation is that the WTAG and WTPL values from the money experiment appear to be the same under all probabilities.

A simple reduced form econometric model is used to test if the observations from Figure 2.2 are statistically sound.

$$Value_T = \alpha_T + \beta_T + \epsilon, \epsilon \sim N(0, \Lambda)$$

T represents treatments as shown in Table 2.2. Estimates are shown in Table 2.4. For both the money and mug experiment, I first estimate a linear regression model with all of the collected data. I then estimate another linear regression which only uses data elicited under non extreme probabilities ($0.05 \leq p \leq 0.95$). All models include probability as an explanatory variable and its interactions with the treatment dummy variables. Probability is treated as a continuous variable although I elicited value under nine probabilities. F test on the three interaction terms (WTAG*Probability, WTPL*Probability, and WTAL*Probability) in all models suggests that we cannot reject the hypothesis that they are jointly equal to zero[7]. In other words, we cannot reject the hypothesis that the four lines share the same slope suggesting statistically same

[7]Model (1) results in F=0.59 with p=0.62. Model (2) results in F=0.80 with p=0.50. Model (3) results in F=1.45 with p=0.23. Model (4) results in F=0.76 with p=0.51.

Figure 2.1: WTAG/WTPG Ratio (of means) under Different Probabilities (money-top; mug-bottom)

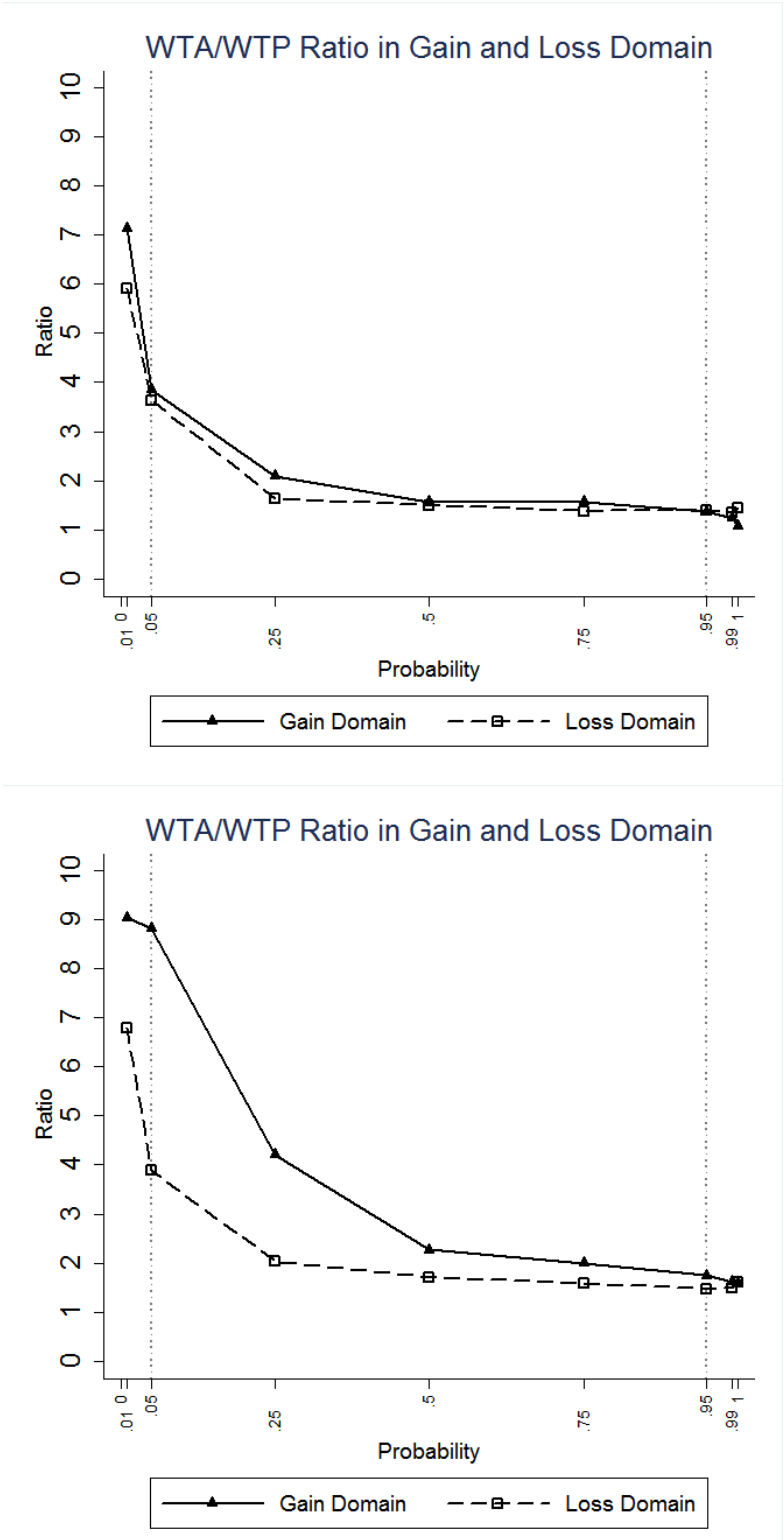
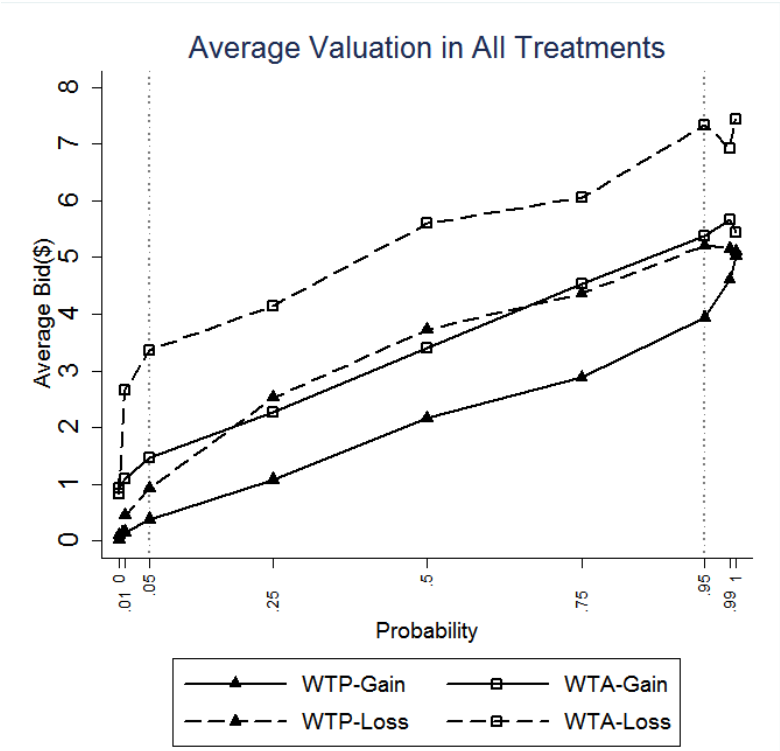


Figure 2.2: Mean (top) and Median (bottom) Valuations from All Money Sessions



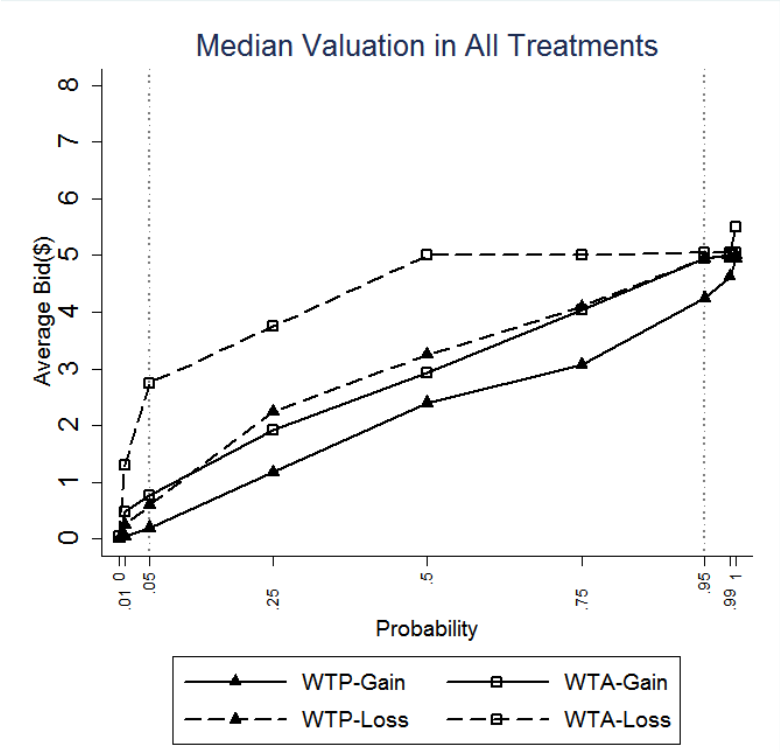
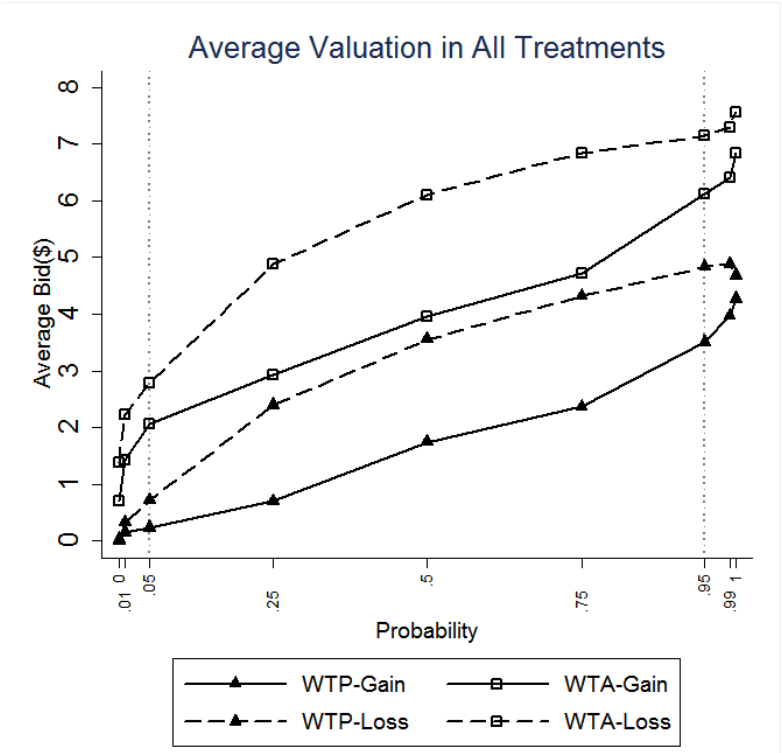
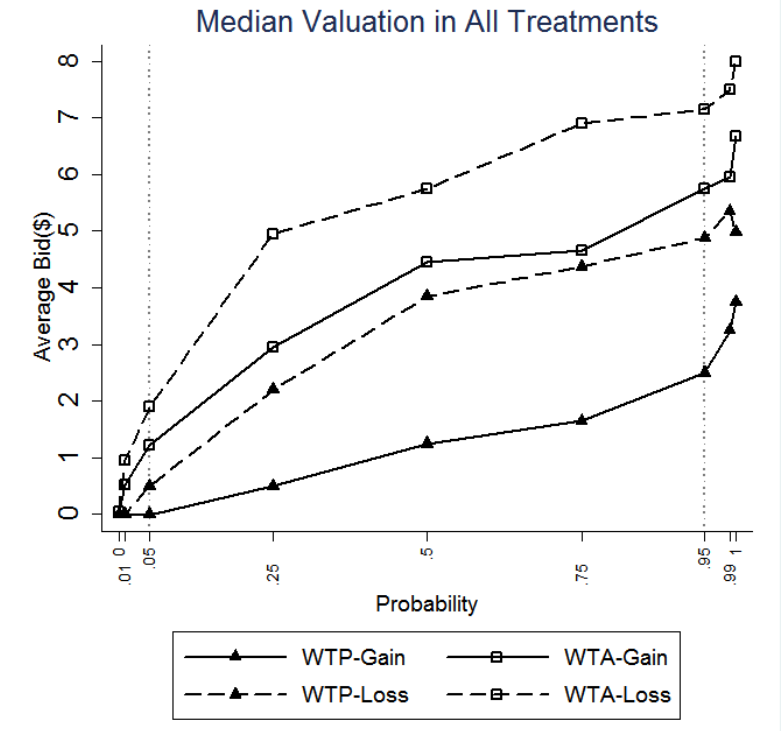


Figure 2.3: Mean (top) and Median (bottom) Valuations from All Coffee Mug Sessions





response to changes in risk. That is, if subjects respond to probabilities linearly, their sensitivities to probability in all treatments are not different.

Table 2.4: Linear Regression Analysis

	Money ($5)		Coffee Mug	
	Full Data	Moderate Ps	Full Data	Moderate Ps
	(1)	(2)	(3)	(4)
Probability	4.43***	3.87***	3.89***	3.57***
	(0.38)	(0.34)	(0.48)	(0.48)
WTAG*Probability	0.08	0.51	1.26*	0.71
	(0.50)	(0.48)	(0.72)	(0.74)
WTPL*Probability	0.36	0.63	0.68	0.84
	(0.44)	(0.41)	(0.72)	(0.74)
WTAL*Probability	0.64	0.39	1.42*	1.05
	(0.56)	(0.54)	(0.82)	(0.79)
WTPG	0.05	0.16	(0.06)	(0.07)
	(0.09)	(0.10)	(0.06)	(0.09)
WTAG	1.10***	1.22***	1.34***	1.83***
	(0.24)	(0.29)	(0.28)	(0.34)
WTPL	0.66***	1.10***	0.57***	0.96***
	(0.10)	(0.16)	(0.12)	(0.20)
WTAL	2.40***	3.17***	2.48***	3.24***
	(0.36)	(0.38)	(0.38)	(0.39)
		Fixed Effects		
Fixed Effects	1.65	1.89	2.09	2.3
Other Factors	1.59	1.21	2.08	1.72
No. of Individuals	186	186	182	182
No. of Obs.	1674	930	1638	910

Top panel shows coefficient estimates. WTPG, WTAG, WTPL, WTAL are dummy variable for WTP-Gain, WTA-Gain, WTP-Loss and WTA-Loss treatments. Probability is treated as continuous variable. WTAG*Probability, WTPL*Probability and WTAL*Probability are interaction terms. Clustered (by subject) standard errors are reported in parentheses. *indicates significance at 10% level; **indicates significance at 5% level while ***indicates significance at 1% level.
(1) uses all data in the money experiment and (3) uses all data in the mug experiment. (2) and (4) only include observations with $0.05 \leq p \leq 0.95$ which are considered non extreme probabilities. Bottom panel reports result from fixed effects estimation. All coefficients and significance levels are suppressed since they are the same as the ones shown in top panel except all intercepts are not identified.

On the other hand, all treatment dummy variables are statistically different from each other at 1 percent level except for WTAG and WTPL in the money experiment[8]. This suggests that although the four lines in Table 2.3 have statistically identical slopes, they do not overlap with each other except for WTAG and WTPL in the money experiment. This contradicts the prediction of expected utility theory but is consistent with previous observed WTA-WTP disparities. At *each* of the nine probabilities, the four valuations behave as prospect theory would predict (WTPG¡WTAG=WTPL¡WTAL). A different set of linear regressions but with fixed effects are reported in the bottom panel of Table 2.4. The fixed effects are at individual level so all intercepts of the four lines are not separately identified since there is only between subject variation in terms of elicitation mode. Also, the estimated slopes are identical to the ones reported in the top panel so they have also been suppressed from the table. This regression, however, shows that individual level fixed effects can explain at least 50% of the remaining variance after accounting for responses to probabilities. Such a pattern indicates some heterogeneity in individual valuations.

2.4 Structural Analysis

The structural analysis seeks to answer two related questions. Can expected utility theory explain the experimental data? If not, can one use existing behavioral theory to form a tractable model to explain the experimental data? In the reduced form analysis, I showed the pattern of how valuations change with probabilities and elicitation modes. In this section, I will firstly provide

[8] A test of WTAG=WTPL gives F=2.92 (p=0.09) in model (1) and F=0.12 (p=0.73) in model (2).

a formal proof why expected utility theory fails to explain behavior observed in the experiment hence requiring reference dependent model. Then, following the Kszegi-Rabin model (Kszegi, 2009; Kszegi and Rabin, 2006), I propose a behavioral model that has both loss aversion and rank-dependent probability weighting to explain the experimental data. The model is flexible enough to accommodate both expected utility theory and prospect theory as special cases. It is then estimated with different imposed constraints to demonstrate the need of both loss aversion and probability weighting in explaining reference dependent behavior under risk and uncertainty.

2.4.1 Expected Utility Theory

Given the experimental design, income effect has been controlled in the experiment. Without income effect, expected utility would predict identical valuations from all four different treatments. I shall show that expected utility theory fails to explain the experimental data under very weak assumptions.

To start, lets assume a DARA (decreasing absolute risk aversion) utility function $u(\cdot)$ with $u'(\cdot) > 0$ and $u''(\cdot) < 0$. Subjects decision rules are shown below under expected utility framework. Note, x^0 represents the subjects wealth before they start the experiment. I show why controlling for wealth effect in the experimental design between WTA and WTP sessions is critical in the appendix. After controlling for any wealth effect, expected utility maximizers with DARA

utility function should not generate the pattern observed in experiment.

$$pu(x^0 + 20 - WTP_{Gain}) + (1-p)u(x^0 + 15 - WTP_{Gain}) = u(x^0 + 15) \quad (2.1a)$$

$$pu(x^0 + 15) + (1-p)u(x^0 + 10) = u(x^0 + 10 + WTA_{Gain}) \quad (2.1b)$$

$$pu(x^0 + 15) + (1-p)u(x^0 + 20) = u(x^0 + 20 - WTP_{Loss}) \quad (2.1c)$$

$$pu(x^0 + 10 + WTA_{Loss}) + (1-p)u(x^0 + 15 + WTA_{Loss}) = u(x^0 + 15) \quad (2.1d)$$

Following concavity of the utility function, $WTP_{Gain} \leq 5p, WTA_{Gain} \leq 5p$ and $WTP_{Loss} \geq 5p, WTA_{Loss} \geq 5p$. Using the DARA assumption on utility function, it can be shown that expected utility theory predicts $WTA_{Gain} \leq WTP_{Gain} \leq 5p \leq WTA_{Loss} \leq WTP_{Loss}$ (see appendix for details). This prediction is not consistent with the experimental data and considering the wealth effect only worsens the prediction. Thus, expected utility fails to explain the observed behaviors even with a general DARA utility function. This is not surprising given all of the studies in the past three decades showing reference dependent behaviors. The rest of this section will examine whether a prospect theory style model explains the observed behavior. The model has both loss aversion and rank dependent probability weighting as its key components. It is also specified to be flexible enough to accommodate expected utility theory as a special case so statistical test can be conducted to demonstrate the need of different components.

2.4.2 Loss Aversion and Possible Reference Points

Many empirical studies suggest loss aversion (Barberis et al., 2001; Benartzi and Thaler, 1995; Coursey et al., 1987; Kahneman et al., 1991; Siegel and Thaler, 1997)

and many theoretical models have formulized this concept. For example, Sugden (2003) incorporated reference dependence into subjective expected utility theory and showed that the theory implies WTA-WTP disparities in lottery valuation. Kszegi (2009); Kszegi and Rabin (2006, 2007) developed a model (KR model hereafter) based on reference dependent preferences and use it to explain risk attitudes and consumption plans. Their original formulation is shown in Equation 2.2a.

$$U(F|r) = \int u(c|r)dF(c)^{9} \tag{2.2a}$$

$$u(c|r) = m(c) + n(c|r) \tag{2.2b}$$

Where c is consumption bundle, r is reference points and F is the probability measure which c is drawn from. $m(c)$ represents the intrinsic consumption utility and $n(c|r)$ represents the gain-loss utility. In short, the KR model argues that not only the absolute level of consumption matters but also the changes in consumption matter in decision making. They also proposed that rational expectations form reference points. Now, consider a KR style model under risk but *without* the endogenous reference point.

$$U(x, x^0) = \sum_{i=1}^{N} p_i[m(x_i) + n(x_i - x^0)] \tag{2.3}$$

p_i is the probability of state i. x_i is the consumption level of x in each state and x^0 is *exogenously* determined reference point.

[9]The essence of their model is endogenous reference points so it requires a somewhat different formulation. $U(F|G) = \int\int(c|r)dG(r)dF(c)$ represents a utility function where the reference point G is also stochastic. I do not adopt this formulation except for the discussion of KR model predictions where reference point is endogenously formed with rational expectation.

Although, theoretically, endogenous reference points proposed by Kszegi and Rabin is appealing because it addes 0 degree of freedom to expected utility theory[10], it may fail to describe behavior. As Kahneman et al. (1991) argued the refernce state usually corresponds to the decision makers current position, it can also be influenced by aspiration, expectations, norms and social comparisons, the identification of the reference point is largely an empirical question and researchers have found different referenc points in different settings (Crawford and Meng, 2011; Fehr and Tyran, 2008; Hart and Moore, 2008; **?**). Thus, I only consider exogenously determined reference points in this study but future study on formation of reference point will definitely contribute to the literature on reference dependence. Table 2.1 lists two candiates for reference points. The first reference point is the endowment which has been widely used in literature. The second reference point is the status-quo[11].

In the WTPG and WTAL treatments the endowment and status-quo are the same. In the WTAG and WTPL treatments, endowment means one faces a possible gain or possible loss. It is, however, quite arbitrary to assume that subjects fully perceive their endowment given the short time frame in the experiment. For this reason, I argue that the endowment and status quo are the two boundaries of subjects reference points. To approximate this, I assume the reference point in WTAG and WTPL treatments to be a linear combination (in probability) of endowment and status-quo. That is, in the money experiment, the reference point in the WTAG treatment is $(x^0 + \Delta x, ap; x^0, 1 - ap)$ with $0 \leq a \leq 1$ (relative

[10]This means the endogenous reference points are determined by consumption plans. That is, once a decision maker figures out a consumption plan, the reference point is also determined so it requires no extra parameter.

[11]I am using this name with risk of confusion. "Status quo" here refers to status where people think they are. People usually do not feel they own the prize even when they hold a lottery ticket; people usually do not feel a loss even when they do not hold an insurance policy (think about driving a car without comprehensive insurance).

weighting on endowment hereafter) and the reference point in WTPL treatment is $(x^0, ap; x^0 + \Delta x, 1 - ap)$. Reference points in the mug experiment are defined in a similar manner.

2.4.3 Rank Dependent Probability Weighting

Another important feature in prospect theory is probability weighting which argues people do not behave according to the given objective probabilities. Instead, they act as if they overweighting small probabilities and underweight large probabilities. The behavioral economic literature has focused less on probability weighting partly because of the difficulty of empirical identification. The laboratory experiment reported in this paper provides an opportunity to do so since objective probabilities of gain or loss are made known to subjects. Therefore, any observed probability distorting behavior should be explained by proability weighting instead of systematic risk misperception. The behavioral model presented in this paper also consider probability weighting as one of its key components and estimation of the model shows why it is necessary.

Fehr-Duda and Epper (2012) provide a survey of relevant studies on probability weighting. Empirical research shows behavior tends to deviate systematically from objective probabilities (Camerer and Ho, 1994; Gonzalez and Wu, 1999; McClelland et al., 1993). To account for anomalies such as Allais Paradox within the framework of expected utility, researchers raised the idea of probability weighting even before prospect theory (Handa, 1977; Karmarkar, 1978). These studies, including the original paper on prospect theory, all seek to transform single outcome probabilities into weighted or edited decision weights.

However, this approach was criticized for violating a fundamental rule stochastic dominance (Bawa, 1975; Hadar and Russell, 1969). Quiggin (1982) proved that there does not exist any non-identity probability weighting function that transforms single probabilities without violating stochastic dominance. He then proposed to transform the cumulative probabilities. That is, decision weights are derived from the entire probability distribution instead of single probabilities. This approach preserves stochastic dominance while still accounting for probability distorting behaviors. Since Quiggins work, many researchers have contributed to the axiomatization of rank dependence theory (Abdellaoui, 2002; Machina, 1987, 2009; Schmeidler, 1989). To account for probability distorting behavior, I replace the probability measure in Equation 2.3 with decision weights in the model shown in Equation 2.4,

$$U(x, x^0) = \sum_{i=1}^{N} \pi_i [m(x_i) + n(x_i - x^0)] \tag{2.4}$$

π_i is the decision weight on state i. x_i is the consumption level of x in each state and x^0 is reference point. Note, I have yet defined or imposed any constraints on π_i.

To accommodate possible probability weighting, while not violating stochastic dominance, I now impose rank dependence on the probability weighting function $\pi_i(\cdot)$. Following Tversky and Kahneman (1992), S is a finite set of states of nature. A capacity W is a function that assigns to each $A \subset S$ a number $W(A)$ satisfying $W(\emptyset) = 0$, $W(S) = 1$ and $W(A) \geq W(B)$ whenever $A \supset B$. The decision weight π_i, associated with a positive outcome, is the difference between the capacities of the two events "the outcome is at least as good as x_i," and "the outcome is strictly better than x_i". The decision weight π_i, associated with a neg-

ative outcome, is the difference between the capacities of the two events, "the outcome is at least as bad as x_i" and "the outcome is strictly worse than x_i".

In a binary-outcome lottery setting, this is easy to implement. For example, in the WTPG treatment, the decision weight on the winning state is $W(\text{“}Win\$5\text{''}) = \pi(p)$ while the decision weight on the non-winning state is $W(\text{“}Win\$0\text{''}) - W(\text{“}Win\$5\text{''}) = 1 - \pi(p)$[12]. Decision weights in other treatments can be defined in the same way.

2.4.4 A Behavioral Model

Based on the discussion of loss aversion and rank dependent probability weighting, I lay out the model here and conduct different estimations next. To examine the prediction of this model while retain parsimony; I assume a linear form for the intrinsic consumption utility function $m(x_i) = x_i$ and a two-part linear form for the gain-loss utility function $n(x_i - x^0) = \begin{cases} \eta(x_i - x^0), & if\, x_i \geq x^0 \\ \lambda\eta(x_i - x^0), & if\, x_i \leq x^0 \end{cases}$ for simplicity[13].

Equation 2.5a shows the decision equations in the money experiment using the model presented in Equation 2.4. The left hand side is the utility from "no action" and right hand side is the utility from "action". A subject "calculates" a value that makes him or her indifferent between the left hand side and the right hand side. Note that Δx has been replace by $\bar{u}$ which is the utility increment of

[12] W is the capacity and the worst outcome for subjects who purchase a lottery ticket is to win \$0 so its capacity is 1

[13] There are many discussions why a concave VNM utility function is not an explanation for risk preferences. More importantly, assuming concave utility function leads to implausible predicted behavior. See previous studies for detailed discussion on this issue (Cox and Sadiraj, 2006; Rabin, 2000; Rabin and Thaler, 2001).

receiving the \$5 while Δx is the increase in terms of money. It is possible that $\bar{u} \neq \Delta x$ and various factors could cause that. For example, subjects could receive additional utility from merely winning a gamble.

$$\begin{aligned} x^0 =& \pi(p)[x^0 - WTP_{Gain} + \bar{u} + \eta(-WTP_{Gain} + \bar{u})] \\ &+[1 - \pi(p)][x^0 - WTP_{Gain} + \lambda\eta(-WTP_{Gain})] \end{aligned} \tag{2.5a}$$

$$\begin{aligned} &\pi(p)[x^0 + \bar{u} + (1 - a\pi(p))\eta\bar{u}] + [1 - \pi(p)][x^0 + a\pi(p)\eta(-\bar{u})] \\ &=x^0 + WTA_{Gain} + \eta[a\pi(p)\lambda(WTA_{Gain} - \bar{u}) \\ &+(1 - a\pi(p))(WTA_{Gain})] \end{aligned} \tag{2.5b}$$

$$\begin{aligned} &pi(p)[x^0 + (1 - a\pi(p))\eta(-\lambda\bar{u})] + [1 - \pi(p)][x^0 + \bar{u} + a\pi(p)\eta\bar{u}] \\ &=x^0 + \bar{u} - WTP_{Loss} + \eta[a\pi(p)(\bar{u} - WTP_{Loss}) \\ &+(1 - a\pi(p))(-\lambda WTP_{Loss})] \end{aligned} \tag{2.5c}$$

$$\begin{aligned} x^0 + \bar{u} =& \pi(p)[x^0 + WTA_{Loss} + \eta\lambda(WTA_{Loss} - \bar{u})] \\ &+[1 - \pi(p)][x^0 + \bar{u} + WTA_{Loss} + \eta(WTA_{Loss})] \end{aligned} \tag{2.5d}$$

The relative weight plays a critical role in the model. When $\eta = 0$, the model degenerates to (rank dependent) expected utility theory. In other words, only intrinsic consumption value matters. When $\eta \to \infty, \beta = \lambda$, agents only care about gain-loss utility. Resulting valuations are shown in Equation 2.6a. The derivation of the valuations in the mug experiment requires considering a consumption good and money simultaneously. The derivation is included in

the appendix.

$$
\begin{aligned}
WTP_{Gain} =& \frac{(1+\eta)\pi(p)\bar{u}}{1+\lambda\eta+(1-\lambda)\eta\pi(p)} = \frac{\bar{u}}{1+\frac{1+\lambda\eta}{1+\eta}(\frac{1}{\pi(p)}-1)} \\
=& \frac{\bar{u}}{1+\beta(\frac{1}{\pi(p)}-1)}
\end{aligned} \tag{2.6a}
$$

$$
WTA_{Gain} = \pi(p)\bar{u} \tag{2.6b}
$$

$$
WTP_{Loss} = \pi(p)\bar{u} \tag{2.6c}
$$

$$
\begin{aligned}
WTA_{Loss} =& \frac{(1+\lambda\eta)\pi(p)\bar{u}}{1+\eta+(\lambda-1)\eta\pi(p)} = \frac{\bar{u}}{1+\frac{1+\eta}{1+\lambda\eta}(\frac{1}{\pi(p)}-1)} \\
=& \frac{\bar{u}}{1+\frac{1}{\beta}(\frac{1}{\pi(p)}-1)}
\end{aligned} \tag{2.6d}
$$

From Equation 2.6a, it is easy to see that one cannot identify λ and η separately but $\beta = \frac{1+\lambda\eta}{1+\eta}$ can be estimated as a single parameter. Another observation is that the relative weight on endowment a which determines the reference point does not exist in any expression in Equation 2.6a. On the one hand, the proposed model is flexible enough to accommodate any reference point[14] in a one dimension setting. On the other hand, we are not able to identify a in this specific environment. In the two dimension case, however, different values of a can lead to different behaviors. Equation 2.7a shows valuations derived for the mug experiment and we can see the relative weight on endowment, a, appears

[14]Strictly speaking, if the model is the underlying model that generates the experimental data, any reference point that is a linear combination of endowment and status-quo listed in Table 2.1 leads to identical behaviors.

in two expressions.

$$\begin{aligned} WTP_{Gain} =& \frac{\pi(p)(1+\eta)\bar{m}}{1+\lambda\eta} = \pi(p)\bar{m}\frac{1+\eta}{1+\lambda\eta} \\ =& \frac{\pi(p)\bar{m}}{\beta} = \frac{\pi(p)'\bar{m}'}{\beta} \end{aligned} \tag{2.7a}$$

$$\begin{aligned} WTA_{Gain} =& \pi(p)\bar{m} + \frac{a\pi(p)^2(\lambda-1)\eta\bar{m}}{1+\eta} = \pi(p)\bar{m} + a\pi(p)^2\bar{m}(\frac{1+\lambda\eta}{1+\eta} - 1) \\ =& \pi(p)\bar{m}[\beta a\pi(p) - a\pi(p) + 1] = \pi(p)'\bar{m}'[\beta\pi(p)' - \pi(p)' + 1] \end{aligned} \tag{2.7b}$$

$$\begin{aligned} WTP_{Loss} =& \pi(p)\bar{m} + \frac{a\pi(p)^2(1-\lambda)\eta\bar{m}}{1+\lambda\eta} = \pi(p)\bar{m} + a\pi(p)^2\bar{m}(\frac{1+\eta}{1+\lambda\eta} - 1) \\ =& \pi(p)\bar{m}[\frac{1}{\beta}a\pi(p) - a\pi(p) + 1] = \pi(p)'\bar{m}'[\frac{1}{\beta}\pi(p)' - \pi(p)' + 1] \end{aligned} \tag{2.7c}$$

$$\begin{aligned} WTA_{Loss} =& \frac{\pi(p)(1+\lambda\eta)\bar{m}}{1+\eta} = \pi(p)\bar{m}\frac{1+\lambda\eta}{1+\eta} \\ =& \beta\pi(p)\bar{m} = \beta\pi(p)'\bar{m}' \end{aligned} \tag{2.7d}$$

Again from Equation 2.7a we can see that $\pi(p)$, $\bar{m}$ and a cannot be simultaneously identified. However, we can redefine $\pi(p)' = a\pi(p)$ and $\bar{m}' = \frac{\bar{m}}{a}$ to estimate the transformed parameters.

2.4.5 Estimation

I assume the stochastic component in valuations is introduced at the final stage bidding - in the experiment. In other words, the behavioral model *fully* determines the valuations and there is no unobservable that *systematically* alters

valuations. The only source of deviation from theoretical prediction can be represented by random noise. This assumption may not be as arbitrary as it first appears to be. The behavioral model does not try to represent the real thinking process. Instead, it is a representation of its outcome. Therefore, valuation derived from the behavioral model should represent average valuation in the population. Other individual characteristics may also affect the valuations but on average they play no role. A simple additive error is used in the econometric model and the model is shown in Equation 2.8.

$$Bid_j = Valuation + \nu_j, \nu_j \sim N(0, \sigma) \tag{2.8}$$

Where j denotes individuals and $Valuation$ is the theoretical value predicted by the behavioral model. ν_j is an additive error term that follows a standard normal distribution. The non-linear (in parameters) nature of the model requires global optimization when using maximum likelihood to estimate the parameters. The behavioral model has been intentionally specified to be flexible so it can take expected utility theory as a special case. More importantly, estimating the model with different constraints answers the critical question: is loss aversion, probability weighting, or both necessary for explaining reference dependence under risk.

Table 2.5 shows parameter estimates for the money experiment. (1) estimates a model without incurring probability weighting by imposing the restriction $\pi(p) = p$. (2) estimates the unrestricted model with both loss aversion and probability weighting. Given the large number of parameters in the unrestricted model, I employed two different estimating techniques to ensure the estimates are at or close enough to optimality. (2) uses the maximum likelihood method

while (3) uses the Markov Chain Monte Carlo (MCMC) method. The consistency between (2) and (3) provides confidence in these estimates. The comparison between (1) and (2) reveals the need of probability weighting to explain the experimental data. Likelihood ratio test reports a score of 239.6 and thus the null hypothesis "no probability weighting" is rejected with a p value of 0.00. One other thing to note is that the estimated transformed parameter $\beta = \frac{1+\lambda\eta}{1+\eta}$ is always statistically greater than 1. This again verifies that $\eta > 0$ and demonstrates loss aversion in preference.

Most previous work has assumed a functional form for the probability weighting function, I treat the decision weight for each probability as a separate parameter so the estimated probability weighting function is non-parametric. Estimation suggests the consumption value is about 7.8 for a \$5 prize. The transformed parameter $\beta = \frac{1+\lambda\eta}{1+\eta}$ is 2.6. Figure 2.4 shows the predicted valuations and the non-parametric probability weighting function from the unrestricted model. Valuations predicted by the behavioral model mimics the experimental data well and the probability weighting function replicates the inverse S-shaped curve found in literature.

The parameters for the mug experiment are estimated in same ways except that some parameters are not separately identifiable because of the relative weight a. Table 2.6 reports the estimates. The estimated loss aversion parameter is about 1.5 for the mug experiment. By simulating different values of relative weight on endowment, a, model predictions and the probability weighting function are drawn in Figure!2.5. The obtained probability weighting function is again of inverse S-shaped. With $a = 0.6$, the probabilityweighting function in the money experiment is replicated and a reasonable consumption value for the

coffee mug of 7 is obtained.

Table 2.5: Maximum Likelihood (ML) and Markov Chain Monte Carlo (MCMC) Estimates of Parameters in Money Experiment

	MLE - Restricted	MLE	MCMC	MCMC W. Heterogeneity
	(1)	(2)	(3)	(4)
$\bar{u}(\mu_{\bar{u}})$	6.013 (0.168)	7.830 (1.075)	7.715 (0.385)	6.677 (0.267)
$\sigma_{\bar{u}}$	–	–	–	1.721 (0.100)
β	11.045 (4.889)	2.647 (0.357)	2.627 (0.229)	3.483 (0.301)
$\pi(0)$	–	0.050 (0.017)	0.049 (0.015)	0.065 (0.014)
$\pi(0.01)$	–	0.139 (0.024)	0.140 (0.019)	0.174 (0.016)
$\pi(0.05)$	–	0.191 (0.025)	0.192 (0.019)	0.220 (0.019)
$\pi(0.25)$	–	0.310 (0.039)	0.307 (0.023)	0.351 (0.026)
$\pi(0.50)$	–	0.477 (0.059)	0.478 (0.034)	0.549 (0.035)
$\pi(0.75)$	–	0.587 (0.073)	0.586 (0.034)	0.674 (0.035)
$\pi(0.95)$	–	0.716 (0.085)	0.722 (0.037)	0.816 (0.037)
$\pi(0.99)$	–	0.747 (0.092)	0.752 (0.042)	0.874 (0.034)
$\pi(1)$	–	0.767 (0.094)	0.766 (0.042)	0.899 (0.031)
σ	2.157 (0.134)	2.021 (0.126)	2.048 (0.385)	1.487 (0.058)
MSE	4.794	4.159	4.155	4.197

No. of Obs.	1,674.000	1,674.000	1,674.000	1,674.000

$\bar{u}$ is marginal utility of \$5. $\beta = \frac{1+\lambda\eta}{1+\eta}$ is loss aversion parameter in the model. $\pi(\cdot)$ is non-parametric probability weighting function. σ is estimated standard deviation of additive econometric error term.
Standard errors reported in parentheses. Bootstrap standard errors for ML estimates (N=100). Standard errors for MCMC estimates are calculated by burning the first 25% of the chain and then thinning the chain by every 200 iteration (Total Chain Length = 10^6).

Table 2.6: Maximum Likelihood (ML) and Markov Chain Monte Carlo (MCMC) Estimates of Parameters in Mug Experiment

	MLE	MCMC
	(1)	(2)
$\frac{\tilde{m}}{a}$	15.760	11.714
	(5.897)	(1.591)
β	1.511	1.488
	(0.089)	(0.039)
$a\pi(0)$	0.045	0.054
	(0.024)	(0.018)
$a\pi(0.01)$	0.084	0.098
	(0.039)	(0.021)
$a\pi(0.05)$	0.118	0.135
	(0.054)	(0.024)
$a\pi(0.25)$	0.207	0.242
	(0.088)	(0.033)
$a\pi(0.50)$	0.277	0.325
	(0.117)	(0.043)
$a\pi(0.75)$	0.323	0.378
	(0.136)	(0.048)
$a\pi(0.95)$	0.375	0.436
	(0.160)	(0.055)
$a\pi(0.99)$	0.389	0.452
	(0.167)	(0.057)
$a\pi(1)$	0.403	0.469
	(0.172)	(0.060)
σ	2.700	2.721
	(0.101)	(0.047)

MSE	7.880	7.355
No. of Obs.	1,638.000	1,638.000

$\bar{m}$ is marginal utility of the coffee mug. $\beta = \frac{1+\lambda\eta}{1+\eta}$ is loss aversion parameter in the model. $\pi(\cdot)$ is non-parametric probability weighting function. a is the linear multiplier in the compound reference point. σ is estimated standard deviation of additive econometric error term.
Standard errors reported in parentheses. Bootstrap standard errors for ML estimates (N=100). Standard errors for MCMC estimates are calculated by burning the first 25% of the chain and then thinning the chain by every 200 iteration (Total Chain Length = 10^6).

2.4.6 Validation

Increasing the degrees of freedom of a model must lead to better fit but it does not necessarily mean the model works better than a more parsimonious one. I validate the proposed model by performing a calibration using part of the sample while using the calibrated model to predict the rest of the sample. Table 2.7 compares four different models including expected value with σ as its only parameter, expected utility theory with an extra parameter of $\bar{u}$ or $\bar{m}$[15], reference dependent utility model without probability weighting[16] and the proposed model in this paper. Log-likelihood function values (LL) are reported for both the calibration and the validation subsamples. The calibration of models also reports the Akaike information criteria (AIC)[17] and Bayesian information criteria (BIC)[18]. The validation of the models reports mean squared error (MSE)[19] and a pseudo R^2 value[20]. The calibration uses 70% of the sample and the validation

[15] Assuming linear form of $u(\cdot)$.

[16] The model used is the one in Equation 2.3 with linear and two-part linear assumption on $m(\cdot)$ and $n(\cdot)$.

[17] $AIC = -2LL + 2k$ where k is the number of parameters.

[18] $BIC = -2LL + k \cdot ln(LL)$.

[19] $MSE = \frac{(Bid-Prediction)^2}{No.of Observations}$

[20] $PseudoR^2 = 1 - \frac{LL_{Model}-k}{LL_{EV}}$. This is the McFaddens definition of pseudo R^2 which is an indication of improvement of the full model from the intercept model. Here the intercept model is the expected value.

Figure 2.4: Model Prediction (top) and Probability Weighting Function (bottom) for Money Experiment

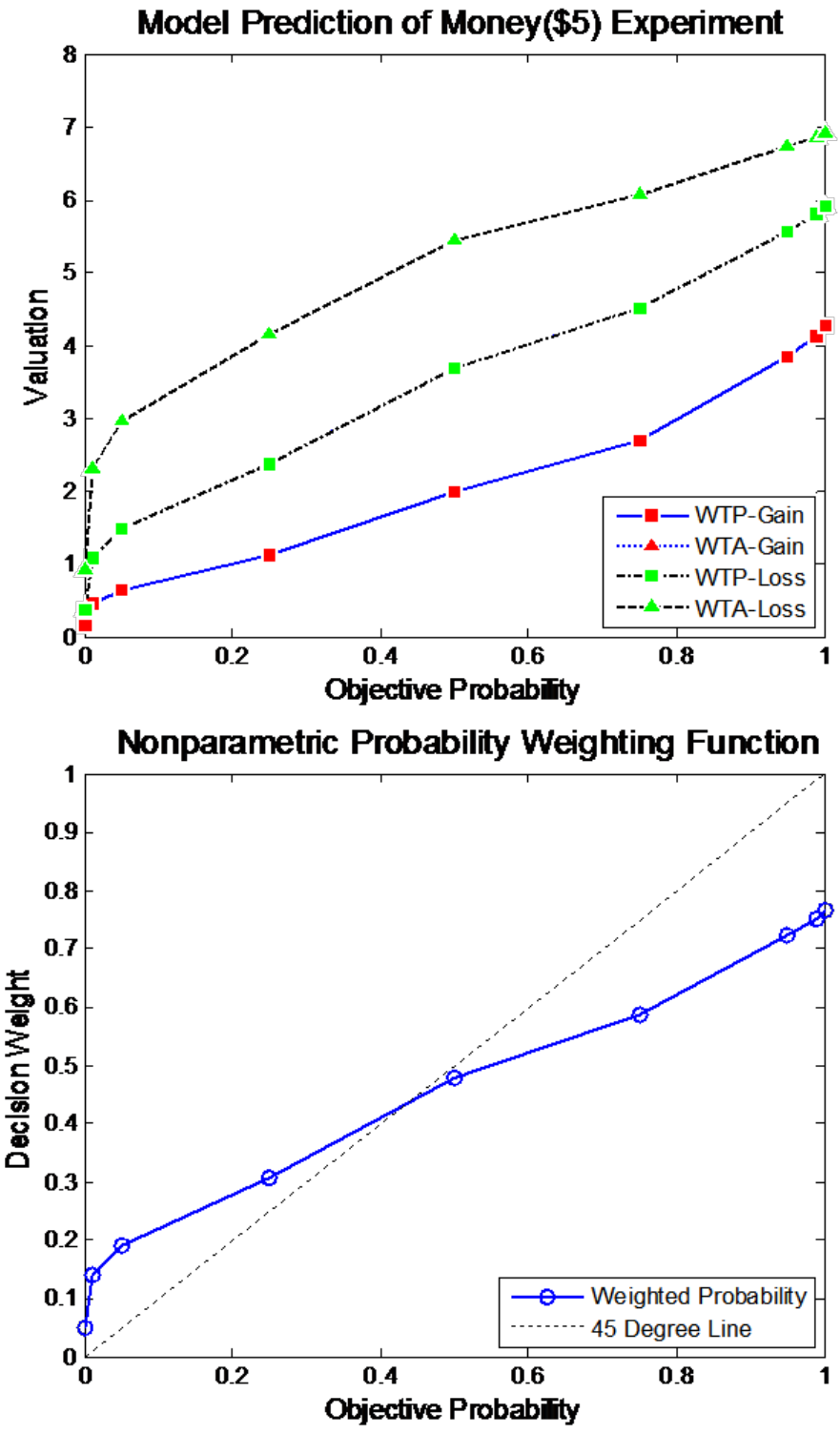
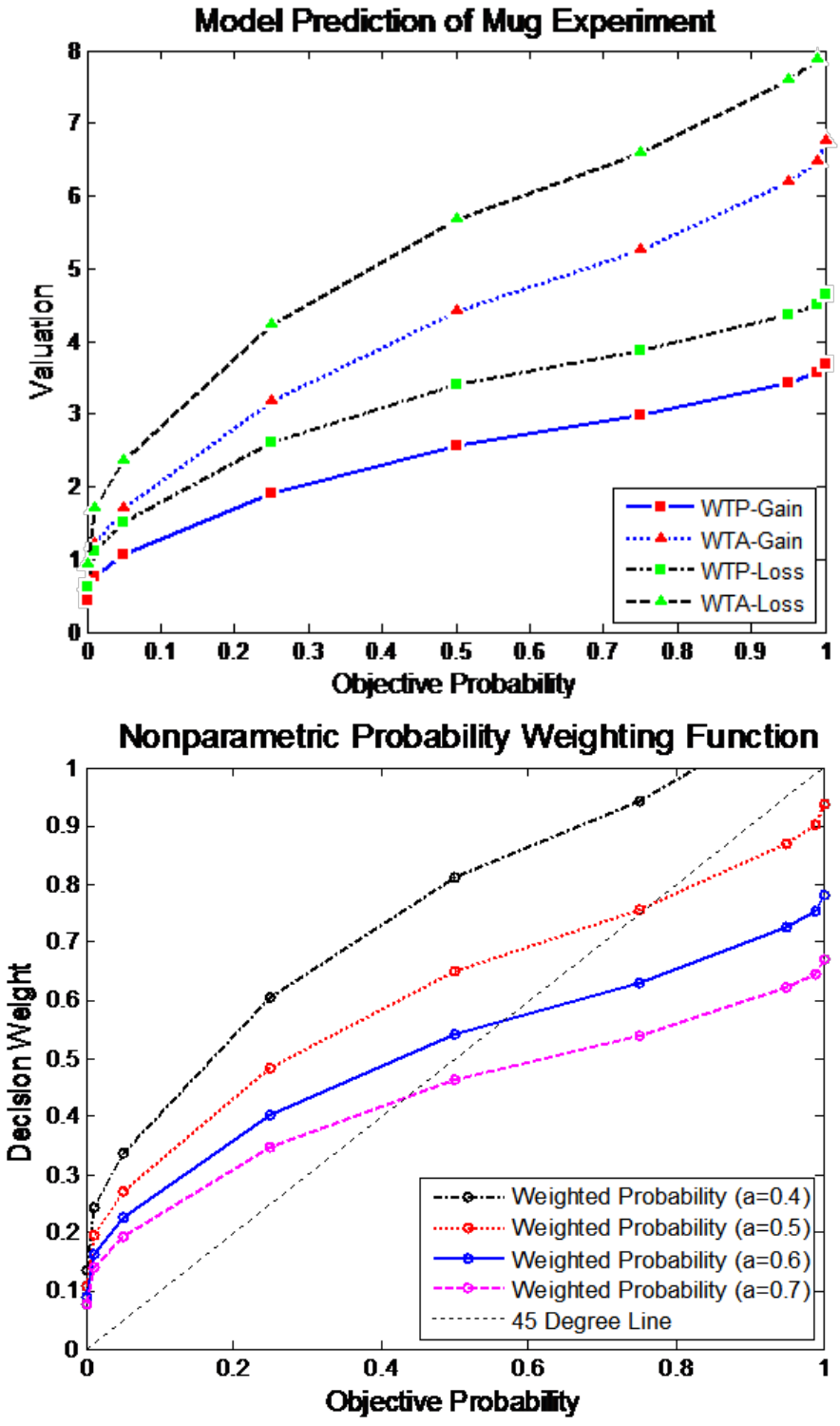


Figure 2.5: Model Prediction (top) and Probability Weighting Function (bottom) for Mug Experiment



uses the rest 30% of the sample. To do this, 70% of the subjects within *each* treatment are randomly drawn to form a calibration sample. The rest of the sample in each treatment are combined together to form the validation sample. This way of drawing observations guarantees balanced observations among different treatments in both the calibration and validation samples.

On the one hand, the calibration practice shows that the proposed reference-dependent utility model with rank-dependent probability weighting performs the best after accounting for parsimony. Note that probability weighting functions that have fewer parameters are likely to perform better. For example, both Prelec (1998) and Tversky and Kahneman (1992) suggested inverse S-shaped probability weighting functions that have only one parameter. However, the purpose of this practice is to show that probability weighting is *necessary* to explain behavior so I avoid discussing specific functional forms of the probability function. On the other hand, the validation practice confirms the explanatory power of the proposed model. The predictions made by the proposed model are the best among the four models after correcting for degrees of freedom.

Table 2.7: Model Calibration and Validation

	Model	No. of Parameters	Calibration (70% of sample)			Validation (30% of sample)		
			LL	AIC	BIC	LL	MSE	Pseudo R^2
Money	EV	1	-2660.83	5323.66	5328.71	-1204.24	5.9065	0.0000
	EUT	2	-2616.02	5236.04	5246.14	-1197.00	5.7394	0.0052
	RDU	3	-2524.52	5055.04	5070.19	-1163.55	5.0404	0.0321
	RDU with PW	12	-2444.53	4913.05	4973.64	-1124.55	4.3438	0.0570
Mug	EV	1	-2949.19	5990.38	5905.41	-1321.83	10.0865	0.0000
	EUT	2	-2860.67	5725.34	5735.39	-1289.4	8.9103	0.0238
	RDU	3	-2803.2	5612.4	5627.48	-1261.43	7.9861	0.0442
	RDU with PW	12	-2718.04	5460.08	5520.39	-1240.87	7.3877	0.0529

EV Expected value; EUT Expected utility theory; RDU Reference-dependent utility model; RDU with PW Reference-dependent utility model with rank-dependent probability weighting; LL Log-likelihood function value; AIC Akaike information criterion; BIC Bayesian information criterion; MSE Mean squared errors.

2.4.7 Robustness and Discussion

The estimates from the unrestricted model fall into reasonable ranges including a loss aversion parameter that is greater than 1 and a probability weighting function that overweights small probabilities and underweights large probabilities. The predictions from the estimated model also recover several important features of the raw data. First of all, it predicts the identical valuations for the WTAG and WTPL treatments in the money experiment as well as the result that these two values are different in the mug experiment. Secondly, as shown in Figure 2.4 the four lines from the money experiment are mostly parallel with each other. Lastly, although the four lines in Figure 2.5 are not quite parallel, the two WTP lines and two WTA lines are parallel respectively. This reflects the results of the reduced form regression model in Figure 2.4. In addition to the plausibility of the model, there are several noteworthy observations.

1. The estimated parameter $\beta = \frac{1+\lambda\eta}{1+\eta}$ is larger in the one dimension (money) case than in the two dimension (mug) case. If the behavioral model is correctly specified, this implies a larger weight (η) on gain-loss utility in the one dimension case.
2. The decision weight under certainty $\pi(1)$ is statistically different from 1 in the money experiment. Moreover, if we believe the relative weight on endowment, $a = 0.6$, is a reasonable assumption, $\pi(1)$ in the mug experiment is also statistically different from 1.
3. The reference point in the mug experiment is possibly "between" the endowment and the status-quo.

Observation 1 suggests that subjects in the money experiment generally care more about the gain-loss utility while subjects in the coffee mug experiment also care about the intrinsic consumption utility.

Many studies on rank dependent theory imposed the restrictions that $\pi(0) = 0$ and $\pi(1) = 1$ (Quiggin, 1982) while there are also other rank dependent models that impose no such restrictions (Tversky and Kahneman, 1992). Note that imposing $\pi(1) = 1$ is essentially restricting the valuations in the money experiment to be identical under certainty. This can be seen directly from Equation 2.5a. Based on the experimental results presented here, this may not be a good assumption since valuations do vary even under certainty. A somewhat straightforward but tautological explanation is that subjects do not treat a lottery ticket with 100% probability to win as a gain with certainty. In other words, given that the model is correctly specified, they behave as if the possibility of adverse outcome (i.e. lose in the lottery) has not been completely eliminated. A more convincing alternative explanation, however, is heterogeneity in the sample. The significant individual level fixed effects in the reduced form analysis indicates that possible heterogeneity exists in the experimental sample.[21]

To account for this possible heterogeneity, I estimate a different set of parameters for the money experiment which is shown in the fourth column of Table 2.5. This specification assumes individuals possess different consumption values for the \$5 and their consumption values are normally distributed in the population. Combining the MCMC method with Gauss quadrature[22], (4) in Table 2.5 shows these estimates. Since the maximum likelihood estimates for this specification are no longer feasible, diagnostics for the MCMC estimates are

[21] Another indication is that, under certainty, the distribution of valuation from money experiment is bimodal. This is also demonstrated by the divergence of mean and median values.

[22] 20 points used to approximate the value of integral.

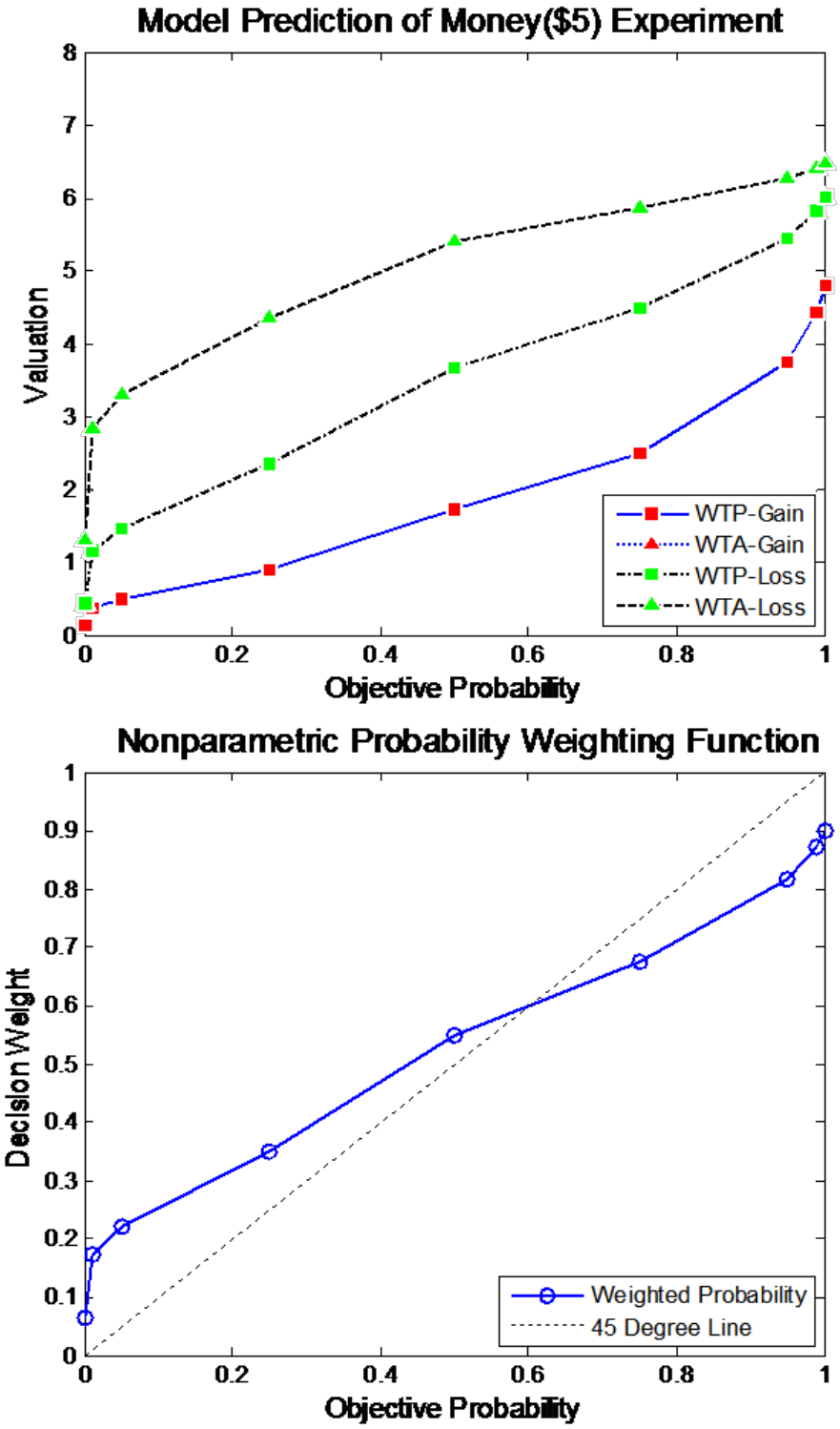
included in the appendix. As anticipated, including heterogeneity in consumption values ($\bar{u}$) reduces variance of econometric error term. It also increases the decision weight under certainty ($\pi(1)$) from 0.77 to 0.90. In addition, Figure 2.6 plots the model predictions and probability weighting function for this set of parameters. This result shows that, when considering heterogeneity, the estimated parameters are even more consistent with the ones reported in literature especially the probability weighting function.

Formation of reference points is largely an empirical question. It may be natural and convenient to take the endowment as the reference point in many cases but this strategy is not a panacea. For instance, Kszegi (2009); Kszegi and Rabin (2006, 2007) argued that people actually take the rational expectations as their reference points. Predictions from the KR model are not discussed in this paper but can be taken as a possible future research topic[23]. In the present experiment, if subjects take the endowment as the reference point, they should use the gamble as a reference point in the WTAG and WTPL treatments which implies a relative weight on endowment of $a = 1$. Although the proposed model cannot separately identify a, it is very likely that subjects on average take a point between endowment and status quo as their reference point. The formation of reference points remains an unresolved question that requires future work.

Before ending the current section, I should also mention recent studies that use mixture model to explain choices under risk based on the argument that considerable heterogeneity exists both within and between individuals (Conte et al., 2011; Harrison and Rutström, 2009). Identification strategies in these studies rely heavily on the chosen functional form of the behavioral models. For ex-

[23]Endogenous reference point specification in KR model can be nested in the flexible specification on reference point in this paper. However, if KR model is assumed, elicitation technique also affects solved equilibrium(s) from the model.

Figure 2.6: Model Prediction (top) and Probability Weighting Function (bottom) for Money Experiment with Heterogeneity in Consumption Utility of Money



ample, Harrison and Rutström (2009) used a CRRA (constant relative risk aversion) utility function to represent expected utility theory in their estimation and indicated that the risk aversion parameter is critical for the identification. Despite its usefulness in recognizing individual heterogeneity, such an approach can be dangerous because it is vulnerable to any error in selecting the functional forms[24]. Instead, I assume a uniform theory that explains behaviors of all individuals in the population and make as few assumptions as possible regarding functional forms. Admittedly this approach ignores heterogeneity (in their sense) in the population; it however tests if a single theoretical model can reasonably explain behavior.

2.5 Conclusion

It has been more than three decades since prospect theory was firstly proposed by Kahneman and Tversky, but economists have yet to settle on a universal theory that both explains and predicts behavior under risk and uncertainty. In this paper, I use a laboratory experiment to study reference dependent behavior under risk and seek an underlying behavioral model to explain the experimental results. The role of probability weighting in the model has been particularly emphasized. The experimental result, like many previous studies, suggests that expected utility theory is not a universal theory. In addition, the experimental result also suggests reference dependence within the full range of probabilities. The reference dependent behavior is more prominent under small probabilities. To explain the observed patterns, I proposed using a structural model

[24]In this particular example, it is implausible to assume a universal risk aversion parameter and fit it to laboratory experimental data. See again Rabin (2000) for a detailed discussion.

that incorporates loss aversion and rank dependent probability weighting. Both loss aversion and rank dependent probability weighting have been extensively tested in previous economic and psychology studies. Thus, the proposed structural model actually builds on existing evidence to provide a possible tractable model to explain reference dependence under risk and uncertainty.

Importantly, assuming a linear utility function, the experimental data allows one to estimate this model without imposing any additional constraint, in particular on the probability weighting function. Estimation shows that subjects behavior is consistent with the model and key parameters are within the range found in the literature. Results suggest people show both loss aversion and probability weighting in determining certainty equivalents for risky prospects, and the magnitude of both is empirically significant. The success of this behavioral model in explaining the experimental data again demonstrates that prospect theory is an appealing alternative theory to explain behavior under risk and uncertainty.

This study, being the first one that systematically examines the reference dependent behavior under risk, complements the literature studying human behavior under risk and uncertainty. The experimental design created an environment that allows one to thoroughly test prospect theory. Moreover, it also provides an explanation for the more prominent reference dependent behaviors for low probability risks such as airline accidents.

Table 2.8: Valuations in Each Money Treatment

			Probability								
Treatment	N		0.00	0.01	0.05	0.25	0.50	0.75	0.95	0.99	1.00
Willingness to Pay in Gain Domain (WTPG)	48	Mean	0.11	0.15	0.38	1.08	2.16	2.88	3.94	4.61	5.02
		S.E.	(0.10)	(0.06)	(0.11)	(0.10)	(0.17)	(0.25)	(0.31)	(0.41)	(0.43)
		Median	0.00	0.05	0.20	1.18	2.40	3.08	4.25	4.63	4.95
Willingness to Accept in Gain Domain (WTAG)	48	Mean	0.94	1.10	1.47	2.27	3.39	4.53	5.38	5.68	5.43
		S.E.	(0.31)	(0.28)	(0.29)	(0.25)	(0.21)	(0.19)	(0.27)	(0.26)	(0.26)
		Median	0.05	0.48	0.78	1.93	2.93	4.05	4.95	5.00	5.05
Disparity	–	Mean	0.83	0.95	1.02	1.19	1.23	1.65	1.44	1.07	0.41
		Median	0.05^{**}	0.43^{**}	0.58^{**}	0.75^{**}	0.53^{**}	0.97^{**}	0.70^{**}	0.37^{**}	0.10^{**}
Ratio	–	Mean	8.55	7.73	3.87	2.10	1.57	1.57	1.37	1.23	1.08
		Median	∞	9.60	3.90	1.64	1.22	1.31	1.16	1.08	1.02
Willingness to Pay in Loss Domain (WTPL)	45	Mean	0.02	0.45^{++}	0.93^{++}	2.53^{++}	3.73^{++}	4.36^{++}	5.21^{++}	5.16^{++}	5.11
		S.E.	(0.02)	(0.11)	(0.16)	(0.20)	(0.28)	(0.23)	(0.25)	(0.25)	(0.28)
		Median	0.00	0.25	0.60	2.25	3.25	4.10	4.95	4.95	5.00
Willingness to Accept in Loss Domain (WTAL)	45	Mean	0.83	2.67^{++}	3.37^{++}	4.15^{++}	5.60^{++}	6.05^{++}	7.34^{++}	6.93^{+}	7.44^{++}
		S.E.	(0.41)	(0.49)	(0.42)	(0.34)	(0.37)	(0.42)	(0.45)	(0.46)	(0.47)
		Median	0.05	1.30	2.75	3.75	5.00	5.00	5.05	5.05	5.50
Disparity	–	Mean	0.81	2.22	2.44	1.62	1.87	1.69	2.13	1.77	2.33
		Median	0.05^{**}	1.05^{**}	2.15^{**}	1.50^{**}	1.75^{**}	0.90^{**}	0.10^{**}	0.10^{**}	0.50^{**}
Ratio		Mean	41.5	5.93	3.62	1.64	1.50	1.39	1.41	1.34	1.46
		Median	∞	5.20	4.58	1.67	1.54	1.22	1.02	1.02	1.10

Table 2.9: Valuations in Each Coffee Mug Treatment

			Probability								
Treatment	N		0.00	0.01	0.05	0.25	0.50	0.75	0.95	0.99	1.00
Willingness to Pay in Gain Domain (WTPG)	41	Mean	0.04	0.16	0.24	0.70	1.75	2.37	3.51	3.98	4.27
		S.E.	(0.03)	(0.06)	(0.08)	(0.12)	(0.23)	(0.31)	(0.47)	(0.50)	(0.50)
		Median	0.00	0.00	0.00	0.50	1.25	1.65	2.50	3.25	3.75
Willingness to Accept in Gain Domain (WTAG)	48	Mean	0.71	1.42	2.07	2.94	3.96	4.72	6.12	6.42	6.84
		S.E.	(0.30)	(0.34)	(0.38)	(0.27)	(0.28)	(0.38)	(0.48)	(0.52)	(0.53)
		Median	0.05	0.53	1.23	2.95	4.45	4.65	5.75	5.95	6.68
Disparity	–	Mean	0.67	1.26	1.83	2.24	2.21	2.35	2.61	2.44	2.57
		Median	0.05**	0.53**	1.23**	2.45**	3.20**	3.00**	2.25**	2.70	2.93
Ratio	–	Mean	17.75	8.88	8.63	4.20	2.26	1.99	1.74	1.61	1.60
		Median	∞	∞	∞	5.90	3.56	2.82	2.30	1.83	1.78
Willingness to Pay in Loss Domain (WTPL)	46	Mean	0.01	0.33	0.72++	2.40++	3.55++	4.32++	4.84	4.89	4.68
		S.E.	(0.01)	(0.14)	(0.16)	(0.28)	(0.34)	(0.41)	(0.53)	(0.55)	(0.57)
		Median	0.00	0.00	0.50	2.20	3.85	4.38	4.88	5.35	4.98
Willingness to Accept in Loss Domain (WTAL)	47	Mean	1.38	2.23	2.79	4.88++	6.11++	6.84++	7.14	7.30	7.55
		S.E.	(0.44)	(0.46)	(0.44)	(0.37)	(0.40)	(0.44)	(0.48)	(0.50)	(0.61)
		Median	0.05	0.95	1.90	4.95	5.75	6.90	7.15	7.50	8.00
Disparity	–	Mean	1.37	1.90	2.07	2.48	2.56	2.52	2.30	2.41	2.87
		Median	0.05**	0.95**	1.40**	2.75**	1.90**	2.52**	2.27**	2.15*	3.02**
Ratio		Mean	138	6.76	3.88	2.03	1.72	1.58	1.48	1.49	1.61
		Median	∞	∞	3.80	2.25	1.49	1.58	1.47	1.40	1.61

Ratios are calculated as $\frac{Mean(WTA)}{Mean(WTP)}$ and $\frac{Median(WTA)}{Median(WTP)}$.

Wilcoxon-Mann-Whitney test conducted to test hypothesis that WTA=WTP in the same domain (gain or loss). Null hypothesis is rejected at 1% level for all probabilities.

Pearson χ^2 test (using medians) conducted to test hypothesis that WTP=WTA in the same domain (gain or loss). *indicates null hypothesis being rejected at 5% level. **indicates hypothesis being rejected at 1% level.

Wilcoxon-Mann-Whitney test conducted to test hypothesis that WTP-Gain =WTP -Loss and WTA -Gain =WTA -Loss separately. $^{+}$ indicates hypothesis being rejected at 5% level. $^{++}$ indicates hypothesis being rejected at 1

CHAPTER 3

EMOTIONS AND SUBJECTIVE PROBABILITIES: AN EXAMPLE OF TERRORISM INSURANCE

3.1 Introduction

The terrorist attacks on the U. S. on September 11, 2001 (hereafter 9/11) caused direct short-term losses estimated at 80 to 90 billion dollars (Kunreuther and Michel-Kerjan, 2004) in addition to long-term costs required to prevent and insure against any comparable attacks in the future. Within the "portfolio of counterterrorism efforts" (Mialon et al., 2012) that the U. S. has subsequently developed, Siqueira and Sandler (2007) categorize the responses as offensive such as the invasion of Afgahnistan or "defensive" such as the creation of a cabinet-level Department of Homeland Security within the federal government. Notwithstanding the reduction in domestic crime that appears to be a side-benefit of increased defense expenditures against terrorist threats (Gould and Stecklov, 2009), researchers have noted that self protection such as insurance commitments and payouts to guard against international terrorist attacks could theoretically dwarf the federal and state commitments for insurance against natural disasters (Lakdawalla and Zanjani, 2005). Against this backdrop, it is clearly important and relevant to understand preferences by the public for programs designed to prevent any future terrorist attacks as well as hazardous events in general.

In this article, we build upon previous experiments concerning responses to terrorism (Arce et al., 2011) and focus on the role of context and emotion on the choice of defensive counterterrorism measures. More specifically, while oth-

ers have explored relying upon a mix of public and private forms of insurance for domains such as health care (Blomqvist and Johansson, 1997), our experiments closely examine decisions to variably support public measures to reduce the likelihood of a terrorist attack and/or private insurance against potential terrorist-related losses incurred by individuals and firms. Given the extreme reactions generated by terrorist attacks, it may be important to examine the role that context and emotion play in motivating efforts to reduce the risks of future terrorist attacks.

3.1.1 Influence of Emotions

Research in psychology, behavioral economics, and neuroeconomics suggests that emotions such as fear and anger can play an important role in decision-making (Schwarz, 2000; Zeelenberg, 1999). These emotions are likely to be a major factor in the public response to terrorist events. Cognitive evaluations of risks often diverge from emotional reactions to the same risks and when that occurs there is ample evidence that emotional reactions often drive behavior (Loewenstein, 2000; Loewenstein et al., 2001). We are particularly interested in the effect of emotions on subjective risk estimations when facing possible terrorist attacks.

3.1.2 Calculations of Risk

It is widely accepted that risk is perceived and acted upon through two routes: (1) feelings, which rely on individuals' fast, instinctive, and intuitive reactions to

danger, and (2) analysis, which brings logic, reason, and scientific deliberation to bear on risk management (Hogarth et al., 2011; Slovic et al., 2005). Examples of "fast" reactions are generated by laboratory experiments that show visceral and negative responses when people are exposed to negatively valenced photographs and startled by 110 decibel (dB) sounds for 100 milliseconds (ms) (Filion et al., 1998). At the same time that the outcome of risk-danger is real, risk assessment is inherently subjective and represents a blending of science and judgment with important psychological, social, cultural, and political factors (Slovic, 1999). In this sense, it is important to acknowledge that risk is, to some extent, socially constructed.

Focusing specifically on the nature and unpredictability of terrorist attacks, it is extremely difficult to calculate risk-adjusted "insurance premiums" for policies that cover losses due to terrorism. Since 9/11 private insurance companies concluded that they could not effectively insure against risks associated with potential terrorist events on their own (Boardman, 2005; Jaffee and Russell, 2003), Congress approved the Terrorism Risk Insurance Act (TRIA) in 2002 with re-authorizations in 2005 and 2007 to help the insurance industry underwrite policies against possible loss caused by terrorist attacks by acting as reinsurer (Kunreuther and Michel-Kerjan, 2004). The two extensions of TRIA, which presently applies through the end of 2014, also show the increasing demand for terrorism insurance.

3.1.3 Previous Field and Experimental Studies

Previous field studies focusing on individual insurance decisions have found that people often do not insure against low probability but high loss risks like hurricanes and floods until after a disaster occurs (Kunreuther and Pauly, 2004; Kunreuther et al., 2013) due to negligence or underestimation of small probabilities (Tversky and Kahneman, 1992). In a field study involving the misperception of behavioral risks related to terrorist attacks, (Blalock et al., 2009) demonstrated that increased fear of flying led to more vehicular fatalities as people considered driving to offer relatively greater protection in the wake of 9/11s plane-based attacks. The common thread illustrated by these field studies is that people tend to respond to risk and uncertainty in ways that are economically suboptimal.

Laboratory studies permit much greater control over the type of information that people are expected to process before making decisions; however, experiments focused on insurance against low-probability, high-cost risks have nonetheless generated a diversity of findings. For example, in a study using hypothetical survey questions, experimenters found that people reduced their investments in insurance in response to reductions in the probability of a catastrophic loss even if the scale of the potential catastrophe remained constant (Slovic et al., 1977) although incentivized experiments showed that a reduction in the probability of a catastrophic loss did not generate a reduction in individual investments in demand for insurance (Laury et al., 2009).

Additional research has demonstrated that people tend to split with respect to willingness to pay (WTP) for insurance against small probability risks and either pay significantly too little (including a WTP=0) or significantly too much (McClelland et al., 1993; Schade, 2002) a bimodal pattern that Schade (2002)

attributes to concern level towards the risk. These dissimilar conclusions can possibly be explained on the basis of framing and contextual effects that play important roles when people make insurance purchase decisions against large loss but small probability risks (Kunreuther et al., 2001; Laury et al., 2009).

Previous studies have not examined how specific framing and contextual factors could affect insurance purchasing decisions. People could engage in either over or under payment on insurance policies against large loss but small probability risks. A field study (Lerner et al., 2003) conducted immediately after 9/11 indicated that emotions may help to predict insurance purchasing behaviors in the context of terrorism insurance. More specifically, Lerner and colleagues found that fear increased risk estimates and plans for precautionary measures while anger did the opposite. In addition, males had less pessimistic risk estimates and more anger than females. Although the emotional effects were significant, the findings were based on surveys and hypothetical questions. Inspired by their study, we conducted a series of controlled laboratory experiment to further demonstrate how different emotions affect behaviors when facing risks such as terrorist attacks. The current research also could help to better explain the observed anomalies in insurance purchasing decision discussed above. More importantly, this paper also suggests a possible mechanism through which specific emotions affect decisions toward both public and private measures to combat hazard events. Since researchers have established certain relations between framing, context, and emotions (Druckman and McDermott, 2008; Gross and D'Ambrosio, 2004), our study also has clear relevance for public policy debates.

3.2 Experimental Design and Procedures

The experiment is designed to investigate the role of emotions in decision-making regarding possible hazard events. To be more specific, we study whether and how emotions could alter subjects' decision on funding a public program which reduces the probability of the hazard event. At the same time, we also investigate the effect of such emotions on decisions towards private insurance that is a form of self-protection. In the current section, we firstly discuss the possible channels through which emotions affect economic decisions in our particular experimental context. We then illustrate the experimental procedures in details.

3.2.1 Theoretical Framework

The possibility of a terrorist event corresponds to the uncertainty concept in economics. It is different from the concept of risk which refers to possible outcomes with *known* probabilities. Thus the Subjective Expected Utility (SEU) theory (Savage, 1954) can be used to explain behavior facing possible terrorist events. (3.1) rewrites the SEU to serve our purpose. V_j is the decision utility from choosing alternative j. v_{jk} is the von Neumann-Morganstern (vNM) utility when outcome k realizes. P_{jk} is the subjectively formed probability of k happening.

$$V_j = \sum_k P_{jk} v_{jk} \tag{3.1}$$

A financial loss and simulated "terrorist event" were used in the experiment to represent monetary and emotional consequences when a hazard event happens.

To reduce the damages of the possible hazard event, subjects had either one or two programs (depending on different treatments) to choose from. The public program reduces the probability of hazard event and thus reduces the probability of both financial loss and emotional suffering. The insurance protects subjects from any possible financial loss but does not alleviate their emotional suffering. Convectional economic theories based on rational choice usually argue that emotion does not lead to irrational financial decisions. Although this view has long been disputed (Loewenstein, 1996, 2000), we are especially interested in testing the following hypotheses:

H1 Subjects only consider monetary gain/loss when they vote on the public program.

It should not be too surprising if H(1) is rejected since substantial evidence exists to show emotions can potentially alter decisions. However, testing H(2) gives us a potentially more interesting result:

H2 Subjects' emotions do not affect their decisions on private insurance because insurance only protects them against financial loss not any emotional suffering.

H(2) is of special interest to policy makers. If people only purchase private insurance to protect their exposed assets, no intervention is needed . If, however, people use private insurance to cope with emotional consequences, the solution is ineffective. Given limited social resources, such behavior suggests a misallocation of resources between public and private solutions that deal with possible hazard events. Moreover, as suggested by Lakdawalla and Zanjani

(2005), use of private insurance may even create negative externality that reduces the social welfare. In this case, government intervention is necessary to correct any resource misallocation. To test these hypotheses, we design 8 treatments that are listed in Table 3.1.

Table 3.1: Treatment Design

Treatment	Hazard Control Cost	Video	Loss	Insurance Cost	No.
A1	\$0.50	Yes	\$5	–	16
A2	\$0.75	Yes	\$5	–	16
A3	\$0.50	No	\$5	–	16
A4	\$0.75	No	\$5	–	16
B1	\$0.50	Yes	\$5	\$1	32
B2	\$0.25	Yes	\$5	\$1	32
B3	\$0.50	No	\$5	\$1	16
B4	\$0.25	No	\$5	\$1	16

In treatments A1, A2, B1 and B2, the hazard event meant losing \$5 and watching a video clip with an intense explosion sound (meant to induce emotions). In other treatments, the hazard event was defined as a \$5 financial loss without watching the video clip. In part A, participants made a decision if they wanted to vote for a hazard control program which lowered the probability of the hazard event. This program cost either \$0.50 (treatments A1 and A3) or \$0.75 (treatments A2 and A4) and was only applicable to the current round. Comparable to many government taxing programs as well as the Provision Point Mechanism described by Rondeau et al. (2005), if the majority voted yes ($N \geq 9$), *all* subjects needed to pay to fund the program. This voting mechanism has been

shown to be preference revealing (Messer et al., 2010). Whenever the public program is funded, the probability of hazard event is 10% and otherwise 20%. These probabilities were made *unknown* to subjects to simulate the uncertainty case in reality. However, it was made very clear to the subjects that funding the hazard control program lowers the probability of the hazard event by *half*. Part B is similar to Part A, except that subjects made two decisions simultaneously in each round. They decided to vote for – or against – the hazard control program, which cost \$0.50 in treatments B1 and B3 or \$0.25 in treatments B2 and B4 and each subject decided whether to purchase insurance, which cost \$1 and only insured him/her against the \$5 financial loss. Those who purchased the insurance still watched the video clip whenever a hazard event happened given the rationale described above. Using SEU and assuming a locally linear utility function v, the four different choices can be formulated as in (3.2a–3.2d). All the four choices are available in Part B but only the first two choices are available in Part A. L represents the financial loss if a hazard event happens while M represents the emotional loss caused by watching the video clip. D is a dummy variable that equals to 1 for the video sessions. Tax is the cost of funding the public program while Ins is the cost of purchasing private insurance. Finally w represents the wealth level of the representative agent.

$$\text{No program} : V_1 = w + P_{11}v_{11} + P_{12}v_{12} = -PL - PMD \tag{3.2a}$$

$$\text{Public only} : V_2 = w + P_{21}v_{21} + P_{22}v_{22} = -\frac{P}{2}L - \frac{P}{2}MD - Tax \tag{3.2b}$$

$$\text{Private only} : V_3 = w + P_{31}v_{31} + P_{32}v_{32} = -PMD - Ins \tag{3.2c}$$

$$\text{Both} : V_4 = w + P_{41}v_{41} + P_{42}v_{42} = -\frac{P}{2}MD - Tax - Ins \tag{3.2d}$$

Note again that we assume the utility v is locally linear. Given the small amount at stake in the laboratory experiment, this is not a too arbitrary assumption. Rabin and Schrag (1999) and **?** provide a detailed discussion of this point. Using this formulation, we will show that the private insurance purchasing decision should not be affected by emotions in a random utility model (RUM).

3.2.2 Experimental Procedure

All experimental sessions were conducted in the Laboratory for Experimental Economics and Decision Research (LEEDR) at Cornell University. Participants were undergraduate students recruited from introductory level classes or through the Lab's online recruitment system. Sessions ran from 45 minutes to an hour depending on treatment. All participants who showed up received a $5 show-up fee. Participants who finished the whole experiment expected an average earning of $20 in addition to the show-up reward. Ten sessions were conducted[1] with exactly 16 participants in each.

Each participant was randomly assigned to a desk equipped with a desktop computer and headphones. Participants read instructions, made their decisions, and received feedback privately through a Visual Basic Application program that ran on their computers[2]. Subjects were able to ask questions at any point throughout the experiment but were not allowed to talk or discuss the experiment with each other. After each session, subjects were asked to finish a demographic survey before they were paid and then left the Lab. In addition to

[1] Eleven sessions were conducted but one was excluded due to sampling problems. Including the extra session does not change our major results. The analyses with data collected from all eleven sessions are available upon request.

[2] See appendix for screen shots.

details specified here, standard economic experiment protocols applied.

To induce negative emotion, negatively valenced images were combined with a startle response to an unexpected very loud sharp noise (Gross and Levenson, 1995) in some of the sessions. The combination has been shown to yield a stronger negative emotional response. A video clip of terrorist events that included several scenes of bombings with selected explosion sounds (not all) raised to a level of 110 db for four milliseconds was shown to all subjects in those sessions. We prepared three versions of the video clips with exactly same video content but different timing for the selected explosion sounds that were amplified to 110 dB[3]. We randomly chose the order in which to play the three versions within each session so that subjects could not prepare themselves for the loud sound. Subjects in sessions with the video were required to wear headphones whenever the video clip was played. All of the headphones were connected to amplifiers, which were in turn connected to a server computer. When a simulated terrorist event happened, the experimenter played one of the video clips on the server computer. Participants watched the video projected on an overhead screen and listened through their own headphones. Each time after the video was played, subjects were asked to complete a questionnaire that measured their emotional reaction[4]. Importantly, participants were either exposed to the video and sound or not or had the opportunity to buy insurance or not, in relevant treatments, so that we could determine the impact of emotion on the allocation decision between public and private mitigation strategies.

In all 10 sessions, subjects made decisions in each of 30 rounds, but they were only told that the experiment consists of "an unknown but predetermined

[3]Volume was calibrated with a sound meter in the Laboratory.

[4]One of the versions can be found at `http://www.4shared.com/video/QwmOz0K9/1st_Blast.html`

number of rounds" to avoid any final-round effects. Before the first round, every participant was endowed with $20 in his/her account. In each of the following rounds, they received $1 as income. A possible "hazard event" was explained to all of the subjects before the first round. The hazard event had different consequences depending on treatments. In every session, a different subject drew a poker chip to decide if a hazard event would happen in that round[5]. As indicated in Table 3.1, eight treatments were implemented, varying the hazard control program cost, the presence or absence of emotion stimuli and the availability of private insurance from session to session.

To implement different probabilities, we prepared two bags with different numbers of colored chips in them. A green bag had 9 white chips and 1 red chip while a red bag had 8 white chips and 2 red chips. If the program was funded in a round, a chip was drawn from the green bag; otherwise, from the red bag. Subjects were informed that both bags had an equal number of chips and there were many more white chips than red chips in both bags. In addition, they were told the red bag had twice as many red chips as the green bag. This procedure attempts to replicate the real world ambiguity surrounding such events. If a red chip was drawn from either bag, all participants lost $5, which was deducted from their personal experimental accounts. The hazard control program reduced the probability of the hazard event from 20% to 10%, which translated to a reduction of $0.50 of expected loss. Subjects were not informed of the probabilities and only knew that the program reduces the probability of an event by 50%.

[5]See appendix for full version of written instructions.

3.3 Results

Data collected from Part A allows us to analyze the price effect and emotion effect induced by the video clip on funding the hazard control program. It is clear from Table 3.2 that both price and emotion stimuli were effective treatments in our experiment. When the price of the hazard control program was low and emotion stimuli were applied, the hazard control program was in effect in all rounds. On the contrary, when price was high and no emotion stimulus was applied, the hazard control program was only funded in the first eight rounds. Lines for the other two treatments A2 and A3 lie in between.

Data collected from Part B show a similar pattern as is depicted in Table 3.2. Note we decreased the hazard control cost by $0.25 in Part B. We added this adjustment after the pilot session to avoid losing variation in either vote or insurance purchase. More importantly, if a subject is risk neutral, then he or she now has the information in the later rounds where participants realized the approximate probabilities that the expected return on insurance is greater than the hazard control program in terms of protecting her money. That is, a $0.5 hazard control program and a $1 insurance policy should be equally attractive to a subject if she were risk neutral. The hazard control program, however, provides an extra benefit since it lowers the probability of exposure to the emotion stimuli. Since most people are risk averse in such situations, we set a relatively lower price for the hazard control program to attract more votes.

We should make clear that there are two different concepts when we talk about effect of emotion stimuli in this paper. The first one refers to the treatment effect which was exogenously determined by the experimental design and we

Table 3.2: Votes in Different Treatments

Votes in Different Treatments				
Treatment	Round 1	Round 10	Round 20	Total
A1	14	13	9	11.767 (7.065)
A2	11	8	10	9.433 (7.879)
A3	11	8	11	11.167 (7.354)
A4	10	3	3	5.400 (7.574)
B1	6.5	4.5	3.5	3.170 (6.489)
B2	13	12	10	10.367 (7.646)
B3	9	8	2	4.733 (7.310)
B4	6	4	0	1.900 (5.181)
Insurance Purchase in Different Treatments				
Treatment	Round 1	Round 10	Round 20	Total
B1	8	8	10	9.950 (7.763)
B2	2	3	7	4.783 (7.329)
B3	6	6	5	8.367 (8.000)
B4	14	12	12	11.333 (7.280)

Standard deviations in parentheses

call it the *treatment effect*. The second one refers to the effect from actual induced emotions that are represented by the measured emotion levels. We call this *emotion effect*. Both concepts will be used in the analysis and we will explicitly refer to one or the other whenever confusion is possible.

Although the above figures clearly show the emotion treatment effect, we are

more interested in the emotional effect that is induced by the emotion treatment. Table 3.3 shows the average emotion levels in different treatments and the pattern is intuitive. To provide a more accurate comparison, Table 3.3 also shows the same set of statistics to compare emotion levels when the *first* simulated hazard event happens in each treatment[6]. One can easily tell from Table 3.3 that the video clip had a significant effect on all emotions. Wilconxon rank-sum test also verifies this observation. Since we only measured emotion levels after each hazard event happened, we used a linear regression to predict emotion levels in all other rounds. This regression analysis assumes emotion levels are determined by treatment and demographic variables. Given the random sampling of our experiment, this is a reasonable assumption[7]. Nonetheless, the predicted emotion levels should be treated with caution since emotion changes could be essentially nonlinear in any of the included explanatory variables. In the following analyses, we use the predicted emotions in addition to the measured emotions to study the emotion effects. This addition can be treated as a robustness check. Details can be found in the appendix.

Based on previous studies (Fischhoff et al., 2003), we focus on the effects of anger and fear in this study. Figure 3.1 and Figure 3.2 show anger and fear levels in different treatments. Detailed Numbers can also be found in Table 3.3. A probit model was employed to analyze data from Part A.

Table 3.4 shows results from the regressions: column (1) explains voting with two treatment variablescost and video as well as several other control variables so it focuses on treatment effects; column (2) explains voting with *measured* emo-

[6]The first hazard event usually happens in different round given its randomness. This makes a "clean" comparison between no-video hazard event and video hazard event.

[7]We started from using all relevant variables we collected to predict emotions. Many of them were very insignificant hence removed from the prediction model.

Figure 3.1: Anger and Fear from All Measurements

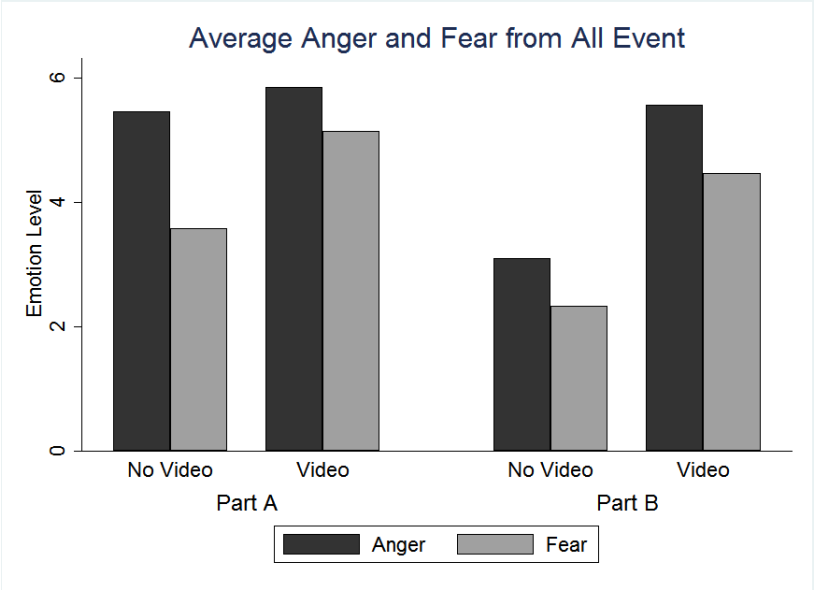


Figure 3.2: Anger and Fear from the First Measurement

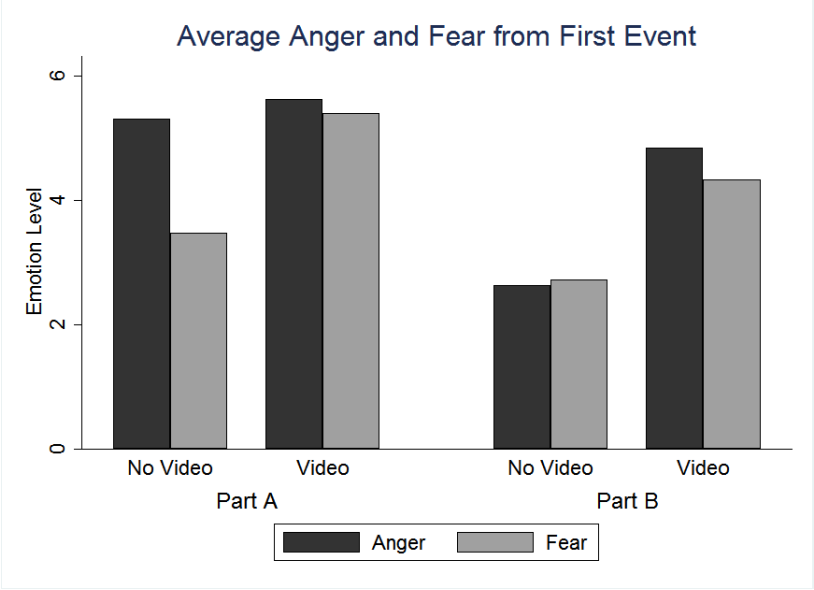


Table 3.3: Average Emotions in Different Treatments

	All Events				First Event Only			
	Part A		Part B		Part A		Part B	
	NV	V	NV	V	NV	V	NV	V
Fear	3.59	5.15*	2.33	4.47*	3.47	5.41*	2.72	4.33*
	(2.55)	(2.59)	(2.03)	(2.57)	(2.44)	(2.44)	(2.28)	(2.30)
Anger	5.46	5.86	3.10	5.57*	5.31	5.63	2.63	4.85*
	(2.79)	(2.49)	(2.71)	(2.63)	(2.81)	(2.27)	(2.57)	(2.37)
Sadness	4.94	6.23*	2.49	5.63*	4.97	6.53+	2.53	5.70*
	(2.74)	(2.33)	(2.29)	(2.64)	(2.62)	(2.09)	(2.51)	(2.42)
Disgust	3.66	6.08*	2.25	5.53*	3.88	6.09*	2.19	5.18*
	(2.94)	(2.09)	(2.05)	(2.57)	(2.92)	(1.89)	(2.16)	(2.32)
Amuse	2.92	2.24*	2.78	1.63*	3.56	2.41	3.59	1.92*
	(2.19)	(1.18)	(2.23)	(1.52)	(2.56)	(1.83)	(2.76)	(1.72)

NV=No Video; V=Video. Standard deviations in parentheses for reported means. p values in parentheses for ANOVA F statistics. Wilconxon rank-sum test performed to test effect of video treatment in each group. *denotes significant difference at 1 percent level and + denotes significant difference at 5 percent level.

tions in addition to cost and control variables. Since we only measure emotions when a hazard event happens, this regression has fewer observations than (1). Column (3) replaces measured emotion variables with *predicted* emotion variables. The video dummy variable was removed from both columns (2) and (3) since the video was used to invoke emotions. Both (2) and (3) look at emotional effects. Although the purpose is to study effects of specific emotions,

specific emotion levels cannot be exogenously imposed. Hence we had to use the simulated terrorist event to invoke them and use the self-reported levels in the analysis. Standard errors are clustered by subject to account from possible correlation between rounds. Results in column (1) verify that our prepared video clip worked as expected and subjects were willing to pay to lower the probability of seeing it. This is not a surprising result; however, column (2) is more interesting since it provides more detailed estimates on the effects of anger and fear. Specifically, it shows that subjects were more likely to fund the hazard control program when they were fearful but less likely to do so when they were angry, although the coefficient of fear is not significant at 5 percent level ($p = 0.087$). This is an interesting finding especially the effect of anger. Anger is usually taken as a negative emotion that people do not seek to experience so we should expect one willing to pay to reduce level of this feeling but we observed the opposite. This observation cannot be optimal from an economic point of view. These results are consistent with the field study (Lerner et al., 2003) except that the experiment was incentivized so subjects' decisions were consequential both emotionally and financially. Therefore, the correlations between anger and voting as well as fear and voting were observed from "real" behaviors not based on hypothetical survey questions.

It is noteworthy that an average of only three to four hazard events happened in each session so column (2) mostly captures between-subject effects. We ran the same regressions with emotion variables replaced by predicted ones in (3) to capture both within- and between-subject effects. Although we attempted to make the emotion prediction as accurate as possible , our linear models only explain 20% of the variation in anger and 18% of the variation in fear. Therefore, coefficients in column (3) should be interpreted with caution. As is shown,

the signs of the coefficients remain unchanged from (2). Regarding the hazard control program, fear encourages supporting votes and anger discourages support. Demographic variables do not help to explain voting decisions when only the hazard control program is available. Only gender is significant at 5 percent level in column (2). We expected Democrats and Republicans to have different attitudes towards the hazard control program since it is essentially a publicly funded program but the results do not favor that hypothesis. We have also included the estimated marginal effects. The significance levels and signs are consistent with the estimated coefficients in the main regression. Because magnitudes of effects are not our focus here, we do not expand the discussion but interested readers can find them in the appendix.

Aside from a public program aiming to reduce probabilities of terrorist attacks, insurance is also widely used in reality to deal with terrorism risks. Usually, commercial insurance only insures people against possible financial losses, but they still suffer from emotions caused by a terrorist event. Therefore, any rational decision maker would not use insurance to ameliorate negative emotions. We added an insurance option in Part B of the experiment to investigate how subjects make their decisions in such a setting. Subjects were given the two options at the same time and they had the opportunity to choose none of them, either of them, or both of them. The four options, which we designate as choices 0, 1, 2, and 3 for the multinomial model that we used for analysis, are: (0) no hazard control program and no insurance, (1) hazard control program but no insurance, (2) no hazard control program but insurance, and (3) hazard control program and insurance. When the hazard control cost is high, the video treatment largely increases use of hazard control program and decreases the use of private insurance. But when hazard control cost is low, the video treatment

Table 3.4: Regression Results on Voting Decisions (part A)

	(1) Treatment Effect	(2) Emotion Effect	(3) Emotion Effect
Tax	-4.089*** (1.468)	-7.397*** (1.850)	-4.325*** (1.486)
Video	0.699* (0.364)		
Democrat	0.067 (0.382)	0.372 (0.534)	0.121 (0.417)
Republican	0.858 (0.659)	0.918 (0.811)	0.704 (0.679)
Male	-0.397 (0.355)	-1.047** (0.481)	-0.447 (0.362)
Anger		-0.270*** (0.091)	
Fear		0.179* (0.099)	
Predicted Anger			-0.105 (0.122)
Predicted Fear			0.233 (0.195)
Constant	2.664** (1.051)	6.147*** (1.361)	2.584** (1.314)
Observations	1920	208	1856

Hazard control cost is either \$0.5 or \$0.75. Video is a dummy variable (1 if required to watch the video clip when a hazard event happened, 0 otherwise). Anger and fear are predicted emotions ranging from 1 to 9. Clustered standard errors are in parentheses. $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$.

actually tends to slightly decrease the use of the hazard control program. This mixed pattern suggests that price effect and emotional effect interact with each other so we need to control one to investigate the effect of the other. To do this, we use a multinomial probit regression to look at effects of the emotion treatment and emotions as shown in Table 3.5.

Table 3.5: Regression Results on Voting and Insurance Decisions (part B)

	(1) Treatment Effect	(2) Emotion Effect	(3) Emotion Effect
Hazard Control Cost (Tax)	-4.531***	-2.290	-4.849***
	(1.544)	(1.600)	(1.684)
1 Public Program			
Male	0.108	-0.490	0.115
	(0.433)	(0.522)	(0.480)
Democrat	1.147**	0.999*	1.174**
	(0.529)	(0.549)	(0.521)
Republican	0.384	0.193	0.511
	(0.598)	(0.611)	(0.555)
Video	1.310**		
	(0.570)		
Anger		-0.120	
		(0.093)	
Fear		0.227**	
		(0.104)	
Predicted Anger			-0.558**
			(0.223)
Predicted Fear			0.802***
			(0.276)
Constant	0.407	0.332	0.682

	(0.650)	(0.796)	(0.924)
2 Private Insurance			
Male	0.614 (0.405)	0.467 (0.467)	0.584 (0.368)
Democrat	1.077** (0.468)	1.198** (0.485)	1.119** (0.458)
Republican	0.398 (0.618)	0.393 (0.687)	0.669 (0.496)
Video	-0.182 (0.393)		
Anger		-0.227*** (0.087)	
Fear		0.202* (0.105)	
Predicted Anger			-0.602*** (0.162)
Predicted Fear			0.431* (0.255)
Constant	4.644*** (1.586)	2.089 (1.728)	5.566*** (1.837)
3 Both			
Male	-1.909*** (0.695)	-1.699 (2.716)	-1.943*** (0.679)
Democrat	0.700 (0.748)	0.593 (0.758)	0.677 (0.787)
Republican	-0.629 (0.853)	-0.510 (4.806)	-0.538 (0.744)
Video	0.186		

	(0.671)		
Anger		-0.215*	
		(0.111)	
Fear		0.276*	
		(0.149)	
Predicted Anger			-0.489*
			(0.258)
Predicted Fear			0.624*
			(0.375)
Constant	5.397***	2.160	5.583**
	(2.025)	(2.487)	(2.414)
Observations	2880	445	2784

Hazard control cost is either \$0.25 or \$0.5. Video is a dummy variable
(1 if required to watch the video clip when a hazard event happened, 0 otherwise).
Anger and fear are predicted emotions ranging from 1 to 9.
Bootstrap standard errors (clustered by subjects) in parentheses.
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

In this multinomial probit model, we take choice 0 as the base choice so that the estimated coefficients are effects on the other three choices relative to choice 0. Following the same structure of Table 3.4, column (1) in Table 3.5 has the hazard control cost and the video dummy variable plus several control variables as independent variables. This regression gives estimates of treatment effects. Column (2) has actual measured emotions and hazard control cost as independent variables. Following the same convention as Table 3.4, this regression estimates the emotional effect of anger and fear. Column (3) uses predicted emotions to replace actual measured emotions in column (2). Since we kept the cost of insurance constant, we only included hazard control program cost in all regressions. Table 3.5 shows the significance and effect of each factor (not magnitudes). We

believe when the hazard control program has a relatively lower cost, for reason discussed in experimental design, it should appear to be more appealing for any risk neutral subject.

Column (1) shows that watching the video increased likelihood of funding hazard control program, but its effect is limited to the hazard control program and does not affect insurance purchases. In a multinomial probit model, all likelihoods are estimated relative to the base choice so there is no ordering of the rest three choices. Since we are more interested in the emotional effect, column (2) in Table 3.5 then provides estimates using measured emotions and we note that the coefficients of both anger and fear have expected signs. Anger again discouraged subjects from funding the hazard control program. In addition, anger also discouraged subjects from purchasing insurance against financial loss. This effect is significant at the 1 percent level on choices 2 and 3 although it has a p value of 0.08 on choice 1. Fear, on the other hand, encouraged subjects both to fund the hazard control program and to purchase insurance. Coefficients for all three choices are significant at 5 percent level and are significant at 1 percent level for choices 1 and 3. With predicted emotions, column (3) indicates that coefficients of anger and fear have negative and positive signs respectively. This is again consistent with the patterns displayed in columns (1) and (2) in Table 3.5.

To sum up, we employed a probit model and a multinomial probit model in this section to analyze decisions regarding the hazard control program and insurance. The stimuli we used in our experiments successfully induced emotions, especially anger and fear. In general, fear encouraged subjects to vote for hazard control program and to purchase insurance while anger did the opposite. One major finding is that although insurance did not protect subjects

from the emotional stimuli, their purchasing decisions still react to the changes in emotions. The other major finding is that the hazard control program does not substitute for insurance purchases even though the program lowered the probability of the simulated terrorist event.

3.4 Possible Explanations

Using the public program to reduce the probability of emotional loss rejects our hypothesis **H1**. This, however, is consistent with economic rationale illustrated in 3.2a and 3.2b. We are more interested in the effect of emotions on private insurance purchasing decisions. Table 3.5 column (1) shows that watching the video does not change the likelihood of purchasing private insurance. This insignificant *treatment effect*, however, should *not* be confused with the *emotion effect*. As argued by Lerner et al. (2003), fear and anger have opposite effects on decisions towards possible terrorist events. Column (2) and column (3) of Table 3.5 confirm this finding. That is, the video clip in the experiment successfully induced both fear and anger [8] but the effects of fear and anger cancel out [9]. At a first glance, the rejection of **H2** seems to be a contradiction to traditional economic wisdom. In this section, we present a possible explanation using random utility model that explains the observed behavior within the SEU framework.

(3.2a)–(3.2d) demonstrate the four choices subjects face in the experiment. Assuming the representative subject is a SEU maximizer and her choice is determined by her subjective expected utility plus a random error term. She always

[8] This has been shown in Table 3.3

[9] Some may worry about the demand effect by eliciting self reported emotions after each hazard event. This concern does not confound our results. Even subjects tend to over report, their behavior indicates the effects are real

chooses the option that gives her the highest utility.

$$U_j = V_j + \epsilon_j \tag{3.3}$$

U_j determines her utility of choosing alternative j while V_j is the subjective expected utility in (3.1). Our agent always chooses the alternative that has the highest U_j. Because the existence of ϵ_j, she may not choose the alternative that has the highest V_j. The researcher observe her final choice and thus the choice leading to the highest U_j. Emotions then alter decisions through affecting the subjective probability.

$$P = c + \alpha Fear + \beta Anger \tag{3.4}$$

Substituting (3.4) into (3.2a)–(3.2d) we have (3.5a)–(3.5d). This allows the subjective probabilities P of the hazard event to vary among individuals with different fear and anger levels. This also helps to explain the observation that why fearful individuals are more likely to fund the public program as well as purchase private insurance[10].

$$\begin{aligned} V_1 &= w - (cL + \alpha LFear + \beta LAnger + cDM + \alpha MFear \\ &\quad + \beta MAnger) \end{aligned} \tag{3.5a}$$

$$\begin{aligned} V_2 &= w - \frac{1}{2}(cL + \alpha LFear + \beta LAnger + cDM + \alpha MFear \\ &\quad + \beta MAnger) - Tax \end{aligned} \tag{3.5b}$$

$$V_3 = w - (cDM + \alpha MFear + \beta MAnger) - Ins \tag{3.5c}$$

$$V_4 = w - \frac{1}{2}(cDM + \alpha MFear + \beta MAnger) - (Tax + Ins) \tag{3.5d}$$

[10]Strictly speaking, explaining the increased likelihood to fund public program does *not* require different subjective probabilities. The emotional loss M induced by watching the video can also explain it.

Admittedly, there is no strong reason for us to believe (3.4) is the only explanation. Within the framework of SEU, another alternative explanation is learning represented by (3.6) where *Round* is the round number and *Experinece* is the number of past hazard events. Substituting (3.6) into (3.2a)–(3.2d) one can derive similar equations as (3.5a)–(3.5d). They have been omitted here.

$$P = c + \gamma Round + \delta Experience \tag{3.6}$$

We estimate both model using the collected experimental data. In addition, a baseline model which assumes neither emotional effects nor learning is also estimated. To estimate the parameters in the structural equation (3.4) and (3.6), we need to impose a structure on the random error term ϵ_j. A $Gumbel(0, \frac{\sigma\pi}{\sqrt{6}})$ distribution is used so the model can be estimated as a logit model (McFadden, 1973).In a logit model, the scale of utility is irrelevant so we normalize the utility of money to 1 to estimate σ–the variance of the unobservables. The corresponding Log-likelihood function is (3.7).

$$LL(c, \alpha, \beta, M, \sigma) = \sum_n \sum_j y_{nj} \ln(\frac{e^{\frac{V_j}{\sigma}}}{\sum_j e^{\frac{V_j}{\sigma}}}) \tag{3.7}$$

To compare different models, the Akaike Information Criterion(AIC) and Bayesian Information Criterion(BIC) are also reported in the estimation. As a robustness check, we estimate the model with both predicted emotions and measured emotions. The learning model and baseline model use the same data as the emotion model. Table 3.6 shows the former and Table 3.7 shows the latter.

Table 3.6: Estimated Random Utility Model with Predicted Emotion Data

	(1) Emotion	(2) Learning	(3) Baseline
α	0.033***	-	-
	(0.005)		
β	−0.037***	-	-
	(0.004)		
γ	-	−0.004***	-
		(0.001)	
δ	-	0.018***	-
		(0.002)	
c	0.275***	0.280***	0.258***
	(0.011)	(0.008)	(0.004)
M	0.034	0.069***	0.055
	(0.027)	(0.031)	(0.034)
$\frac{1}{\sigma}$	3.183***	3.047***	3.052***
	(0.126)	(0.117)	(0.125)
Observations	4640	4640	4640
$Log-likelihood$	-4712	-4723	-4760
AIC	9433	9457	9526
BIC	9465	9489	9546

Bootstrap (N=100) standard errors in parentheses. Column (1) uses all data with predicted emotions. Column (2) and (3) use data from the same rounds as column (1). *** significant at 1%. ** significant at 5%. * significant at 10%.

Table 3.7: Estimated Random Utility Model with Measured Emotion Data

	(1) Emotion	(2) Learning	(3) Baseline
α	0.020***	-	-
	(0.005)		
β	−0.020***	-	-
	(0.005)		
γ	-	−0.005***	-
		(0.002)	
δ	-	0.005	-
		(0.008)	
c	0.245***	0.285***	0.221***
	(0.019)	(0.027)	(0.010)
M	0.034*	0.217	0.236
	(0.163)	(0.154)	(0.201)
$\frac{1}{\sigma}$	2.658***	2.582***	2.574***
	(0.256)	(0.291)	(0.291)
Observations	653	653	653
$Log-likelihood$	-705	-713	-721
AIC	1421	1436	1448
BIC	1443	1458	1462

Bootstrap (N=100) standard errors in parentheses. Column (1) uses all data with predicted emotions. Column (2) and (3) use data from the same rounds as column (1). *** significant at 1%. ** significant at 5%. * significant at 10%.

The results from Table 3.6 and Table 3.7 are consistent with the baseline model being the worst in both cases [11]. The learning model performs better than the baseline model and the estimates show history matters. The proposed emotion model performs the best out of the three models. We also calculate the pseudo R^2 values for the emotion and learning models[12]. The learning model improves the explanatory power by 0.73 % and 0.86% with the full data and measured rounds respectively. The emotion model, on the other hand, improves the explanatory power by 0.98% and 1.94% respectively. To conclude, our proposed emotion model outperforms both the baseline model and the learning model. Although both the emotion model and the learning model are only linear approximations, this comparison is still meaningful. It shows the possible significant roles of emotions in decision making regarding possible terrorist events.

3.5 Conclusion

In this article, we designed and conducted a controlled laboratory experiment to study factors that may affect decisions when facing possible terrorism events. Results show the experimental design effectively separates the effects of emotions to support public program and purchase insurance. The experiment also simulated real world terrorism risks in a laboratory setting by providing subjects with ambiguous probabilities and emotional stimuli. Consistent with field research (Lerner et al., 2003), we found anger decreases likelihood that a subjects vote for public program while fear increases the likelihood. Moreover, we

[11] In terms of AIC and BIC values.

[12] We use McFadden's definition of Pseudo R^2. $R^2 = 1 - \frac{LL_{Model} - k}{LL_{Baseline}}$ where k is the number of parameters on top of the parameters in the baseline model.

found that anger and fear had similar effects on insurance purchasing decisions. Insurance only insures against financial loss and does not change probability of the simulated event (which is the source of emotions) so being affected by emotions is an irrational response. Besides the effects of emotions, the results also indicate that subjects were insensitive to the relative prices and existence of hazard control program when they made insurance purchasing decisions.

These experimental results can help us to better understand behaviors regarding terrorism risks in the real world. Decisions affected by emotions such as anger and fear are not evidence of irrationality. On the contrary, we propose a emotion model that explains the experimental results within the SEU framework. Therefore, when trying to analyze behavior or make policy, emotions are an important factor. For example, do companies pay excessive amounts to purchase terrorism insurance? This study presents evidence that emotions can play an important role in the decision process. Our results support the view that economic agents make decisions using both external information *and* internal emotions.

Paying too much for terrorism insurance may lead the industry to inefficiency since the probabilities of terrorist attacks are unknown by nature and committing funds to insurance can be misplaced since other means such as terrorism prevention could be much more efficient. As argued by Slovic (1999), danger is real but risk is socially constructed, so "objective risk" does not exist. Instead, risk is subjective because it is influenced by a persons sex, worldview, emotions and many other individual factors. Our experimental findings reported in this article identify particular emotions that influence decisions when facing terrorism risks. In that sense, policies may focus more on ways to alter

public attitudes towards terrorist attacks (and possibly other risks). Likewise, our findings indicate that news that arouses anger in the public does not help to attract more funds for Homeland Security. The extent to which our experimental results hold outside of the laboratory is unclear but our findings nonetheless provide a unique chance to study the effect of emotions on decisions regarding terrorism risk . In a more general setting, results from this experiment also shed some light on decision making regarding small probability risks such as floods and hurricanes. If natural experimental data could be observed, it would enhance the reliability of conclusions drawn from the laboratory experiment.

CHAPTER 4

IS REAL-TIME PRICING GREEN? A SIMULATION STUDY USING DETAILED NETWORK MODEL

4.1 Introduction

Real-time pricing (RTP) has been long discussed by economists and many previous studies have demonstrated the efficiency gain by switching from flat-rate pricing (FRP) to RTP (Borenstein, 2005; Borenstein and Holland, 2005a). Switching from FRP to RTP not only influences the efficiency of the electricity market but also affects the welfare through other channels. For example, the environmental consequence of electricity generation under different pricing schemes should not be ignored by policy makers. In the United States, a large portion of air pollutants including CO_2, SO_2, and NO_X are due to electricity generations. RTP may increase or decrease welfare at the societal level by changing emissions from generators.

Holland and Mansur (2008) employed an econometric model to estimate the effect of *load variation* on emissions from electricity generators. They argued that implementing RTP likely leads to reductions in load variations. Using empirical data on load and emission, they found that reducing load variation has different environmental impacts in different regions of the United States. The effects depend on the composition of the generation capacities in each region. This inconclusiveness was also found in other studies (Cochell et al., 2012). Recognizing their contribution on this issue, we use a simulation method with detailed network model to study the similar question in this paper. How does RTP change emissions from electricity generation? We hope this paper can contribute to

the literature at least in the following two ways. First, we consider a detailed network model in our simulation. This detailed network model allows to simulate outcomes of policy or new institutions for the electricity industry (Shawhan et al., 2014). Second, we are also able to simulate the consumers responses to RTP for different demand-price elasticities (demand elasticity hereafter).

Conventional wisdom argues that RTP helps to reduce load during peak hours and possibly increases load during off–peak hours. This is generally true but ignoring the complex network constraints in the electrical power system may result in misleading outcomes[1]. Any change in the load distribution patterns must also satisfy transmission line constrains to maintain the reliability of the system. In reality, system operators dispatch different generators to minimize the cost of the system while subject to all the line constraints[2]. Hence, implementing RTP does not necessarily mean using more base load capacity and less peak load capacity. Previous economic research also emphasized the importance of network constraints in the electricity market analysis (Bohn, 1984). We focus on the short run (i.e. no new generation capacity or transmission line is built) environmental effect of RTP in this study.

The responsiveness to RTP is not easy to identify because it is determined by many different factors. The demand elasticity is a major factor but it should not be surprising that different end users have very different demand elasticities[3]. For instance, big industrial customers tend to be more responsive compared

[1]Electricity flow along transmission lines are not under the control of the generators or system operators. The physical law determines the flow of electricity if two nodes are connected by more than one possible routes.

[2]The environmental cost only enters this process by dirty generators biding higher prices in the wholesale market.

[3]We confine the discussion of demand elasticities to the scope of own price elasticity. The cross hour elasticities is not considered in the current work. The cross elasticity has also been shown to be negligible in previous work (Holland and Mansur, 2006)

with residential customers. Also, the longer the time horizon is, the more responsive customers are. Economists have strived to estimate both short run and long run demand elasticities (Smith, 1980; Sweeney, 1984; Taylor et al., 2005). We approach this issue from a different angle in this paper. Instead of identifying a specific demand elasticity that best reflects reality, we simulate different elasticities to reflect the emission changes in different scenarios.

Unlike Holland and Mansur (2008), we try to capture the adaptation of RTP by generators and customers with our simulation method. These behavioral changes are critical in analyzing the environmental consequences of RTP due to the shift in consumption and generation patterns. The next section provides a simple conceptual analysis. Section III summarizes the simulation model and empirical data. Section IV discusses the simulation results and section VI concludes the paper with some discussions on the future research.

4.2 Conceptual Analysis

The benefit from RTP adoption is shown in Figure 4.1. The shaded area in the graph shows the deadweight loss under FRP. On the one hand, customers tend to consume too little during off-peak hours when the FRP price is higher than the marginal cost of generating electricity. On the other hand, customers consume too much during peak hours since they are not paying the much higher marginal cost of generation. The under and over consumption then lead to the deadweight losses.

The situation in reality, however, is more complicated because of the power grid network. Figure 4.2 shows an extremely simple network that has 3 nodes

Figure 4.1: Dead Weight Loss Under FRP

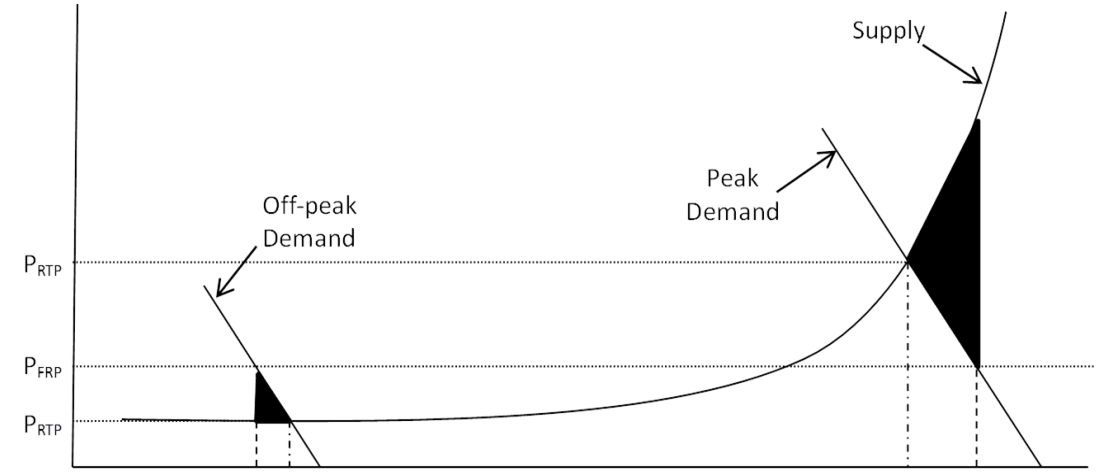
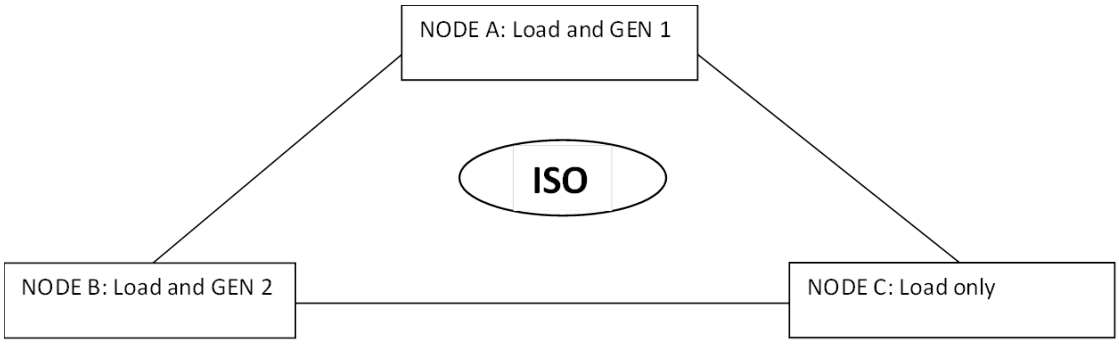
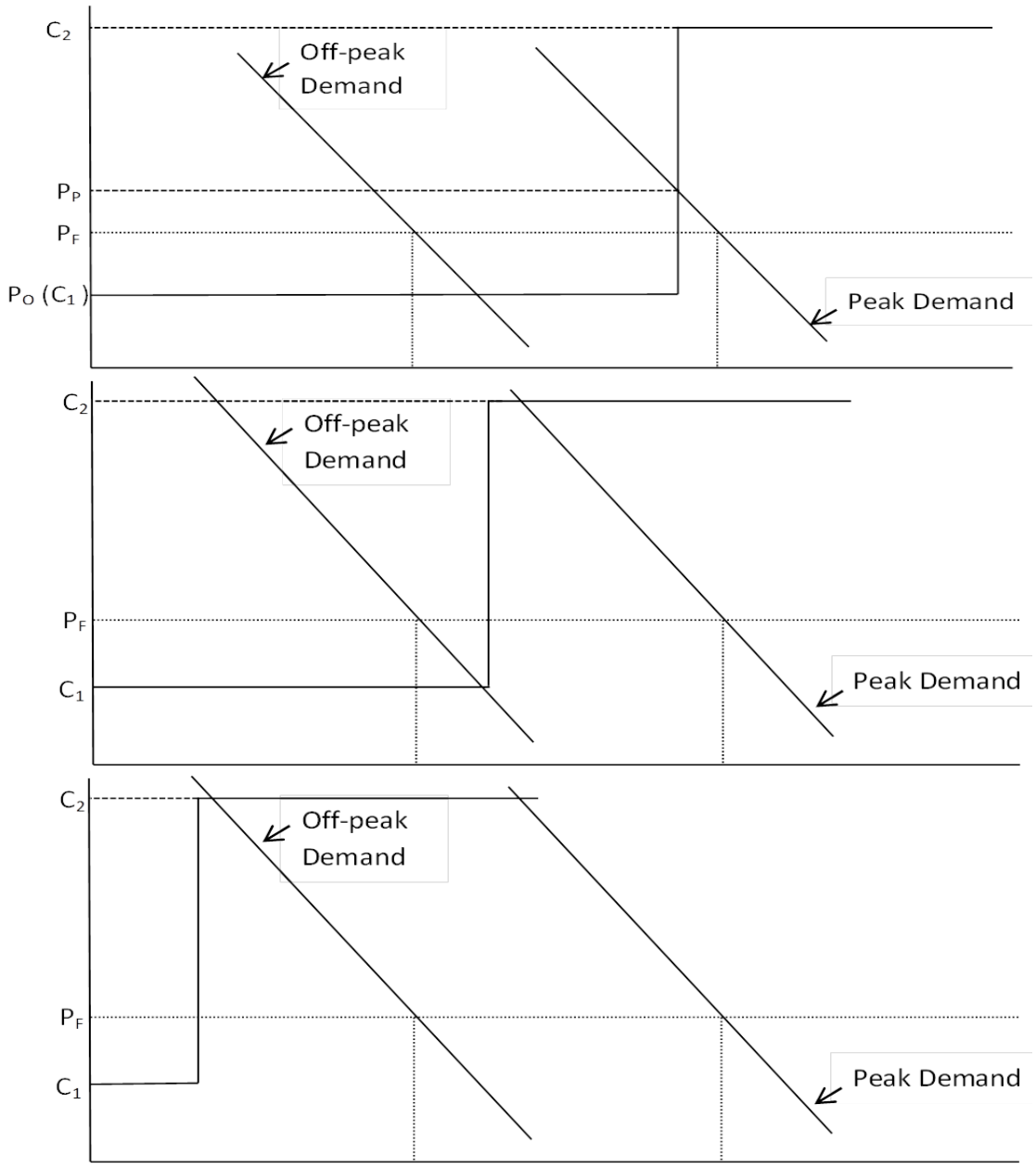


Figure 4.2: A Simple Network with 3 Nodes



and 3 transmission lines. Without the network topology, generators GEN1 and GEN2 can serve load at all 3 nodes at the aggregated level. This is not true in reality. The Independent System Operator (ISO) is required to maintain the reliability of the system by ensuring no line limit is exceeded. Suppose GEN2 has a higher marginal cost than GEN1. Figure 4.3 plots three different scenarios at Node B. The top graph shows the case in which no transmission line constraint is reached. If RTP were available, customers at Node B would pay price P_P during peak hours and P_0 during off-peak hours instead of the flat rate P_F. The middle graph shows the case in which the availability of GEN1 at Node B is lowered. Therefore, customers would pay a higher price C_2 which is the marginal

Figure 4.3: Supply and Demand at Node B



cost of GEN2 during peak hours. Finally, the bottom graph has a even more limited transmission capacity from Node A to Node B. In this case, customers would pay a higher price (C_2) instead of the flat rate during both off-peak and peak hours. Hence they are worse off in the world of RTP. The extremely simple example, however, shows the importance of network topology in the analysis of RTP.

In reality, there are more than two hour types. Customers consume different amount of electricity in different hours within a day. They also change their consumption patterns in different seasons within a year. Meanwhile, the network has far more than 3 nodes. We take the Eastern Interconnection (EI) [4]as an example to analyze the environmental effect of RTP. Figure 4.4 shows the location of EI in North America and the 6 NERC[5] regions in the EI. In the next section, we will show the simulation results for the EI and its different NERC regions. We can then compare our results to the conclusion reached by Holland and Mansur (2008). Figure 4.5 shows all the electric nodes and transmission lines in EI. The whole EI system has 62,094 electric nodes with different transmission lines connecting them. Each of these transmission lines has its own line limit. It is obvious that one could not derive an analytical solution that optimizes the system. Moreover, the scale of the problem also makes any simulation study of the problem computationally infeasible. We discuss how to reduce the scale of the problem while retaining characteristics of the network in the next section.

[4]The Eastern Interconnection is one of the two major alternating-current (AC) electrical grids in North America. The other major interconnection is the Western Interconnection. The three minor interconnections are the Quebec, Alaska, and Texas interconnections. All of the electric utilities in the Eastern Interconnection are electrically tied together during normal system conditions and operate at a synchronized frequency operating at an average of 60 Hz. The Eastern Interconnection reaches from Central Canada eastward to the Atlantic coast (excluding Quebec), south to Florida, and back west to the foot of the Rockies (excluding most of Texas).

[5]North American Electric Reliability Corporation.

Figure 4.4: The NERC Regions

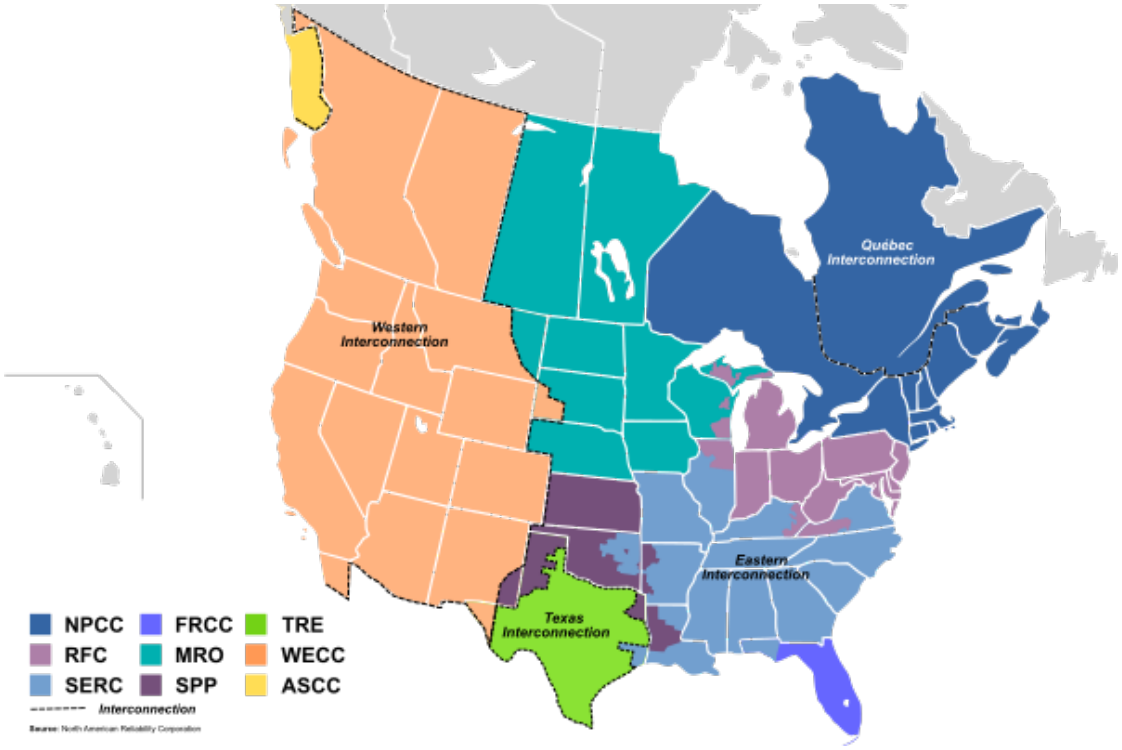
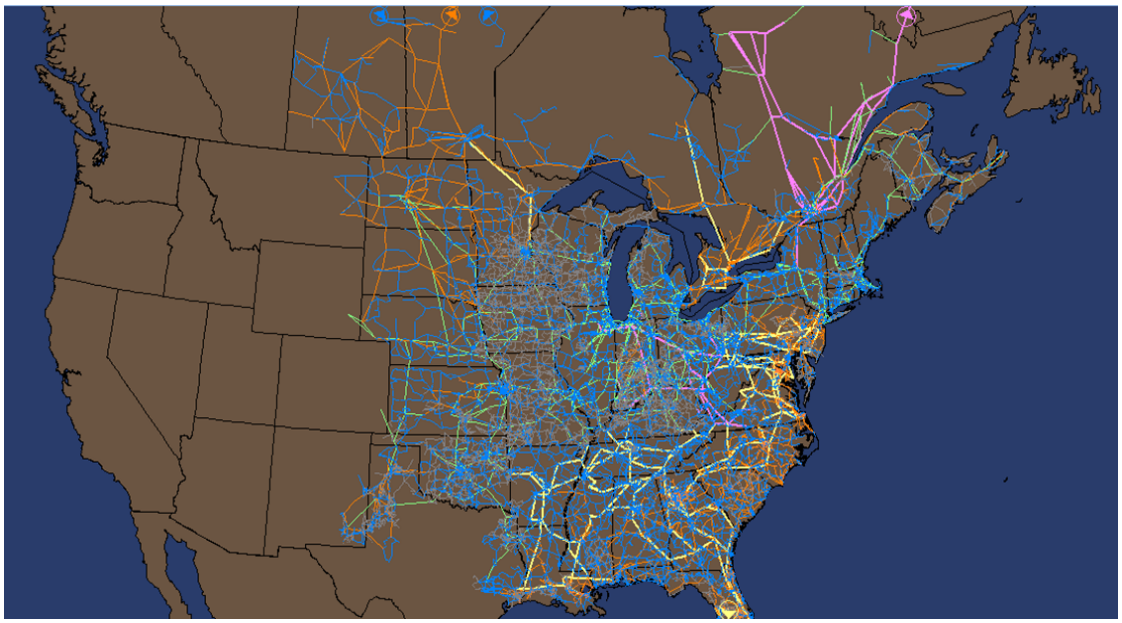


Figure 4.5: The Eastern Interconnection(EI) Network



4.3 The Simulation Model and Data

The simulation model employed is the same as the one discussed in Shawhan et al. (2014). Holland and Mansur (2006), Borenstein and Holland (2005b) also provide some details on how to formulate the simulation problem. Without repeating all the details, we only reiterate the relevant aspects to the study of RTP and focus on the optimization problem. Our simulation model differs from Holland and Mansur (2006) in two aspects. Firstly, our simulation model features a detailed network model. Secondly, we simulate the environmental effect of RTP in a much larger region. The following optimization problem best describes the simulation model.

$$\max_{p_{ijk},I_{ij},R_{ij}} \{\sum_i \sum_j [\sum_k H_k(B_{jk} - c_i p_{ijk})]\}$$

$$s.t.$$

$$p^0_{ij} \geq p_{ijk}$$

$$p_{ijk} \geq \alpha^{min}_i p^0_{ij}$$

$$\sum_i p_{ijk} - L_{jk} - \sum_{j'} S_{jj'}(\Theta_{jk} - \Theta_{j'k}) = 0$$

$$F_{jj'} > |S_{jj'(\Theta_{jk}-\Theta_{j'k})}|$$

where i is the generator index, j is the node index, k is the representative hour index, and l is the pollutant index. p_{ijk} is the aggregated real power output[6] from generator i at node j during representative hour k. Note that the nodal demand

[6] In alternating current circuits, immediate power transferred through any phase varies periodically. Energy storage elements such as inductors and capacitors may result in periodic reversals of the direction of energy flow. The portion of power that, averaged over a complete cycle of the AC waveform, results in net transfer of energy in one direction is known as real power (active power). The portion of power due to stored energy, which returns to the source in each cycle, is known as reactive power.

in the power system is modeled as *negative* real power output at each node. p_{ij}^0 is the capacity of generator i at node j. c_i is the per megawatt-hour cost of generator i. This includes cost of fuel and variable operations and maintenance costs. $\alpha_i^{min}$is the minimum generation fraction of capacity for type i. $\sum_l a_{jkl} e_{il}$ is the environmental cost of generating one megawatt-hour electricity by generator i at node j during hour k. H_k is the hours per year represented by representative hour k. B_{jk} represents the piecewise linear consumer surplus function associated with non–fixed portion of demand. L_{jk} is the maximum quantity demanded at node j in representative hour k. $F_{jj'}$ is the flow limit on line from node j to node j'. $S_{jj'}(\Theta_{jk} - \Theta_{j'k})$ is the power flow from node j to node j'[7]. Finally, $F_{jj'}$ is the limit of power flow on line from node j to node j'.

This optimization problem optimizes annual gross consumer surplus minus the sum of operating costs subject to the listed constraints. The first two constraints are generation constraints[8] and the last two are line limit constraints[9]. The decision variables are the quantity of generation of each generator in each representative hour, and the quantity of demand at each node in each representative hour. The optimization problem is solved with interior-point solver in the Gurobi solver.

The first empirical element of the simulation is the representation of the electric power grid. The 5000- node network model we use in this paper is the simplification of the network topology of the Eastern Interconnection (EI). It has been reduced from a 62,000- node network representation provided by Energy

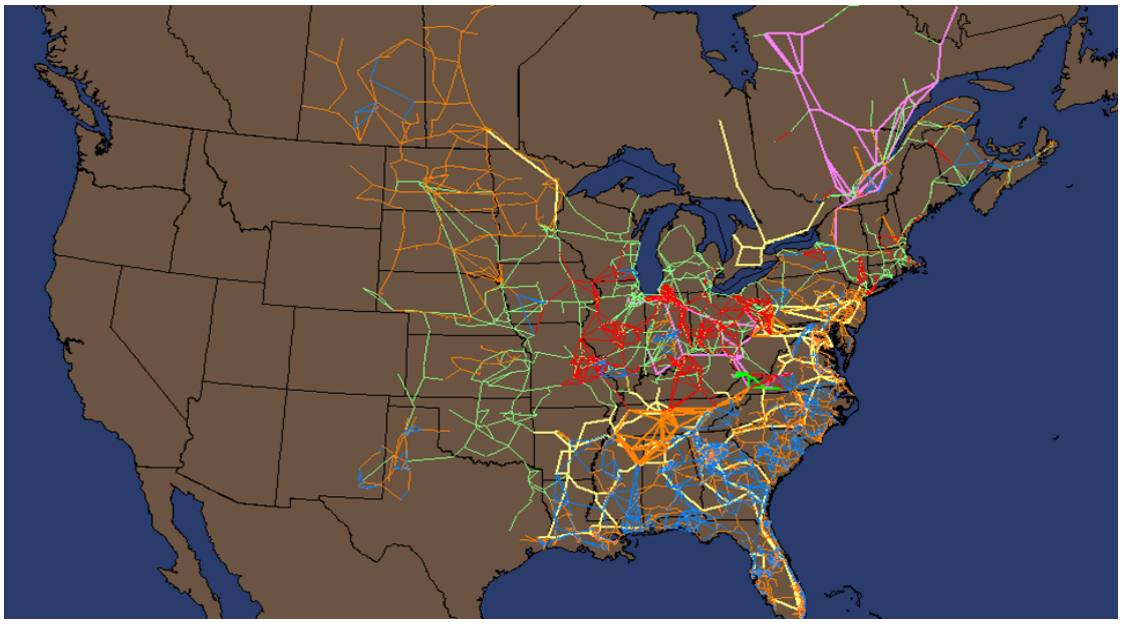
[7] $S_{jj'}$ is a constant parameter known as the susceptance of the line from node j to node j' and $\Theta_{j'k}$ is the phase angle of node j in hour k.

[8] Generation cannot exceed the pre-existing capacity and each generator that is on must produce at least its minimum output.

[9] Generation minus quantity demanded at each node equals the sum of the net outflows over all line segments that touch that node and the electricity flow on each line cannot exceed the lines flow limit.

Visuals. The essence of the network reduction is to retain some lines and their connected nodes in the network. The generators at other nodes are then aggregated to these retained nodes. This process forms equivalent lines that precisely and correctly predicts flows in the retained lines. Of course that no network reduction retains *all* the information in the original network but this simplification is critical to make our simulations computationally feasible. Shi et al. (2012) provides details of this reduction process.

Figure 4.6: The Reduced Eastern Interconnection(EI) Network



Secondly, it is essential to have hourly specific electricity demand and price in the RTP simulations. One should ideally simulate all 8760 hours in a given year. However, the complexity and the details of the problem would make the simulation computationally infeasible. Therefore, we instead use representative hours to represent the 8760 within a given year. We select a set of 38 hours from 8760 hours throughout the year. These hours will represent the joint distribu-

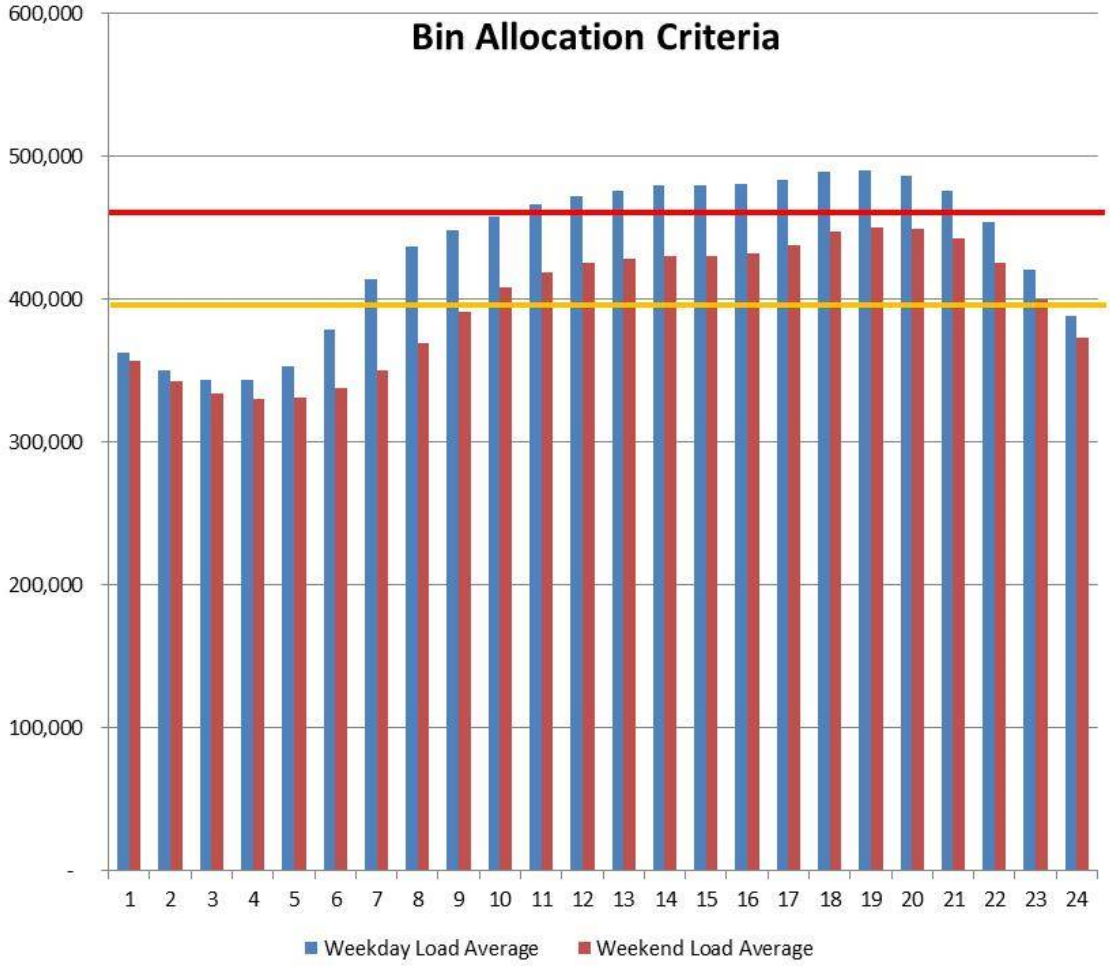
tion of electricity demand[10], wind generation and solar generation[11]. We use an algorithm to optimally choose the 38 hours out of the 8760 hours and to assigns weights to them in such a way that the frequency distribution of electricity demand, wind and solar generation of the 38 selected hours is similar to that of the original 8760 hours. Moreover, the weighted averages of the chosen hours will be within 3% of the actual average of all the 8760 hours combined. To do this, we firstly divide the yearly hour data into three bins. The "high" bin contains hours from the times of the week that tend to have the highest values of demand (load). The purpose is to highlight the extreme situations of high load and lower generation in the simulations especially under FRP. Shoulder and low bins have hours that tend to have medium and low values of load. The criteria used to select the 38 representative hours are mean and standard deviation. 38 hours are randomly drawn from the 8760 hours to calculate mean and standard deviation of the representative hours. This process of random drawing continues until we reach a group of representative hours that matches the mean and standard deviation of the 8760 hours in both load and wind solar generation. Figure 4.7 and Figure 4.8 show this process.

Lastly, we summarize the empirical data that are used in this paper. The simulations use data from three major data files. The generator level operating cost data are extracted from the Energy Information Administration (EIA) generator list. This generator list is matched with the generator list provided by Energy Visuals (EV) to gain additional information. We chose to match these two datasets because the EIA list is a comprehensive list of generators while the

[10]In this study, we use the term demand and the term load interchangeably. They are both defined as the energy consumed in each hour so have the unit of MW or GW. Consumption is the total energy consumed within a certain period and thus has the unit of MWh or GWh

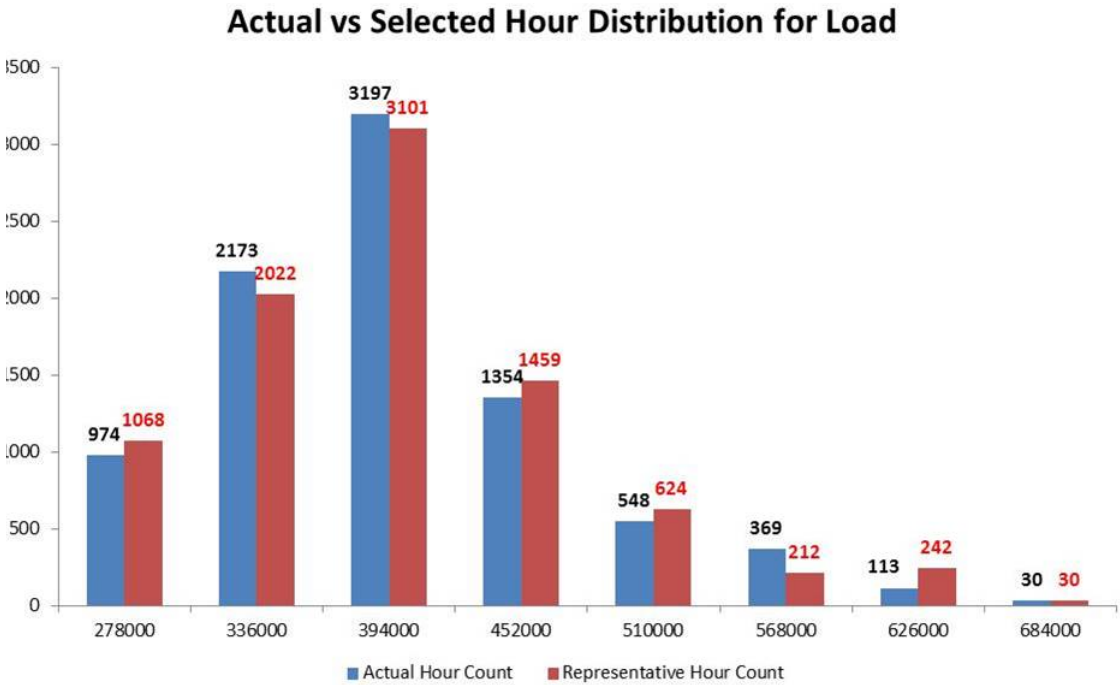
[11]Wind and solar generation only takes up a small portion of the total electricity generation of the current system. Nevertheless, they should still be considered since they will become more and more important in the future.

Figure 4.7: Bin Allocation Criteria



EV list provides network information for generators (i.e. where a specific generator is located in the electric network). All the information we need for the generators are in this matched list including fuel type, maximum generation capacity, and geographic location. The data used for the network reduction is also provided by Energy Visuals in a separate data file. Detailed descriptions can be found in Shawhan et al. (2014) which uses the same simulation tool to study environmental policies. In addition, we obtain the load profile data from NERC.

Figure 4.8: Representative Hours vs. Actual Hours Load



4.4 Results and Discussions

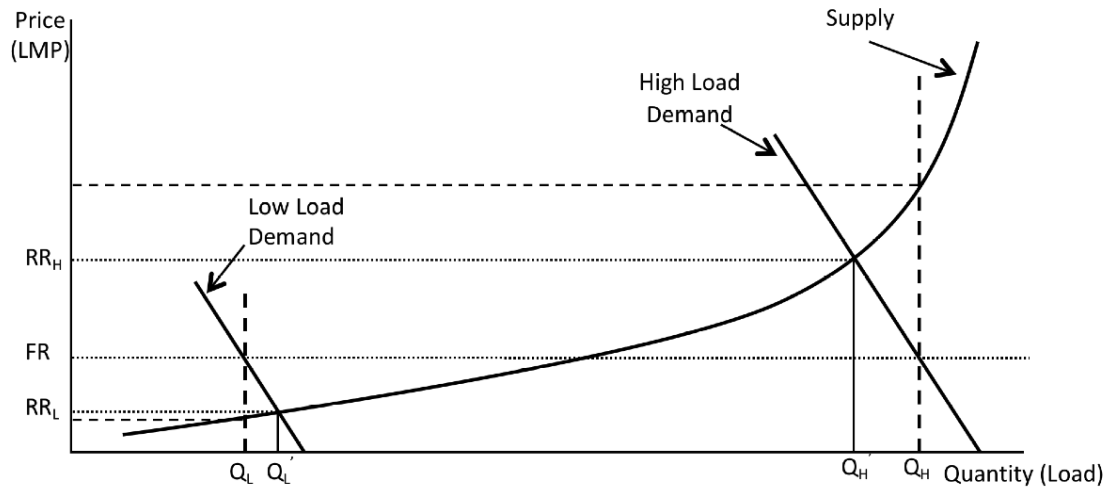
To determine the flat rate used in FRP, we run our simulation with a zero price elasticity of demand. The flat rate $\boldsymbol{FR}$ is then determined using the following formula.

$$\boldsymbol{FR} = \frac{\sum_k \boldsymbol{R_k} p_k H_k}{\sum_k p_k H_k}$$

Note that $\boldsymbol{FR}$ is a vector that consists nodal LMPs at all electric nodes. It is also called nodal annual average LMPs. p_k is the real power consumed in hour k and H_k is the number of hour k within a year. $\boldsymbol{R_k}$ is the nodal LMPs of hour k under optimal dispatch. It is jointly determined by the load profile, generation capacity and line constraints. $\boldsymbol{R_k}$ approximates the wholesale prices that retail companies pay in reality. Assuming that the retail companies operate to recover

their costs on the wholesale market, a flat rate is determined in this way[12]. This formulation implies that any response to RTP is at the nodal level. That is, the flat rate prices and real time prices are different from node to node.

Figure 4.9: Flat Rate Prices and Real Time Prices



This specification of the model also assumes a different demand function at each different electric node. Of course, the load profile we obtained from NERC only provides us *one point* on the demand curve so we need to make assumptions on the demand function in order to simulate the effect of RTP. Specifically, we assume that the demand function at each node is a constant elasticity demand function and is approximated with a step function in the simulation. This process at a *particular node* is shown in Figure 4.9. The load profile gives us Q_H and Q_L which are the demands during the high load and low load hours respectively. The dashed lines represent a demand function with 0 price elasticity. Our simulation tool then determines the prices (LMPs) according to the capacity and constraints of the system. Using the formula discussed above, we can calculate the flat rate which is FR in the graph. The simulation tool can then add elastic-

[12]This also assumes ignoring other costs.

ity to the demand function. The elastic demand curves are represented by solid lines in the graph[13]. With these new elastic demand functions, the simulation tool can solve for the real time prices–RR_H and RR_L. Aside from quantities and prices, the simulation tool also output other information including generation by fuel type by region and emissions by region. This information allows us to examine the environmental effects of RTP and compare the conclusions with previous study (Holland and Mansur, 2008).

To simulate RTP, we use a range of different demand elasticities in different simulations. Since the demand elasticity is specified at the nodal level, it can represent two theoretically different situations. On the one hand, a higher demand elasticity (in absolute value) represents more responsive customers. On the other hand, a higher demand elasticity can also represent a higher RTP penetration rate. For example, assume that all customers at a particular node are homogeneous meaning they share the same demand elasticity. Then their individual demand elasticity is the chosen elasticity. However, if customers are heterogeneous which is likely to be true in reality, the chosen elasticity reflects *both* individual demand elasticity and the composition of customers at a node[14]. Although customers have different demand elasticities and we cannot accurately estimate the composition of customers at different nodes, our simulation tool enables us to simulate the environmental effects of RTP under different *aggregate* nodal demand elasticities. Our hope is that these results under different chosen elasticities can at least inform us the possible environmental effects of RTP.

[13]For simplicity, the graph does not show constant elasticity curves.

[14]For example, assume half of the customers at a node have demand function $Q = AP^{e_1}$ and the other half have demand function $Q = AP^{e_2}$. If customers are exactly the same except for the different demand elasticities, the aggregate demand at the node is $Q = \frac{1}{2}A(P^{e_1} + P^{e_2})$. This is no longer a constant elasticity demand function since the demand elasticity is now $e = \frac{e_1 P^{e_1} + e_2 P^{e_2}}{P^{e_1} + P^{e_2}}$.

The four chosen short run elasticities (0, -0.1, -0.25, -0.5) covers a wide range of previously estimated aggregate elasticities. We also conduct two different sets of simulations in our analysis. The first set tries mimic the real world that allows for behavioral change in consumption patterns. That is, when RTP becomes available, customers may consume more during off-peak hours and consume less during peak hours. This change in consumption patter will also affect the total electricity consumed within a given year. The second set keeps the consumption of electricity constant under different demand elasticities[15]. The first scenario is a more natural simulation of the real world and the second scenario provides us a opportunity to better compare with Holland and Mansur (2008). We first discuss the case in which behavioral change is accounted for and then focus on the role of demand variability across different hours.

Table 4.1 shows the consumption of electricity in each separate NERC region in the EI while Table 4.2 shows the electricity generation in corresponding regions under different assumed demand elasticities. RTP leads to increased generation in most regions although the total load increase is only about 1.14% in the -0.5 elasticity case. Note that a certain portion of demand in NPCC is met by electricity generated in other regions (majorly RFC and MRO). It is also worth noting that average LMPs decrease in all regions except NPCC with more responsive aggregated demand. This is shown in Table 4.3. This also indicates that the generation capacity in NPCC have higher cost so the system operator tries not to dispatch the more expensive generators unless necessary.

Figure 4.10 to Figure 4.12 summarize the emission changes in the corresponding NERC regions. It is obvious that NPCC and MRO tend to have higher

[15]We achieved this by iterating the simulation to rescale the exogenously determined load profile in each NERC region.

Table 4.1: Electricity Consumption in Each NERC Region in the EI

	Elasticity			
	0 (FRP)	-0.1	-0.25	-0.5
NPCC	622,842.06	630,399.44	640,484.89	657,411.50
RFC	912,720.08	912,286.55	912,784.47	913,785.29
SERC	1,073,314.58	1,073,455.02	1,073,833.85	1,074,691.59
FRCC	229,089.10	229,131.81	229,196.43	229,429.16
SPP	216,428.95	216,467.36	216,554.43	216,661.11
MRO	280,295.66	280,341.61	280,403.81	280,654.74
Total	3,334,690.43	3,342,081.79	3,353,257.88	3,372,633.39

Table displays the demand in GWh. 0 elasticity represents the case of flat rate pricing by assuming all customers are on flat rate.

emissions when RTP is made available. This observation is especially true for NPCC. One apparent explanation is the load increase in NPCC. Since this increase is mainly satisfied by generation within the region, we observe a big increase in emissions in NPCC. Another possible explanation would be the increased generation from coal power generators under RTP. NPCC is quite different from other regions in terms of generation sources. Nearly half of the demand is met by hydro in the region. When demand becomes more elastic, more coal is being used. This is shown in Table C.2 in the appendix. This explanation holds in the short run even the share of coal generation keeps constant. Since no new generation capacity can be built in the short run, system operators can only make use of existing capacities. This means they need to dispatch dirtier generators in the case of short run load increase. This also helps to explain the

Table 4.2: Electricity Generation in Each NERC Region in the EI

	Elasticity			
	0 (FRP)	-0.1	-0.25	-0.5
NPCC	570,224.90	573,649.29	581,149.39	594,851.64
RFC	1006,740.42	1,008,753.80	1,011,081.24	1,015,035.10
SERC	1,036,426.83	1,036,793.94	1,037,358.06	1,038,624.80
FRCC	191,049.15	191,039.51	191,115.32	190,922.13
SPP	221,486.30	221,500.93	221,857.19	221,385.20
MRO	308,762.83	310,344.32	310,696.67	311,814.52
Total	3,334,690.43	3,342,081.79	3,353,257.87	3,372,633.39

Table displays the generation in GWh. 0 elasticity represents the case of flat rate pricing by assuming all customers are on flat rate.

emission increase in MRO and RFC that both have coal serving more than half of its load.

In the second set of simulations, we keep the demand in each NERC region constant[16] to make it more comparable with Holland and Mansur (2008). The resulting emissions change can be found in Figure 4.13 to Figure 4.15. It is evident that the observed emission increase *without* load scaling is mainly due to increase in demand.

The power system has both low marginal cost generators to meet base load

[16]In the nonlinear numerical simulation, it is not possible to keep the demand (load) change at 0. We control the demand through iterating the simulation. That is, we run the simulation for the first time and observe demand in each region under different elasticities. We then scale the demand in the base case (input load in the case where elasticity is 0) but since the optimization problem is not linear, the scaling only allows us to reduce the difference to a certain level.

Figure 4.10: CO_2 Emission Change by Region

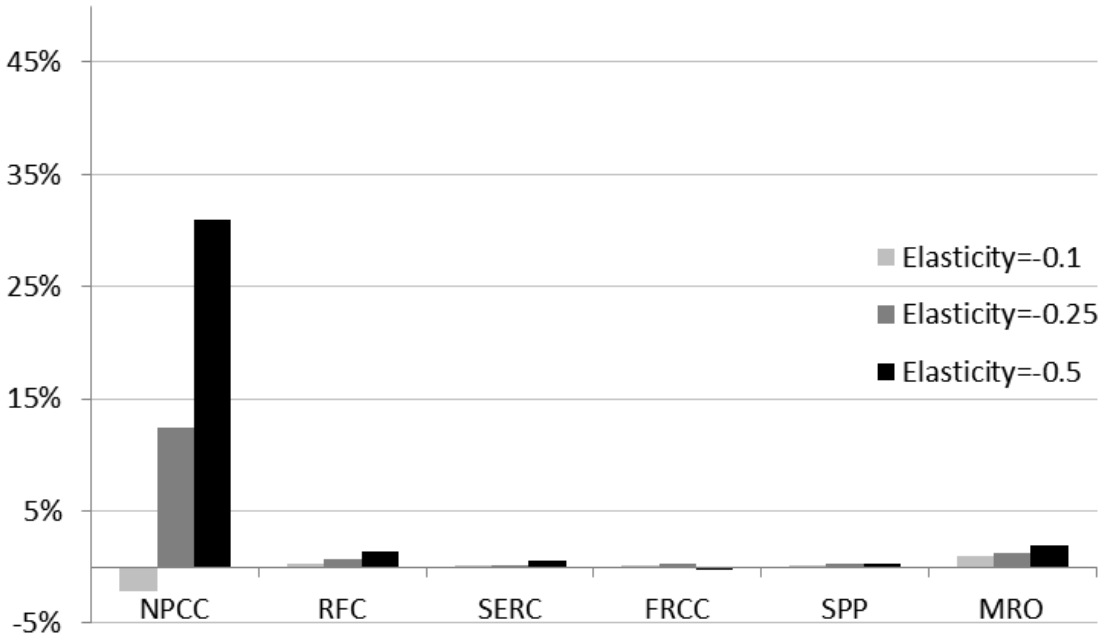


Figure 4.11: NO_X Emission Change by Region

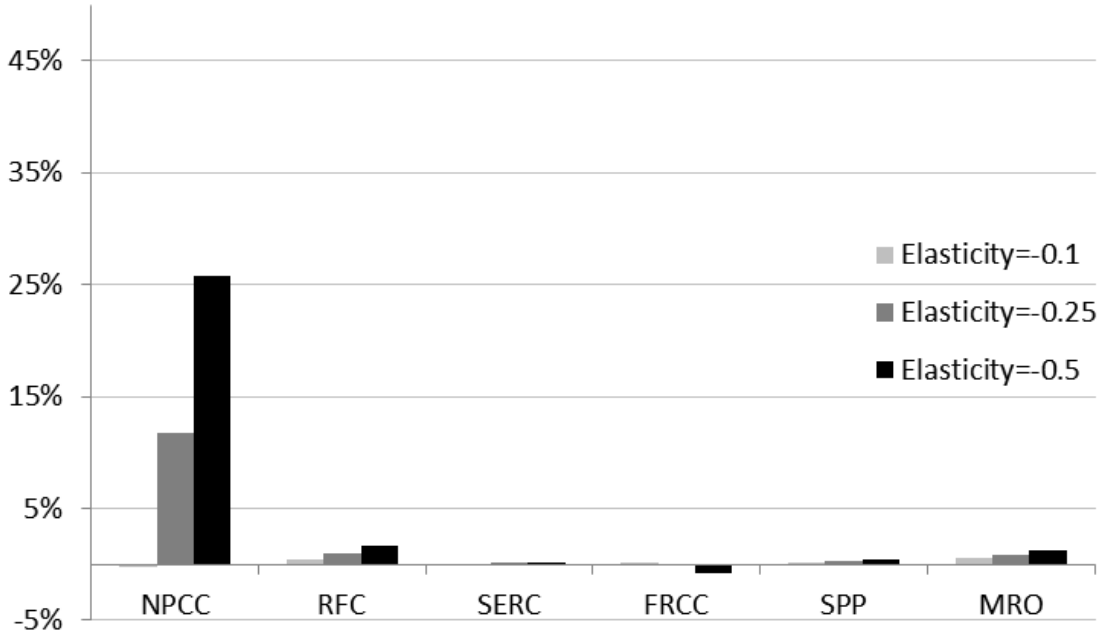


Figure 4.12: SO_2 Emission Change by Region

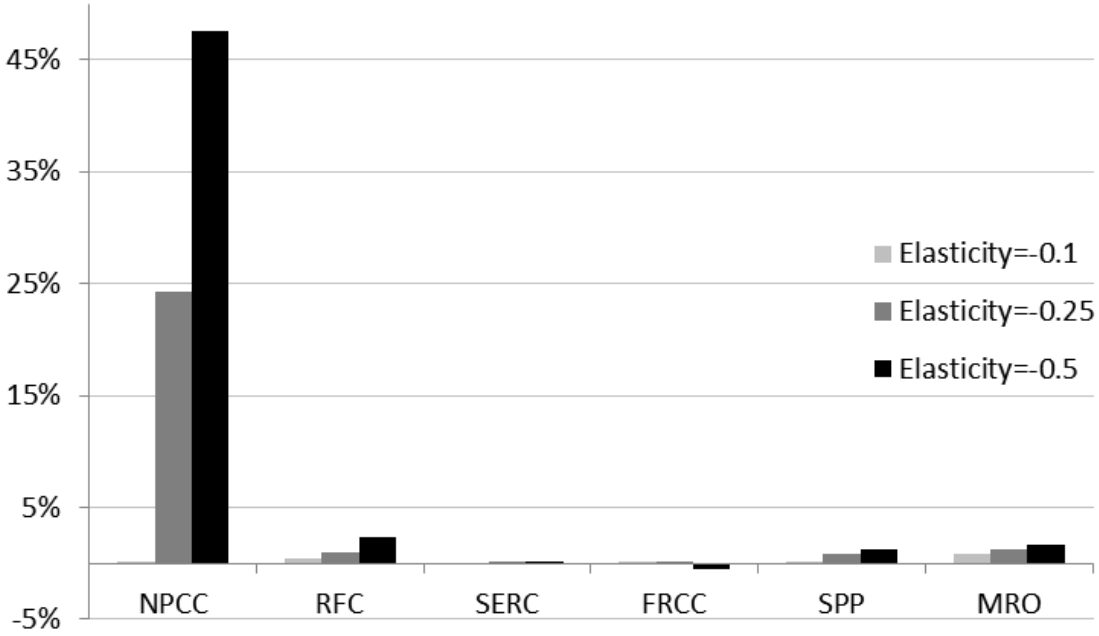


Figure 4.13: CO_2 Emission Change by Region with Load Scaling

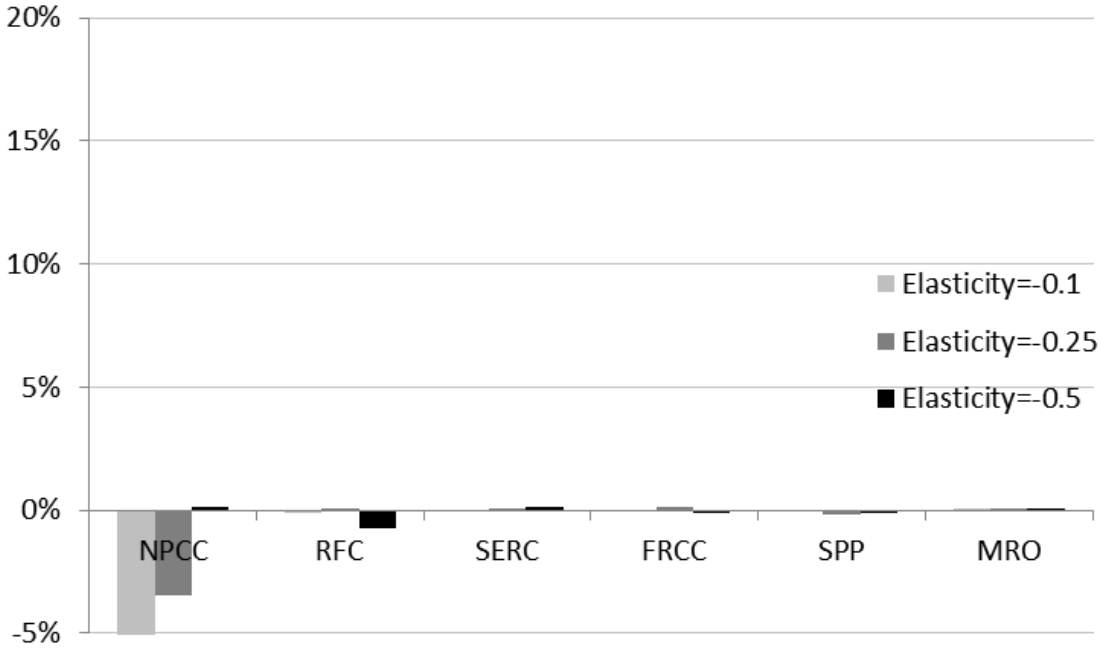


Figure 4.14: NO_X Emission Change by Region with Load Scaling

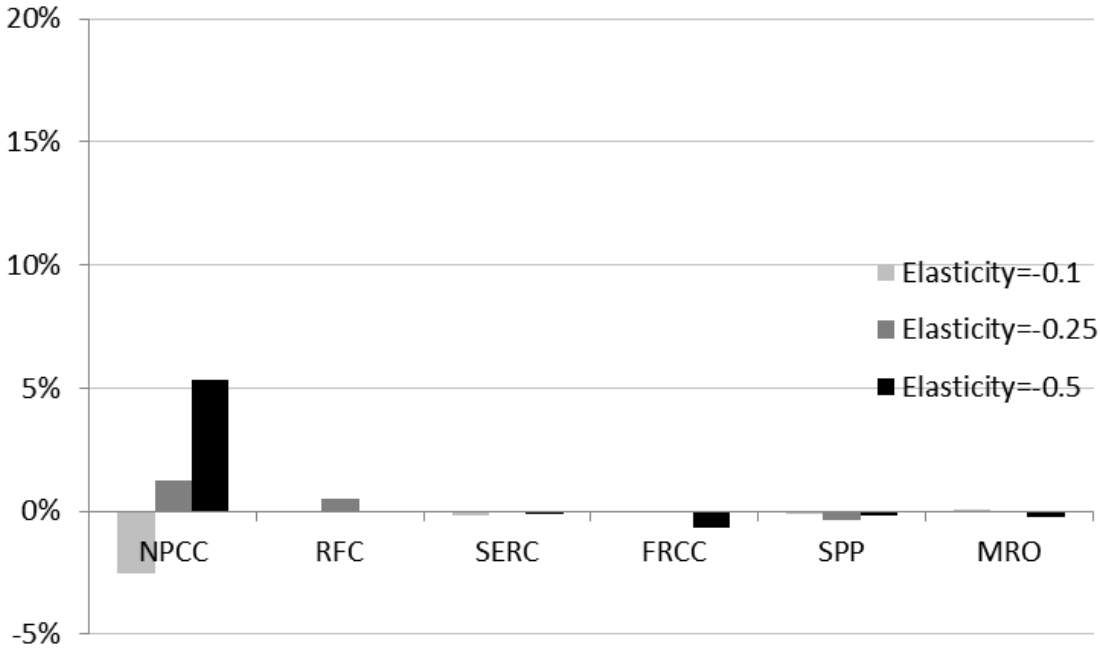


Figure 4.15: SO_2 Emission Change by Region with Load Scaling

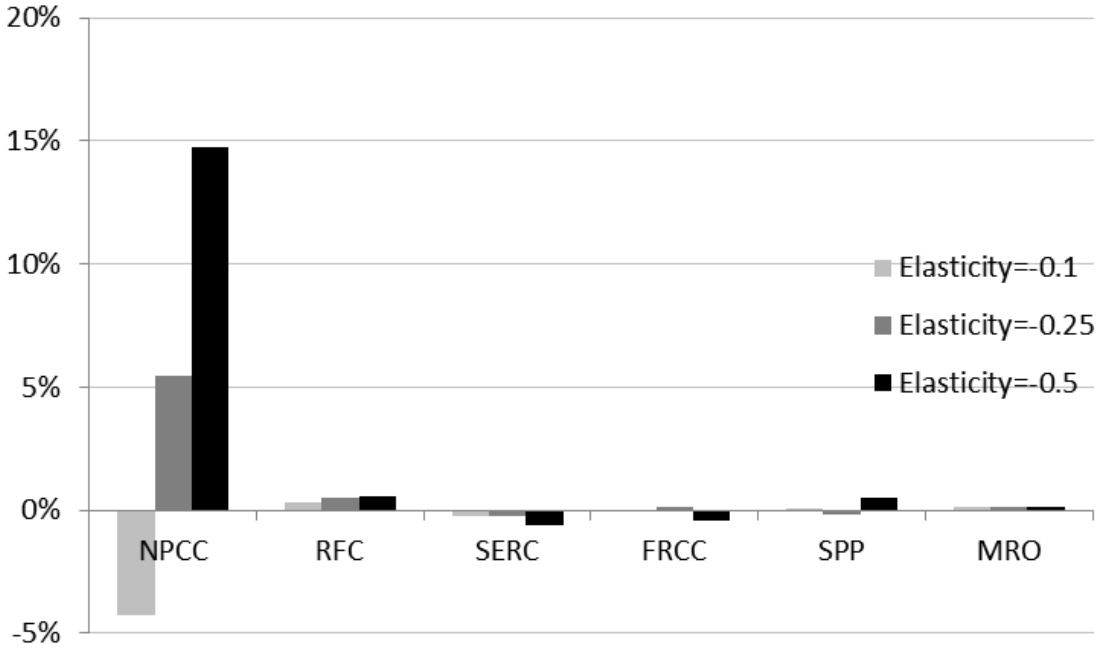


Table 4.3: Regionsl LMP ($) in Each NERC Region in EI

	Elasticity			
	0 (FRP)	-0.1	-0.25	-0.5
NPCC	34.94	31.09	38.72	42.01
RFC	30.75	30.66	30.52	30.50
SERC	33.26	33.20	33.12	33.06
FRCC	43.43	43.38	43.34	43.19
SPP	28.12	28.05	28.00	27.97
MRO	23.53	23.50	23.46	23.37
Average	32.43	31.66	33.04	33.66

Table displays the regional spatially and temporally load weighted LMP. 0 elasticity represents the case of flat rate pricing by assuming all customers are on flat rate.

and high marginal cost generators to meet peak load. The peakers usually cause more pollutions by generating one MWh electricity. However, to maintain the reliability of the system, all types of generators are necessary. When demand drastically increases in the short term, system operators are forced to dispatch more expensive and dirtier generators. Hence the per MWh emission calculated by Holland and Mansur (2008) may fail to reflect the reality. In reality, a marginal demand increase can lead to much higher increase in emissions than the "average emission rate". Our second set of simulation shows that when demand is more elastic (which approximates the penetration of RTP), CO_2 emissions tend to decrease while NO_X and SO_2 emissions tend to increase in NPCC. In other regions, the changes are not significant. The generation pattern change is again shown in Table C.4 in the appendix. Notice that the increment in

coal generation and decrement in natural gas generation explain the emission changes in NPCC.

With these results we reach a general conclusion similar to Holland and Mansur (2008) that RTP may not help to reduce emissions in certain regions in the United States. However, our simulations suggest different explanations. The implementation of RTP induced higher usage of coal generation while reduced the usage of natural gas capacity. Since coal is in general cheaper than natural gas when not considering environmental costs, it is more likely to be used when the load variance decreases.

4.5 Conclusion

We use a simulation tool that features a detailed network model and generator level cost/emission data to study the environmental effect of RTP. Conventional wisdoms have argued that RTP may also benefit the environment by using less peak generation capacities. However, we found this argument is not necessarily true in reality. Especially when coal is more intensively used due to its lower cost compared to natural gas and other cleaner sources. This conclusion is similar to the one that Holland and Mansur (2008) reached with a econometric analysis though we provide a different explanation for this result.

When conducting cost benefit analysis including the environmental effects, behavioral changes induced by RTP should not be ignored. The consumption change can not be easily studied with existing data since RTP has *not* been made available in large regions in the United States. However, learning the effect of RTP is an important policy question. Hence, we believe our simulation study at

least provide a way to tackle this question. Admittedly, we have imposed fairly strong restrictions on the demand function because our understanding of the short run electricity demand elasticity is still limited. Nonetheless, the method and the detailed model we introduced can be used to study the benefit and cost of RTP with any specified demand function. It provides policy makers a more reliable counterfactual.

Given the availability of the simulation tool (E4ST), different studies regarding RTP can be easily conducted including testing long run effect of RTP when building/retiring generation capacities becomes feasible.

APPENDIX A

APPENDICES OF CHAPTER 2

A.1 Predicted Valuations under DARA Utility Function

Assuming subjects wealth is x^0 before they start the experiment, one can write the decision equations as facing a same gamble at different wealth levels.

$$
\begin{aligned}
WTPG :& pu(x^0 + 15 - WTP_{Gain} + 5) + (1-p)u(x^0 + 15 - WTP_{Gain} + 0) \\
&= u(x^0 + 15 - WTP_{Gain} + WTP_{Gain}) \\
WTAG :& pu(x^0 + 10 + 5) + (1-p)u(x^0 + 10 + 0) = u(x^0 + 10 + WTA_{Gain}) \\
WTPL :& pu(x^0 + 20 - 5) + (1-p)u(x^0 + 20 - 0) = u(x^0 + 20 - WTP_{Loss}) \\
WTAL :& pu(x^0 + 15 + WTA_{Loss} - 5) + (1-p)u(x^0 + 15 + WTA_{Loss} - 0) \\
&= u(x^0 + 15 + WTA_{Loss} - WTA_{Loss})
\end{aligned}
$$

So in the gain domain subjects always face the lottery $(5, p; 0, 1-p)$ and in the loss domain they always face the lottery $(-5, p; 0, 1-p)$. Certainty equivalents are WTP_{Gain}, WTA_{Gain}, $-WTP_{Loss}$, and $-WTA_{Loss}$ respectively. Use subscripts to denote the different wealth levels in different treatments. For example $u_{WTPG}(\Delta x) = u(x^0_{WTPG} + \Delta x)$ where $x^0_{WTPG} = x^0 + 15 - WTP_{Gain}$ is the initial wealth and Δx is the change in wealth. Given DARA utility function, because all certainty equivalents are smaller than 5, the absolute risk aversions $r_A(x, u_{WTAG}) > r_A(x, u_{WTPG}) > r_A(x, u_{WTAL}) > r_A(x, u_{WTPL})$. Now, I prove $WTP_Gain \geq WTA_{Gain}$. For any given x, we always have $u_{WTAG}(x) = \psi(u_{WTPG}(x))$ where $\psi(\cdot)$ is an increasing function. Differentiate both sides of the equation

(twice) we have

$$u'_{WTAG}(x) = \psi'(u_{WTPG}(x))u'_{WTPG}(x)$$
$$u''_{WTAG}(x) = \psi'(u_{WTPG}(x))u''_{WTPG}(x) + \psi''(u_{WTPG}(x))u'_{WTPG}(x)^2$$

Divide both sides of the second equation above by $-u'_{WTAG}(x)$ we have

$$\begin{aligned}\psi(u_{WTPG}(WTA_{Gain})) &= u_{WTAG}(WTA_{Gain}) = pu_{WTAG}(5) + (1-p)u_{WTAG}(0) \\ &= p\psi(u_{WTPG}(5)) + (1-p)\psi(u_{WTPG}(0)) \\ &\leq \psi(pu_{WTPG}(5) + (1-p)u_{WTPG}(0)) = \psi(u_{WTPG}(WTP_{Gain}))\end{aligned}$$

Since $\psi\cdot$ and $u_{WTPG}(\cdot)$ are both increasing, $WTA_{Gain} \leq WTP_{Gain}$. In a similar manner, it can be shown that $WTA_{Loss} \leq WTP_{Loss}$. Follow the concavity of utility function, we have $WTA_{Gain} \leq WTP_{Gain} \leq 5p \leq WTA_{Loss} \leq WTP_{Loss}$.

If one ignores different wealth when subjects make decisions, then

$$\begin{aligned}WTPG: &pu(x^0 - WTP_{Gain} + 5) + (1-p)u(x^0 - WTP_{Gain} + 0) \\ &= u(x^0 - WTP_{Gain} + WTP_{Gain}) \\ WTAG: &pu(x^0 + 5) + (1-p)u(x^0 + 0) = u(x^0 + WTA_{Gain}) \\ WTPL: &pu(x^0 - 5) + (1-p)u(x^0 - 0) = u(x^0 - WTP_{Loss}) \\ WTAL: &pu(x^0 + WTA_{Loss} - 5) + (1-p)u(x^0 + WTA_{Loss} - 0) \\ &= u(x^0 + WTA_{Loss} - WTA_{Loss})\end{aligned}$$

One can show that $WTP_{Gain} \leq WTA_{Gain} \leq 5p \leq WTP_{Loss} \leq WTA_{Loss}$ in this case. The difference shows controlling for wealth effect in the experimental design is critical in an expected utility world.

A.2 Predicted Valuations in Coffee Mug Experiment

To derive valuations in the mug experiment, assume a two-part linear value function. The intrinsic consumption utility of the coffee mug is assumed to be $\bar{m}$. w_1 and w_2 are decision weights with $w_1 = \pi(p)$ and $w_2 = 1 - \pi(p)$. Note in the mug experiment, there are two dimensions (mug and money). Gains and losses are confined to its own dimension although utility is additive.

WTP-Gain:

$$\begin{aligned} x^0 =& \pi(p)[\bar{m} + \eta(\bar{m}) + x^0 - WTP_{Gain} + \eta(-\lambda WTP_{Gain})] \\ &+[1 - \pi(p)][x^0 - WTP_{Gain} + \eta(-\lambda WTP_{Gain})] \\ WTP_{Gain} =& \frac{\pi(p)(1+\eta)\bar{m}}{1+\lambda\eta} = \pi(p)\bar{m}\frac{1+\eta}{1+\lambda\eta} = \frac{\pi(p)\bar{m}}{\beta} \end{aligned}$$

WTA-Gain:

$$\begin{aligned} &\pi(p)[\bar{m} + (1 - a\pi(p))\eta\bar{m} + x^0] + [1 - \pi(p)][a\pi(p)\eta(-\lambda\bar{m}) + x^0] \\ &= a\pi(p)\eta(-\lambda\bar{m}) + x^0 + WTA_{Gain} + \eta WTA_{Gain} \\ WTA_{Gain} &= \pi(p)\bar{m} + \frac{a\pi(p)^2(\lambda-1)\eta\bar{m}}{1+\eta} = \pi(p)\bar{m} + a\pi(p)^2\bar{m}(\frac{1+\lambda\eta}{1+\eta} - 1) \\ &= \pi(p)\bar{m}[a\beta\pi(p) - a\pi(p) + 1] \end{aligned}$$

WTP-Loss:

$$\pi(p)[(1-a\pi(p))\eta(-\lambda\bar{m})+x^0]+[1-\pi(p)][\bar{m}+a\pi(p)\eta\bar{m}+x^0]$$

$$=\bar{m}+a\pi(p)\bar{m}+x^0-WTP_{Loss}+\eta(-\lambda WTP_{Loss})$$

$$WTP_{Loss}=\pi(p)\bar{m}+\frac{a\pi(p)^2(1-\lambda)\eta\bar{m}}{1+\lambda\eta}=\pi(p)\bar{m}+a\pi(p)^2\bar{m}(\frac{1+\eta}{1+\lambda\eta}-1)$$

$$=\pi(p)\bar{m}[\frac{a\pi(p)}{\beta}-a\pi(p)+1]$$

WTA-Loss:

$$x^0+\bar{m}=\pi(p)[\eta(-\lambda\bar{m})+x^0+WTA_{Loss}+\eta WTA_{Loss}]$$

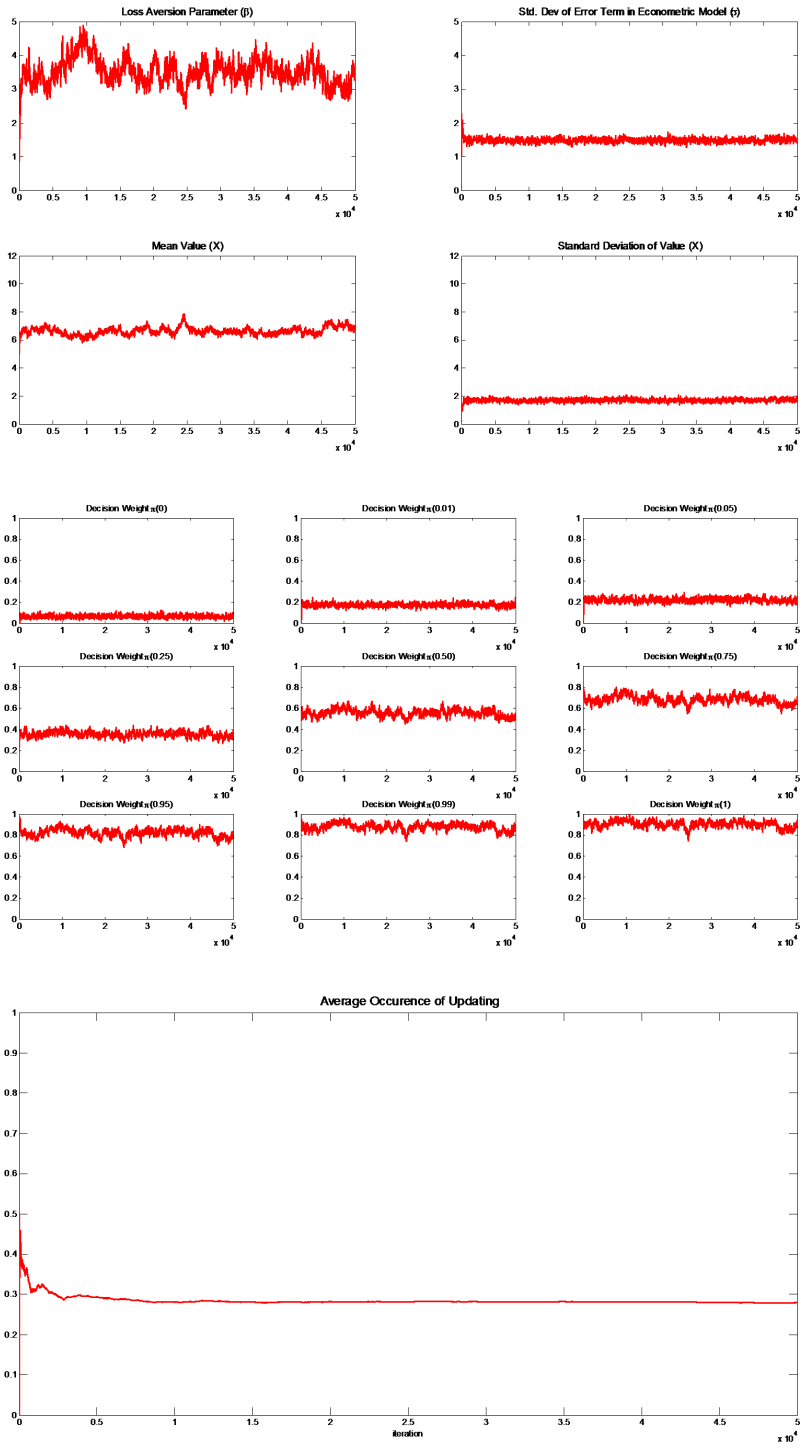
$$+[1-\pi(p)][\bar{m}+x^0+WTA_{Loss}+\eta WTA_{Loss}]$$

$$WTA_{Loss}=\frac{\pi(p)(1+\lambda\eta)\bar{m}}{1+\eta}=\pi(p)\bar{m}\frac{1+\lambda\eta}{1+\eta}=\pi(p)\beta\bar{m}$$

Parameters that need to be estimated are $\pi(p)$, $\bar{m}$ and $=\frac{1+\lambda\eta}{1+\eta}$.

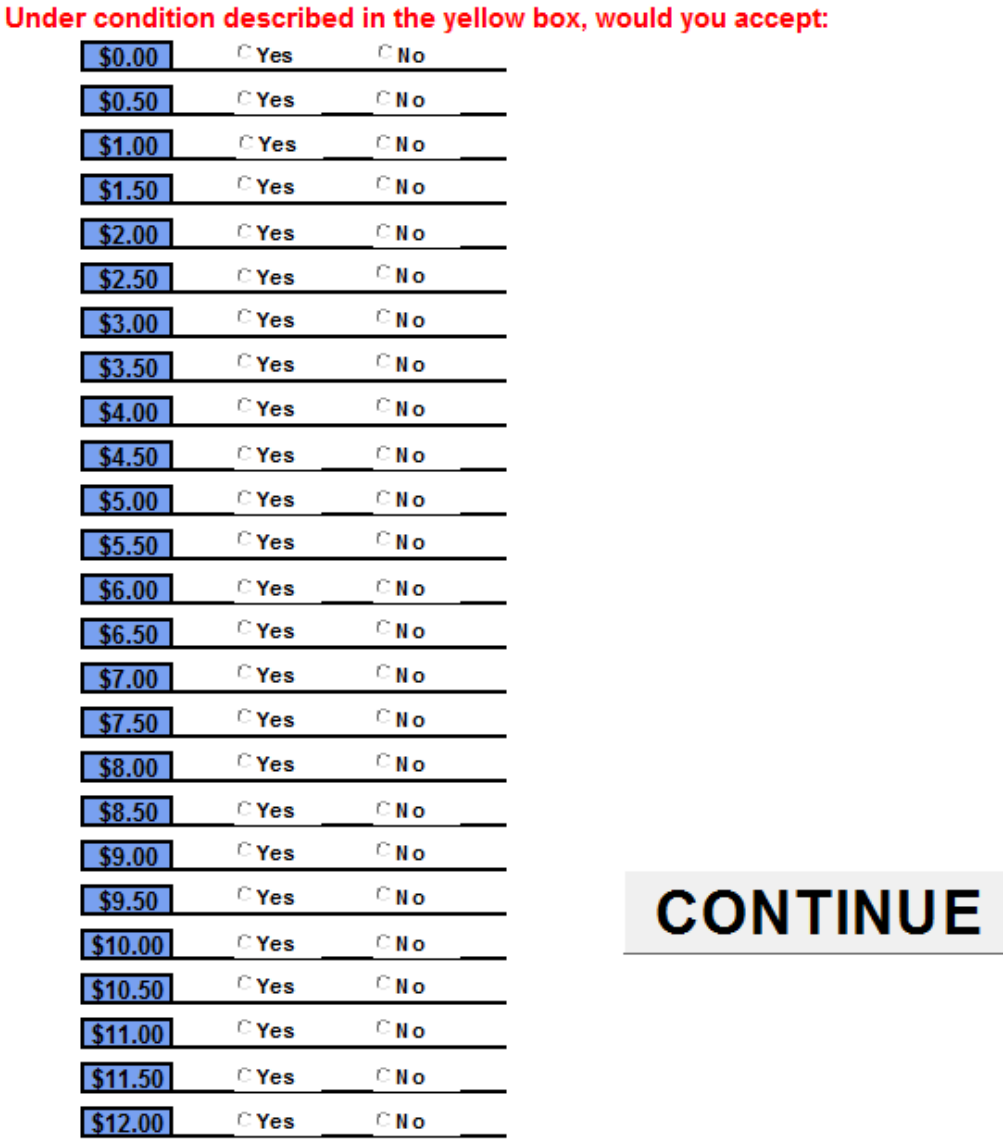
A.3 Markov Chain of Estimates with Heterogeneity

Figure A.1: Markov Chain of Estimates with Heterogeneity



A.4 Visual Basic Application (VBA) Programs

Figure A.2: Visual Basic Application (VBA) Programs



The program automatically checks the legitimacy of answers. For example, in the WTP sessions, once a subject rejects a certain price, he/she has to reject all higher prices. In WTA sessions, once a subject accepts a certain price, he/she has to accept all higher prices. In each part of the experiment, prices increase in $0.05 increment. After a subject answers questions on the above screen, he/she is then led to a second screen which shows finer price points but works in the same way.

A.5 Sample Written Instructions

[Instruction WTP Loss Domain]

This experiment is about how much you value a Cornell mug. Please look at the mug on your desk. Note that deception is NOT allowed in economic experiments. You will be compensated in cash for your participation at the end of the experiment. The amount you receive is based on choices you make during the experiment. If you have any questions during the experiment, please raise your hand and someone will come to assist you. You have an initial balance of $15 for participating in this experiment that is yours to spend or keep as you wish.

The Cornell mug sitting on your desk is yours. The experiment has 9 parts. In each part there will be a chance (probability) that you will lose your mug. Only one part will be implemented. We will determine which part to implement by drawing one ball from a bingo cage with 9 balls numbered from 1-9 in it. In part 1, there is a 0% chance that you will lose your mug; in part 2, there is a 1% chance that you will lose your mug; in part 3, there is a 5% chance that you will lose your mug; in part 4, there is a 25% chance that you will lose your mug; in part 5, there is a 50% chance that you will lose your mug; in part 6, there is a 75% chance that you will lose your mug; in part 7, there is a 95% chance that you will lose your mug; in part 8, there is a 99% chance that you will lose your mug; in part 9, there is a 100% chance that you will lose your mug.

In each part, you have a chance to buy an insurance policy out of your initial $15 participation balance that protects you from losing your mug. We will ask you whether you want to buy the insurance policy at different prices that would

protect you against loss of your mug in that part of the experiment. It is in your best interest to answer EACH question in EACH part truthfully. Here are the reasons.

Since the valuing of your mug (how much you do not want to lose it) is demonstrated by your answers in each part, you should make your choices as if each part was the one to be implemented. Since you can only end up buying one insurance policy out of your $15 balance for the part that is actually implemented, you have up to $15 to spend on insurance for each part.

In this experiment you will answer a set of yes/no questions in each part. We will then determine a price for the insurance policy (for the part of the experiment drawn) by randomly drawing a poker chip from a bag with different prices on each chip. If you said yes to the drawn selling price, that is, if you are willing to pay that price, you pay us the drawn selling price (that is, the price of the insurance policy is subtracted from the earning you get for being in this experiment) and you will receive the insurance policy (therefore not exposed to the risk of losing your mug!). If you said no to the drawn selling price, you dont pay us and you do NOT receive the insurance policy (therefore, you are still exposed to the risk of losing your mug

The risk of losing your mug in each part is represented by the number of red chips in a bag that contains red and white chips. 1 red chip and 99 white chips indicate 1% risk, 5 red chips and 95 white chips indicate 5% risk and so on. For example, if we draw bingo ball 5, we will put 50 red chips and 50 white chips in the bag. To implement the risk of losing your mug, we will ask one of you to draw a chip from the bag. If a red chip is drawn, you will lose your mug UNLESS you are covered by an insurance policy you bought for that part.

Here is how things will look on your computer: Each part consists two steps in which you can indicate the amount you want to pay for the insurance policy. For each part 1-9, there are a set of questions about the price of the insurance policy. There are two ways you can record your answer:

Click Yes or No for each price;

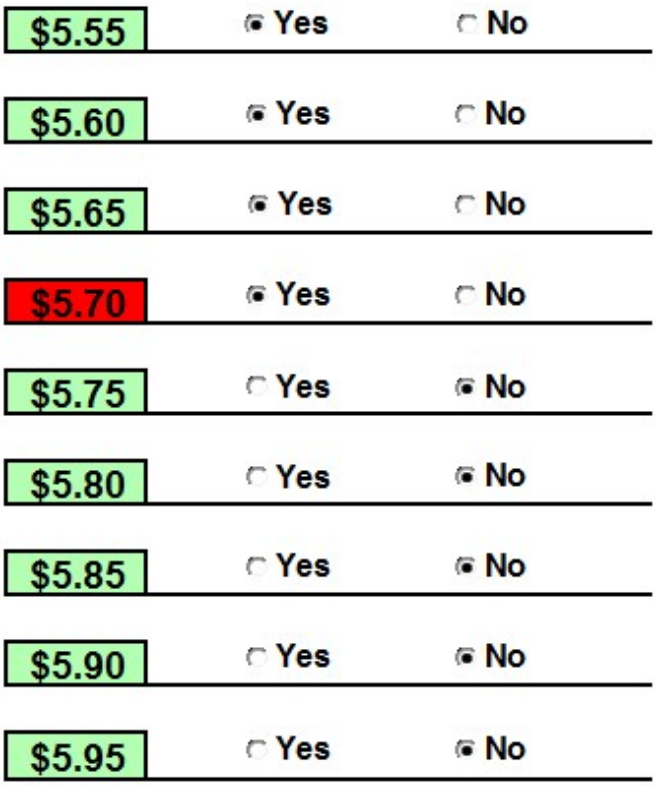
Click the price itself then you automatically say Yes to all prices lower than, or equal to, the clicked price, and No to all prices higher than the clicked price.

For example, suppose you want to say yes to prices of $5.70 or below; that is, that you decide that $5.70 is the maximum price you would pay. You could either click Yes on the buttons $0, $0.50, and $1.00, etc., up $5.50 and then No to $6.00 up to $11.00. OR, you can do it the easier way, which is to click on the $5.50 (see the highlighted price). In the latter case, the program helps you fill in your answer for all Yes/No questions. Note, you can still make changes to the Yes/No questions after you click a price. Once your final choices are made, we collect your Yes/No answers. Then you will proceed to the second step in the SAME part.

After your click the CONTINUE button in the first step of each part, you will be led to the second step and repeat the procedure in first step (as shown in the following screen shot) with finer price points. After you finish the second step, you can submit your decisions.

Now, suppose you made the above choice in part 2, and that part is the one that is randomly chosen to be implemented (played out), and then the $3.00 selling price was randomly drawn from the bag of prices. In that case, you will pay from your $15 balance the randomly drawn selling price of $3.00 and get

$0.00	Yes	No
$0.50	Yes	No
$1.00	Yes	No
$1.50	Yes	No
$2.00	Yes	No
$2.50	Yes	No
$3.00	Yes	No
$3.50	Yes	No
$4.00	Yes	No
$4.50	Yes	No
$5.00	Yes	No
$5.50	Yes	No
$6.00	No	Yes
$6.50	No	Yes
$7.00	No	Yes
$7.50	No	Yes
$8.00	No	Yes
$8.50	No	Yes
$9.00	No	Yes
$9.50	No	Yes
$10.00	No	Yes
$10.50	No	Yes
$11.00	No	Yes



the insurance policy. Then finally, in the event that a red chip is drawn from the bag, you will KEEP your mug.

In comparison, if $8.00 was randomly drawn as the selling price for that part, you do not pay anything from your balance, and you will not have the insurance policy that would let you keep your mug if a red chip is drawn. You will then LOSE your mug in the event that a red chip is drawn because you did not insure against its loss, but you will have your $15 participation balance.

Note, although we introduced each part sequentially, they will appear randomly.

APPENDIX B

APPENDICES OF CHAPTER 3

B.1 Supplementary figures and tables

Figure B.1: Part A Screen-shot

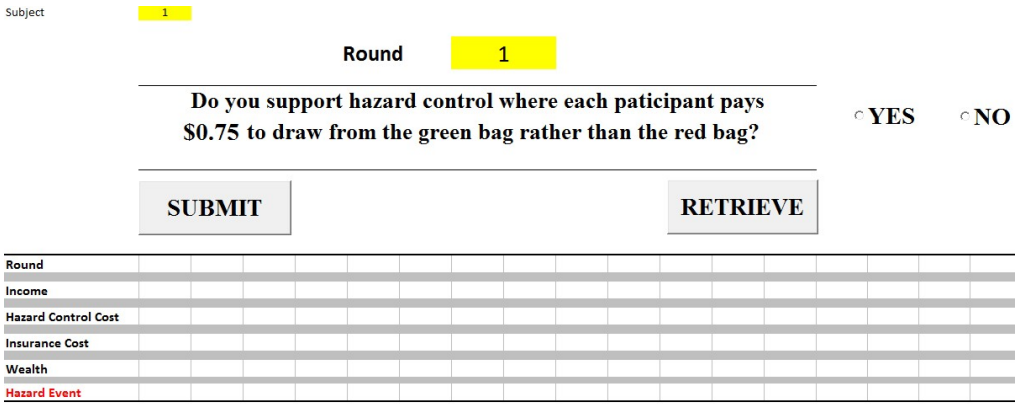


Figure B.2: Part B Screen-shot

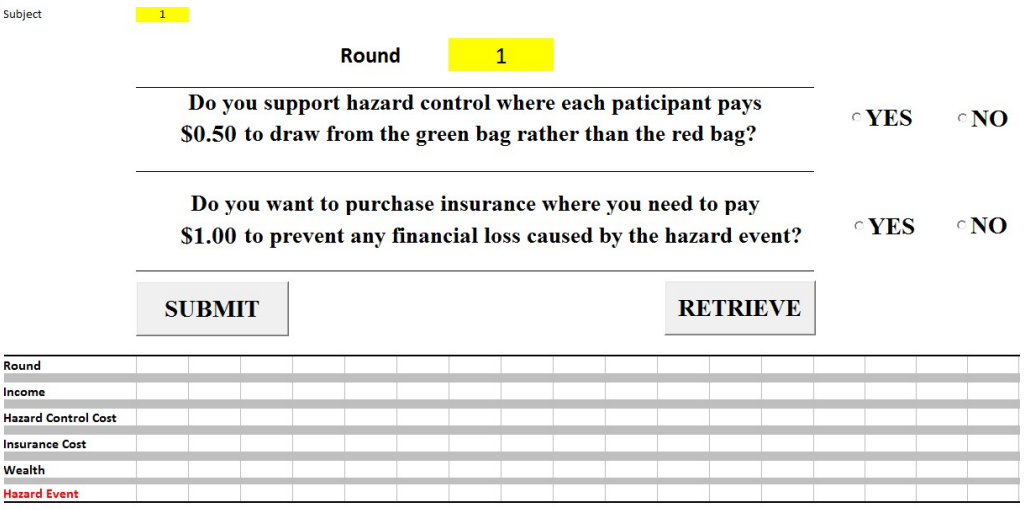


Figure B.3: Post Event Questions Screen-shot

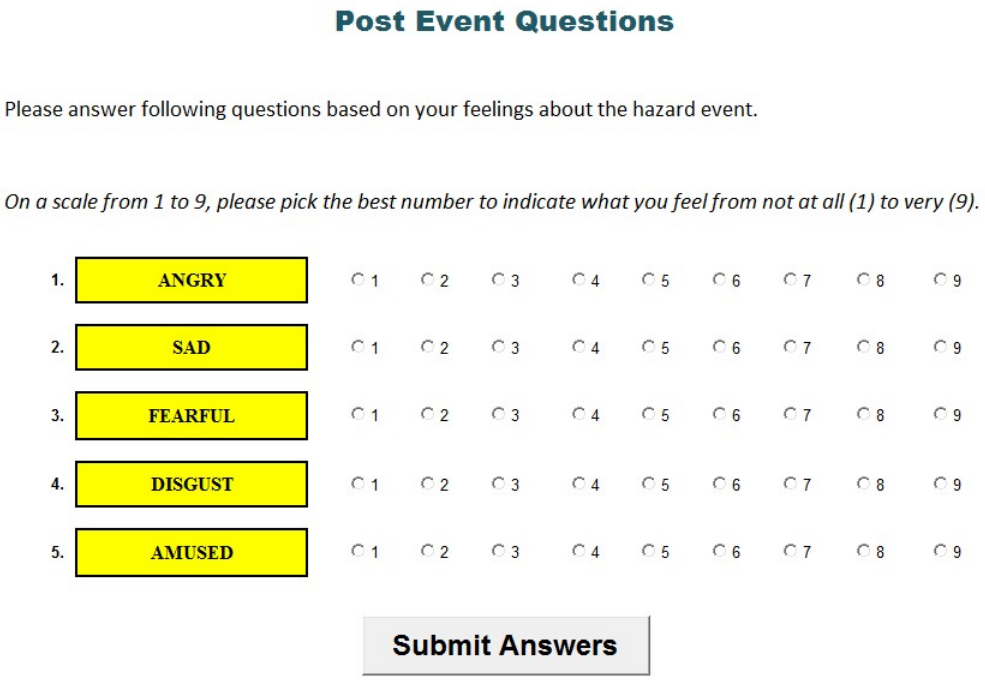


Table B.1: Predict Emotions with Linear Model

	(1) Anger	(2) Fear
Video	1.404*** (0.388)	1.748*** (0.344)
Financial Loss	0.327*** (0.065)	-0.005 (0.054)
Experienced Events	0.379** (0.147)	0.252* (0.135)
Round	-0.057** (0.025)	-0.059** (0.024)
Age_1	3.342*** (0.706)	1.148 (0.780)
Age_2	4.398*** (0.970)	1.741 (1.058)
Asian	1.112* (0.621)	1.347** (0.641)
Constant	-0.047 (1.415)	1.014 (1.485)
Observations	653	653

Video is dummy variable (1 if required to watch the video clip when a hazard event happened, 0 otherwise). Insurance is a dummy variable (1 for part B and 0 for part A). Financial loss is a dummy variable (5 if no insurance was purchased AND a hazard event happened, 0 otherwise). Number of past events is the total number of hazard events that had happened before the current emotion measurement. Round number is the actual round number from 1 to 30. Age_1 is a dummy variable (1 if falls in the smallest age group). Age_2 is a dummy variable (1 if falls in the second smallest age group). Asian is a dummy variable. Standard errors are in parentheses. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

B.2 Experimental instruction

Instruction (Part A)

This is an experiment in the economics of hazards. Your task is to make decisions in your best interest while earning money. It should be noted that no deception is allowed in an economics experiment. The experiment will consist of a large number of rounds. The experiment will end when a predetermined number of rounds have been completed but you will not be told this number. All money remaining in your computer account at the end of the experiment will be given to you in cash and is yours to keep. In addition you will receive $5 for showing up for the experiment.

You will begin the experiment with an initial balance of $20 in your account. On each round you will be given an additional $1 and will be asked to vote if you want all participants including yourself to each pay the same amount for hazard control for that round. The risk of the hazardous event occurring on a round is represented by drawing one poker chip from either the red bag or the green bag. All draws will be made by participants in the experiment. Each bag contains the same total number of chips with few red chips and many white chips. However, the red bag has twice as many red chips in it as the green bag. The hazardous event occurs if the red chip is drawn and nothing occurs if a white chip is drawn. You will not be told the number of red or white chips in either bag. If a majority of participants, more than half, vote in favor of hazard control, the chip for that round will be drawn from the green bag. If a majority do not vote in favor of hazard control on a round, the chip will be drawn from the red bag which doubles the odds of the event occurring on

that round. The hazardous event consists of the loss of $5 from the account of each participant in the experiment [and the showing of a video containing unpleasant photos of actual events with very loud and unpleasant noises, up to 115 dB for approximately 100 ms, equivalent to a gunshot 3 feet away, delivered through headphones] . Once the hazardous event is over, the experiment will continue as before.

We will begin the experiment with five practice rounds that will not count towards your earnings. You will be instructed how to vote on each round so you can practice entering your decisions on the computer.

Instruction (Part B)

This is an experiment in the economics of hazards. Your task is to make decisions in your best interest while earning money. It should be noted that no deception is allowed in an economics experiment. The experiment will consist of a large number of rounds. The experiment will end when a predetermined number of rounds have been completed but you will not be told this number. All money remaining in your computer account at the end of the experiment will be given to you in cash and is yours to keep. In addition you will receive $5 for showing up for the experiment.

You will begin the experiment with an initial balance of $20 in your account. On each round you will be given an additional $1 and will be asked to vote if you want all participants including yourself to each pay the same amount for hazard control for that round. The risk of the hazardous event occurring on a round is represented by drawing one poker chip from either the red bag or the green bag. All draws will be made by participants in the experiment.

Each bag contains the same total number of chips with few red chips and many white chips. However, the red bag has twice as many red chips in it as the green bag. The hazardous event occurs if the red chip is drawn and nothing occurs if a white chip is drawn. You will not be told the number of red or white chips in either bag. If a majority of participants, more than half, vote in favor of hazard control, the chip for that round will be drawn from the green bag. If a majority do not vote in favor of hazard control on a round, the chip will be drawn from the red bag which doubles the odds of the event occurring on that round. The hazardous event consists of the loss of $5 from the account of each participant in the experiment [and the showing of a video containing unpleasant photos of actual events with very loud and unpleasant noises, up to 115 dB for approximately 100 ms, equivalent to a gunshot 3 feet away, delivered through headphones] . In addition, in each round you will be offered insurance for the amount shown on the computer screen that will only protect against the financial loss[, not the unpleasant video and very loud noise]. Once the hazardous event is over, the experiment will continue as before.

We will begin the experiment with three practice rounds that will not count towards your earnings. You will be instructed how to vote on each round so you can practice entering your decisions on the computer.

APPENDIX C

APPENDICES OF CHAPTER 4

C.1 Supplementary Tables

Table C.1: Emissions in Each NERC Region in EI

	0 (FRP)	-0.1	-0.25	-0.5
		CO_2 Emissions (million short tons)		
NPCC	57.74	56.46	64.91	75.64
RFC	661.24	663.43	665.97	670.35
SERC	613.28	613.60	614.59	616.38
FRCC	97.16	97.27	97.38	96.98
SPP	188.56	188.67	189.16	189.02
MRO	189.88	191.74	192.18	193.48
Total	1807.85	1881.18	1824.20	1841.85
		NO_X Emissions (million lbs)		
NPCC	174.33	173.87	194.19	219.24
RFC	1430.87	1437.31	1444.26	1454.59
SERC	947.04	946.39	948.16	948.56
FRCC	111.99	112.06	111.98	111.08
SPP	437.14	437.40	438.51	438.85
MRO	585.32	588.83	590.50	592.53
Total	3686.67	3695.86	3728.10	3764.85
		SO_2 Emissions (million lbs)		
NPCC	286.11	286.15	355.64	422.02
RFC	5721.14	5748.31	5774.54	5858.29
SERC	2389.09	2385.46	2390.35	2389.24
FRCC	173.26	173.44	173.47	172.31
SPP	657.27	658.54	662.99	665.36
MRO	1002.30	1010.70	1014.48	1019.48
Total	10229.17	10262.60	10371.48	10526.70

Table displays the emissions in absolute values under different assumed constant demand elasticities. 0 elasticity represents case of flat rate pricing.

Table C.2: Shares of Major Generation Sources

	0 (FRP)	-0.1	-0.25	-0.5
		Coal (percentage)		
NPCC	5.43	5.41	6.80	8.07
RFC	60.71	60.85	61.04	61.33
SERC	49.14	49.19	49.33	49.53
FRCC	24.67	24.88	25.07	25.03
SPP	66.96	67.04	67.14	67.44
MRO	54.36	54.65	54.72	54.94
Total	45.42	45.50	45.78	46.06
		Hydro (percentage)		
NPCC	46.64	47.22	46.62	45.55
RFC	2.50	2.49	2.49	2.48
SERC	6.27	6.27	6.26	6.26
FRCC	0.02	0.02	0.02	0.02
SPP	2.51	2.51	2.50	2.51
MRO	18.85	18.74	18.73	18.66
Total	12.59	12.71	12.67	12.60
		Natural Gas (percentage)		
NPCC	8.08	7.59	7.35	7.71
RFC	6.85	6.77	6.66	6.50
SERC	16.50	16.46	16.34	16.18
FRCC	53.77	53.56	53.38	53.40
SPP	16.73	16.62	16.52	16.18
MRO	0.49	0.43	0.41	0.35
Total	12.82	12.66	12.51	12.42
		Nuclear (percentage)		
NPCC	33.19	33.18	32.76	32.00
RFC	24.82	24.77	24.72	24.62
SERC	25.49	25.48	25.47	25.44
FRCC	16.26	16.26	16.25	16.27
SPP	4.06	4.06	4.05	4.06
MRO	10.23	10.18	10.17	10.13
Total	23.24	23.22	23.14	23.01

Table displays the percentage of generation from different fuel types in each region. Only major generation sources have been included. The left out sources include biomass, oil, refuse, solar, storage, and wind. They have been left out for two reasons. Firstly, they do not cause any emission and secondly, their shares are small.

Table C.3: Emissions in Each NERC Region in EI with Load Scaling

	0 (FRP)	-0.1	-0.25	-0.5
		CO_2 Emissions (million short tons)		
NPCC	57.74	54.64	55.74	57.83
RFC	661.24	660.59	661.66	656.44
SERC	613.28	613.09	613.28	614.12
FRCC	97.16	97.13	97.28	97.05
SPP	188.56	188.45	188.21	188.38
MRO	189.88	190.04	190.06	189.98
Total	1807.85	1803.95	1806.24	1803.81
		NO_X Emissions (million lbs)		
NPCC	174.33	169.89	176.55	183.60
RFC	1430.87	1430.52	1438.17	1430.10
SERC	947.04	945.58	946.24	945.91
FRCC	111.99	111.98	111.92	111.21
SPP	437.14	436.64	435.45	436.43
MRO	585.32	585.53	584.96	583.77
Total	3686.67	3680.13	3693.28	3691.02
		SO_2 Emissions (million lbs)		
NPCC	286.11	273.96	301.75	328.27
RFC	5721.14	5739.73	5749.04	5753.10
SERC	2389.09	2383.29	2383.14	2373.93
FRCC	173.26	173.12	173.47	172.49
SPP	657.27	657.50	656.29	660.77
MRO	1002.30	1003.89	1003.42	1003.67
Total	10229.17	10231.50	10267.11	10292.24

Table displays the emissions in absolute values under different assumed constant demand elasticities. 0 elasticity represents case of flat rate pricing.

Table C.4: Shares of Major Generation Sources with Load Scaling

	0 (FRP)	-0.1	-0.25	-0.5
		Coal (percentage)		
NPCC	5.43	5.16	5.80	6.35
RFC	60.71	60.80	61.03	61.06
SERC	49.14	49.20	49.29	49.47
FRCC	24.67	24.84	25.07	25.02
SPP	66.96	67.06	67.06	67.38
MRO	54.36	54.43	54.47	54.50
Total	45.42	45.42	45.66	45.81

		Hydro (percentage)		
NPCC	46.64	47.37	47.50	47.45
RFC	2.50	2.50	2.5	2.51
SERC	6.27	6.27	6.27	6.27
FRCC	0.02	0.02	0.02	0.02
SPP	2.51	2.51	2.51	2.51
MRO	18.85	18.84	18.83	18.84
Total	12.59	12.74	12.74	12.76
		Natural Gas (percentage)		
NPCC	8.08	7.57	6.74	6.41
RFC	6.85	6.73	6.51	6.29
SERC	16.50	16.42	16.34	16.17
FRCC	53.77	53.58	53.36	53.42
SPP	16.73	16.61	16.58	16.20
MRO	0.49	0.43	0.41	0.35
Total	12.82	12.64	12.39	12.20
		Nuclear (percentage)		
NPCC	33.19	33.29	33.38	33.34
RFC	24.82	24.85	24.84	24.99
SERC	25.49	25.50	25.50	25.49
FRCC	16.26	16.27	16.27	16.26
SPP	4.06	4.06	4.06	4.07
MRO	10.23	10.23	10.23	10.23
Total	23.24	23.27	23.28	23.01

Table displays the percentage of generation from different fuel types in each region after scaling the input load. Only major generation sources have been included. The left out sources include biomass, oil, refuse, solar, storage, and wind. They have been left out for two reasons. Firstly, they do not cause any emission and secondly, their shares are small.

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