THREE ESSAYS ON ECONOMICS AND RISK PERCEPTION

DISSERTATION

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By

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ABSTRACT

This dissertation consists of 3 essays involving economics and risk perception. The title of first essay is "An Empirical Analysis of United States Consumers' Concerns about Eight Food Production and Processing Technologies", the second essay is "Does Price Signal Quality? Strategic Implications of Price as a Signal of Quality for the Case of Genetically Modified Food", and the third essay is "Measuring Individual Risk Attitudes from Observed High-Stakes Gambles: Are Professional Poker Players Risk Averse?"

In the first essay, U.S. consumers' ratings of concern toward eight food production and processing technologies (antibiotics, pesticides, artificial growth hormones, genetic modification, irradiation, artificial colors/flavors, pasteurization, and preservatives) are analyzed using a representative sample of U.S. consumers. Concern is highest for pesticides and hormones, followed by concern toward antibiotics, genetic modification and irradiation. Standard relationships between many demographic, economic and attitude variables and the average concern level are documented. The main contribution of the essay is identifying three clusters of technologies that engender similar patterns of concern ratings among respondents and estimating models that correlate key personal and household characteristics to these underlying technology concern factors. It is found that several individual characteristics that yield little explanatory power for average ratings have discriminatory power for explaining concern across different technology clusters.

The second essay analyzes consumers' use of price as a quality signal by testing for non-monotonicity of consumer demand in the price for genetically modified food using data collected from a nationally representative mail survey featuring several hypothetical choice scenarios. Mixed evidence was found across three products for non-monotonicity of demand in price. It is argued that survey respondents may use price as a signal of the quality of genetically modified products for at least one of the three products investigated. Implications for firm strategy and regulation are discussed.

The third essay estimates individual poker players' utility functions and tests for the stability of this utility function across different phases of the game and across different strategic positions within the game using the data obtained from the World Poker Tour Series. Each player's subjective probability of winning is estimated using a probit model while the expected winning and losing amounts are estimated by double-hurdle tobit models. Using these results, a nonlinear probit model is used to estimate players' utility functions under Constant Absolute Risk Aversion and Constant Relative Risk Aversion utility specifications. The estimation results suggest that risk attitudes are not constant across strategic positions but are constant across phases of the game (e.g., earlier or later within a given hand). Overall, players were risk averse regardless of the

phase of the game. Amateur players might be less risk averse or rather risk neutral (or risk loving) than professional players. Also, players may display less risk aversion when playing last within a given round of betting than when moving earlier.

Deticated to

My mother and father, Eun-Soo Han and Min-Young Hwang

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PUBLICATIONS

Research Publication

1. Y. J. Hwang, B. Roe and M. F. Teisl, "An Empirical Analysis of United States Consumers' Concerns about Eight Food Production and Processing Technologies." AgBioForum, 8(1), 40-49, (2005).

2. Y. J. Hwang, B. Roe and M. F. Teisl, "Does Price Signal Quality? Strategic Implications of Price as a Signal of Quality for the Case of Genetically Modified Food." IFAMR, 9(1), (2006).

FIELDS OF STUDY

Major Field: Agricultural, Environmental, and Development Economics

TABLE OF CONTENTS

Page

LIST OF TABLES

ESSAY 3

LIST OF FIGURES

ESSAY 1

AN EMPIRICAL ANALYSIS OF UNITED STATES CONSUMERS' CONCERNS ABOUT EIGHT FOOD PRODUCTION AND PROCESSING TECHNOLOGIES

CHAPTER 1

INTRODUCTION

Modern science is capable of generating incredible advances in food production and processing technologies that can produce more food, reduce costs and enhance attributes in ways not imagined only decades ago. However, due to the intimate and ubiquitous role that food plays in our life, the impacts of food production and processing on the environment, and the social and physical distance between consumers and the food production process, consumers scrutinize not only the cost and attributes of food but, increasingly, the technology and methods used in food production and processing.

The adoption of emerging food technologies or the rejection of existing technologies hinges on the outcome of this increasingly intense scrutiny. In this article we analyze the concerns that U.S. consumers express toward several prominent food production and processing technologies using data from a large, representative survey. First, consumer concerns across eight technologies (antibiotics, pesticides, artificial growth hormones, genetic modification, irradiation, artificial colors and flavors, pasteurization, and preservatives) are ranked. Second, correlations across the level of concern expressed for each technology are presented. Third, common, unobserved factors driving common concerns across the eight technologies are identified using factor analysis. Finally the economic, demographic and attitudinal variables that explain both the average level of concern with the eight technologies of interest and the unobserved concern factors are investigated using regression techniques.

Ranking the level of concern for each technology is of interest because the data are gathered from a representative sample of U.S. consumers; hence, it provides a view of which technologies are of greatest concern at the time the data were collected (summer 2002). The correlation across concern expressed for different technologies is of interest because it allows for speculation about the common elements of technologies that can cause consumer reticence. The factor analysis formalizes this speculation by statistically identifying common, unobserved factors that explain the correlation of ratings across the eight technologies. Finally, exploring the demographic, economic and attitudinal correlates of expressed concern in terms of both the average concern rating and the concern factors has several possible benefits. First, such analysis using U.S. data can be compared to similar analyses of data from other countries to look for commonalities and differences, i.e., are differences in expressed concern between the U.S. and European consumers due to a simple difference in demographics, attitudes or other characteristics? Second, how might U.S. consumer acceptance of technologies change over time as demographics shift or, alternatively, do niches of U.S. consumers currently exist that are more accepting of various technologies?

The remainder of the paper is organized as follows. First previous work analyzing consumer concern with food production and processing technologies is reviewed. Next the data and the statistical methods used to analyze the data are described. Then the results and accompanying discussion is presented. The final section provides conclusions and outlines avenues for future research.

CHAPTER 2

LITERATURE REVIEW

Many researchers have studied consumer attitudes, perceptions and acceptance of various food production and processing technologies with the bulk of recent efforts focused on genetic modification, irradiation, artificial hormones, and pesticides. Many studies document consumer demand for products differentiated with respect to a single technology (e.g., pesticides, Baker; irradiation, Hayes, Fox, and Shogren; genetically modified foods, Teisl et al.) or several technologies (organic, Sylvander and Le Floc'h-Wadel; hormones and genetic modification, Lusk, Roosen, and Fox). Several organizations have also conducted opinion polls to document public awareness and attitude towards various technologies (Center for Science in the Public Interest, genetic modification; International Food Information Council, genetic modification; Abt Associates, Fox, Bruhn, and Sapp, several technologies; Gallop, several technologies). Closer in spirit to the current article are studies decomposing consumer attitudes and perceptions of one or more technologies (e.g., Govindasamy and Italia, pesticides; Verdurme and Viaene, genetic modification; Misra et al., irradiation; Grobe, Douthitt and Zepeda, bovine growth hormone; Dosman, Adamowicz, and Hrudey, additives and pesticides; Hoban, genetic modification; Frewer, Howard, and Shepherd, genetic engineering; Fife-Schaw and Rowe, several technologies).

Several common findings emerge across these articles. In most, women perceived greater risks than men (Misra et al., 1995; Fox et al., 2001; Dosman et al., 2001, Grobe, Douthitt, and Zepeda). Misra et al. (1995) found that females treated food irradiation as more serious problem even though women had lower stated awareness of irradiation. Dosman et al. (2001) found that gender was the only variable that was robust across risk perception models estimated for food additives, food bacteria, and pesticides.

In some research household income is associated with risk perception (Misra et al., 1995; Dosman et al, 2001; Grobe, Douthitt and Zepeda). Lower income respondents generally perceived more risk than higher income respondents. Misra et al. (1995) found that education level significantly affects risk perception for irradiation and suggested that female respondents with less than a college education and low income treat irradiation as a more serious problem. Dosman et al. (2001) also suggest that highly educated respondents usually perceive less risk in the sphere of food safety.

Fox et al. (2001) included the presence of children in their study; Grobe, Douthitt and Zepeda included the presence of children younger and older than six years of age; and Dosman et al. (2001) included the number of children. Both the presence of children and the number of children had significant effects. Households with children had more negative views of irradiation than households without children (Fox et al., 2001) and, as households had more children, they perceived more risk related with food safety (Dosman et al., 2001). Grobe, Douthitt and Zepeda find that only households with younger children had significantly higher perceived risks of bovine growth hormone.

CHAPTER 3

DATA AND METHODOLOGY

During the summer of 2002 a mail survey was administered to a nationally representative sample of 6,172 U.S. residents, which included an additional over-sample of 710 individuals from one researcher's home state. In total 2,387 individuals responded (38.7 percent). For the questions analyzed in this article, 1,656 respondents provided complete information, yielding an effective response rate of 26.8 percent.

Due to the over-sampling of residents from one researcher's home state, the entire sample was weighted by U.S. census measures of state level population. Except for race, survey respondents have characteristics similar to those of the U.S. adult population (Table 1). The differences in race may reflect a bias in our sampling frame or may reflect differences in the phrasing of the race question between our survey and the U.S. census. Weighting the sample by both state and race category was considered but rejected as many weighting cells (e.g., non-white respondents from North Dakota) were not represented in the sample.

	Survey	U.S. Census
Percent male	46	48
Average age	53	47
Average years of education	14	13
Percent white	89	75
Average household income	$60,900	$57,000

Table 1. Socio-economic characteristics of respondents

The key data recorded in the survey are raw ratings provided in response to the following prompt: “Listed on this page are different items related to the way foods are produced or processed. Review the list and rate how concerned you are with each item.” For each technology, respondents circled a number on a scale that ranged from one (not at all concerned) to three (somewhat concerned) to five (very concerned).

The list included the following terms: antibiotics, pesticides, artificial growth hormones, genetically modified ingredients, irradiation, artificial colors or flavors, pasteurization, and preservatives. The order of presentation of these items within the survey was uniform across all respondents. Hence, we are unable to test for the presence of order effects, i.e., to test for the possibility that the order of presentation of the items influences the rating each item receives. Thus, we cannot rule out that the results are an artifact of item ordering.

Only four questions and a cover letter preceded this set of questions, and none of these materials mentioned or described any of the eight technologies nor attempted to gauge individual awareness of any technology. Hence, responses should be considered 'top of the mind' reactions that rely upon the respondent's knowledge base at the time of the survey and not upon reaction to any information provided in the survey.

Standard income and demographic variables (age, education, race, gender, occupation) were also collected, as were several attitudinal variables that might correlate to concern about food technologies. These include the respondent's general concern with the food production and processing practices in the United States and foreign countries (not specifically related to technology); the respondent's tendency to read nutrition labels; whether the respondent follows any type of special diet (e.g., low salt, low fat); whether the respondent regularly purchases organic foods; whether the respondent purchases food at farmers' markets or health food stores; and whether the respondent frequents food cooperatives or grows his/her own produce. Each response may be correlated with underlying concerns about specific food production and processing technologies and may help clarify our portrait of these concerns.

Beyond summarizing how respondents rated their concern for each of the eight technologies of interest (antibiotics, pesticides, artificial growth hormones, genetic modification, irradiation, artificial colors and flavors, pasteurization, and preservatives) and assessing correlation of concerns across these technologies, we conduct a factor analysis of the sequence of responses to the eight technology concern ratings. Factor analysis is a statistical technique that is commonly used to identify unobservable factors underlying respondents' answers to a series of questions. In essence, factor analysis finds underlying commonalities or 'factors' in responses. For each respondent, i¸ and each identified concern factor, k, a factor score, $y_{i,k}$, is estimated using principal factor analysis.

These factor scores are then modeled as a function of income, demographic and other household and personal characteristics. The resulting model for respondent *i's* technology concern factor *k* is:

$$y_{i,k} = X_i \beta_k + u_{i,k} \tag{1}$$

where X_i is a vector of explanatory variables for respondent *i*, β_k is a conformable vector of parameters for technology factor *k* to be estimated, and $u_{i,k}$ an unobserved component driving technology factor score *k* for respondent *i*.   The factor scores are continuous variables and a common block of explanatory variables is used for each factor score; hence, ordinary least squares regression provides consistent and efficient estimates of the model parameters in (1).

A model is also estimated to find correlations between the average raw concern rating across all eight technologies and the common block of explanatory variables. To accommodate some censored observations, e.g., a respondent rating all technologies at the highest level of concern, a double-hurdle tobit model is employed.

CHAPTER 4

RESULTS

4.1. Rating the level of concern for all eight technologies

The average ratings of the eight technologies are listed in Table 2 and reveal the average state of concern for this sample of U.S. consumers during the summer of 2002. The ratings suggest pesticides and artificial growth hormones generated the most concern from U.S. consumers, while technologies such as pasteurization, artificial colors and flavors and preservatives generated significantly less concern. Antibiotics, genetic modification and irradiation raised intermediate levels of concern.

The two technologies of greatest concern share several commonalities. First, both artificial hormones and pesticides can reside in or on food eaten by consumers, though the exact amount that enters the body and the exact health impacts of this consumption remain uncertain. The use of both can also have spillovers for the environment, with popular press accounts of the appearance of both pesticides and artificial hormones in water supplies and the ecosystem. The higher average rating for pesticides may derive from its broader reach – nearly all non-organic fruits, vegetable and grains use pesticides – while artificial growth hormones are only issues for a subset of animal products.

The technologies of intermediate concern – antibiotics, genetic modification, and irradiation – have fewer ways of affecting the consumer or have attributes that may be positive. For example, unlike pesticides and artificial hormones, the concern for antibiotics arises not from the possibility of direct consumption by consumers, but because some worry that widespread antibiotic use in animal agriculture will speed the general rate of antibiotic resistance. Consumers may also view antibiotic use to have some upside, i.e., improving the health of animals and, hence, the quality of animal products consumed.

Pesticides	4.17 a
Artificial growth hormones	4.00 b
Antibiotics	3.77 c
GM ingredients	3.73 c
Irradiation	3.58 d
Preservatives	3.21 e
Artificial colors/flavors	3.07 f
Pasteurization	2.77 g

a. Raw ratings are as follows: 1 = not at all concerned, 3 = somewhat concerned and 5 = very concerned
b. Results sharing the same letter are not significantly different
c. These results were first reported in a companion paper previously published by several of the authors.

Table 2. Average raw ratings of concerns about food technologies.

Consumer concern about genetically modified ingredients tends to lie with unknown long-term concerns about human and environmental health, but consumers may also be aware of GM technologies that reduce environmental damage or food's healthfulness. Likewise, irradiation is seen by some as an efficient means for preserving food safety while others worry about its affect on food nutrient value and the environment.

The technologies of least concern are all 'well established' in the minds of most consumers. Preservatives and artificial colors/flavors are often revealed in ingredient lists and have not stirred much media attention since the 1970s while pasteurization is a well accepted technology associated with improving the safety of milk and other beverages.

4.2. Correlation of relative concerns across technologies

Nearly all correlation coefficients for the eight normalized ratings are significantly different from zero at the one percent level of significance (Table 3). Large, positive correlation exists among several clusters. The first cluster involves the technologies of lesser concern: relative concern for preservatives is positively correlated with relative concern for pasteurization and artificial colors and flavors. Two of the technologies with moderate concern ratings are positively correlated (genetically modification and irradiation) as are the top two technologies of concern (pesticides and hormones).

Relative concern for antibiotics is significantly correlated to relative concern for pesticides (though the absolute magnitude of the coefficient is rather small), but antibiotic concern is uncorrelated with concern for artificial hormones. Also, the relative ratings for antibiotics and genetic modification are negatively correlated despite the statistical similarity of absolute concern for both technologies. That is, the average rating of concern is almost identical but individuals rarely rated the two technologies on the same side of average. This suggests that different forces may drive the concern behind each technology: a topic which will be explored in greater detail below.

	Antibiotics	Pesticides	Hormones	Pasteur.	Art. Col./Fla.	GM	Irradiation	Preserv.
Antibiotics	1.000							
Pesticides	0.071 (0.006)	1.000						
Hormones	0.021 (0.426)	0.080 (0.002)	1.000					
Pasteur.	-0.250 (0.000)	-0.263 (0.000)	-0.514 (0.000)	1.000				
Art. Col./Flav.	-0.152 (0.000)	-0.250 (0.000)	-0.235 (0.000)	-0.070 (0.006)	1.000			
GM	-0.123 (0.000)	-0.130 (0.000)	0.358 (0.000)	-0.398 (0.000)	-0.258 (0.000)	1.000		
Irradiation	-0.265 (0.000)	-0.094 (0.000)	-0.052 (0.046)	-0.191 (0.000)	-0.217 (0.000)	0.147 (0.000)	1.000	
Preserv.	-0.222 (0.000)	-0.188 (0.000)	-0.451 (0.000)	0.352 (0.000)	0.112 (0.000)	-0.434 (0.000)	-0.314 (0.000)	1.000

a. *p*-values are in parentheses

Table 3. Correlation coefficients between ratings (N=1,504)

4.3. Factor Analysis

The factor analysis reveals three significant, underlying factors influencing responses to the eight technology concern questions (Table 4). One factor features heavy loadings by individuals' responses to concern about artificial growth hormones, genetically modified ingredients and irradiation (hereafter, the HGI factor). Factor two relates to the concern surrounding several 'older' technologies including pasteurization, artificial colors/flavors, and preservatives (hereafter, the OLDTECH factor) while concerns about antibiotics and pesticides load heavily on a third factor (hereafter, the ANTIPEST factor). The analysis formalizes and refines the intuition gained by studying the correlation coefficients among the raw concern ratings, with three distinct technology clusters being identified.

Technology	---*Standardized Rotated Factor Loadings*--- Factor 1: HGI	Factor 2: OLDTECH	Factor 3: ANTIPEST
Antibiotics	-0.32	-0.09	**0.86**
Pesticides	-0.02	-0.05	**0.46**
Artificial Growth Hormones	**0.36**	-0.20	0.12
Genetic Modification	**0.50**	-0.09	-0.17
Artificial Colors & Flavors	0.05	**0.31**	-0.10
Irradiation	**0.50**	0.06	-0.35
Pasteurization	-0.13	**0.52**	-0.12
Preservatives	-0.16	**0.46**	0.03
Variance Explained by Factor	2.27	2.13	1.53

Table 4. Factor analysis of concern ratings for eight technologies.

4.4. Average Concern Ratings Model

The model of average concern across all technologies reveals several strong predictors (Table 5, column 5). The strongest positive influence on average concern is the respondent's general stated level of concern about how food is produced in other countries (recall this question does not mention technology). Previous focus group work suggests that people with concerns about foreign produce often focus on the general level of sanitation of imported produce and animal products or the presence of chemical residues on imported produce (where respondents are often worried that other countries may allow application of chemicals currently banned in the United States, see Roe *et al*. for a more detailed discussion). Hence, if the latter element dominates the respondent's thinking, the positive relationship is quite logical: these individuals are generally concerned with technologies such as pesticides that could be consumed with foreign food. If the former element is the true trigger of concern about foreign food production, the link to concern about food technologies is less obvious and may instead be linked to individuals who have reflected upon the interconnectedness of food systems, even across national borders.

A respondent that purchases organic food, reads nutrition labels and shops at farmers' markets or health food stores also provides higher average ratings. Organic purchasing guarantees that many of the eight technologies are not used; organic and other 'natural' foods are often widely available in health food stores; and label readers are motivated to learn about the content of processed foods.

Controlling for the above lifestyle and concern characteristics, we find that several economic and demographic variables are significantly associated with average rating. Females and lower income respondents provided higher average ratings and, compared to those with the highest levels of formal education, individuals with a high school degree and some college education, provided significantly higher average ratings. Higher concern by female respondents is consistent with previous findings and may suggest greater female responsibility in food preparation, which persists despite significant increases in female workforce participation over the past decades. The higher ratings from those with lower levels of formal education are also consistent with previous findings (Dosman *et al*.).

Lower average ratings are associated with the oldest (> 65 years) and youngest (< 30 years) respondents. This is consistent with Teisl, Levy and Derby (1999) who found that health related awareness is lower when young, increases with age through middle age, and then decreases with further increases in age. Lower average ratings are also associated with households with older children (compared to no children); Caucasian respondents; higher income respondents; and respondents employed in food system occupations. We note that our finding that respondents with older children have lower levels of concern is inconsistent with previous findings in the literature, and may warrant future research to refine the correlation between concern and household structure.

4.5. Factor Models

Columns two, three and four in Table 5 provide the estimated parameters for the models that correlate individual factor scores to personal and household characteristics. A positive coefficient means that the characteristic is positively correlated with the particular underlying factor mentioned in that column, i.e., the characteristic is positively correlated with the unobserved factor, which is positively correlated with higher levels of concern for that particular cluster of technologies.

These factor models refine the insight provided by the average rating model listed in column 5 of Table 5 by decomposing the characteristics that correlate to the underlying factors of technology concern. Some characteristics have the same qualitative influence on average rating and on all factor scores (e.g., concern with how food is produced in the United States and the youngest age category). However, some characteristics that are not significantly correlated to the overall level of concern are significantly correlated to individual factors (e.g., growing a vegetable garden or adhering to a dietary restriction like a low-sodium diet). Other characteristics that are significant correlates of the overall concern rating may have a positive significant correlation to one factor while simultaneously having a negative significant correlation to another factor (e.g., gender and the oldest age category).

In general, factor score models provide a more nuanced statistical view of the characteristics that drive individual concern for clusters of technologies. Similar models have been estimated for concern with each individual technology, i.e., eight regression equations linking normalized, raw concern ratings to individual and household characteristics have been estimated. Similar correlations between characteristics and technologies in the same cluster are strong, i.e., a similar portrait of technology clusters and correlations to individual characteristics is revealed by the system of eight equations. These more detailed regression analyses are not presented for sake of brevity, but are available from the corresponding author upon request.

Perhaps the most interesting comparison to draw is between those respondents who have high levels of concern for the cluster of technologies including artificial growth hormones, genetic modification and irradiation (HGI) and the cluster featuring antibiotics and pesticides (ANTIPEST). Both clusters feature technologies that feature high raw levels of concern and technologies that have received considerable attention by policymakers and the media.

Several characteristics have significant correlations to the HGI and ANTIPEST factors where the correlations are of the opposite sign; such characteristics help identify the unique aspects of the profile of a typical respondent that is deeply concerned about each cluster of technologies. For example, female respondents have significantly higher HGI factor scores and significantly lower ANTIPEST factor scores than do males. A similar pattern holds for those who express a high degree of concern about how food is grown in other countries and for those whose highest educational achievement is a high school degree. Those respondents who are older than 65 hold the opposite pattern: on average they have lower scores for the HGI factor and higher scores for the ANTIPEST factor.

For several characteristics there exists a significant correlation to one factor but not to the other. For example, income level and race were correlated to factor scores of HGI, with higher concern for this technology cluster held by respondents with a lower income and of a minority racial group; these characteristics were not significantly correlated to ANTIPEST factor scores. Furthermore, those who regularly purchase organic food, read nutrition labels, grow home vegetable gardens, and have some college education have higher HGI factors scores, while these characteristics do not predict

ANTIPEST factor scores. Respondents who frequent farmers' markets are more likely to have a higher ANTIPEST factor score, though this characteristics does not predict the HGI factor score.

Several characteristics have the same significant, qualitative association with both HGI and ANTIPEST factors: those who express a low degree of concern with the way food is processed in the United States and those who are less than 30 years old have lower factor scores for both HGI and ANTIPEST.

These correlates of concern for the HGI factor share several similarities with Misra *et al.*'s 1995 portrait of those who expressed concern about irradiation. In short, both studies found that women with less formal education and lower incomes tend to view irradiation as a more serious concern, though the present study finds the correlation to a factor in which irradiation is but one of three technologies that load heavily upon the factor.

The characteristics of the typical respondent with a higher OLDTECH factor score are distinct from those concerned with the other two technology clusters. For example, those concerned with the older technologies typically display less concern about how food is processed in the United States, do not read nutrition labels, are older than 65 years of age, are not adhering to any special dietary requirements (e.g., low sodium diet), and have less than a college education.

Explanatory Variable	HGI	OLDTECH	ANTIPEST	Average Rating
	-----------------Factors--------------------			
Intercept	-2.394***	0.517***	0.097	1.214***
	(-17.98)	(2.99)	(0.56)	(9.94)
Conc US	0.433***	0.016	0.105***	0.417***
	(19.60)	(0.56)	(3.66)	(20.63)
Conc Otr	0.074***	-0.041*	-0.066***	0.916***
	(3.88)	(-1.66)	(-2.67)	(5.19)
Purch Org	0.129***	-0.035	-0.033	0.779***
	(5.53)	(-1.17)	(-1.10)	(3.63)
Nutr Label	0.038*	-0.073**	0.025	0.656***
	(1.69)	(-2.50)	(0.85)	(3.21)
Female	0.247***	0.006	-0.100*	0.245***
	(6.01)	(0.12)	(-1.88)	(6.48)
Age < 30	-0.180**	-0.126	-0.161*	-0.151**
	(-2.47)	(-1.34)	(-1.70)	(-2.23)
Age > 65	-0.162***	0.121*	0.147**	-0.899**
	(-3.00)	(1.74)	(2.10)	(-1.84)
Child 5	0.069	-0.065	-0.059	0.279
	(1.60)	(-1.16)	(-1.06)	(0.69)
Child 10	-0.107**	-0.111*	-0.025	-0.858**
	(-2.40)	(-1.91)	(-0.43)	(-2.07)
Child 18	-0.059**	-0.031	-0.050	-0.508*
	(-1.96)	(-0.79)	(-1.29)	(-1.81)
Grow Veg	0.073*	-0.021	0.033	0.333
	(1.66)	(-0.38)	(0.59)	(0.83)
Food Coop	-0.158	-0.173	-0.318	0.109
	(-0.89)	(-0.75)	(-1.39)	(0.73)
Farm Mkt	0.050	0.025	0.103*	0.726*
	(1.04)	(0.40)	(1.65)	(1.65)
No Diet	-0.023	-0.107*	-0.071	-0.406
	(-0.52)	(-1.86)	(-1.24)	(-1.00)
Edu1	0.131	0.380***	-0.041	0.114
	(1.20)	(2.69)	(-0.29)	(1.15)
Edu2	0.320***	0.111	-0.215**	0.319***
	(4.72)	(1.27)	(-2.44)	(5.10)
Edu3	0.181***	0.166**	-0.066	0.186***
	(2.87)	(2.03)	(-0.81)	(3.18)
Edu4	0.098	-0.007	-0.032	0.558
	(1.55)	(-0.08)	(-0.39)	(0.94)
White	-0.182***	-0.100	-0.116	-0.197***
	(-2.85)	(-1.20)	(-1.40)	(-3.42)
Food Job	-0.102	0.036	-0.022	-0.236***
	(-1.29)	(0.35)	(-0.21)	(-3.19)
Inc Low	0.317***	0.058	0.050	0.324***
	(2.82)	(0.40)	(0.34)	(3.32)
Inc High	-0.199***	0.031	0.005	-0.168***
	(-3.58)	(0.43)	(0.07)	(-3.26)
R^2	System-weighted: 0.22			Consistent: 0.42
Observations	1,504			

a. *t*-values are in parentheses
b. *,**,*** signifies significances at the ten, five and one percent level, respectively
c. the consistent R^2 value associated with the average rating model is obtained after dropping 152 observations with values of '1' or '5' for an average rating and estimating the model using OLS.

Table 5. Models of average concern and three technology concern factor scores.

CHAPTER 5

SUMMARY AND CONCLUSION

For a representative sample of U.S. consumers, we analyze ratings of concern toward eight food production and processing technologies. We find concern is highest for pesticides and artificial growth hormones, followed by concern toward antibiotics, genetic modification and irradiation. Correlations among ratings generally reflect differences in raw ratings, with similarly (differently) rated pairs of technologies displaying positive (negative) correlation. Factor analysis suggests that respondents' concern about a cluster of technologies including artificial growth hormones, genetic modification and irradiation (HGI) share a common, unobservable component; this analysis similarly identified that concern for antibiotics and pesticides share a common factor (ANTIPEST) as do a cluster of older technologies including artificial colors/flavors, preservatives and pasteurization (OLDTECH).

While the clusters featuring 'newer' technologies (ANTIPEST and HGI) received similar raw concern ratings across the sample, the profiles of respondents who were highly concerned about each technology cluster were distinct. Those with high concern with the HGI cluster were more likely to be female, be between 30 and 65 years of age, have no children, be in the lowest income category, be of a minority racial group, have less than a college degree, express great concern for the way both domestic and imported food is grown and handled, purchase organic produce, read nutrition labels, and grow a vegetable garden. Those with high concern for the ANTIPEST cluster are also likely to express high concern for how domestic produce is grown and handled, but are less likely to be concerned with how imported produce is grown and handled. Furthermore, respondents with high concern for the ANTIPEST cluster are more likely to be male, more likely to have formal education beyond high school, more likely to be 65 years or older, and more likely to shop at farmers' markets.

Respondents with a higher concern for the OLDTECH cluster are likely to be less concerned about how food is processed in the United States, do not read nutrition labels, are older than 65 years of age, are not adhering to any special dietary requirements (e.g., low sodium diet), and have less than a college education.

Results from models that explain the average raw ratings across technologies are similar to many of the previous findings in the literature about consumer concern toward food risks. For example, we find respondents with higher levels of general concern and awareness towards food and food risks; are female; have less formal education and lower incomes; are middle-aged; or are of minority racial groups express greater concern toward food technologies on average. Contrary to some previous literature, we find respondents with young children have similar levels of concern as respondent with no children while households with older children express less concern than childless households.

Our exploration of the models of factor scores for each technology cluster reveals considerable heterogeneity in how personal and household characteristics affect stated concern. We reveal a wealth of differential effects of characteristics across technologies clusters and show that variables that have little effect in explaining average concern toward food technologies may have discriminatory power in explaining relative ratings across technologies.

Analysis of the relative ratings may provide insight into market niches that may be more accepting of certain types of technologies. Significant work remains towards understanding the roots of the myriad of results presented above, particularly with regard to how various personal and household characteristics impact relative concerns for various technologies. Greater insights may be possible if theories of risk communication and response are brought to bear on the current empirical regularities.

ESSAY 2

DOES PRICE SIGNAL QUALITY? STRATEGIC IMPLICATIONS OF PRICE AS A SIGNAL OF QUALITY FOR THE CASE OF GENETICALLY MODIFIED FOOD

CHAPTER 6

INTRODUCTION

In the general economic theory of undifferentiated goods, price has a monotonic relationship with consumption – consumption decreases as price increases, *ceteris paribus*. When products are differentiated, however, price's monotonic relationship to consumption need no longer hold. In fact, when product quality is highly subjective (e.g., fashion or art), novel (e.g., a new technology), or difficult to verify prior to purchase (e.g., credence attributes), consumers may turn to one or more signals, including price, to form quality perceptions. Products containing genetically modified (GM) ingredients meet each of these criteria, i.e., GM ingredients are novel, their presence is difficult to verify, and their impact on quality may be viewed differently across individuals with the same knowledge. This leads to additional difficulty for product managers attempting to formulate pricing strategy in the presence of more a complex quality signaling environment.

Many theoretical models explore whether price or some combination of price and another quality signal such as advertising can effectively signal product quality when consumers are not fully informed (e.g., Klein and Leffler, 1981; Wolinsky, 1983; Milgrom and Roberts, 1986) and how the introduction of price as a quality signal may impact the shape of consumer demand functions (Pollak, 1977) and alter the nature of market equilibrium (Balasko, 2003). Jones and Hudson (1996) developed a model of the price-quality relationship at different price levels and concluded that there is a critical price interval in which price is used as a signal of quality. However, the results of their paper exclude the role of price as a signal of quality at lower price level. They suggest that the price above a critical price is used to signal quality while the price below a critical price is not.

While empirical tests are not as common as theoretical work in this area, several authors have explored the predictions of various signaling models by correlating objective quality assessments of various consumer goods with price, advertising and other signals of product quality within particular markets (Landon and Smith, wine, 1998; Nichols, cars, 1998; Esposto, cigars, 1998) or across several markets (e.g., Hjorth-Andersen, 1991; Caves and Greene, 1996). Caves and Greene (1996) show that quality-price correlations exist in many markets and that the level of correlation is higher for product categories that include more brands and is lower for convenience goods.

Although all these papers approached the issues differently, they each suggest that price acts as a signal of quality. However, most of these papers focus on the empirical relationship itself rather than the behavioral effects induced from the relationship. In other words, most of these papers analyze the relationship between observed price and objectively-measured quality rather than individual consumer's purchase decisions induced by particular combinations of price and non-price quality signals. For instance, Caves and Greene (1996) analyze the correlations between product quality and price using data from *Consumer Reports*, in which experts rate the quality of various products. Esposto (1997) analyzes the relationship between price and quality by estimating a hedonic equation in which price is explained by experts' product quality ratings. However, these papers do not analyze consumers' consumption choice as a function of price and non-price quality signals.

The social and private efficacy of GM technology in food production is an increasingly studied issue in food consumption research. Many studies have examined GM acceptance as a food safety issue because, for some people, the perceived safety of GM technology is unresolved. That is, for some, food produced with GM technology indicates low quality. However, others suggest that the application of GM technology in food production could decreases food expenditures, reduce production costs, improve food attributes such as nutritional content and limit environmental problems such as agricultural chemicals residues (the Institute of Food Science & Technology, 2004). For example, Baker et al. (2001) document consumer segments that believe GM technologies represent high quality in the corn flakes cereals market.

Individuals' perceptions of the risk associated with particular products vary by product and can be greatly influenced by emotion and other subjective factors. In fact, some researchers define risk perception as psychological interpretation of product properties (Rozin et al., 1986; Yeung and Morris, 2001). Hence, signals of food safety and other dimensions of quality, enter into the consumer's decision calculus. In the case of GM technology, food safety is likely to be more subjective because the safety of its adoption does not meet with uniform perception across all segments of consumers, i.e., GM ingredients may horizontally differentiate the product, finding favor with some consumers and disfavor with others. This heterogeneity leads to a particularly interesting interaction with price, which is often used as a signal of quality. For consumers with an initial view that GM food is safe or beneficial, a higher price may reinforce this initial view of high quality and reinforce decisions to purchase the product despite the higher price. However, for consumers with an initial view of GM food as low quality, a low price may reinforce these low quality perceptions and nullify price discounts as a means of enticing product trial or expanding market share. Hence, the monotonicity of the price-demand relationship may be challenged.

This paper is concerned with the role of price as a quality signal in GM foods. To explore the price-quality relationship, we analyze data collected from the administration of a mail-based survey that featured a conjoint (stated-preference) instrument in which a nationally representative cross-section of consumers chose among differentiated bread, corn and egg products. Product attributes such as price, GM content level and negative and positive GM attributions for each product in a choice set were experimentally manipulated and randomly assigned across respondents.

These data are used to test the hypothesis that GM product prices act as quality signal and the hypothesis that the effectiveness of price as a quality signal differs by the type of product. The remaining structure of this paper is as follows. Chpater 7 describes the data and reports summary statistics. Chapter 8 explains descriptive model which used for analysis. Chapter 9 reports empirical results of the econometric analysis and Chapter 10 summarizes and concludes.

CHAPTER 7

DATA

The data were collected from a survey that was sent to 5,462 US residents nationally and to an over-sample of 710 residents from one of the authors' home state. Two thousand and twelve people from the general sample and 375 people from the home-state sample returned surveys for a response rate of 37 % and 53 %, respectively. Responses were weighted to account for the over-sampling of the home-state residents.

The basic framework of the survey is as follows. First respondents answer several sections of questions that deal with food consumption, food technology and genetic modification. Then, respondents are presented with a choice set for a particular product (bread, frozen corn, and eggs) where each set features three options: the respondent's normal brand, a brand with 100 % GM content, and brand with no GM content. Labels for the GM and non-GM product were presented and included information concerning relative price (cents more or less than normal brand), GM content, benefits or warnings associated with GM content, and the name of a firm or agency that certified the presence or absence of GM content. No label was presented for the respondent's normal brand; rather, the words 'your normal brand' were mentioned in a parallel fashion as a possible choice.

Respondents were asked to assume that their normal brand was produced with a particular mix of both GM and Non-GM ingredients; the exact percent of ingredients that respondents were told to assume came from GM sources was randomly assigned across respondents. Respondents were also told that all brands shared the same appearance, taste, texture, and smell.

After viewing the product choices and being reminded of their household budget constraint, respondents chose the most preferred option. Some respondents viewed one of the three product choice sets, some viewed two product choice sets and others viewed all three product choice sets with the number and order of viewing randomized across respondents. Usable responses include 1,336, 793 and 950 choices made for the bread, corn and eggs categories, respectively. The prices used in the survey ranged from 40 cents more to 40 cents less than the cost of a package of the normal product.

The final portion of the survey asks for respondents' gender, age, education level, race, income level, and household composition (see Table 6 for descriptive statistics). Our sample features more females, is older, has fewer children in the household, is richer, has obtained more formal education, and features fewer minority respondents than the general U.S. population.

	Summary statistics [a]			U.S. Census [b]		
	Average	%		Average	%	
Gender		Male	5.0		Male	48.3
		Female	55.0		Female	51.7
Age	52			47		
No. of Children	0.6			0.9		
Household Income($)	63,000			57,000		
Education	15	0-11 years	5.5	13	0-11 years	9.6
		12 years	27.1		12 years	28.6
		1-3 years college	28.5		1-3years college	27.3
		College graduate	22.5		College graduate	15.5
		More than college	16.4		After college	8.9
Race		White	90.0		White	77.1
		Black	4.6		Black	12.9
		Hispanic or Spanish origin	2.2		Asian/Pacific Islander	4.5c
		Asian or Pacific Islander	1.9		Others	6.6d
		Others	1.4		(Hispanic/Latino)	12.5

[a] The summary statistics are based on the modified data for the paper. The income data and education data were collected in ranges and midpoints of each range were used for the table.

[b] Source: U.S. Census Bureau, Census 2000.

[c] Asian or Pacific Islander includes Asian, Native Hawaiian and other Pacific islander.

[d] Others include all other respondents not included in the categories of White, Black, and Asian or Pacific Islanders.

Table 6. Descriptive Statistics for Socio-Demographics (N=1,967)

During the initial portion of the survey, respondents were asked to rate their concern toward the use of GM technology in food production and processing by choosing a number from one to five with one implying “not at all concerned” and five implying “very concerned” (Table 7). The average concern on the GM technology was 3.7. More than half, but not all, of respondents rated their concern as ‘somewhat’ or ‘very’ concerned.

Respondents were also asked to rate their opinions on the importance of GM technology as a way to reduce consumers’ and producers’ costs and to rate the importance of GM technology as a way to deliver potential benefits to consumers and producers. Each respondent rated the importance of 16 potential benefits and 16 potential concerns related to GE foods on a five-point scale. A factor analysis was then used to distill these responses into four primary underlying factors influencing their responses to these 32 questions.

Concern / Technology	1	2	3	4	5	Average Concern
GM	**5.2**	**9.8**	**23.2**	**23.5**	**38.3**	**3.7**
Growth Hormones	4.0	6.7	19.0	21.4	48.9	4.0
Preservatives	8.5	16.6	31.0	19.9	24.0	3.3

Table 7. Consumers’ concern on the GM technology (N=1,967)

Table 8 lists descriptive statistics for these four factors, which feature a population average near zero by design. This helps categorize each respondent's attitudes toward GM technology as one that is positive or negative toward a view that the technology can help reduce costs for consumers and producers and bring benefits to producers and consumers.

	Consumers' Benefits	Producers' Benefits	Consumers' Costs	Producers' Cost
Average	-0.02	0.01	0.02	-0.01
Max	2.99	2.80	2.63	3.53
Min	-3.87	-3.76	-4.57	-3.91

Table 8. Factor analysis results of respondents' rating of the potential of benefit and cost-reduction produced by GM technology (N=1,967)

Respondents also estimated the proportion of GM ingredients that they thought currently existed in processed foods currently on the shelf in US supermarkets. This number was later used to construct product-specific proxies for each respondent's perception of the percent of GM ingredients in their normal brand of each of the three products. Specifically, the respondent's reported estimate of the percent of GM ingredients in all processed food was averaged with the percent of GM ingredients in each of the three products to construct a proxy of the respondent's perception of the percent of GM ingredients in their normal brand of bread, corn and eggs (Table 9). This procedure basically assumes a simple Bayesian updating scheme on the part of the consumer where equal weight is given to both pieces of information. Other weighting schemes, including the sole use of only one piece of data, provided a poorer fit to the observed data, and are not considered.

	Bread	Corn	Eggs
Average	42.5	42.0	41.5
Max	90	90	90
Min	2	1	1

Table 9. Estimated proportion of GM ingredients in normal brand (N=1,967)

Several non-price product-specific attributes were also included on some product labels. Some randomly assigned GM products included the following health (environmental) warning statement: "Long-term health (environmental) effects are currently unknown." Some randomly assigned GM products featured claims stating that the product was genetically modified to improve either a health attribute (increased levels of antioxidants for bread and corn and reduced levels of cholesterol for eggs) or an environmental attribute (reduced pesticide use for bread and corn). All claims of GM content or absence were accompanied by a certifying statement endorsed by either a government agency, environmental organization, or an independent certification firm.

Table 10 summarizes the product choices made by respondents. About half of the respondents chose the Non-GM brand in each product category while about 20 % chose the GM brand.

	Bread	Corn	Eggs
GM	242 (18%)	167 (21%)	165 (17%)
Non-GM	675 (51%)	406 (51%)	523 (55%)
Normal	419 (31%)	220 (28%)	262 (28%)
Total	1,336 (100%)	793 (100%)	950 (100%)

Table 10. Preferred product in choice set

CHAPTER 8

MODEL

To estimate the factors that drive respondents' choices of GM versus non-GM products, a binomial logit model of the form:

$$\text{Prob}(Y = 1 | X) = \exp\{\boldsymbol{X}'\beta\}/[1 + \exp\{\boldsymbol{X}'\beta\}] = \Lambda(\boldsymbol{X}'\beta) \qquad (2)$$

is employed, where Y is a binary categorical variable. $Y = 1$ when respondent chooses the GM brand and $Y = 0$ otherwise. Vector $\boldsymbol{X}$ contains the set of known factors that drive respondents' decisions, β is a conformable vector of parameters and, $\Lambda(\cdot)$ is the logistic cumulative distribution function. The parameters, which are estimated via the maximum likelihood method, dictate the probability of choosing the GM brand over alternative brands for the set of characteristic $\boldsymbol{X}$. The individual-specific data and product-specific variables included in the vector $\boldsymbol{X}$ are detailed in Table 11. Note that several approaches are used to capture relative prices. Summary statistics for each variable is presented in Table 12.

Variable Name	Description
Dependent Variable:	($i \in$ {B, C, E} where B=Bread, C=Corn, E=Eggs)
Choice_B, Choice_C, Choice_E	= 1 if respondents choose GM brand for product *i* = 0 if respondents choose other brands for product *i*
Independent Variable:	
DP_i	The price of the normal brand less the price of the GM brand in cents for product category *i*.
$D_{i,k}$	$D_{i,k}$ = 1 if the price of the normal brand in category *i* less the price of the GM brand in cents is in the range of [k, $k + 5$] for k = -40, -30, -20, -10, 5, 15, 25, 35; = 0 otherwise.
DP_i_SQ	$(DP_i + 40)^2$
DP_i_TR	$(DP_i + 40)^3$
$DPNGM_i$	The price of the normal brand less the price of the non-GM brand in cents for product category *i*
GOV	= 1 if certifying agency was a government agency = 0 otherwise
ENV	= 1 if certifying agency was an environmental agency = 0 otherwise
IND	= 1 if certifying agency was an independent certifier = 0 otherwise
BANTIA, CANTIA	= 1 if GM bread (BANTIA) and GM corn (CANTIA) claims to be more healthful due to heightened levels of antioxidants = 0 otherwise
BLTHA, CLTHA, ELTHA	= 1 if GM bread (BLTHA), GM corn (CLTHA), and GM eggs (ELTHA) have a health warning label 0 otherwise
BLTEA, CLTEA, ELTEA	= 1 if GM bread (BLTEA), GM corn (CLTEA), and GM eggs (ELTEA) have an environmental warning label = 0 otherwise
LBPREDA	ln(% reduction in pesticides used in growing wheat for GM bread + 1)
LCPREDA	ln(% reduction in pesticides used in growing GM corn + 1)
LEPREDA	ln(% reduction in cholesterol due to use of GM eggs + 1)
GMCONCERN	= 1 if respondent rated GM technology a '5' on a 5-point scale of concern, = 0 otherwise
OWNBEN	Respondent factor score relating to GM's benefits for consumers
PRODBEN	Respondent factor score relating to GM's benefits for producers
OWNCOST	Respondent factor score relating to GM's cost reductions for consumers
PRODCOST	Respondent factor score relating to GM's cost reductions for producers
BREADGM	Respondent's estimate of % of normal bread made from GM wheat
CORNGM	Respondent's estimate of % of normal corn made from GM corn
EGGSGM	Respondent's estimate of % of normal eggs made from GM eggs
MALE	= 1 if male, = 0 if female
RACE	= 1 if White, = 0 otherwise
AGE_30	= 1 if under 30 years old, = 0 otherwise
AGE_70	= 1 if over 70 years old, = 0 otherwise
ED16	= 1 if obtained a Bachelor's degree or more, = 0 otherwise
INC_L	= 1 if annual household income ≤ \$5,000, = 0 otherwise
INC_H	= 1 if annual household income ≥ \$95,000, = 0 otherwise
CHILD	= 1 if children present in household, = 0 otherwise

Table 11. Description of Variables for Logit model of GM brand choice

Variable Name	Average	Share (%)	MIN	MAX
Choice_B		18.0		
Choice_C		21.0		
Choice_E		17.0		
GOV		77.1		
ENV		4.8		
IND		7.1		
BANTIA		8.6		
CANTIA		7.2		
BLTHA		34.0		
CLTHA		33.8		
ELTHA		32.8		
BLTEA		33.4		
CLTEA		30.8		
ELTEA		34.4		
LBPREDA	2.01		0	4.62
LCPREDA	1.99		0	4.62
LEPREDA	2.14		0	4.62
GMCONCERN		37.7		
OWNBEN	-0.02		-3.87	2.99
PRODBEN	0.01		-3.76	2.80
OWNCOST	0.02		-4.57	2.63
PRODCOST	-0.01		-3.91	3.53
BREADGM	42.50		2	90
CORNGM	42.00		1	90
EGGSGM	41.50		1	90
MALE		45		
RACE		90		
AGE_30		9.8	18	29
AGE_70		17.5	70	93
ED16		22.1		
INC_L		4.2		
INC_H		16.3		
CHILD		32.5		

Table 12. Summary Statistics for Variables of Logit model of GM brand choice

CHAPTER 9

RESULTS

9.1. Visual inspection of share data by relative price

As an initial investigation of the price-quality relationship, the percent of respondents who choose the GM brand in each product category (also referred to as GM market share) is plotted for each price level used in the survey design (Figures 1 – 3). Because the other attributes of GM brand (e.g., health claims) are randomly assigned across respondents in a fashion that is not correlated with the relative price that is assigned, the average profile of the GM products for each relative price level should be similar, meaning one can draw intuition from these simple plots.

The graphs show a non-monotonic pattern between price and respondents' choices for all products. That is, the market share for the GM good among our respondents is not monotonically decreasing in price, and this motivates our inquiry of price as a quality signal for the GM technology.

Also, the graphs show that the deviation from the normal monotonic patterns differs across products. For example, the graph for GM bread shows that market share decreases as price increases at higher price levels. This is similar to the standard theory in which demand decreases as price increases. However, market share increases as relative price increases for price levels below that of their normal brand. This might indicate that consumers interpret prices below a certain threshold as a negative signal of quality for GM bread (a "something must be wrong with it" heuristic) and choose other options. This pattern contradicts theoretical results forwarded by Jones and Hudson (1996) who suggested that only prices above a critical price threshold are used for signaling quality (a "if its this expensive, it must be good" heuristic). A similar pattern is observed in the case of GM corn. In the case of GM corn the graph shows that consumers react to a possible quality signal not only at lower price levels but also at the highest price levels. Market share more strictly adheres to a monotonically decreasing function of price in the case of GM eggs. Although there are some indications that prices act as quality signals at extreme levels of price, the visual evidence from the graphs is less convincing.

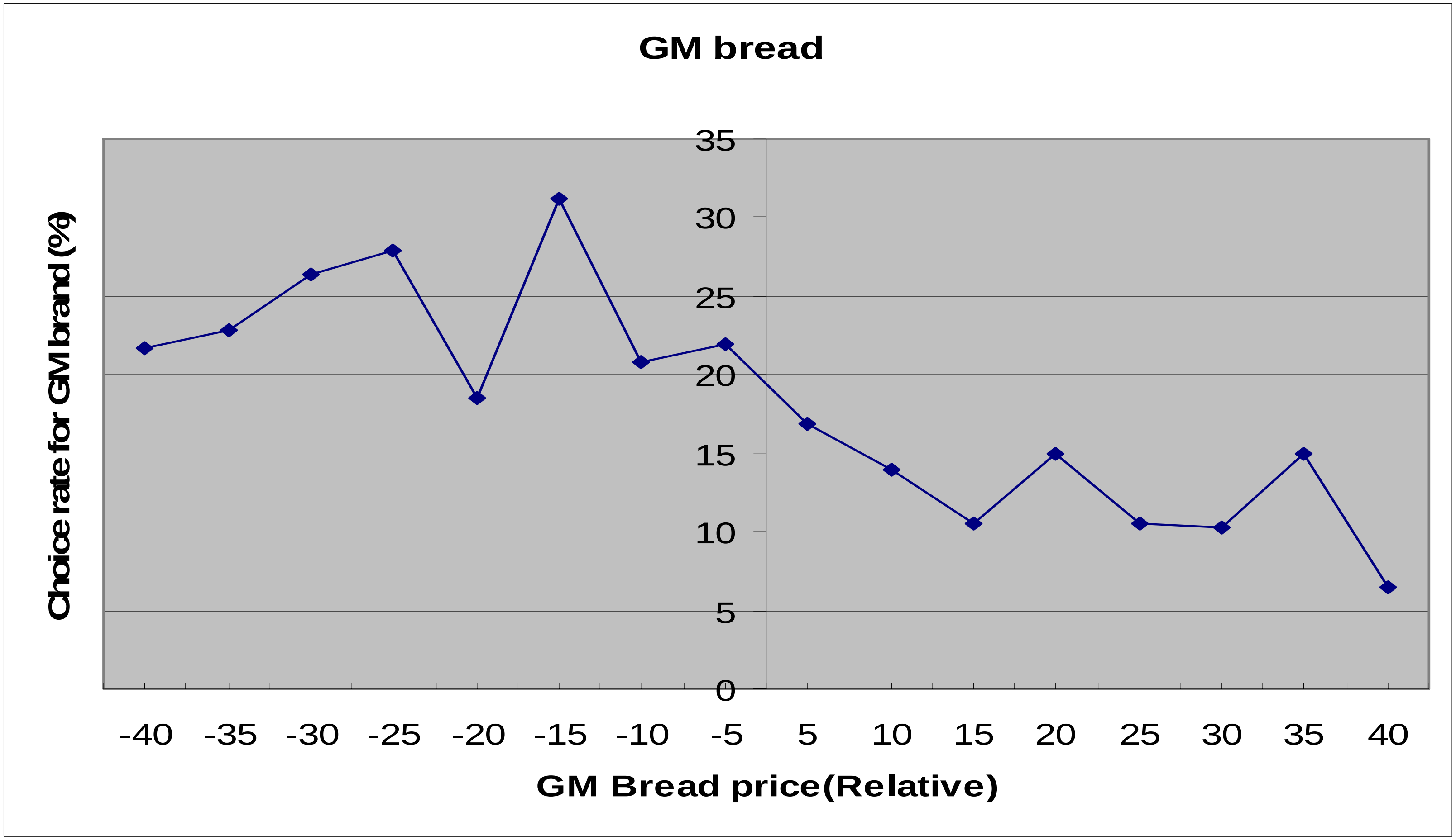

Figure 1. The relationship between the price of GM bread and respondents’ consumption choice

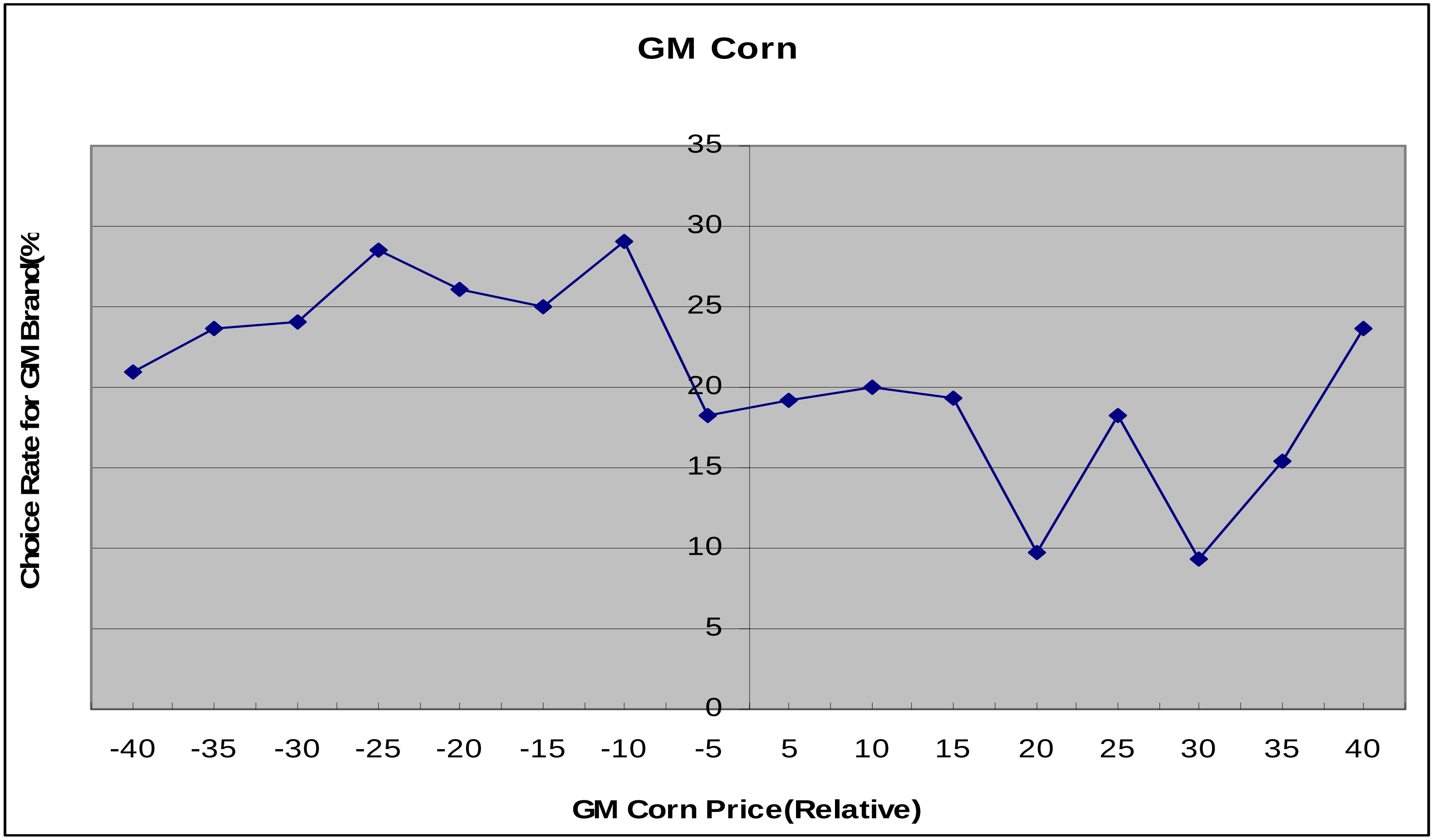

Figure 2. The relationship between the price of GM corn and respondents' consumption choice

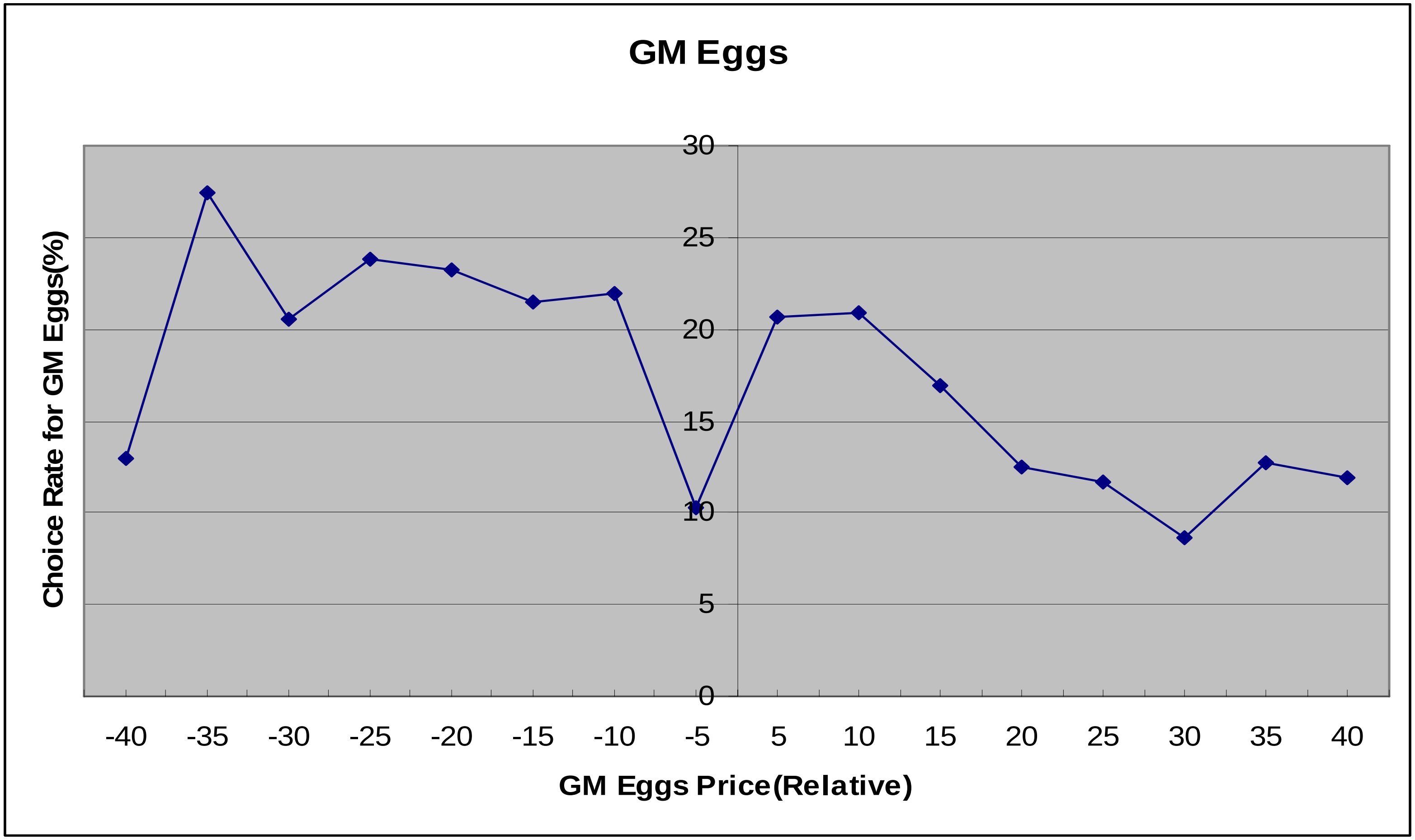

Figure 3. The relationship between the price of GM eggs and respondents' consumption choice

9.2. Econometric analysis

To formally test the trends that appear in the simple graphical exploration of market shares by price, a binomial logit model is estimated for each GM product of the following form:

$$Y^{*} = \alpha_0 + \Sigma\, \alpha_i F_i\,(p_{GM}) + \boldsymbol{X}'\boldsymbol{\beta} + \varepsilon \qquad (3)$$

where Y^{*} is a latent preference index that, when it is greater than zero, triggers purchase of the GM product (i.e., causes, Y, the observed variable, to equal one if the GM product is purchased and equal zero otherwise); α_0 is an intercept parameter; $F_i(\bullet)$ is the ith function of the relative price of the GM brand (p_{GM}); α_i is the ith parameter associated with the ith function of price; $\boldsymbol{X}$ is a vector of all independent variables except GM brand prices; $\boldsymbol{\beta}$ is a conformable vector of parameters; and ε is the error term. Two general forms of the $F_i(\bullet)$ functions were articulated in Table 11: one where dummy variables are created to represent eight different price categories and one where a polynomial in the price of the GM food is created. The polynomial representation is $F_j = (DP + 40)^j$, where 40 is added to all relative prices of GM products, i.e., all prices are normalized to the lowest possible price offered, to avoid squaring a negative number.

The estimation results for each product are in Tables 13-15. To test the hypothesis that the market share of GM products is monotonic in price, the following hypotheses are formulated when price is represented by categorical dummy-variables:

(4) H_0: $\alpha_i > \alpha_{i+1}$ $i = 1, 2, \ldots, 7$
H_1: $\alpha_i \leq \alpha_{i+1}$ $i = 1, 2, \ldots, 7$

(5) H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \alpha_8$
H_1: $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq \alpha_6 \neq \alpha_7 \neq \alpha_8$

(6) H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4$
H_1: $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4$

(7) H_0: $\alpha_5 = \alpha_6 = \alpha_7 = \alpha_8$
H_1: $\alpha_5 \neq \alpha_6 \neq \alpha_7 \neq \alpha_8$

The first hypothesis (4) postulates seven separate inequalities where the parameter for each lower price category is strictly larger (i.e., more likely to induce the choice of the GM product) than the parameter for the higher, adjacent price category. Rejection of this hypothesis means that strict monotonicity of market share does not hold for a particular adjacent pair of price categories. The second hypothesis (5) flips the approach by postulating that all price parameters are equal; rejection merely confirms all price points do not have the same effect on market share. Hypotheses (6) and (7) are limited versions of (5) and test for insensitivity to price across all price points lower than the respondent's normal brand (α_1 - α_4) and all higher price points higher than the respondent's normal brand (α_5 - α_8). Hypothesis testing results for each product category are listed in Table 16.

Explanatory Variable	Polynomial Approach		Dummy Variable Approach	
	Estimated Coefficient	t-ratio [a]	Estimated Coefficient	t-ratio [a]
Dependent Variable: Choice_B				
INTERCEPT	**-2.61**	**-6.82*** **	**-**	**-**
DP_B	**-0.02**	**-5.22*** **	**-**	**-**
$D_{B,-40}$	**-**	**-**	**-2.14**	**-5.22*** **
$D_{B,,-30}$	**-**	**-**	**-1.97**	**-4.79*** **
$D_{B, -20}$	**-**	**-**	**-2.37**	**-5.40*** **
$D_{B, -10}$	**-**	**-**	**-2.34**	**-5.58*** **
$D_{B, 5}$	**-**	**-**	**-2.89**	**-6.51*** **
$D_{B, 15}$	**-**	**-**	**-2.93**	**-6.42*** **
$D_{B, 25}$	**-**	**-**	**-3.09**	**-6.70*** **
$D_{B, 35}$	**-**	**-**	**-3.16**	**-6.85*** **
$DPNGM_B$	**0.01**	**1.90***	**0.01**	**1.90***
GOV	**0.44**	**1.65***	0.44	1.64
ENV	-0.37	-0.71	-0.33	-0.64
IND	-0.09	-0.23	-0.09	-0.21
BANTIA	**1.06**	**3.81*** **	**1.02**	**3.63*** **
BLTHA	**-0.58**	**-3.07*** **	**-0.57**	**-3.02*** **
BLTEA	-0.30	-1.64	-0.29	-1.61
LBPREDA	**0.29**	**6.68*** **	**0.30**	**6.64*** **
GMCONCERN	**-0.60**	**-3.41*** **	**-0.61**	**-3.45*** **
OWNBEN	-3.10E-03	-0.05	-0.01	-0.16
PRODBEN	3.47E-03	0.06	0.01	0.16
OWNCOST	**-0.16**	**-2.54** **	**-0.16**	**-2.58*** **
PRODCOST	**0.16**	**2.53** **	**0.16**	**2.57** **
BREADGM	0.01	1.60	0.01	1.54
MALE	-0.03	-0.21	-0.04	-0.28
RACE	1.53E-03	1.52	1.61E-03	1.60
AGE_30	**-0.82**	**-2.21** **	**-0.83**	**-2.26** **
AGE_70	0.23	1.17	0.22	1.10
ED16	**0.46**	**2.53** **	**0.46**	**2.53** **
INC_L	-0.01	-0.05	-0.02	-0.11
INC_H	0.01	0.05	0.02	0.11
CHILD	**-1.56E-03**	**-2.00** **	**-1.65E-03**	**-2.12** **

[a] *, **, ***: significant at the ten, five, and one % level, respectively.

Table 13. Regression results for Bread (binary logit) (N=1,336)

Explanatory Variable	Polynomial Approach		Dummy Variable Approach	
	Estimated Coefficient	t-ratio [a]	Estimated Coefficient	t-ratio [a]
Dependent Variable: Choice_C				
INTERCEPT	**-1.82**	**-3.55*** **	**-**	**-**
DP_C	0.05	1.64	-	-
DP_C_SQ	**-1.89E-03**	**-2.00** **	**-**	**-**
DP_C_TR	**1.53E-05**	**1.95** *	**-**	**-**
$D_{C,-40}$	-	-	**-1.66**	**-3.46*** **
$D_{C,-30}$	-	-	**-1.43**	**-3.01*** **
$D_{C, -20}$	-	-	**-1.48**	**-2.93*** **
$D_{C, -10}$	-	-	**-1.41**	**-2.91*** **
$D_{C, 5}$	-	-	**-1.94**	**-3.76*** **
$D_{C, 15}$	-	-	**-2.17**	**-4.30*** **
$D_{C, 25}$	-	-	**-2.17**	**-4.00*** **
$D_{C, 35}$	-	-	**-1.94**	**-4.03*** **
$DPNGM_C$	1.76E-03	0.48	1.87E-03	0.51
GOV	0.11	0.36	0.10	0.34
ENV	-0.22	-0.39	-0.26	-0.47
IND	**-1.40**	**-2.09** **	**-1.45**	**-2.15** **
CANTIA	**0.59**	**1.65** *	0.58	1.62
CLTHA	**-0.66**	**-2.85*** **	**-0.67**	**-2.85*** **
CLTEA	-0.26	-1.21	-0.26	-1.20
LCPREDA	**0.24**	**4.81*** **	**0.24**	**4.86*** **
GMCONCERN	**-0.45**	**-2.08** **	**-0.45**	**-2.06** **
OWNBEN	0.11	1.55	0.12	1.62
PRODBEN	-0.11	-1.55	-0.12	-1.62
OWNCOST	**-0.14**	**-1.93** *	**-0.14**	**-1.88** *
PRODCOST	**0.14**	**1.93** *	**0.14**	**1.87** *
CORNGM	-1.19E-03	-0.22	-8.68E-04	-0.16
MALE	0.28	1.44	0.29	1.50
RACE	-2.48E-05	-0.02	-6.94E-05	-0.06
AGE_30	0.04	0.10	0.03	0.07
AGE_70	0.31	1.22	0.30	1.18
ED16	0.33	1.53	0.32	1.50
INC_L	0.26	1.15	0.26	1.12
INC_H	-0.26	-1.16	-0.26	-1.12
CHILD	9.98E-04	0.66	1.02E-03	0.68

[a] *, **, ***: significant at the ten, five, and one % level, respectively.

Table 14. Regression results Corn (binary logit) (N=793)

	Polynomial Approach		Dummy Variable Approach	
Explanatory Variable	Estimated Coefficient	t-ratio [a]	Estimated Coefficient	t-ratio [a]
Dependent Variable: Choice_E				
INTERCEPT	**-2.11**	**-4.68*****	-	-
DP_E	**-0.01**	**-2.98*****	-	-
$D_{E,-40}$	-	-	**-1.78**	**-3.60*****
$D_{E,-30}$	-	-	**-1.82**	**-3.64*****
$D_{E,-20}$	-	-	**-1.70**	**-3.27*****
$D_{E,-10}$	-	-	**-2.18**	**-4.30*****
$D_{E,5}$	-	-	**-1.92**	**-3.80*****
$D_{E,15}$	-	-	**-2.32**	**-4.45*****
$D_{E,25}$	-	-	**-2.62**	**-4.81*****
$D_{E,35}$	-	-	**-2.47**	**-4.64*****
$DPNGM_E$	**0.01**	**2.91*****	**0.01**	**2.88*****
GOV	0.45	1.32	0.46	1.34
ENV	0.06	0.11	0.07	0.12
IND	-0.23	-0.42	-0.23	-0.42
ELTHA	-0.21	-0.96	-0.21	-0.96
ELTEA	**-0.42**	**-1.86***	**-0.42**	**-1.87***
LEPREDA	**0.20**	**4.35*****	**0.20**	**4.31*****
GMCONCERN	**-0.56**	**-2.80*****	**-0.56**	**-2.80*****
OWNBEN	**0.14**	**1.98****	**0.13**	**1.89***
PRODBEN	**-0.14**	**-1.98****	**-0.13**	**-1.89***
OWNCOST	**-0.15**	**-2.15****	**-0.15**	**-2.15****
PRODCOST	**0.15**	**2.15****	**0.15**	**2.15****
EGGSGM	0.01	0.94	4.16E-03	0.83
MALE	-0.02	-0.08	-0.02	-0.10
RACE	8.02E-05	0.10	-4.93E-06	-0.01
AGE_30	-0.41	-1.20	-0.38	-1.10
AGE_70	-0.34	-1.29	-0.34	-1.27
ED16	0.01	0.06	0.02	0.11
INC_L	0.19	0.79	0.19	0.81
INC_H	-0.19	-0.79	-0.19	-0.81
CHILD	-1.69E-04	-0.20	-7.30E-05	-0.08

[a] *, **, ***: significant at the ten, five, and one % level, respectively.

Table 15. Regression results for Eggs (binary logit) (N=950)

Hypothesis	i	Bread	Corn	Eggs	Critical Values
	1	0.39	0.45	0.02	
(4)	2	2.16	0.02	0.14	
	3	0.01	0.04	1.87	3.84(5%)
	4	3.36*	2.08	0.54	
H₀: $\alpha_i > \alpha_{i+1}$ H₁: $\alpha_i \le \alpha_{i+1}$ $i = 1,\cdots,7$	5	0.02	0.31	1.23	2.71(10%)
	6	0.18	4.40E-05	0.57	
	7	0.43	0.32	0.12	
(5)					
H₀: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \alpha_8$		31.76**	9.94	11.39	[1.69, 16.01](5%) [2.17, 14.06](10%)
H₁: $\alpha_1 \ne \alpha_2 \ne \alpha_3 \ne \alpha_4 \ne \alpha_5 \ne \alpha_6 \ne \alpha_7 \ne \alpha_8$					
(6)					
H₀: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4$		2.97	0.65	2.42	[0.22, 9.35](5%) [0.35, 7.81](10%)
H₁: $\alpha_1 \ne \alpha_2 \ne \alpha_3 \ne \alpha_4$					
(7)					
H₀: $\alpha_5 = \alpha_6 = \alpha_7 = \alpha_8$		0.81	0.64	3.44	[0.22, 9.35](5%) [0.35, 7.81](10%)
H1: $\alpha_5 \ne \alpha_6 \ne \alpha_7 \ne \alpha_8$					

*,** signifies the hypothesis is rejected at the ten and five % level, respectively.

Table 16. Likelihood Ratio Test Results

The null hypothesis in (4), i.e., monotonicity, is rejected at the ten % significance level for all adjacent price points of all products except for $i = 4$ in the bread category, which means that monotonicity between the price categories of [-$0.10, -$0.05] and [$0.05, $0.10] cannot be rejected. For all other adjacent price points and all products, cheaper GM products are not significantly more likely to be chosen than ones slightly more expensive.

The null hypothesis of (5), i.e., equivalence of the effect of all price categories on purchase decisions, is rejected at the ten % significance level only in bread category. It suggests that there is significant sensitivity of choice to price in the bread category but not much price sensitivity in the corn and egg categories. The null hypotheses of (6) and (7) refine the results by validating that, across all relative prices that share the same sign, there is no significant difference in market share's response across price categories. Taken together the test results suggest that a monotonic relationship is not present for most products and, for the one category in which some monotonicity exists, it is only significant when crossing the threshold from prices that are greater than the normal brand's reference price to prices that are less than the reference price.

Despite category-by-category monotonicity of market share in price, a simpler regression featuring choice as a linear function of price may reveal the expected negative relationship. Therefore, a second approach to examining monotonicity is used to test for non-monotonicity: we test for the significance of higher-order terms in polynomial representations of GM price. For the model of GM bread and GM egg choices, however, only the linear relative price variables (DP_B and DP_E) were significant; results featuring higher order terms are omitted. DP_B and DP_E affected consumer choices of GM bread and eggs in negative manner, which is consistent with standard theory and suggests that the role of price in signaling quality is not strong enough to cause a non-monotonic relationship between price and market share.

For the model of the GM frozen corn choice, the square and cube of the relative price of GM corn are also significant (DP_C_SQ and DP_C_TR, respectively). This suggests the possibility of a significant, non-monotonic change in the consumption pattern as price changes. At lower prices, the probability of choosing the GM corn decreases even if price is lowered further. However, the probability of choosing GM corn increases at higher prices when price is raised further. This retains the basic shape observed from the raw data plot in figure 2. The ability of such a cubic relationship to hold beyond the narrow price range explored is, of course, highly questionable. Minimally as price continues toward zero market share can go no lower than zero, while, at very high prices, market share will suffer.

9.3. Discussion

Taking the results from the dummy variable approach and polynomial approach together, there appears to be some evidence that demand for the GM products in non-monotonic in price. The most convincing evidence exists for GM corn: both the dummy variable and polynomial approaches reject monotonicity. The weakest case exists for GM bread: the dummy variable approach suggests monotonicity for price categories surrounding the reference price of the respondent's normal brand and no higher-order terms are significant in the polynomial approach. An intermediate case exists for GM eggs: the dummy variable approach finds no case for monotonicity while the polynomial case finds no significance for higher-order terms.

While there is some evidence against monotonity of demand in price, one may argue that factors other than price-quality signals drive this lack of monotonicity. One argument could be that respondents faced hypothetical choices and, hence, did not seriously weigh price when contemplating GM product choice. Indeed, such critiques of hypothetical questionnaires are common in the early literature concerning hypothetical choices. However, more recent research involving parallel hypothetical and market decisions suggests that analysis of hypothetical choices provide an unbiased view of individual preferences in many settings, particularly those involving familiar private goods, though estimates are typically noisier, i.e., individual parameter estimates have a greater variance (Louviere et al. 1999). Our own data suggest that respondents did treat price variables seriously: the price of non-GM products, which are presented to the same respondents in the same manner, are significant in two of the three product regressions. This suggests that prices were impacting respondent decisions in a traditional way for non-GM goods. The category in which the non-GM price was insignificant was corn, which is also the category for which the case on non-monotonicity of GM demand in price was the strongest. All tolled this leaves a mixed though intriguing case for the possibility that respondents were using price as a signal of quality when evaluating GM products.

CHAPTER 10

SUMMARY AND CONCLUSION

The purpose of this paper is to analyze how prices of GM products may act as quality signals and affect consumers' purchase decisions. Three products (GM bread, corn, and eggs) are analyzed using conjoint data generated from a nationally representative mail survey. Plots of the raw relationship between price and the share of consumers choosing GM products in each category suggest a non-monotonic relationship between price and market share and an estimated binary logit model of choices supports the lack of monotonicty in two of the three product categories.

The plots of GM bread and GM corn suggest that consumers may use price as a signal of product quality when price deviates enough from the normal brand's price. Consumers' purchase intentions for GM bread increased as price declined modestly below the reference price down to a critical price level; after this price threshold, lowering prices had no real traction in increasing market share in GM bread. The plot of GM eggs showed no significant difference from general economic theory. That is, the price-demand relationship was monotonic over the whole price range. Hence, there was no obvious indication of the existence of price signaling quality.

Logit models of the respondent choice of the GM product as a function of price and other factors are used to formally test for non-monotonicity of demand in price. The strongest case for non-monotonicity in price appears for the GM corn product, while the weakest case exists for the GM bread. The logical link between non-monotonicity of demand for GM products in price and respondents' use of GM product price as a signal of quality requires evidence that respondents properly weighed price data during the decision making process. Mixed evidence is found, with prices for the non-GM product being significant and of the expected sign in two of the three categories. In summary, the evidence is suggestive that respondents use the price of GM products as a signal of quality. Further survey work would need to be conducted where respondents are specifically asked to rate perceived product quality after viewing price and non-price information for GM and non-GM products.

Food products with labeled GM ingredients are in an introduction (start-up) period of their life cycle in most product categories. Firms who try to gain public awareness for their products and to expand their market share might, for example, have to decide between a low introductory pricing strategy, a price matching strategy, or strategy that sets price higher than competing, non-GM brands. If consumers use price as a signal of quality, however, some of these pricing strategies might be less effective or disastrous in certain product categories. For the hypothetical GM corn product in our research, for example, firms pursuing a low-introductory price strategy may fight an uphill battle because respondents may interpret low prices as a negative quality signal and avoid the trial purchases necessary to spur current and future sales.

Consumption patterns for GM products are likely to vary widely across different consumer segments, where each segment may hold distinct ideas concerning the value, efficacy and safety of GM ingredients. Hence, choosing a marketing strategy will not be a simple matter. In fact, applying a pricing strategy alone as a marketing strategy without considering consumers' characteristics might not be effective for expanding market share of GM products. Pricing strategies may need to be tailored to the type of retail outlet (e.g., high-end food emporiums versus discount chains) and coordinated with non-price quality signals (advertising and in-store promotions) and existing regulatory interventions (labeling or public position papers on the safety of genetically modified foods).

ESSAY 3

MEASURING INDIVIDUAL RISK ATTITUDES FROM OBSERVED HIGH-STAKES GAMBLES: ARE PROFESSIONAL POKER PLAYERS RISK AVERSE?

CHAPTER 11

INTRODUCTION

11. 1. Problem Statement

Risk aversion plays a significant role in theories of individual decision making that govern production to consumption decisions and shape markets from consumer goods to financial instruments. For example, producers who are more risk averse than others may deal with market situations in relatively passive manner while consumers who are more risk averse may avoid fatty foods, fast cars, and fast-talking salespeople. Similar examples can be forwarded for investors who participate in financial markets.

There has been a considerable amount of theoretical and empirical research on risk aversion and risk attitudes during the past decades. Early empirical studies of risk aversion relied heavily upon data generated from laboratory experiments due to the lack of detailed market data. Laboratory experiments provide well controlled economic data along with abundant background information on subjects such as demographics and other socioeconomic characteristics. However, laboratory experiments generally involve small stakes, which reveals information about subjects' aversion to relatively small risks. Natural experiments can provide data induced from relatively large and real stakes although natural experiments are not controlled by researchers and generally offer less background information than laboratory experiments.

Empirical studies of risk aversion and risk attitudes using natural experiments and other individually observed data have increased recently. Several interesting results have been provided by the papers that used data from game shows and televised gambles. Several papers have used data encoded from television game shows such as *Jeopardy!* (Metrick, 1995), *Card Sharks* (Gertner, 1993), *Illinois Instant Riches* (Hersch and McDougall, 2001), *Lingo* (Beetsma and Schotman, 2001), and *Hoosier Millionaire* (FullenKamp *et al*., 2003) while others have used data encoded from individuals' decisions made during race track gambling (Jullien and Salanie, 2000). Given the individual nature of the data and the broad array of decision frame works that each scenario requires, it is not surprising that these authors forward a wide variety of conclusions surrounding individuals' risk attitudes and risk aversion. Metrick (1995) and Hersch and McDougall (2001) found subjects to exhibit risk neutrality, while Gertner (1993), Beetsma and Schotman (2001), and FullenKamp *et al.* (2003) found mild to significant risk aversion. Moreover, FullenKamp *et al*. (2003) concluded that some players may prefer risk.

Risk attitudes arise from an individual's behavioral tendencies when facing and managing hazards. When analyzing individual decisions to infer risk aversion, one must consider whether the decision is a clear indication of preferences for risk or whether other issues such as long-term decision strategy are also driving individual decisions. For example, purchase decisions surrounding a product that might fail with a known probability represent a case where the decision yields a clean observation concerning the consumer's risk preference. Alternatively, a player's decision in a repeated prisoner's dilemma game may be swayed both by risk preferences and by strategic concerns. In fact, people frequently face economic situations in which their decisions reflect both risk preferences and strategic concerns.

The game of poker provides an excellent example of a decision making situation in which decisions reflect both an individual's risk preferences and strategy. Poker's popularity has soared over the past five years both in terms of participation by the public and in terms of television viewership. For example, the number of participants in the world's pre-eminent poker event, the Main Event at the World Series of Poker in Las Vegas, Nevada, has increased from 52 entrants in 1982 to more than 5,000 in 2005, while, during the past four years, three separate television series have aired that televise poker games featuring special cameras that reveal players' hidden card to television viewers.

Poker serves as an intriguing natural laboratory for studying decision making under risk for several reasons. First, the game features decisions that require players to balance risk and strategy. Second, players' decisions have monetary consequences large enough to dramatically alter their personal wealth and, unlike controlled laboratory experiments and most game shows, the players have put forth their own money to enter the tournament. Finally, because the game of poker is a highly structured zero-sum game of asymmetric information, and because televised games reveal players' hidden 'hole' cards, the observer can have perfect information regarding the information structure of the game including all informational asymmetries.

Given the recent explosion in televised poker game shows, it is somewhat surprising that there is only one other paper (to my knowledge) that utilizes televised poker data (Lee 2004). That paper analyzed poker players' risk taking in an indirect manner. He found that more changes in the ranking of players during the course of games that featured lower payments, which is consistent with risk-averse behavior among players.

This essay shares same general interest as Lee (2004) – the use of professional poker data to draw inferences concerning risk aversion – but differs from Lee (2004) by focusing on estimating individual players' risk aversion using detailed data on players' individual decisions within the poker game.

11. 2. Objectives

The purpose of this essay is to measure risk attitudes using data encoded from the World Poker Tour's Texas Hold'em Poker Tournament Series. The specific objectives of this study are:

(1) to estimate individual players' utility functions using data from decisions made during poker games and

(2) to test for the stability of this utility function across different phases of the game, where the phases of the game are differentiated by

(a) the number of public (common) cards upon display,

(b) different strategic positions within the game, where strategic positions correspond to order of play.

The specific hypotheses of this study are:

(1) Professional poker players are not risk neutral;

(2) Measurements of risk aversion are not stable across phases of the game or across strategic position within a hand.

CHAPTER 12

LITERATURE REVIEW

Many empirical studies have focused on individual decision makers' attitudes toward risk. One way to categorize this vast literature is by the type of data collected. Two major approaches exist: analyzing data generated from (1) individuals participating in controlled economic experiments and from (2) individuals making decisions in settings not controlled by the experimenter such as markets or publicized games. The former approach often involves experimenters recruiting students to choose among competing real or hypothetical lotteries of modest or moderate stakes (Holt and Laury, 2002), though more recent work also relies upon purely hypothetical questions asked via surveys administered to a broad cross-section of the population (Dohmen et al., 2005). While such investigations have allowed for rapid advancement in the testing of alternative theories of economic behavior under risk, the approach has several fundamental limitations. First, the sizes of the stakes at risk are usually small due to the limited budgets of researchers. The few researchers who have explored moderately sized stakes (e.g., Holt and Laury, 2002, have several experiments where lotteries may pay several hundred dollars while Binswanger, 1981, started a tradition of experimentation with subjects from less developed countries where small stakes in U.S. terms translate to major stakes for most subjects from developing countries) draw different conclusions concerning risk preferences depending upon the size of stakes involved, i.e., response to small risks may not inform us about response to large risks. Furthermore, experiments involving large *losses* (as opposed to *gains*) to individual subjects cannot be explored due to ethical considerations. Finally, the student and lesser-developed country subjects typically studied may possess characteristics that limit the generalizability of the results to broader segments of the population.

An alternative approach to data collection is to identify highly structured settings that have generated field data. Examples in the literature include data from financial markets (Friend and Blume, 1975), gambling (Jullien and Salanie, 2000), and television game shows (Gertner, 1993; Metrick, 1995; Beetsma and Schotman, 2001; Hersch and Mcdougall, 2001; FullenKamp *et al*., 2003). The advantage of these natural experiments is that the stakes involved are real and large compared to laboratory experiments. One limitation of natural experiments is that subjects' background information such as demographics and socioeconomics are rarely collected, which limits the researcher's ability to analyze the relative influence of other factors in decision making (Binswanger, 1981). Also, in natural experiments, there are many factors left uncontrolled (Metrick, 1995).

Gertner (1993) estimated individual risk-taking behavior in the bonus round of the television game show *Card Sharks*. The data were the betting decisions of all adults who played the bonus round on the show over a three-year period. A total of 457 contestants made 844 bonus round decisions. Two approaches were developed to estimate a lower bound on the level of risk aversion. The first approach was to estimate a lower bound on the coefficient of absolute risk aversion by estimating a nonlinear probit model using a constant absolute risk aversion (CARA) utility specification. The second approach was to compare the sample distribution of outcomes with the distribution of outcomes if a contestant played the optimal strategy for a risk-neutral contestant. Gertner found the degree of risk aversion was higher than that estimated in previous studies of risk aversion.

Metrick (1995) evaluated risk attitudes by analyzing data collected from the final round of the television game show *Jeopardy!* broadcast between October 1989 and January 1992. A total of 393 games featuring more than 1,000 subjects was included. A logit analysis was used to estimate the coefficient of absolute risk aversion under a constant absolute risk aversion utility specification. The coefficient of absolute risk aversion was much lower than that estimated by Gertner (1993) from the *Card Sharks* game show. Metrick could not reject the null hypothesis that the representative player was risk neutral.

Hersch and Mcdougall (2001) analyzed data collected from the game show *Illinois Instant Riches*, which is an extended part of that state's lottery game and involves stakes larger than the Gertner and Metrick studies. Two approaches were used to assess risk attitudes. The first approach was to regress a contestant's willingness to accept an offered wager on the wager's expected value and a proxy for household income. The second approach was to directly estimate the Pratt-Arrow coefficient of absolute risk aversion under constant absolute risk aversion and quadratic utility specifications. The results from two approaches supported the notion of risk neutrality under high stakes.

Jullien and Salanie (2000) investigated the risk attitudes of bettors in British horse races and estimated the parameters of the utility function of the bettors. The data contained bets from 34,443 races conducted between 1986 and 1995. A multinomial model was estimated under expected utility, rank-dependent utility, and cumulative prospect theory frameworks. Cumulative prospect theory had higher explanatory power than the other theories. Rank-dependent utility models did not fit the data better than expected utility models and showed similar results to expected utility models.

Bettors were somewhat risk-loving under the constant absolute risk aversion utility specification of the expected utility models; the rank-dependent utility models led to similar qualitative conclusions. The cumulative prospect theory representation consisted of three continuous, increasing functions: a value function, which measures the subjective value of the outcome, and two probability-weighting functions, which measure the impact of probability on the desirability of the prospect for gain and loss. The weighting function for gains was slightly convex but close to the bisectrix and the weighting function for losses was concave for most of the relevant range under the cumulative prospect theory framework.

Beetsma and Schotman (2001) analyzed data collected from the 979 final rounds of a Dutch television game show *Lingo,* which involves simple lotteries. The degree of risk aversion was estimated under the assumptions of the expected utility theory. There was clear evidence of substantial risk aversion for the sample of finalists. The estimated degree of risk aversion increased when the model was generalized such that players' utility not only depended on monetary gains, but also on the act of playing itself, and generalized such that their decision was based on decision weights rather than the actual probabilities. Players had a strong tendency to overestimate their chances of success.

FullenKamp *et al*. (2003) analyzed data collected from the television game show *Hoosier Millionaire*, which involved high-stakes situations. The data contained the winnings and census tract characteristics of all the participants in the game from 1989. The distribution of the risk-aversion parameter from an expected utility framework was estimated using a probabilistic approach under constant absolute risk aversion (CARA) and constant relative risk aversion (CRRA) specifications. The parameter estimates for the CARA and CRRA specifications yield similar results. The results supported the hypothesis that the individuals in the sample were risk averse on average even though some might be risk-neutral or risk-loving.

CHAPTER 13

METHODOLOGY

13. 1. Overview of the Poker Game: Texas Holdem

Numerous variants of poker are commonly played around the world. The poker game analyzed in this essay is Texas Hold'em, which has gained great popularity due to various media events. At the beginning of a hand of Texas Hold'em each player pays a fixed amount to participate in the hand (the ante) and is then randomly dealt two cards, called 'hole cards,' face down. The player immediately to the left of the dealer[1] is required to bet a fixed amount, called the small blind, regardless of the strength of the player's hand. Similarly the player second to the left of the dealer is required to bet a larger, fixed amount, called the big blind, regardless of hand strength.

[1] One player is designated as the dealer, though, to guarantee fairness, that player does not actually distribute the cards in professional tournaments. A non-playing person distributes cards as needed. The dealer designation merely dictates the sequence of action among the players at the table and rotates clockwise around the table so that, over the course of an extended game, no player gains strategic advantage from the order of play.

Information Revelation	Subsequent Action Taken[a]
Two Hole Cards (Private Information)	Pre-Flop Betting --→ Declare Winner
Three Flop Cards (Public Information)	Post-Flop Betting --→ Declare Winner
One Turn Card (Public Information)	Post-Turn Betting --→ Declare Winner
One River Card (Public Information)	Post-River Betting → Declare Winner

[a] Dashed arrows refer to the possibility that actions will result in declaring a winner should all but one player fold; a solid line implies that a winner is declared following this action.

Figure 4. Game phases and terminology in the poker game

Thereafter, each player, in a clockwise sequence, must decide whether to fold or whether to continue the hand. If the player decides to continue, the player chooses whether to simply match the largest bet currently on the table (i.e., to 'call')[2] or to bet an amount larger than any previous bet (i.e., to 'raise'). In the 'No Limit' variant of the game, which is the subject of the current analysis, the size of a raise is restricted from below to be at least as large as the forced bet made by the big blind[3] and restricted from above only by the number of chips held by the bettor. Other 'Limit' variants of the game regulate the size of the bet any player can make at a particular point in the game.

[2] When a player calls before any other player has raised the pot, this action is referred to as a 'check.'
[3] One exception applies to this lower limit. If the player in the 'small blind' wants to raise and no other non-blind player has yet raised, the size of the raise must be the size of the big blind's raise plus the difference in chips between the big blind's forced bet and the small blind's forced bet.

Play continues clockwise around the table until all players have either 'folded', i.e., surrendered their ante and any previously wagered 'blinds' or bets, or until all players have called the largest bet forwarded by any player. Next, the dealer draws three cards called 'the flop' which are placed face up in the middle of the table for all players to see and to use to construct the best five-card hand possible. Starting with the player immediately to the left of the dealer (the player forced to contribute the small blind), the remaining players again decide whether to fold, to call, or to raise the largest previous bet made in the round.[4] After all players have folded or called, the dealer draws a single card called 'the turn card' and places it face up along side the flop; the betting sequence is repeated as before. Finally, the dealer reveals a fifth face-up card called 'the river card' and a final round of betting occurs. All players then reveal their hole cards and the player with the dominant hand is identified. The winning hand receives all the chips bet during the hand and as well as the antes (called 'the pot'), enforcing a zero-sum structure upon the game. If two or more players reveal a winning hand of identical strength, the pot is split equally among these players.

Many hands end when only one player remains because all opponents have folded. This often occurs even before any of the common cards have been revealed if players sense a small probability of winning with the cards they have been dealt. This also provides an opportunity for weak players to signal strength via large bets in the hope of inducing opponents to fold, e.g., to bluff their way to winning the bets and antes of other players.

[4] In a heads-up match, where only two players are in the hand, the player with the small blind is the dealer and plays first before the flop but plays last after the flop.

13. 2. Characteristics of Poker as a Natural Experiment

Texas Hold'em shares a common characteristic with other laboratory experiments and natural experiments in that players' decision making involves risk. Furthermore, it shares similar features with some of the previous natural experiments because it involves real incentives and the ability to bet varying amounts (*Jeopardy*, *Card Sharks*, race track betting) and whether to participate or withdraw from the process (Lingo and Hoosier Millionaire). However, Texas Hold'em has some unique features. First, the game, while finite, has no fixed duration and may last for many hours. Furthermore, individuals may choose not to continue (fold) in a particular hand, but return to compete in futures hands so long as the players retain enough chips to pay the ante. Second, this is zero-sum game, so competition is intense and long-term cooperation of the participants is not observed. Third, players in each hand may make multiple sequential decisions. That is, each player has to make several decisions about the continuation of the game and then the size of the bet in a hand until either he/she folds or the hand ends. This facet, when added to the fact that individuals are observed over many hands of play, yields the potential data necessary for estimating robust models of each individual's utility. Finally, each player must pay hundreds to thousands of dollars to enter the competition, making the observed subjects a self-selected group of highly motivated and adept decision makers. Compared to participants in the papers based on lottery participants, which require only a minimal fee to enter, or game shows, which require a different set of skills (e.g., trivia) to enter, the current subjects have superior decision making skills that have often been honed in other avenues of life such as business and academia. Indeed, many of the players in the data analyzed here declare poker as their profession.

13. 3. Basic Model

The basic game structure of Texas Hold'em consists of a simple decision – fold or continue – which is similar to the some of games in previous research. For example, in the *Lingo* game analyzed by Beetsma and Schotman, players decide whether to stop taking their current stake or to continue facing a binary lottery. Similarly, players choose between keeping the accumulated stake or taking the offered wager in *Illinois Instant Riches* analyzed by Hersch and Mcdougall. However, unlike these games, a decision to continue requires another decision concerning the amount to be bet, and the results of the hand are affected by this secondary decision in Texas Hold'em. The level of risk aversion is estimated by adapting the method used by Hersch and Mcdougall (*Illinois Instant Riches).*

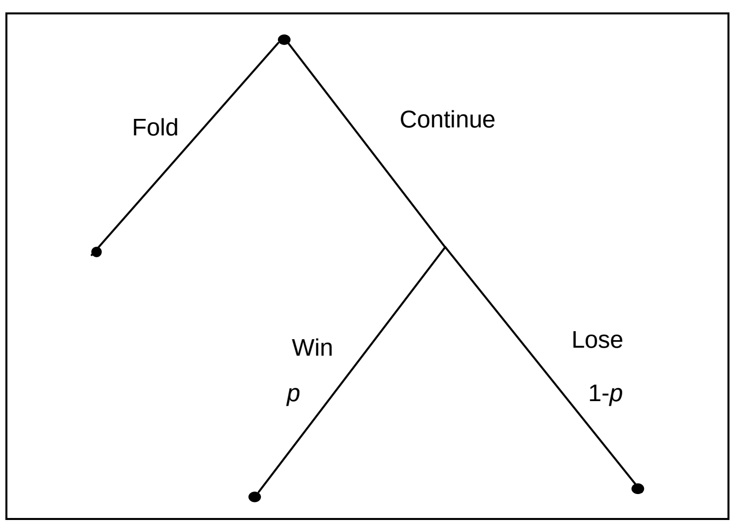

Figure 5. Basic game structure of Texas Hold'em

The main approach is as follows. The expected utility $U(A)$ of a player who decides whether to fold ($A = f$) or continue ($A = c$) is

$$U(f) = U(m_i - w_i) + \varepsilon_{if} = V_{if} + \varepsilon_{if} \tag{8}$$

$$U(c) = p_i U(m_i + E_i(y_W \mid X)) + (1 - p_i) U(m_i + E_i(y_L \mid X)) + \varepsilon_{ic} = V_{ic} + \varepsilon_{ic} \tag{9}$$

$$E_i(y_W \mid X) > 0 \text{ and } E_i(y_L \mid X) < 0$$

where m_i is the initial chip count of player i, w_i is the sum of the ante, blind and previous bets made by player i, $E_i(y_W \mid X)$ is expected winning amount conditional on continuing in the hand, $E_i(y_L \mid X)$ is expected losing amount of player i conditional on continuing in the hand, and p_i is the subjective probability of winning the hand. V_{ij} and ε_{ij} are the expected utility term and an error term for the i th player for his/her j th option in which $j = f$ if the player decides to fold and $j = c$ if the player decides to continue.

The players' continuation decision depends on the expected utility $U(A)$. Players will decide to continue if $U(c) = (V_{ic} + \varepsilon_{ic}) > (V_{if} + \varepsilon_f) = U(f)$, and fold otherwise. The probability of the player choosing to continue is then:

$$p_{ic} = prob(\varepsilon_{if} - \varepsilon_{ic} < V_{ic} - V_{if}) \tag{10}$$

which can be estimated applying a nonlinear probit model and assuming a particular utility specification. For example, two typical utility specifications are a constant absolute risk aversion (CARA) function, $U(\omega) = -\frac{1}{\gamma}\exp[-\gamma(W + \omega)]$, and a constant relative risk aversion (CRRA) function, $U(\omega) = \frac{(W + \omega)^{1-\gamma} - 1}{1-\gamma}$, which can be adopted where W is wealth level, ω is a change to the wealth level, and γ is the coefficient of the degree of risk aversion.

CHAPTER 14

DATA

The data were obtained from watching individual episodes of the 2003 and 2004 World Poker Tour (WPT) Series. The WPT consists of a series of Texas Hold'em tournament games in which there is no upper limit set upon players' bet amount, i.e., players may bet up to their currently available number of chips on any given hand. More than 95 different players are included in the data set with several players contributing more than 50 individual decisions. The data set contains the structural elements of the game for each player such as the player's initial chip count, order of play, bet amount, pot size, drawn cards, winnings, blind bet amounts, and antes. Also, the data set encodes several key demographic variables such as gender, age, national origins, professional poker status (professional vs amateur), and the other occupation of amateur players. The paper defines players who make their living by having additional occupations besides by participating poker games as amateur players and players who make their living mainly by participating poker games as professional players. In addition, each player's objective partial-information winning probabilities are calculated by simulating game play under the assumption that the player does not have knowledge of other players' cards, e.g., the probability of winning for a player holding a pair of queens prior to any information being available concerning flop cards. Some key summary statistics for the observations are as follows (Table 17).

	Total	Average	Min	Max
Total Episodes	21			
Total Hands Played	2,297			
Number of Players	95		2 (Per Hand)	6 (Per Hand)
Ante (in chips)			0	10,000
Big Blind (in chips)			50	100,000
Initial Chip Count per Hand (in chips)		538,075	19,000	5,475,000

Table 17. Summary Statistics for the data

CHAPTER 15

RESULTS

15.1. Subjective Probability of Winning and Expected Winning and Losing Amounts

The main purpose of this essay is to measure risk attitudes using data encoded from the World Poker Tour's Texas Hold'em Poker Tournament Series. The probability of winning a particular hand and the winning and losing amounts conditional on continuing in a hand are essential components for estimating players' utility functions. The subjective winning probability and the expected winning and losing amounts were estimated using a probit model for the probability and a double hurdle tobit model for the amounts. To study risky decision making, a logical starting point is identifying the risk that players face. In poker, a player can avoid risk by folding, which results in a guaranteed forfeiture of the ante, any forced bets, and any non-forced bets. Alternatively, the player can assume additional risk by continuing the hand (by calling or raising the prevailing bet).

For each player that folds, the guaranteed loss is non-stochastic. However, for continuing players, the expected value is stochastic. A key issue is understanding the expected value of continuation is the probability of winning, p, which is estimated by the probit model:

$$z^* = X'\alpha + \varepsilon \qquad (11)$$

where z^* is the unobserved dependent variable of relative hand strength. While each player knows the absolute strength of his hand (e.g., a player holding two queens knows this is a very strong hand), he remains uncertain of its relative strength (e.g., does someone else hold two kings?). At the completion of the hand, relative hand strength is revealed and a binary variable, z, is observed where $z = 1$ if $z^* > c$, and otherwise $z = 0$. The term c represents a threshold for relative hand strength (i.e., the strength of the strongest hand held by someone else), and it is normalized to zero for convenience. X is a vector of independent variables, and ε is an error term.

Conditional on continuation, the expected amount of winning and the expected amount of losing are estimated with double-hurdle tobit models. The models were introduced because the winning amount and losing amounts are bound by certain cutoff values. For example, a player cannot lose more than all his chips or less than his previous bet including ante and any blind bets. The maximum and minimum limits of both expected winning and expected losing amounts would depend on several aspects such as the player's and other players' chip counts, the ante amount, the blind amount and so on.

$$y_j^* = X_j^{'}\beta_j + \varepsilon_j, \qquad j = W, L \qquad i = 1, \cdots, N \quad (12)$$

$$y_j = y_j^* \text{ if } L_{ij} < y_j^* < U_{ij}$$

$$y_j = U_{ij} \text{ if } y_j^* \geq U_{ij}$$

$$y_j = L_{ij} \text{ if } y_j^* \leq L_{ij}$$

where y_j^* is a latent number of chips for the winning hand ($j = W$) or losing hand ($j = L$), X_j is a vector of independent variables, and ε_j is a normal error term with zero mean and standard deviation σ. L_{ij} and U_{ij} are constants that represent bounds on winning and losing amounts for the winning hand ($j = W$) or losing hand ($j = L$) and that vary from player to player depending upon individual chip counts, antes, blinds, and so on.

Each player's expected winning amount and expected losing amount for each stage of each hand were predicted using the results from the estimated tobit models. The expected winning amount for the players with losing hands was predicted using the estimation results of expected winning model. The expected losing amount for players with winning hands was predicted following similar steps. The following formations were used for predictions:

$$E(y_{ij} \mid X_{ij}) = L_{ij} \Pr[y_{ij}^* \le L_{ij} \mid X_{ij}] + U_{ij} \Pr[y_{ij}^* \ge U_{ij} \mid X_{ij}] + \Pr[L_{ij} < y_{ij}^* < U_{ij} \mid X_{ij}] E[y_{ij}^* \mid L_{ij} < y_{ij}^* < U_{ij} \mid X_{ij}] \quad (13)$$

Assuming that $\Phi(\bullet)$ is the standard normal CDF, $\phi(\bullet)$ is the standard normal PDF, and σ is a standard deviation, equation (13) is converted to following equation (14).

$$E(y_{ij} \mid X_{ij}) = L_{ij}\Phi_{L_{ij}} + U_{ij}(1-\Phi_{U_{ij}}) + (\Phi_{U_{ij}} - \Phi_{L_{ij}})\beta' X_{ij} + \sigma_{ij}((\phi_{L_{ij}} - \phi_{U_{ij}}) \quad (14)$$

where $\Phi_l = \Phi[(l - \beta' X_{ij}) / \sigma_{ij}]$, $\phi_l = \phi[(l - \beta' X_{ij}) / \sigma_{ij}]$, $l = L_{ij}, U_{ij}$, $i = 1, \cdots, N$, and $j = W\, or\, L$

The estimation results of probit model of winning probability are as follows (Table 19).

$$z^* = \alpha_0 + \alpha_1 \bar{p} + \alpha_2 Num + +\alpha_3 Pot_{net} + \alpha_4 Chip + \sum_{\substack{i=5 \\ j=S,B,FM,DB}}^{7} \alpha_i Chair_j + \alpha_8 pro + \varepsilon \quad (15)$$

where z^* is a latent variable of relative hand strength in which $z = 1$ if $z^* > 0$ and $z = 0$ otherwise, $\bar{p}$ is an actuarial probability of winning calculated without the knowledge of other players' cards but with the knowledge of the number of other players still eligible to compete in the hand and also, in case of post flop, with the knowledge of the new common cards (flop), and Num is the total number of players still eligible to compete (not yet folded) at the moment the player's decision is made. Pot_{net} is the amount of previous bets excluding antes and blind bets and past bets placed by the decision maker, $Chip$ is each player's initial chip count, $Chair_j$ is the players' order of play (seat position) where subscript j indicates the player position, i.e., small blind (S), big blind (B), first mover (FM), and dealer (DB) during each stage of the hand. The dummy variable pro equals one for professional players and ε is an error term. Quantitative variables were normalized by the size of amount the player had to pay in dollars to 'buy-in' to the tournament, which is different between episodes.

Separate models were estimated for pre-flop and post-flop data. A likelihood ratio test results (Table 20) rejects pooling of the two models. There were a total of 2,284 pre-flop and 572 post-flop hands. Summary statistics for the models are as follows (Table 18).

	Pre Flop (N=2,284)				Post Flop (N=572)			
	Total	Average	Min	Max	Total	Average	Min	Max
Winner	564				264			
$\bar{p}$	2,284	0.36	0.11	0.84	572	0.55	0.09	0.96
Num	2,284	3.48	2	6	572	2.28	2	4
Pot_{net}	2,284	10.12	0	935.25	572	14.11	0.17	450
$Chip$	2,284	93.43	0.5	2846.67	572	103.41	5.63	2100
$Chair_S$	564				188			
$Chair_B$	562				219			
$Chair_{FM}$	564				262			
$Chair_{DB}$	562				147			
pro	1,376				97			

Table 18. Summary Statistics for the Winning Models

	Pre Flop (N=2,284)		Post Flop (N=572)	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-2.77	0.32***	-0.88	0.40**
$\overline{p}$	5.76	0.33***	2.15	0.28***
Num	0.02	0.06	-0.19	0.11*
Pot_{net}	-3.29E-03	1.33E-03**	-3.01E-03	2.22E-03
$Chip$	1.00EE-05	2.21E-04	5.44E-04	5.72E-04
$Chair_S$	-0.44	0.13***	-0.21	0.16
$Chair_B$	-0.49	0.16***	-0.07	0.16
$Chair_{FM}$	0.11	0.08	0.02	0.15
$Chair_{DB}$	-0.09	0.10	0.18	0.17
pro	0.06	0.07	0.06	0.12
McFadden's R^2	0.22		0.10	

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

Table 19. The Estimation Results of the Subjective Probability of Winning Models

	Pre Flop	Post Flop	Pooled	LR test
Value	1987.48	708.23	2775.37	79.66***

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

Table 20. The Likelihood Ratio Test Results of the Subjective Probability of Winning Models

The actuarial probability of winning, $\bar{p}$, is the only variable that significantly explains a player's winning at the both stages (pre flop and post flop). As expected, a higher actuarial probability of winning, $\bar{p}$, strengthens the chance of winning at the both stages. While Pot_{net}, $Chair_S$, and $Chair_B$ are significantly related to pre-flop winning, these variables are not significant for post-flop data. Similarly, Num explains post-flop winning only. Prior to the flop, a player's chance of winning decreases if the amount bet by other players is larger (Pot_{net}). A larger pot will cause more players to persist until the end of the hand (i.e., not subsequently fold), which lowers the chances for the player to be the eventual winner. Seat position is also associated with winning. The estimation based on pre-flop data shows that players in the big or small blind are less likely to win than players in other positions.

	Pre Flop (N=2284)	Post Flop (N=572)
$Chair_S = Chair_B = Chair_{FM} = Chair_{DB}$	18.76***	3.00
$Chair_S = Chair_B$	0.31	0.92
$Chair_S = Chair_{FM}$	12.85***	2.62
$Chair_S = Chair_{DB}$	9.71***	0.96
$Chair_B = Chair_{FM}$	11.89***	1.83
$Chair_B = Chair_{DB}$	11.00***	0.22
$Chair_{FM} = Chair_{DB}$	1.93	1.07

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

Table 21. Hypothesis Test Results Concerning Players' Seat Positions in the Winning Model

The predicted probability of winning, $\hat{p}$, is then introduced as one of the independent variables in the expected winning and losing amount models. The results of double-hurdle tobit models for the expected winning amount and the expected losing amount are as follows (Table 24 and Table 25).

$$Amt_j = \alpha_{0j} + \alpha_{1j}\hat{p}_j + \alpha_{2j}Num_j + \alpha_{3j}Pot_{adjj} + \alpha_{4j}Chip_j + \alpha_{5j}Ante_j + \alpha_{6j}Blind_j + \sum_{\substack{i=7 \\ l=S,B,FM,DB}}^{9} \alpha_{ij}Chair_{lj} + \alpha_{10j}pro_j + \varepsilon_j$$
(16)

where Amt_j is the number of chips won ($j = W$, $Amt_W > 0$) or lost ($j = L$, $Amt_L < 0$), $\hat{p}_j$ is the estimated probability of winning, and Num_j is the total number of players remaining (not folded) at the moment of the decision node. Pot_{adjj} is the maximum number of chips in the current pot that the player can win. For example, assume that there are only two players and both players decide to bet all their chips. Further suppose that player A has 100 chips and player B has 250 chips. If player A wins the hand, he cannot receive more than 200 chips – the 100 he bet and 100 of player B's chips. $Chip_j$ is an initial chip count, $Ante_j$ is ante amount, $Blind_j$ is the big blind amount, $Chair_{lj}$ is the players' order of play (seat position) where subscripted letters are the same as before (S for small blind, etc.). The dummy variable pro indicates the professional versus amateur status of each player, and ε is an error term.

The upper and lower limits of a double-hurdle tobit model are different for each player and depend upon that player's chip count and the blinds. Also, these are calculated differently between pre- and post-flop. The lower limit for the winning amount is the antes, blinds plus bets placed by other players while the upper limit is the number of chips held by the player times the number of other players remaining in the hand.[5] The lower limit for the losing amount is the number of chips already committed by the player in terms of antes, blinds and past bets, while the upper limit is the player's total number of chips.[6]

	Pre(N=564)				Post(N=264)			
	Total	Average	Min	Max	Total	Average	Min	Max
Amt_W	17234.56	30.56	0.17	1566.67	6921.54	26.22	0.33	1100
$\hat{p}$		0.43	2.10E-02	0.96		0.53	0.17	0.85
Num		2.91	2	6		2.20	2	4
Pot_{adj}	8589.66	15.23	0	433.33	5236.18	19.83	0.67	620
$Chip$	58941.88	104.51	2.33	1603.33	27034.92	102.41	6.25	1066.67
$Ante$	253.69	0.45	0	10	91.02	0.34	0	10
$Blind$	1468.31	2.60	0	100	566.03	2.14	0	100
$Chair_S$	170				79			
$Chair_B$	189				99			
$Chair_{FM}$	145				116			
$Chair_{LM}$	161				77			
pro	348				183			

Table 22. Summary Statistics for the Winning Amount Models

[5] However, if another player has fewer chips, then the player in question can only win all of that player's chips.
[6] If the player has more chips than any other player, then the most the player can lose is the number of chips held by the other player still in the hand with the second largest chip total.

	Pre(N=1,720)				Post(N=308)			
	Total	Mean	Min	Max	Total	Mean	Min	Max
Amt_L	-17259.50	10.03	-1566.67	0	-6415.28	-20.83	-0.33	-1100
$\hat{p}$		0.18	1.60E-04	0.94		0.40	0.07	0.79
Num		3.67	2	6		2.36	2	4
Pot_{adj}	26739.87	15.55	0.25	406.67	6154.04	19.98	0.97	620
$Chip$	154452.2	89.80	0.5	2846.67	32117.07	104.28	5.63	2100
$Ante$	596.94	0.35	0	10	99.63	0.32	0	10
$Blind$	2334.33	1.36	0	100	622.78	2.02	0	100
$Chair_S$	394				109			
$Chair_B$	373				120			
$Chair_{FM}$	419				146			
$Chair_{DB}$	401				70			
pro	1028				203			

Table 23. Summary Statistics for the Losing Amount Models

	Winning Amount(N=828)			
	Pre flop(N=564)		Post flop(N=264)	
	Coefficient	Chi-Square	Coefficient	Chi-Square
Intercept	-86.25	12.38***	-58.66	8.56***
$\hat{p}$	40.44	10.49***	49.12	10.32***
Num	13.96	7.80***	7.26	1.57
Pot_{adj}	0.08	0.23	0.20	1.14
$Chip$	0.13	19.96***	0.04	1.50
$Ante$	11.94	3.98**	-19.58	6.01**
$Blind$	7.12	32.05***	10.27	87.54***
$Chair_S$	7.71	0.47	-17.86	6.39**
$Chair_B$	22.44	2.54	-13.54	2.99*
$Chair_{FM}$	0.34	0.00	27.32	16.58***
$Chair_{DB}$	22.77	6.26**	23.51	9.11***
pro	-0.34	0.00	2.31	0.18
σ	60.53		36.09	
$Log\,L$	-2593.47		-839.41	

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

Table 24. The Estimation Results of Winning Amount Models

	Losing Amount(N=2028)[b]			
	Pre flop(1720)		Post flop(308)	
	Coefficient	Chi-Square	Coefficient	Chi-Squre
Intercept	92.71	46.54***	68.98	9.00***
$\hat{p}$	-155.85	262.09***	-106.73	24.93***
Num	-3.81	2.12	5.64	0.88
Pot_{adj}	1.23	90.85***	-0.40	7.33***
$Chip$	-0.05	12.87***	-0.19	16.64***
$Ante$	-33.57	110.31***	-81.22	39.38***
$Blind$	-4.96	149.17***	10.70	94.27***
$Chair_S$	-23.15	16.73***	-19.50	5.15**
$Chair_B$	-11.17	2.38	-25.54	9.23***
$Chair_{FM}$	4.25	1.23	7.42	0.87
$Chair_{DB}$	-8.82	3.16*	1.64	0.03
pro	-7.19	5.19**	0.73	0.01
σ	45.84		44.01	
$Log\,L$	-3256.23		-909.33	

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level
b. losing amount in the estimation is always counted as negative numbers

Table 25. The Estimation Results of Losing Amount Models

	Pre Flop	Post Flop	Pooled	LR test
Winning Amount	5186.94	1678.82	6941.78	76.02***
Losing Amount	6512.46	1818.66	8552.00	202.88***

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

Table 26. The Likelihood Ratio Test Results of the Winning Amount and Losing Amount Models

There were a total of 828 winning amounts and 2,028 losing amounts. Separate models were estimated for pre-flop and post-flop data for winning amounts models and losing amount models. A likelihood ratio test results (Table 26) rejects pooling of the two models for each stage.

The estimation results show that the winning probability, $\hat{p}$, is significantly related to the winning and losing amounts for each stage. Strong cards lead to larger wins and larger losses. Num is only significant in the winning amount model for the pre–flop stages. A player wins more as more players participate. Pot_{adj} is only significant in the losing amount. While a larger size of Pot_{adj} is related to smaller losing amounts at pre flop, it is related to a larger losing amount at post flop.

The size of $Chip$, $Ante$, and $Blind$ significantly explain players' winning amount and losing amounts at most of stages. Players that begin with more chips tend to win larger sums and lose larger sums. Larger blind bets and larger antes also lead to the similar patterns for most cases. A larger ante is related to a smaller winning amount at post flop and a larger blind is related to a smaller post-flop losing amount.

$Chair_S$ is significant in most models except the pre-flop winning amount model. Players in the small blind ($Chair_S$) position win less and lose more. $Chair_B$ is significant in both the post-flop winning and losing models. Similar to $Chair_S$, the player in the big blind tends to win less and lose more. $Chair_{FM}$ is only significant in the post-flop winning model; first movers tend to win more. $Chair_{DB}$ is significant in the most models except the post-flop losing amount model. The estimation result indicates that the dealer ($Chair_{DB}$) position tends to win more and lose less. pro is only significant in the pre-flop losing amount; professional players tend to lose more.

15.2. The measurement of risk attitudes

Players' utility functions are estimated by a nonlinear probit model. I then test for differences in the parameters of the utility model 1) across different phases of the game, 2) between professional poker players and amateur poker players, and 3) across different strategic positions.

First, I use all players' data to estimate a pooled CARA and CRRA utility model (Table 27). The estimation results of CARA utility specifications reveal significant risk aversion during pre-flop decisions but cannot reject the null hypothesis of risk neutral behavior for post-flop decisions. The point estimate for the post-flop CARA model is actually larger than the pre-flop point estimate; the degree of precision surrounding the post-flop point estimate is much lower and does not allow me to reject that it is significantly different than zero. A likelihood ratio test of the CARA specification reveals that pooling pre- and post-flop data is not restrictive; the pooled estimates support a significant degree of risk aversion by players. A similar test performed for the CRRA specification also supports pooling pre- and post-flop data. The estimation results of CRRA utility specification indicate that players are significantly risk averse in both pre-flop and post-flop. As was the case with the CARA specification, the point estimate for post-flop decisions is larger, but measured with less precision. The lack of precision associated with post-flop estimates may stem simply from a smaller sample size or from strategic issues, i.e., players may find it optimal to bluff more often and, hence, represent a different degree of risk aversion to opponents. Pre-flop decisions typically involve more players and less strategy, e.g., it may be easier to convince a single post-flop opponent via a bluff but more difficult to convince several pre-flop opponents that you are not bluffing.

	Stage	N	Estimates	t-value	Lower	Upper	-2logL
CARA	Pre-Flop	2247	5.68E-03	2.44**	1.12E-03	1.02E-02	3097.40
	Post-Flop	563	8.34E-03	1.59	-1.99E-03	1.87E-02	773.00
	Pooled	2810	6.29E-03	2.88***	2.02E-03	1.06E-02	3870.70
LR test				0.30			
CRRA	Pre-Flop	2247	0.63	26.93***	0.58	0.67	3039.10
	Post-Flop	563	0.71	19.26***	0.64	0.78	747.00
	Pooled	2810	0.66	33.88***	0.62	0.70	3790.40
LR test				4.30			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 27. Poker Players' Risk Attitude: Pre Flop and Post Flop Stages

Second, utility functions (CARA and CRRA) of professional players' utility functions and amateur players' utility function were estimated 1) for all hands (pre and post flop), 2) for pre flop and post flop separately, and 3) for individual players.

The results for pooled hands are listed in Table 28. The estimation results indicate that both professional players and amateur are significantly risk averse under the CARA utility specification. However, risk neutrality is rejected for amateur players only at the ten percent level for this utility specification. The estimation results of CARA utility specifications indicate that amateur players may be less risk averse than professional players.

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Amateur	1064	5.63E-03	1.69*	-9.00E-04	1.22E-02	1465.70
	Professional	1746	6.68E-03	2.38**	1.18E-03	1.22E-02	2045.00
	Pooled	2810	6.29E-03	2.88***	2.02E-03	1.06E-02	3870.70
LR test				360.00***			
CRRA	Amateur	1064	0.70	20.44***	0.63	0.77	1442.30
	Professional	1746	0.63	27.15***	0.59	0.68	2345.82
	Pooled	2810	0.66	33.88***	0.62	0.70	3790.40
LR test				2.30			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level
b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 28. The Risk Attitude of Amateur and Professional Players (Pre- and Post-flop Decisions)

The likelihood ratio test results support that there are differences between amateur players' risk attitude and professional players' risk attitude. Under the CRRA utility specifications, both professional players and amateur players are risk averse at the one percent level. The likelihood ratio test indicates that there are no differences between their risk attitudes, though the point estimates suggest that amateurs hold a modestly higher degree of risk aversion.

Next, amateur and professional players' risk attitudes were estimated separately for both pre-flop and post-flop decisions (Table 29 and Table 30). In the case of pre-flop decisions, there were a total of 2,247 hands - 884 hands for amateur players and 1,363 hands for professional players.

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Amateur	884	6.17E-03	1.51	-1.82E-03	1.42E-02	1217.10
	Professional	1363	5.40E-03	1.88*	-2.20E-04	1.10E-02	1880.30
	Pre-Flop	2247	5.68E-03	2.44**	1.12E-03	1.02E-02	3097.40
LR test				0.00			
CRRA	Amateur	884	0.63	17.19***	0.56	0.70	1183.50
	Professional	1363	0.62	20.29***	0.56	0.68	1855.50
	Pre-Flop	2247	0.63	26.93***	0.58	0.67	3039.10
LR test				0.10			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 29. Estimated Pre-flop Risk Attitudes of Amateur and Professional Players

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Amateur	180	3.80E-03	0.62	-8.26E-03	1.59E-02	248.50
	Professional	383	1.03E-02	1.55	-2.76E-03	2.34E-02	524.10
	Post-Flop	563	8.34E-03	1.59	-1.99E-03	1.87E-02	773.00
LR test				0.40			
CRRA	Amateur	180	0.90	5.71***	0.59	1.21	250.40
	Professional	383	0.64	17.90***	0.57	0.71	489.50
	Post-Flop	563	0.71	19.26***	0.64	0.78	747.00
LR test				7.10			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 30. Estimated Post-flop Risk Attitudes of Amateur and Professional Players

Professional players are significantly risk averse in both utility specifications (though only at the ten percent level for the CARA specification) and amateur players are only significantly risk averse in CRRA utility specification significantly. Also, the hypothesis of the no differences in risk attitudes between professional and amateur could not be rejected for either utility specification. In the post-flop cases, there were a total of 563 hands - 180 hands for amateur players and 383 hands for professional players. The hypothesis that professional and amateur players display identical risk attitudes could not be rejected for either utility specification.

Several individual-player utility functions were also estimated (Table 31, Table 32, and Table 33). A total of 33 professional poker players and 22 amateur players appeared in a sufficient number of pre-flop cases and a total of 3 professional poker players appeared in enough post-flop cases to be included for the analysis. Figure 6 shows the plot of estimation results of CARA and CRRA utility specifications for individual poker players in both pre-flop and post-flop cases.

As can be seen, professional players and amateur players show a similar range of risk aversion coefficients, which are mainly distributed in between 0 and 0.02 for the CARA utility specification and between 0 and 1 for the CRRA utility specification. The results of professional players are more dispersed than those of amateur players for the CARA utility specification, though there are a few outliers among the professional ranks. While most of the CRRA utility specifications were significant, none of the CARA utility specifications was significant in the estimation of individual players in the pre-flop stage. Two professional players' estimations give significant results for CRRA specifications during the post-flop stage.

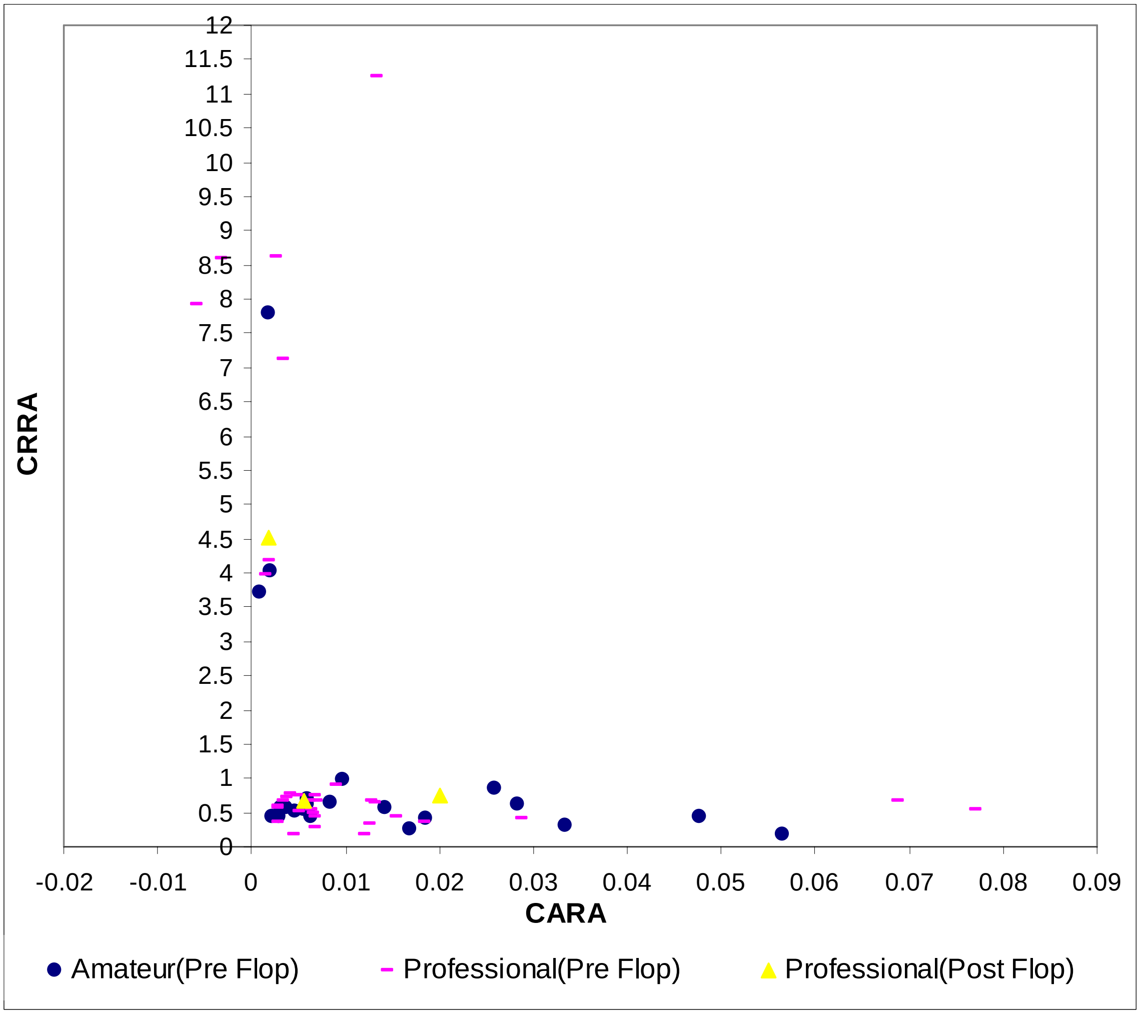

Figure 6. Estimation Risk Aversion Coefficients from CRRA and CARA Utility Specifications

		CARA				CRRA			
ID	N	Estimates	t-value	Lower	Upper	Estimates	t-value	Lower	Upper
6	29	9.31E-04	0.16	-1.11E-02	1.30E-02	3.71	0.02	-331.34	338.76
7	50	4.57E-03	0.59	-1.11E-02	2.02E-02	0.52	5.17***	0.32	0.72
13	21	4.76E-02	0.63	-1.09E-01	2.04E-01	0.43	2.53***	0.08	0.79
14	38	1.68E-02	0.54	-4.57E-02	7.93E-02	0.26	2.74***	0.07	0.45
17	24	1.43E-02	0.55	-3.93E-02	6.78E-02	0.57	2.49**	0.10	1.05
21	50	6.02E-03	0.47	-1.98E-02	3.19E-02	0.69	5.65***	0.45	0.94
22	41	8.43E-03	0.45	-2.94E-02	4.63E-02	0.64	2.68***	0.16	1.13
23	29	3.61E-03	0.39	-1.53E-02	2.25E-02	0.57	4.62***	0.32	0.82
25	27	1.90E-03	0.12	-3.20E-02	3.58E-02	7.80	0.01	-1266.28	1281.87
34	21	5.66E-02	0.50	-1.79E-01	2.92E-01	0.19	0.85	-0.27	0.64
40	22	5.55E-03	0.31	-3.18E-02	4.29E-02	0.55	2.68***	0.13	0.98
42	35	5.90E-03	0.73	-1.06E-02	2.24E-02	0.61	6.18***	0.41	0.81
44	24	2.59E-02	0.36	-1.23E-01	1.75E-01	0.84	1.58	-0.26	1.94
49	27	2.83E-02	0.49	-9.00E-02	1.47E-01	0.62	2.12**	0.02	1.22
56	35	2.87E-03	0.35	-1.39E-02	1.97E-02	0.44	5.28***	0.27	0.61
58	23	1.86E-02	0.56	-5.03E-02	8.76E-02	0.41	2.07**	-5.20E-04	0.83
63	27	6.28E-03	0.41	-2.53E-02	3.78E-02	0.44	2.41**	-0.01	0.89
64	25	2.25E-03	0.31	-1.25E-02	1.70E-02	0.44	3.20***	0.16	0.73
67	46	3.06E-03	0.40	-1.22E-02	1.83E-02	0.58	5.15***	0.35	0.81
68	22	3.34E-02	0.41	-1.36E-01	2.03E-01	0.30	1.36	-0.16	0.75
75	30	2.03E-03	0.18	-2.07E-02	2.47E-02	4.03	0.02	-367.70	375.75
90	36	9.74E-03	0.34	-4.91E-02	6.86E-02	0.97	1.48	-0.36	2.30

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level
b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 31. Estimated Pre-flop Risk Aversion Coefficients: Individual Amateur Players

		CARA				CRRA			
ID	N	Estimates	t-value	Lower	Upper	Estimates	t-value	Lower	Upper
3	28	4.02E-03	0.28	-2.56E-02	3.36E-02	0.77	2.45**	0.13	1.41
4	46	1.31E-02	0.39	-5.41E-02	8.03E-02	0.64	2.44***	0.11	1.16
8	30	2.72E-03	0.35	-1.34E-02	1.88E-02	0.58	4.02***	0.29	0.88
9	20	3.39E-03	0.36	-1.63E-02	2.30E-02	0.68	1.99*	-0.03	1.40
15	21	6.87E-02	0.41	-2.83E-01	4.21E-01	0.67	1.98*	-0.04	1.37
16	20	3.71E-03	0.21	-3.38E-02	4.12E-02	0.71	1.93*	-0.06	1.48
19	22	6.69E-03	0.31	-3.87E-02	5.20E-02	0.28	2.60***	0.06	0.51
26	21	6.33E-03	0.44	-2.34E-02	3.60E-02	0.53	3.79***	0.24	0.83
28	33	1.27E-02	0.49	-4.04E-02	6.58E-02	0.68	3.42***	0.28	1.09
29	30	6.65E-03	0.17	-7.53E-02	8.86E-02	0.74	1.38	-0.36	1.84
30	52	4.81E-03	0.67	-9.50E-03	1.91E-02	0.75	3.46***	0.31	1.18
32	43	2.66E-03	0.31	-1.47E-02	2.01E-02	0.60	7.68***	0.44	0.76
35	99	2.59E-03	0.45	-8.84E-03	1.40E-02	8.61	0.01	-1781.29	1798.51
36	40	-3.34E-03	-0.25	-3.06E-02	2.40E-02	8.60	0.01	-1172.71	1189.90
37	33	2.87E-02	0.39	-1.23E-01	1.80E-01	0.41	3.23***	0.15	0.66
38	51	1.88E-03	0.26	-1.24E-02	1.62E-02	4.19	0.03	-327.65	336.03
47	24	1.20E-02	0.40	-5.01E-02	7.40E-02	0.17	1.89*	-0.02	0.36
48	29	6.47E-03	0.37	-2.92E-02	4.21E-02	0.50	3.34***	0.19	0.81
51	27	6.76E-03	0.23	-5.48E-02	6.83E-02	0.43	1.61	-0.12	0.99
53	28	3.36E-03	0.19	-3.23E-02	3.90E-02	7.13	0.01	-1208.33	1222.60
54	33	1.33E-02	0.47	-4.48E-02	7.14E-02	11.25	0.01	-2700.11	2722.61
59	33	1.26E-02	0.21	-1.11E-01	1.36E-01	0.34	2.05**	2.33E-03	0.68
65	37	1.47E-03	0.35	-7.02E-03	9.96E-03	3.97	0.02	-320.80	328.74
66	32	-5.98E-03	-0.33	-4.24E-02	3.04E-02	7.93	0.02	-965.16	981.03
69	21	6.81E-03	0.46	-2.38E-02	3.74E-02	0.67	2.36**	0.08	1.26
70	49	8.97E-03	0.46	-3.03E-02	4.82E-02	0.90	2.58***	0.20	1.61
71	70	1.84E-02	0.79	-2.81E-02	6.48E-02	0.35	3.43***	0.15	0.56
78	49	1.53E-02	0.60	-3.57E-02	6.63E-02	0.43	3.99***	0.21	0.65
79	25	6.05E-03	0.42	-2.33E-02	3.54E-02	0.67	2.75***	0.17	1.17
81	27	7.70E-02	0.87	-1.05E-01	2.59E-01	0.54	3.37***	0.21	0.86
83	23	5.02E-03	0.36	-2.37E-02	3.37E-02	0.51	2.85***	0.14	0.87
92	20	4.41E-03	0.48	-1.47E-02	2.35E-02	0.19	2.11**	1.96E-03	0.37
95	37	2.82E-03	0.56	-7.45E-03	1.31E-02	0.37	4.40***	0.20	0.54

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level
b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 32. Estimated Pre-flop Risk Aversion Coefficients: Individual Professional Players

		CARA				CRRA			
ID	N	Estimates	t-value	Lower	Upper	Estimates	t-value	Lower	Upper
35	49	5.53E-03	0.55	-1.48E-02	2.59E-02	0.67	6.05***	0.45	0.90
38	21	1.83E-03	0.16	-2.21E-02	2.58E-02	4.51	0.01	-1107.06	1116.08
71	27	2.01E-02	0.49	-6.49E-02	1.06E-01	0.76	2.40**	0.11	1.41

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level
b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 33. Estimated Post-flop Risk Aversion Coefficients: Individual Professional Players

The final set of results examine players' utility functions at different strategic positions – blinds versus non-blinds and first mover versus non-first movers. These were estimated for pre flop, post flop, and for both stages combined. Most estimates of risk aversion coefficients for CARA and CRRA utility specifications in pre flop and pooled stages were significantly different from zero for players in both non-blind positions and blind positions (Table 34, Table 35, and Table 36). Risk aversion coefficients estimated from non-blind decision nodes are significantly smaller than coefficients estimated from blind nodes in the CRRA utility specification in most of cases. Likelihood ratio tests also support this conclusion. Among post-flop data, only the estimation results for the CRRA utility specification from non-blind data yield a risk aversion coefficient that is significantly different from zero.

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Non Blind	1154	1.26E-02	1.59	-2.89E-03	2.80E-02	1591.80
	Blind	1093	4.25E-03	2.04**	-1.60E-04	8.33E-03	1504.00
	Pre-Flop	2247	5.68E-03	2.44**	1.12E-03	1.02E-02	3097.40
LR test				1.60			
CRRA	Non Blind	1154	0.38	14.57***	0.32	0.43	1461.80
	Blind	1093	0.73	18.96***	0.65	0.81	1519.70
	Pre-Flop	2247	0.63	26.93***	0.58	0.67	3039.10
LR test				57.60***			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 34. Estimated Pre-flop Risk Aversion Coefficients from Non Blind and Blind Decisions

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Non Blind	160	1.61E-02	1.48	-5.37E-03	3.76E-02	214.80
	Blind	403	3.54E-03	0.94	-3.88E-03	1.10E-02	556.50
	Post-Flop	563	8.34E-03	1.59	-1.99E-03	1.87E-02	773.00
LR test				1.70			
CRRA	Non Blind	160	0.51	14.01***	0.44	0.58	155.10
	Blind	403	9.97	0.02	-927.21	974.15	558.70
	Post-Flop	563	0.71	19.26***	0.64	0.78	747.00
LR test				33.20***			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 35. Estimated Post-flop Risk Aversion Coefficients from Non Blind and Blind Decisions

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Non Blind	1314	1.40E-02	2.17**	-1.35E-03	2.67E-02	1806.60
	Blind	1496	4.10E-03	2.25**	5.29E-04	7.67E-03	2060.50
	Pooled	2810	6.29E-03	2.88***	2.02E-03	1.06E-02	3870.70
LR test				3.60			
CRRA	Non Blind	1314	0.44	20.35***	0.40	0.48	1626.40
	Blind	1496	0.78	19.86***	0.70	0.86	2089.90
	Pooled	2810	0.66	33.88***	0.62	0.70	3790.40
LR test				74.10***			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 36. Estimated Risk Aversion Coefficients from Non Blind and Blind Decisions (Pooled Pre and Post Flop)

In case of first movers versus other players at pre-flop and post-flop decision nodes, all of estimates are significant except for first movers in the CARA utility specification fit to pre-flop data. None of the post-flop estimates are significant (Table 37, Table 38, and Table 39). While players in non-first-mover positions are generally risk averse, players in first-mover positions could be risk neutral or risk loving at both stages under the CARA specification. Under the CRRA specification, however, the results suggest that first movers display more risk aversion than other players at pre-flop. Pooling the data between first and non-first movers is not rejected in any case (pre-flop, post-flop or all decision nodes).

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Non FM	1684	6.76E-03	2.18**	6.84E-04	1.28E-02	2318.70
	FM	563	3.28E-03	1.01	-3.10E-03	9.67E-03	778.20
	Pre-Flop	2247	5.68E-03	2.44**	1.12E-03	1.02E-02	3097.40
LR test				0.50			
CRRA	Non FM	1684	0.59	24.33***	0.54	0.64	2243.90
	FM	563	0.76	8.73***	0.59	0.93	788.60
	Pre-Flop	2247	0.63	26.93***	0.58	0.67	3039.10
LR test				6.60			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 37. Estimated Pre-Flop Risk Aversion Coefficients for First Movers and Other Players

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Non FM	303	1.09E-02	1.26	-6.05E-03	2.78E-02	415.70
	FM	260	6.25E-03	1.10	-4.96E-03	1.75E-02	357.10
	Post-Flop	563	8.34E-03	1.59	-1.99E-03	1.87E-02	773.00
LR test				0.20			
CRRA	Non FM	303	0.77	13.18	0.66	0.89	407.90
	FM	260	0.63	14.36	0.54	0.71	335.10
	Post-Flop	563	0.71	19.26***	0.64	0.78	747.00
LR test				4.00			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 38. Estimated Post-Flop Risk Aversion Coefficients for First Movers and Other Players

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Non FM	1987	7.48E-03	2.45**	1.49E-03	1.35E-02	2734.70
	FM	823	4.38E-03	1.50	-1.36E-03	1.01E-02	1135.50
	Pooled	2810	6.29E-03	2.88***	2.02E-03	1.06E-02	3870.70
LR test				0.50			
CRRA	Non FM	1987	0.65	28.95***	0.61	0.70	2663.70
	FM	823	0.68	17.37***	0.60	0.76	1126.20
	Pooled	2810	0.66	33.88***	0.62	0.70	3790.40
LR test				0.50			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 39. Estimated Risk Aversion Coefficients for First Movers and Other Players (Pooled Pre- and Post-flop Data)

The estimation results related to strategic position of players who are last movers are in Table 40, Table 41, and Table 42. Most of estimates are significant except estimates from the CARA specification for post-flop data. In the CARA utility specification, the hypothesis that last and other movers have equal risk aversion coefficients cannot be rejected for pre-flop, post-flop or pooled data. Under the CRRA specification, however, last movers are statistically less risk averse compared to other players during pre-flop decisions, but not during post-flop decisions. When pre- and post-flop decisions are pooled, the equality between last movers and others cannot be rejected.

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Non LM	1717	5.33E-03	1.66*	-9.50E-04	1.16E-02	2373.50
	LM	530	6.03E-03	1.79*	-6.00E-04	1.27E-02	723.90
	Pre-Flop	2247	5.68E-03	2.44**	1.12E-03	1.02E-02	3097.40
LR test				0.00			
CRRA	Non LM	1717	0.69	17.84***	0.62	0.77	2375.50
	LM	530	0.54	17.50***	0.48	0.60	653.50
	Pre-Flop	2247	0.63	26.93***	0.58	0.67	3039.10
LR test				10.10***			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 40. The Estimation Results of Risk Attitude for Non Last Mover and Last Mover (Pre Flop)

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Non LM	308	6.01E-03	1.09	-4.82E-03	1.68E-02	423.80
	LM	255	1.13E-02	1.28	-6.07E-03	2.86E-02	349.00
	Post-Flop	563	8.34E-03	1.59	-1.99E-03	1.87E-02	773.00
LR test				0.20			
CRRA	Non LM	308	0.67	13.62***	0.57	0.76	408.50
	LM	255	0.74	13.86***	0.64	0.85	337.40
	Post-Flop	563	0.71	19.26***	0.64	0.78	747.00
LR test				1.10			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 41. The Estimation Results of Risk Attitude for Non Last Mover and Last Mover (Post Flop)

		N	Estimates	t-value	Lower	Upper	-2logL
CARA	Non LM	2025	5.52E-03	1.99**	7.90E-05	1.10E-02	2797.30
	LM	785	7.17E-03	2.10**	4.71E-04	1.39E-02	1073.30
	Pooled	2810	6.29E-03	2.88***	2.02E-03	1.06E-02	3870.70
LR test				0.20			
CRRA	Non LM	2025	0.68	22.40***	0.62	0.74	2784.20
	LM	785	0.64	24.93***	0.59	0.69	1004.70
	Pooled	2810	0.66	33.88***	0.62	0.70	3790.40
LR test				1.50			

a. * significant at the 10 percent level ** significant at the 5 percent level *** significant at the 1 percent level

b. Lower and Upper are lower and upper bounds of 95% confidence intervals

Table 42. The Estimation Results of Risk Attitude for Non Last Mover and Last Mover (Pooled)

CHAPTER 16

CONCLUSION

The purpose of this paper is to measure poker players' risk attitudes using data encoded from the World Poker Tour's Texas Hold'em Poker Tournament Series. Subjective winning probability and expected winning and losing amount were estimated using probit models and double-hurdle tobit models to provide data for estimating players' utility functions. Using these data, individual players' utility functions were estimated and the stability of risk aversion parameters was tested across different phases of the game and different strategic positions within the game.

Overall, players are generally risk averse in both the pre-flop and post-flop stages of the game. Although players could be risk neutral (or even risk loving) at post-flop in case of CARA utility specification, the likelihood ratio tests indicate that there are no significant differences in players' risk attitudes between pre-flop and post-flop for either utility specification when no distinction is made regarding the players' order of play (e.g., being a first or last mover). That is, although some of the game structure changes between pre-flop and post-flop decisions (e.g., introduction of additional public information via the revelation of common cards, a change of the number of players normally participating, the order of play[7], and so on), it does not affect the nature of overall players' risk attitudes in a statistically significant manner.

The estimated differences in risk attitudes between amateur and professional players provide a mixed picture. Generally, both groups were risk averse, especially under the CRRA utility specification, but risk neutrality could not be rejected for both groups for most of stages for the CARA utility specification (e.g., pooled, pre-flop, or post-flop). In particular, under CARA, amateur players could be risk neutral and have different level of risk attitudes compared to professional players who are more likely risk averse. That is, when decisions are pooled over all stages of the game and a CARA specification is assumed, amateur players are significantly less risk averse than professional players. However, under CRRA, the professional players are less risk averse, but this difference with amateurs is not statistically significant.

Amateurs basically do not make their entire livings by playing poker compared to professionals (following the definition of this essay) and could be less experienced than professionals in most of cases. These distinctive characteristics which distinguish amateurs from professionals might affect the different level of their risk attitudes.

When inspecting risk aversion coefficients estimated for individual players, amateurs and professionals show a similar range of risk aversion for both utility specifications in general. However, the estimation results for professionals are more

[7] For example, the big blind is always a last player to play before the flop while the dealer is the last to move after the flop.

dispersed than those of amateurs. Several professional players appear to be outliers, i.e., some professionals have extremely high and extremely low coefficients of risk aversion, with some professionals exhibiting negative risk aversion coefficients under the CARA specification.

Players' utility functions were estimated for different strategic positions – blinds, first mover and last mover positions. The estimation results suggest that the strategic position can affect the estimated value of players' risk attitudes. This was more apparent between blinds and non blinds in most of stages and between last-mover and non-last-mover positions in the pre-flop stage of the game, but was less apparent between first-mover and non-first-mover positions. This might indicate that some strategic positions such as blinds and non blinds or last movers and non-last movers give players more incentives to portray a different risk attitude to the other players at the table than does another strategic position such as being the first mover.

For example, in pre-flop decisions, the last mover has a significantly lower risk aversion coefficient than other players. Perhaps last-movers acting prior to the revelation of the public (flop) cards find it to be advantageous to act as if they are more risk neutral to establish a reputation that will serve them at later junctures of the game. Commentators for televised professional tournaments call this 'playing loose' and advice books written by professional poker players (e.g., Sklansky 2002) advise novice players that it is strategically advantageous to randomize the appearance of one's tolerance for risk during the course of a game.

An alternative interpretation of differences in estimated risk aversion by position is that players in different strategic positions adopt a different way of evaluating the prospects before them, and that this different evaluation frame manifests as a different risk aversion coefficient. The last mover during pre-flop decisions is the player that contributes the big blind – the larger of the two forced bets made during each hand. These players tend to participate in the game more frequently than other players, sometimes despite of the strength of their hands. For example, a player in the big blind with a weak hand may continue without raising if no other player at the table has raised the prevailing 'big blind' bet. This forced situation could make the big blind manage the game more passively than others, which could be construed as lower risk aversion.

Also, the player in the big blind has more information than other players for making the first decisions, including the types of information such as facial expressions that are not used as explanatory variables in the prediction of winning and losing amounts or the prediction of winning probabilities. Hence, the actual risk aversion displayed at this strategic position may be similar, but it is construed as being riskier merely because some facets of information are not being coded in the projected benefits of continuing the hand.

Finally, a player in the big blind may suffer from the sunk cost fallacy, which has been shown to persist among professional decision makers in other settings (see Camerer and Weber, 1999). In such cases, players tend to feel committed to participating in a game once bets have been placed. In the case of the big blind, the player has been forced to make a bet and may be tempted to continue even in the face of a weak hand, i.e., to throw good money after bad.

Estimates based upon an underlying model of expected utility maximization suggest significant risk aversion in many cases. However, estimation results for individual players suggest that decision making may be governed by theories (e.g., prospect theory) other than expected utility theory since both CARA and CRRA utility specifications do not provide meaningful results. More work is needed to investigate the application of other theories to explain players' risk attitudes in some cases.

APPENDIX A

DEFINATION OF EXPLANATORY VARIABLES FOR ESSAY 1

Variable	Description
Conc US	Concern about the way foods are produced and processed in the United States on a five point scale with 1 implying 'not at all concerned,' 3 implying 'somewhat concerned' and 5 implying 'very concerned'.
Conc Otr	Concern about the way foods are produced and processed countries other than the United States on a five point scale with 1 implying 'not at all concerned,' 3 implying 'somewhat concerned' and 5 implying 'very concerned'.
Purch Org	The frequency of purchase of organic food on a five point scale with 1 implying 'never' and 5 implying 'always'.
Nutr Label	The frequency of reading of food nutrition labels on a five point scale with 1 implying 'never' and 5 implying 'always'.
Female	Qualitative variable (Male=0, Female=1)
White	Qualitative variable. 1 if Caucasian, 0 otherwise.
AGE	Qualitative variables.
	AGE <30: 1 if age ≤ 30 years.
	AGE 30-65 1 if 30 < age ≤ 65 years, 0 otherwise.
	AGE >65: 1 if age > 65 years, 0 otherwise.
EDU	Qualitative variables.
	Edu1: 1 if 0-11 years, 0 otherwise.
	Edu2: 1 if 12 years (high school graduate or equivalent), 0 otherwise.
	Edu3: 1 if 1-3 years college (some college), 0 otherwise.
	Edu4: 1 if college graduate, 0 otherwise.
	Edu5: 1 if more than an undergraduate degree, 0 otherwise.
Child 5	Number of children ≤ 5 years old.
Child 10	Number of children 6 to 10 years old.
Child 18	Number of children 11 to 18 years old.
Grow Veg	1 if household grows own vegetables, 0 otherwise.
Farm Mkt	1 if respondent shops at a farmers' market or health food store regularly, 0 otherwise.
Food Coop	1 if respondent is a member of a food cooperative, 0 otherwise.
No Diet	1 if respondent follows no dietary restrictions,[s] 0 otherwise.
Food Job	1 if respondents works in certain food system jobs,[b] 0 otherwise.
Income	Qualitative variable.
	Inc Low: 1 if income is < $5,000 per year, 0 otherwise.
	Inc Med: 1 if income is between $5,000 and $95,000, 0 otherwise.
	Inc High: 1 if income is > $95,000, 0 otherwise.

[a] Dietary restrictions include diabetic diet, low fat diet, high fiber diet, food allergies/sensitivities, vegetarian diet, low sodium diet, kosher sodium diet, and others.

[b] The fields include large scale conventional farming, small scale conventional farming, large scale organic farming, small scale organic farming, dairy farming or livestock farm, food processing, grocery store, cook, caterer or restaurant owner, other agricultural or food processing work.

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