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Stochastic Expected Utility and Prospect Theory in a Horse Race: A Finite Mixture Approach*

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March 20, 2008

Abstract

This study compares the performance of Prospect Theory versus Stochastic Expected Utility Theory at fitting data on decision making under risk. Both theories incorporate well-known deviations from Expected Utility Maximization such as the Allais paradox or the fourfold pattern of risk attitudes. Stochastic Expected Utility Theory parsimoniously extends the standard microeconomic model, whereas Prospect Theory, the benchmark for aggregate choice so far, is based on psychological findings. First, the two theories' fit to representative choice is assessed for two experimental data sets, one Swiss and one Chinese. In a second step, finite mixture regressions reveal a consistent mix of two different behavioral types suggesting that researchers may take individual heterogeneity into account in order to avoid aggregation bias.

KEYWORDS: Stochastic Expected Utility Theory, Prospect Theory, Finite Mixture Models

JEL CLASSIFICATION: D81, C49

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1 Introduction

Many economic decisions, especially the most important ones, such as choosing the optimal career, asset allocation, or partner, involve risky consequences. Even though a sound understanding of how individuals deal with uncertain outcomes is crucial for characterizing various markets' outcomes there is, so far, no single best model for individual decision making under risk. To explain the St. Petersburg Paradox, Daniel Bernoulli hypothesized in 1738 that individuals maximize their expected utility, which is computed as the sum of utilities of a lottery's outcomes weighted by their corresponding probabilities of realization (Bernoulli, 1954). Expected utility became a cornerstone of standard microeconomic theory as it applies to any regular preference relation defined over a finite number of states (von Neumann and Morgenstern, 1947). However, there is abundant empirical evidence indicating that expected utility theory in its standard form is violated (Starmer, 2000). For example, individuals tend to be risk seeking for small-probability gains and large-probability losses, whereas they are risk averse for large-probability gains and small-probability losses. This fourfold pattern of risk attitudes (Tversky and Kahneman, 1992), where individuals switch between risk averse and risk seeking behavior depending on the outcomes' probabilities, is incompatible with expected utility maximization. In light of these descriptive shortcomings of expected utility theory a plethora of alternative decision models have been developed (Starmer, 2000).

The most prominent alternative is Prospect Theory (PT) (Kahneman and Tversky, 1979), which offers a psychologically plausible account of expected utility theory violations, based on the notion of diminishing sensitivity. In PT individuals evaluate prospects with respect to a specific reference point which defines monetary outcomes as gains or as losses. The value functions over gains and over losses are both characterized by declining rates of marginal value and, thus, result in a typical S-shaped curve. As certainty and impossibility constitute obvious reference points as well, any deviations from probabilities of either zero or one are perceived at a diminishing rate of sensitivity, which leads to characteristically inversely S-shaped probability weighting functions. Such a tendency to overweight small and underweight large probabilities, in conjunction with the sign-dependent valuation of monetary outcomes, directly implies a fourfold pattern of risk attitudes. Consequently, PT and its rank-dependent extension to Cumulative Prospect Theory (Tversky and Kahneman, 1992) turn out as some of the best fitting models for aggregate choices (Hey and Orme, 1994; Camerer and Ho, 1994). Besides its descriptive qualities, recent studies in neuroeconomics and evolutionary psychology indicate that PT even seems to have a neuronal representation in the frontal regions of the brain (Trepel et al., 2005; Camerer et al., 2005), the origins of which may be explained by optimal foraging theory (McDermott et al., 2008). To achieve a good fit, however, parametric models based on PT tend to require rather complex specifications and large data sets, which makes estimation at the individual level often difficult. Moreover, PT is silent on the determinants of the reference point for evaluating monetary outcomes.

Another problem common to all deterministic decision models, such as expected utility theory and PT, is their inability to describe preference instability. Various studies report subjects to reverse their preferences in roughly 25%-45% of the cases when facing the same decisions for a second time (Camerer, 1989; Starmer and Sudgen, 1989; Wu, 1994; Hey and Orme, 1994). Since such a behavior contradicts deterministic choice, researchers often introduce some kind of ad-hoc stochastic error to make their models operational. Blavatskyy (2007), on the other hand, develops a more elaborate structure for the error term which constitutes Stochastic Expected Utility Theory's (SEUT) key feature.

In SEUT, individuals behave as expected utility maximizers but make errors when computing a lottery's expected utility. By assumption, the value attributed to any given lottery can never exceed the value of its highest payoff, nor can it fall below the value of its lowest payoff. Since a lottery's most extreme payoffs represent obvious bounds for its valuation, such an assumption not only seems plausible but also is supported by findings of Gneezy et al. (2006) who attribute observed certainty equivalents lying outside the lottery's range solely to errors individuals make when converting payoffs from one denomination to another. Consequently, SEUT implies a truncated error term with a support confined to the lottery's range. Such a truncated error distribution, which is generally asymmetric, directly incorporates the fourfold pattern of risk attitudes, as a lottery's expected utility is likely to get overvalued (undervalued) when it is close to the utility of the lowest (highest) outcome. Since the fourfold pattern in risk taking behavior results from the error structure, SEUT is only a descriptive model and does not explain why empirical violations of expected utility theory come about. Nevertheless, the model remains fairly parsimonious and, as a moderate extension of expected utility theory, fits well into standard microeconomic theory. When comparing SEUT and PT in various well-known data sets, Blavatskyy (2007) attests SEUT a superior performance at describing representative choices. However, these comparisons ignore potential individual heterogeneity and are based on fairly homogeneous subject pools which all stem from developed Western countries.

Furthermore, there is vast heterogeneity in individual risk taking behavior (Hey and Orme, 1994) rendering purely representative agent approaches questionable, especially when markets are imperfect and there is risk of aggregation bias (Fehr and Tyran, 2005). With the advent of finite mixture models in the field (Stahl and Wilson, 1995; El-Gamal and Grether, 1995; Houser et al., 2004), experimental economists are now equipped with a convenient econometric tool to deal with latent individual heterogeneity in a parsimonious way. These models allow identifying and characterizing different behavioral types in the population and provide an endogenous individual classification into these types. Independent studies by Conte et al. (2007) and Bruhin et al. (2007) apply finite mixture specifications to a total of four different experimental data sets on risk taking behavior and find roughly 20% of the participants to behave essentially risk neutrally, whereas the majority of about 80% of the participants clearly exhibit the fourfold pattern of risk attitudes.

For two quite diverse populations, this study first examines PT's and SEUT's performance in fitting aggregate choices. It uses data from two different experiments which were conducted in Zurich, Switzerland as well as in Beijing, People's Republic of China. In both experiments, which have the same basic design in common, the certainty equivalents of a large number of binary lotteries, framed either as gains or losses, are elicited for a total of 271 participants. In contrast to Blavatskyy (2007), the results on the aggregate level are mixed since, depending on the data set, either PT or SEUT superiorly describe a representative agent's choices. In fact, an inspection of the individual mean squared errors reveals that SEUT provides a superior fit compared to PT for only roughly one third of the participants in both data sets. Such stable shares call representative agent approaches into question and suggest a mix of theories, as applied in the second part of the analysis.

To control for individual heterogeneity, a finite mixture model estimates the behavioral parameters of two types, one PT the other SEUT, while it endogenously determines which one of the two theories best describes a specific subject's choices. In both data sets the resulting individual classifications are remarkably clean and robust: With low measures of entropy, about 25% of the subjects are assigned to the SEUT group whereas PT delivers a superior fit for about 75% of the subjects. Moreover, the subjects identified as SEUT types value outcomes linearly and, with only a few exceptions, coincide with the subjects reported to behave risk neutrally by Bruhin et al. (2007), i.e. subjects identified as expected utility types. The participants assigned to the other group seem to distort probabilities by a pattern which is best explained by PT, rather than SEUT.

Thus, previous results on individual heterogeneity that, on average, about one forth of the population seems to behave almost risk neutrally, whereas the majority shows a pronounced fourfold pattern in risk taking behavior are confirmed. Furthermore, even when SEUT fits into general microeconomic theory and describes aggregate choices quite well but not without exceptions, the rigid patterns it imposes on deviations from expected utility seems to prevent it from outperforming PT in a finite mixture context. Consequently, as soon as individual heterogeneity is taken into account, SEUT neither outperforms PT nor does it deliver any additional qualitative insights.

The paper is structured as follows: Section 2 discusses the experimental setup and the procedure applied to elicit the certainty equivalents. Section 3 explains the two theories' formulations as econometric models for representative choice before it introduces the finite mixture specification. Some estimation issues typical to finite mixture models are also briefly addressed in this part. In section 4 the results of the representative choice models as well as the finite mixture model are interpreted. Finally, 5 sums up and concludes.

2 Experimental Design

The study uses experimental data from Bruhin et al. (2007). The experiments were conducted in Zurich 2006 and in Beijing 2005. The participants for the Zurich experiment were randomly selected from the subject pool of the Institute for Empirical Research in Economics consisting of students from various fields of the University of Zurich and the Swiss Federal Institute of Technology Zurich. The Chinese subjects were recruited by flier among the students of Peking University and Tsinhua University. As both experiments have the same basic design in common, this section presents the Zurich experiment in detail and discusses in which respects the experimental design in Beijing 2005 deviates. Table 1 summarizes the most important differences between the two experiments.

Table 1: Differences in Experimental Design

	Zurich 06	Beijing 05
Number of:		
Subjects	118	153
Lotteries	40	28
Observations	4,669	4,281
Procedure	computerized	paper and pencil

The experiments both aimed at eliciting participants' certainty equivalents for 28 to 40 two-outcome lotteries. One half of the lotteries were framed as choices between risky and certain gains ("gain domain"), the other half as options between risky and certain losses ("loss domain"). For each lottery in the loss domain the participants received an initial monetary endowment to cover their potential losses.

The certainty equivalents were elicited by applying the following choice menu (Kahneman et al., 1991): For any given lottery under consideration the decision sheet contained two options, the lottery and a certain outcome which varied in 20 equal steps from the lottery's maximum payoff to the lottery's minimum payoff, as shown in Figure 1. For each row the subjects had to reveal whether they prefer the lottery or the actual certain payoff. The certainty equivalent was calculated as the arithmetic mean between the smallest certain amount preferred to the lottery and the subsequent certain amount, were the lottery was first chosen. In the example depicted in Figure 1 the subject's choices are indicated by the small circles implying a certainty equivalent of 13.5 Swiss Francs.[1] The experiment conducted in Zurich used a computerized procedure programmed in the software z-Tree (Fischbacher, 2007) whereas in Beijing the decision sheets were printed out on paper. In both experiments the lotteries appeared in random order.

Figure 1: Design of the Decision Sheet

Decision situation:
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	Option A	**Your Choice:**				**Option B Guaranteed payoff amounting to:**
1		A		o	B	20
2		A		o	B	19
3		A		o	B	18
4		A		o	B	17
5		A		o	B	16
6		A		o	B	15
7	A profit of CHF 20 with	A		o	B	14
8		A	o		B	13
9	probability 75%	A	o		B	12
10		A	o		B	11
11	and a profit of CHF 0 with	A	o		B	10
12		A	o		B	9
13	probability 25%	A	o		B	8
14		A	o		B	7
15		A	o		B	6
16		A	o		B	5
17		A	o		B	4
18		A	o		B	3
19		A	o		B	2
20		A	o		B	1

OK

[1] One Swiss Franc equals about one U.S. dollars.

Table 2: Gain Lotteries $(x_1, p; x_2)$

Zurich 06						Beijing 05					
p	x_1	x_2	p	x_1	x_2	p	x_1	x_2	p	x_1	x_2
0.05	40	0	0.50	20	0	0.05	15	4	0.75	20	7
0.05	40	10	0.50	20	10	0.05	20	7	0.90	7	4
0.05	50	20	0.50	40	10	0.05	55	20	0.95	15	4
0.05	150	50	0.50	50	20	0.10	7	4	0.95	20	7
0.10	20	10	0.75	40	10	0.25	15	4			
0.10	150	0	0.75	50	20	0.25	20	7			
0.25	40	0	0.90	20	10	0.50	7	4			
0.25	40	10	0.95	40	10	0.50	15	4			
0.25	50	20	0.95	50	0	0.50	20	7			
0.50	10	0	0.95	50	20	0.75	15	4			

Outcomes are denominated in Swiss Francs (Zurich 2006) and Chinese Yuan (Beijing 2005), respectively.

Payoffs per subject averaged out at approximately 31 Swiss Francs and 20 Chinese Yuan, considerably more than a local student assistant's hourly compensation, plus a show up fee of 10 Swiss Francs and 20 Chinese Yuan, respectively, thus generating salient incentives[2]. In Zurich the lotteries' outcomes, x_1 and x_2, varied between zero to 150 Swiss francs. The payoffs in the Beijing 2005 experiment were comparable in terms of typical local stundent's compensation and ranged from zero to 55 Chinese Yuan. Probabilities p of the lotteries' higher gain or loss x_1 varied between 5% and 95%. Table 2 shows the two experiments' lotteries in the gain domain.

After reading the instructions, the subjects had to correctly calculate the payoffs for two hypothetical choices before they were permitted to start working on the experimental decisions.[3] In the computerized experiments, there were two trial rounds to familiarize the subjects with the procedure. At the end of the experiment, one row number of one decision sheet was randomly selected for each subject, and the subject's choice in that row determined her payment. The subjects were paid in private afterward. They could work at their own speed, the vast majority of them needed less than an hour to complete the experiment.

[2] One Chinese Yuan equals about 0.14 U.S. dollars.

[3] The instructions are available on request.

3 Econometric Models

This section covers the econometric models' formulation and some associated estimation issues. The first two models for fitting aggregate choices are based on a single decision model, SEUT or PT, respectively. The third specification, a finite mixture model, combines these two approaches by simultaneously estimating the behavioral parameters of a group of SEUT as well as PT types. As such a model endogenously determines which of the two decision models best describes a specific subject's choices, it provides an estimate of their respective shares among the population. This procedure yields a basis for deciding whether to take potential heterogeneity into account or to assume a representative decision maker.

3.1 Prospect Theory for Representative Choice

In PT a subject $i \in \{1, \ldots, N\}$ values any given lottery $\mathcal{G}_g = (x_{1g}, p_g; x_{2g})$, $g \in \{1, \ldots, G\}$, where $|x_{1g}| > |x_{2g}|$, by

$$v\left(\mathcal{G}_g\right) = v\left(x_{1g}\right) w\left(p_g\right) + v\left(x_{2g}\right)\left(1 - w\left(p_g\right)\right). \tag{1}$$

The sign-dependent function $v(x)$ denotes how monetary outcomes, x, are valued, whereas $w(p)$ assigns a subjective weight to every outcome probability, p. The gambles certainty equivalent $\hat{ce}_g$ can be written as

$$\hat{ce}_g = v^{-1}\left[v\left(x_{1g}\right) w\left(p_g\right) + v\left(x_{2g}\right)\left(1 - w\left(p_g\right)\right)\right]. \tag{2}$$

To make the model operational both the value function, $v(x)$, and the probability weights, $w(p)$, need to be specified by assuming a functional form. A natural candidate for $v(x)$ is a sign-dependent power function

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -(-x)^{\beta} & \text{otherwise,} \end{cases} \tag{3}$$

which has a convenient interpretation and turned out to be the best compromise between parsimony and goodness of fit in the context of PT (Stott, 2006). The probability weighting curve, $w(p)$, is modeled as two-parameter function as proposed by Goldstein and Einhorn (1987) and Lattimore et al. (1992):

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}, \ \delta \geq 0, \gamma \geq 0. \tag{4}$$

This specification has not only proven to account well for individual heterogeneity (Wu et al., 2004) but also its parameters have a neat interpretation: The parameter γ largely governs the slope of the curve, whereas the parameter δ largely governs its elevation. The smaller the value of γ, the more strongly the probability weighting function deviates from linear weighting. The larger the value of δ, the more elevated the curve, ceteris paribus. Linear weighting is characterized by $\gamma = \delta = 1$. In a sign-dependent model, the parameters may take on different values for gains and for losses.

As PT explains *deterministic* choice a stochastic error term needs to be assumed in order to estimate the model's parameters based on the elicited certainty equivalents, ce_{ig}. There could be many different sources of error, such as carelessness, hurry or inattentiveness, resulting in wrong answers. Thus, as suggested by Hey and Orme (1994), the model assumes an additive Fechner-type error ϵ_{ig}, such that $ce_{ig} = \hat{ce}_g + \epsilon_{ig}$. The Central Limit Theorem indicates that the errors are normally distributed and simply add white noise. Furthermore, the model has to account for heteroskedasticity in the error variance. For each lottery the subjects have to consider 20 certain outcomes, which are equally spaced throughout the lottery's range $|x_{1g} - x_{2g}|$. Since the observed certainty equivalents ce_{ig} are calculated as the arithmetic mean of the smallest certain amount preferred to the lottery and the subsequent certain amount the measurement error in the model's dependent variable is proportional to the lottery range. This yields the form $\sigma_g = \sigma|x_{1g} - x_{2g}|$ for the standard deviation of the error term distribution, where σ denotes an additional parameter to be estimated.

Given these assumptions on the distribution of the error term, the individual contribution to the model's likelihood can be expressed as

$$f\left(ce_i, \mathcal{G}; \theta\right) = \prod_{g=1}^{G} \frac{1}{\sigma_g} \phi\left(\frac{ce_{ig} - \hat{ce}_g}{\sigma_g}\right), \tag{5}$$

where ϕ denotes the density of the standard normal distribution. The vector of parameters, $\theta = (\alpha, \beta, \gamma', \delta', \sigma)'$ is estimated by maximizing the model's likelihood given by the product of (5) over all individuals.

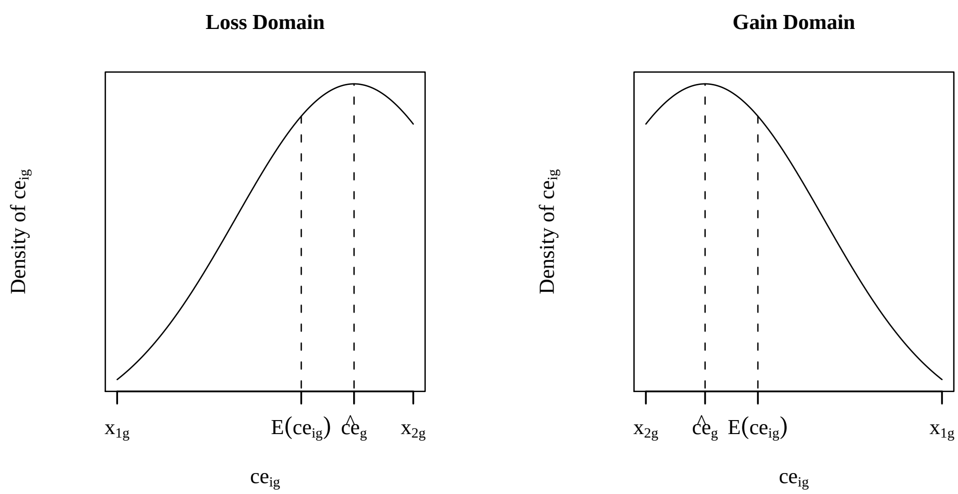
3.2 Stochastic Expected Utility Theory for Representative Choice

In the standard microeconomic model with deterministic preferences a given lottery $\mathcal{G}_g$ is valued by its expected utility, which implies the following certainty equivalent

$$\hat{ce}_g = u^{-1}\left[u\left(x_{1g}\right)p_g + u\left(x_{2g}\right)\left(1 - p_g\right)\right], \tag{6}$$

where $u(x)$ represents a subjective utility function. A convenient parametric specification in terms of interpretability and parsimony is, again, a power function, $u(x) = |x|^{\eta}$, where η measures $u(x)$'s curvature.

Figure 2: Distribution of ce_{ig} under SEUT ($p_g = 0.2$, $\xi = 0.4|x_{1g} - x_{2g}|$, $\eta = 1$)



As a purely descriptive theory, SEUT does not aim at explaining the fundamentals underlying such robust phenomena as the fourfold pattern. Hence, subjects do not explicitly distort probabilities, but they are allowed to make random errors when computing the expected utility of a risky lottery. However, as the lottery's most extreme payoffs represent obvious bounds, SEUT assumes that a lottery's value cannot exceed the value of its highest outcome nor can it fall below the value of its lowest outcome. Thus, instead of applying the standard Fechner model with symmetric and unbounded errors, Blavatskyy (2007) suggests truncating the error term, ω_{ig}, at $x_{1g} - \hat{ce}_g$ and at $x_{2g} - \hat{ce}_g$, so that the certainty equivalent $ce_{ig} = \hat{ce}_g + \omega_{ig}$ is limited to lie within the lottery's range, x_{1g} and x_{2g}. As Figure 2 illustrates, ce_{ig} can only be symmetrically distributed if $p = 0.5$, and is the more asymmetrically distributed the more p differs from 0.5. Consequently, for $p \neq 0.5$, the expected error $\text{E}(\omega_{ig}) \neq 0$, and ce_{ig} deviates from $\hat{ce}_g$ with a higher probability towards the lottery's center than towards its bounds. So in the gain (loss) domain for $p < 0.5$, the realized certainty equivalent, ce_{ig}, tends to be larger (smaller) than the value predicted by expected utility theory, $\hat{ce}_g$. A decision maker behaving according to SEUT, therefore, still exhibits a specific fourfold pattern in her choices which is driven by stochastic errors, even if she weights probabilities completely linearly.

Analogous to the assumed structure in the PT model, ω_{ig} has a (truncated) normal distribution and is affected by the same source of heteroskedasticity, i.e., its standard deviation is denoted by $\xi_g = \xi\,|x_{1g} - x_{2g}|$, with an unknown parameter ξ. Under these assumptions, the individual contribution to the model's likelihood can be written as

$$h\left(ce_i, \mathcal{G}; \psi\right) = \prod_{g=1}^{G} \frac{\frac{1}{\xi_g}\phi\left(\frac{ce_{ig} - \hat{ce}_g}{\xi_g}\right)}{\left|\Phi\left(\frac{x_1 - \hat{ce}_g}{\xi_g}\right) - \Phi\left(\frac{x_2 - \hat{ce}_g}{\xi_g}\right)\right|}\ , \tag{7}$$

where Φ denotes the standard normal's cumulative distribution function. Taking the product over all individuals and maximizing the resulting likelihood function yields the maximum likelihood estimates of the model's parameters $\psi = (\eta, \xi)'$.

3.3 Finite Mixture Model to Control for Heterogeneity

Since there is evidence for individual heterogeneity in risk taking behavior (Hey and Orme, 1994), aggregating the data and estimating one single decision model veils potentially important behavioral differences and may deliver misleading results. However, estimating all decision models under consideration for each participant separately is highly inefficient and is often rendered impossible by the limited amount of data available per individual. Furthermore, to draw meaningful conclusions, the subjects would still need to be classified by some method into different groups, based on their estimated behavioral parameters.

Thus, instead of operating at the individual level, the finite mixture model proposed here relaxes the assumption of one single representative decision maker by introducing two behavioral types, one PT the other SEUT. *A priori* an individual i's group membership is unknown. Hence, her contribution to the model's likelihood consists of the two decision models' individual likelihoods, (5) and (7), weighted by the probability that she belongs to the respective type:

$$\ell\left(\Psi; ce_i, \mathcal{G}\right) = \pi_{SEUT}\, h\left(ce_i, \mathcal{G}; \psi\right) + \left(1 - \pi_{SEUT}\right)\, f\left(ce_i, \mathcal{G}; \theta\right)\ , \tag{8}$$

where the vector $\Psi = \left(\eta, \alpha, \beta, \gamma', \delta', \xi, \sigma, \pi_{SEUT}\right)'$ contains all the model's parameters. Note that the probability of being drawn from the SEUT group, π_{SEUT}, equals the fraction of SEUT types among the population and needs to be estimated too. After taking logs, the product over all individuals of (8) represents the finite mixture model's log likelihood

$$\ln L\left(\Psi; ce, \mathcal{G}\right) = \sum_{i=1}^{N} \ln\left[\pi_{SEUT}\, h\left(ce_i, \mathcal{G}; \psi\right) + \left(1 - \pi_{SEUT}\right)\, f\left(ce_i, \mathcal{G}; \theta\right)\right]. \tag{9}$$

As any finite mixture model's likelihood, (9) is highly nonlinear even after taking logs and the log likelihood still contains products, π_{SEUT}, cannot be estimated separately from the two types' average parameters, ψ and θ, respectively. Moreover, (9) may be multimodal and unbounded (for more details see McLachlan and Peel (2000) and Render and Walker (1984)), which renders direct maximum likelihood estimation difficult. In order to cope with these problems effectively, the estimation routine, programmed in the R environment (R Development Core Team, 2006), first applies the Expectation Maximization (EM) algorithm (Dempster et al., 1977) before it switches to the much faster BFGS algorithm.[4] The EM algorithm iteratively proceeds in two steps, E and M. During the E-step, an individual *a posteriori* probability of belonging to the SEUT-group, $\tau_{i,SEUT}$, is computed given the actual fit of the data, $\hat{\Psi}$:

$$\tau_{i,SEUT} = \frac{h\left(ce_i, \mathcal{G}; \hat{\psi}\right)}{\hat{\pi}_{SEUT}\, h\left(ce_i, \mathcal{G}; \hat{\psi}\right) + \left(1 - \hat{\pi}_{SEUT}\right)\, f\left(ce_i, \mathcal{G}; \hat{\theta}\right)} \tag{10}$$

In the following M-step, the model's so called complete data log likelihood is maximized, where $\tau_{i,SEUT}$ replaces unobserved individual group membership. This yields an analytical expression for the relative group size's update, $\hat{\pi}_{SEUT} = 1/N \sum_{i=1}^{N} \tau_{i,SEUT}$, which is computed separately from the model's remaining parameter updates: $\hat{\theta}$ and $\hat{\psi}$. Furthermore, after convergence is achieved, the individual probabilities, $\tau_{i,SEUT}$, obtained at the maximum likelihood estimate, not only provide a way of endogenously assigning the subjects to either of the two types, but also, they allow to assess how well the two groups are segregated. A clean segregation reflects good performance at capturing individual heterogeneity, whereas relatively high levels of ambiguity in individual group assignment may indicate overfitting, lack of identification, or misspecification.

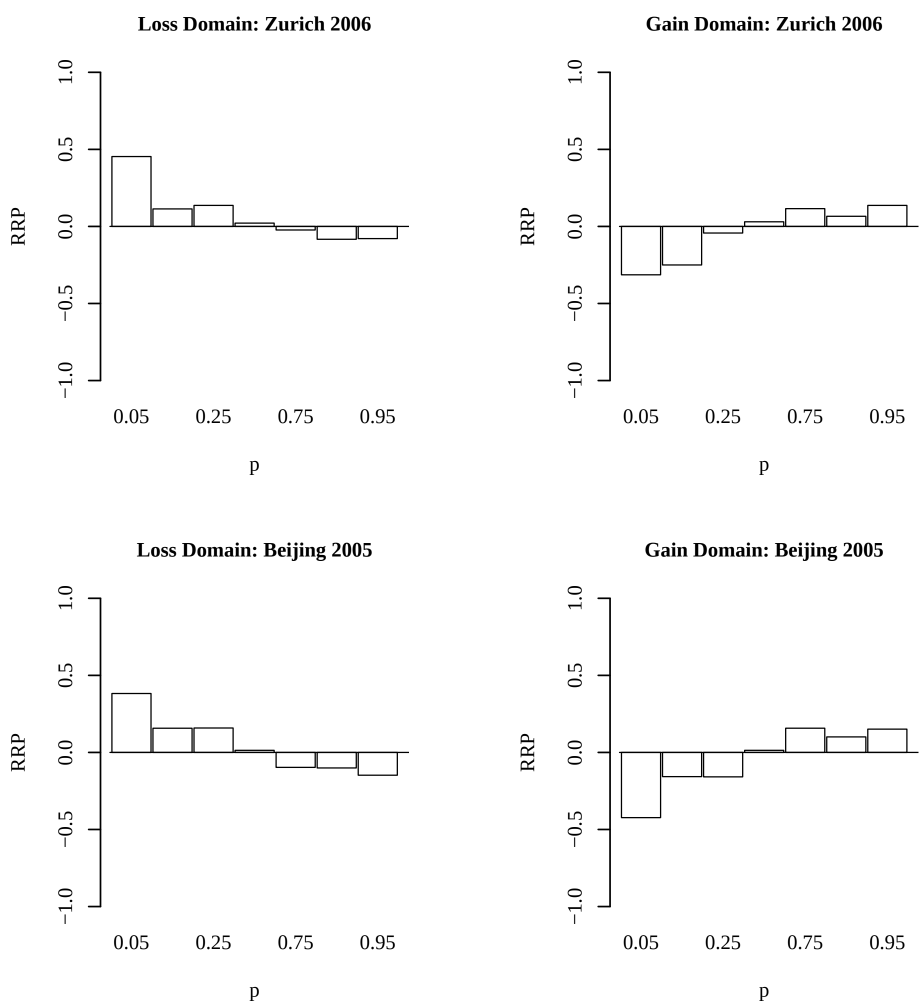
4 Results

The first part of this section discusses the fourfold pattern in risk taking behavior which is found in both data sets. As both theories, PT and SEUT, are able to describe this pattern their goodness of fit for aggregate choices is assessed in a second part. The last part accounts for potential heterogeneity and interprets the finite mixture regressions by inspecting the two type's relative sizes and behavioral parameters, as well as by assesssing the ambiguity in individual group assignment.

The data of both experiments clearly exhibit the fourfold pattern of risk attitudes, which violates expected utility theory. In Figure 3, the bars represent the median value of the observed relative

[4] The Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm is a Quasi-Newton method which allows solving unconstrained non-linear optimization problems (see for example Broyden (1970)). It is one of the standard hill-climbing optimization routines implemented in the R environment as well as other statistical packages such as STATA.

Figure 3: Observed Median Relative Risk Premia by p



risk premia, $RRP = (ev - ce)/|ev|$, where ev denotes the lottery's expected value, sorted by the probability p that the most extreme payoff is realized. Thus, people are risk averse ($RRP > 0$) for small-probability losses and large-probability gains, whereas they are risk seeking ($RRP < 0$) for large-probability losses and small-probability gains.

4.1 Representative Choice

For both data sets, Tables 3 and 4 show the maximum likelihood estimates of the representative PT and SEUT models, respectively. The standard errors, in parentheses, are based on the bootstrap method with 2,000 replications (Efron and Tibshirani, 1993).

Table 3: Cumulative Prospect Theory Regressions

Parameter Estimates	Zurich 06	Beijing 05
Gain Domain		
α	0.910	0.451
	(0.025)	(0.115)
γ	0.455	0.293
	(0.010)	(0.009)
δ	0.867	1.316
	(0.022)	(0.083)
Loss Domain		
β	1.123	1.202
	(0.045)	(0.127)
γ	0.490	0.352
	(0.010)	(0.009)
δ	1.040	0.887
	(0.037)	(0.163)
σ	0.146	0.163
	(0.002)	(0.002)
$\ln L$	10,089	9,149
BIC	-20,119	-18,239

Standard errors (in parentheses) are based on the bootstrap method with 2,000 replications.

In the case of PT, as depicted in Table 3, the estimated α and β are both close to unity for the Swiss subjects indicating an almost linear value function. Hence, for gains as well as for losses, the Swiss participants' observed risk attitudes are mostly driven by nonlinear probability weighting: With γ smaller than one and δ close to unity, the estimated probability weighting curve is inversely S-shaped as typically found in other studies (Stott, 2006; Wu et al., 2004). The Chinese people, on the other hand, value monetary gains at a declining rate of marginal utility ($\alpha = 0.451$), while they weight probabilities much more optimistically than their Swiss colleagues. The smaller value of $\gamma = 0.293$ makes them less sensitive to changes in probabilities, whereas the larger $\delta = 1.316$ corresponds to a generally more elevated probability weighting function. For losses, however, there is no substantial cultural difference, as in both data sets the participants' value functions are only slightly curved and the probability weights are clearly inversely S-shaped. The estimates of σ correspond to an average standard deviation of the error term lying between 14.6% and 16.3% of the lotteries' ranges.

Table 4: Stochastic Expected Utility Regressions

Parameter Estimate	Zurich 06	Beijing 05
η	0.952	0.947
	(0.016)	(0.059)
ξ	0.211	0.283
	(0.004)	(0.004)
$\ln L$	10,094	8,796
BIC	-20,171	-17,576

Standard errors (in parentheses) are based on the bootstrap method with 2,000 replications.

The results for SEUT, on the other hand, are depicted in Table 4. The model's only behavioral parameter, η, is estimated to lie in the vicinity of one which implies an almost linear utility function for the Swiss as well as the Chinese subjects. In SEUT, deviations from expected utility theory are directly related to the model's asymmetric error structure. So, the pronounced fourfold pattern observed in the data immediately translates into relatively high estimates for the error's standard deviation, ξ.

Regardless of its more rigid specification, which requires five parameters fewer than PT, SEUT achieves a better fit to the Zurich data even in terms of log likelihood. This is in line with recent findings by Blavatskyy (2007) who reports a good fit of SEUT to several data sets on aggregate choices from different Western countries. In the Beijing data set, however, PT performs better, even when being judged by the Bayesian Information Criterion (BIC), which penalizes its less parsimonious specification ($BIC_{PT} = -18,239$ vs. $BIC_{SEUT} = -17,576$). As mentioned before and indicated by the estimates in Table 3, the Chinese subjects judge risky prospects asymmetrically between the gain and loss domain, which cannot be fitted by the model based on SEUT. This may be a reason for SEUT's inferior performance.

Moreover, since these mixed results on the aggregate level may reflect individual heterogeneity, I assess the models' goodness of fit based on the individual mean squared errors in relative risk premia over all lotteries, $MSE_i = 1/G \sum_{g=1}^{G} \left(\widehat{RRP}_g - RRP_{ig}\right)^2$, which increases in the differences between the predicted $\widehat{RRP}_g$ and the observed RRP_{ig} relative risk premia. Comparing the MSE_i between PT and SEUT indeed reveals some individual heterogeneity in the data: In Zurich and Beijing the share of participants for which SEUT performs better, i.e. delivers smaller MSE_i than PT, amounts to 38% and 36%, respectively. Even though the relative overall performance of SEUT seems to be superior for the Swiss and inferior for the Chinese data, the fraction of people for which it leads to smaller MSE_i is robust. By requiring only two parameters to be estimated SEUT is very parsimonious, but the other side of the coin is that the pattern of deviations from expected utility theory is rigidly determined by the shape of the truncated normal distribution and its standard deviation (see Figure 2 for an illustration). So, its overall performance may react quite sensitively to outliers, domain-specific behavioral asymmetry and the overall composition of the data sets.

4.2 Finite Mixture Model

The fact that in both data sets PT and SEUT seem to superiorly fit the subjects' choices by a ratio of about 6:4, suggests using a mix of both theories rather than estimating just one single decision model. Indeed, the BIC reported in Table 5 consistently attributes a better performance to the finite mixture regressions than to either of the two representative choice models. Examining the posterior probabilities of individual group membership, $\tau_{i,SEUT}$, allows to assess how well the individual heterogeneity is captured by the assumption of two behavioral types. If the subjects are cleanly segregated all the $\tau_{i,SEUT}$ are either close to zero, indicating members of the PT group, or are close to one, indicating members of the SEUT group. The histograms in Figure 4 show the distribution of these probabilities of individual group membership for the two estimated finite mixture regressions. By exhibiting only two prominent spikes, one close to $\tau_{i,SEUT} = 0$ the other

Table 5: Finite Mixture Regressions

Parameter Estimates	Zurich 06	Beijing 05
Share of SEUT Types: π_{SEUT}	0.288	0.223
	(0.096)	(0.030)
η	0.974	0.974
	(0.018)	(0.056)
ξ	0.112	0.127
	(0.059)	(0.070)
Share of PT Types: $1 - \pi_{SEUT}$	0.712	0.777
	(0.096)	(0.030)
Gain Domain		
α	0.902	0.377
	(0.035)	(0.132)
γ	0.372	0.212
	(0.027)	(0.013)
δ	0.843	1.371
	(0.033)	(0.099)
Loss Domain		
β	1.167	1.197
	(0.075)	(0.147)
γ	0.398	0.272
	(0.028)	(0.013)
δ	1.029	0.885
	(0.059)	(0.070)
σ	0.151	0.160
	(0.033)	(0.099)
$\ln L$	10,603	9,636
BIC	-21,122	-19,188
ANE	0.048	0.007
Number of Observations	4,669	4,281

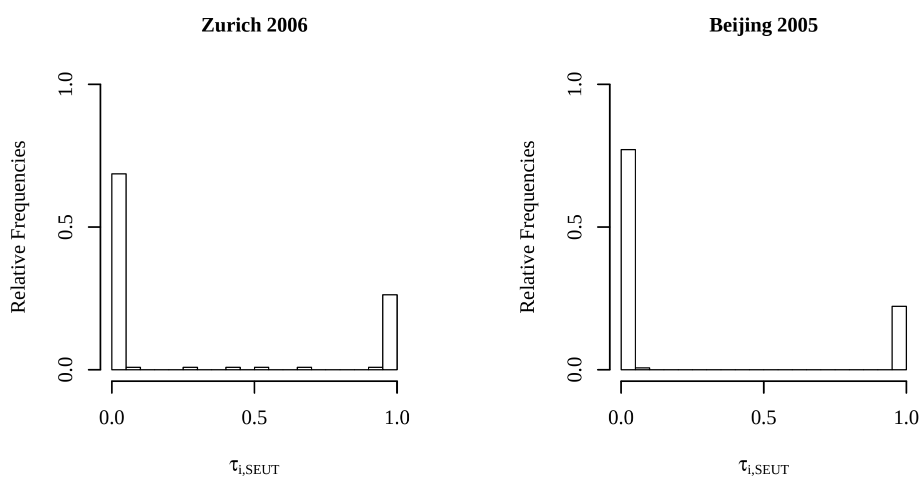
Standard errors (in parentheses) are based on the bootstrap method with 2,000 replications.

close to $\tau_{i,SEUT} = 1$, the histograms reveal graphically that individual group assignment is very clean in both data sets. Another way of assessing the quality of individual group assignment is to look at some measure of entropy which maps the ambiguity in $\tau_{i,SEUT}$ into a single number. For example, the Average Normalized Entropy (El-Gamal and Grether, 1995) defined as

$$ANE = -1/N \sum_{i=1}^{N} \tau_{i,SEUT} \log_2 (\tau_{i,SEUT}) + (1 - \tau_{i,SEUT}) \log_2 (1 - \tau_{i,SEUT}) \tag{11}$$

is normalized to lie within $[0, 1]$. In the case of perfect individual group assignment all $\tau_{i,SEUT}$ equal zero or one, implying $ANE = 0$. $ANE = 1$, on the other hand, reflects complete ambiguity, i.e. all the $\tau_{i,SEUT} = 0.5$, and a failure of classification. Table 5 reveals that the ANE only amounts to 0.7% and 4.8% of its maximum value, respectively. These low numbers of entropy, again, reflect the remarkably good performance of the finite mixture model in dealing with individual heterogeneity by cleanly classifying each subject either as a SEUT or a PT type. So, while staying fairly parsimonious the finite mixture model consistently achieves a lower BIC and maps individual heterogeneity very well. Hence for purely statistical reasons, it may be preferred over a representative agent approach.

Figure 4: Probability Distribution of Individual Group Membership



Whether the individual classification into a SEUT and PT group also bears economic meaning can be assessed on the basis of the corresponding behavioral parameters, ψ and θ, and the mixing proportion, π_{SEUT}. And indeed, by looking at the estimates shown in Table 5, a consistent picture emerges:

The SEUT types are estimated to constitute 28.8% and 22.3% of the population, respectively.

Figure 5: Observed Median Relative Risk Premia by p and Type (Zurich 2006)

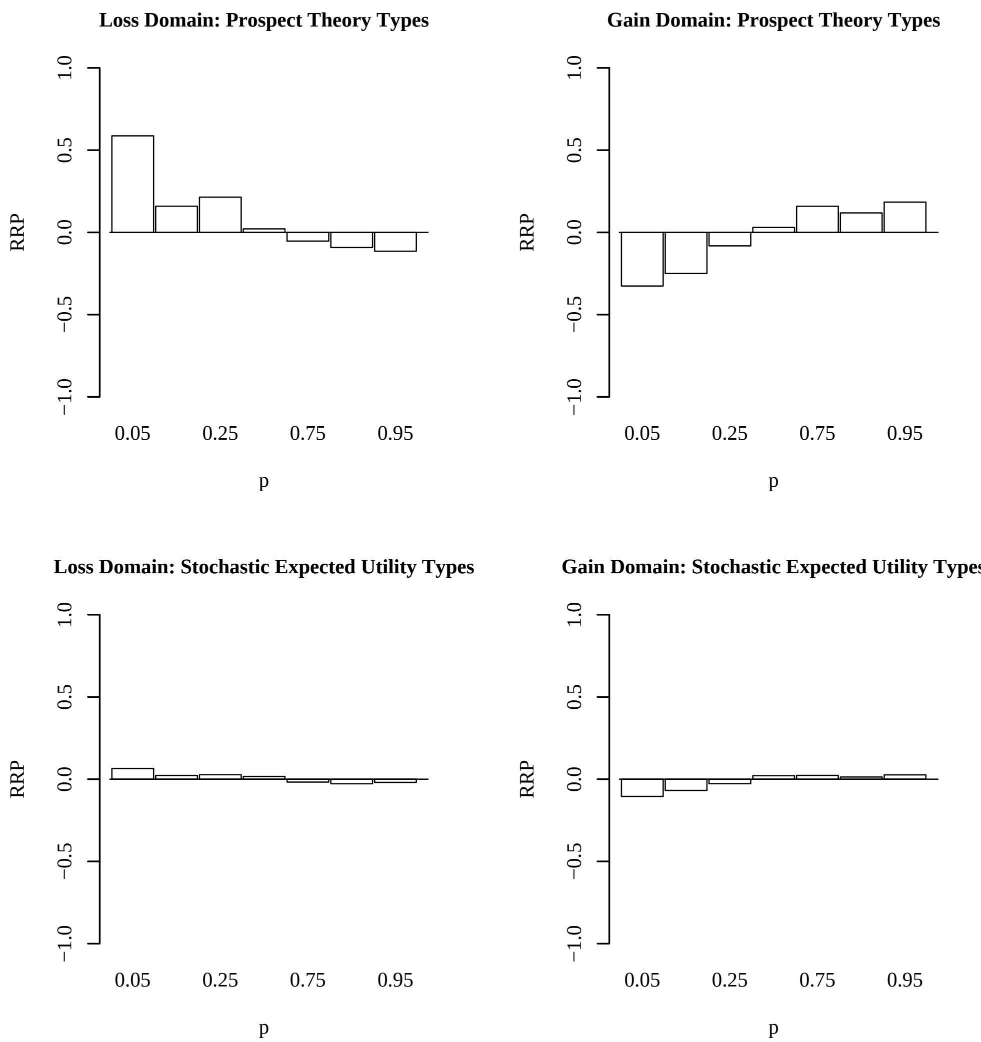
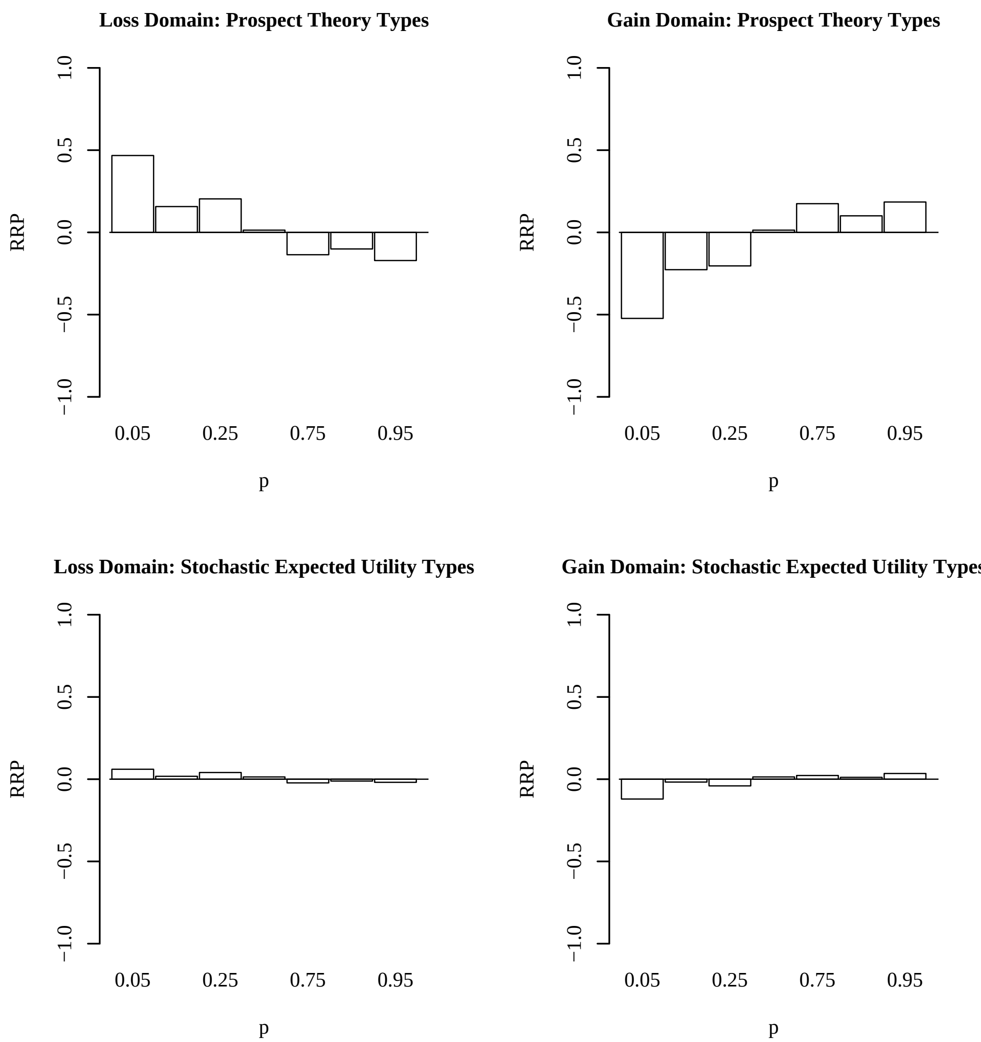


Figure 6: Observed Median Relative Risk Premia by p and Type (Beijing 2005)



Their underlying utility function $u(x)$ is, on average, almost linear with an estimated $\eta = 0.974$. In contrast to the SEUT model for representative choice, the estimates of the error's standard deviation, ξ, amount to only 11.2% and 12.7% of the lotteries' ranges. The deviations from standard expected utility theory are therefore much less pronounced than in the aggregate model. In conjunction with the nearly linear utility function, this implies a behavior much closer to risk neutrality than predicted by the previously discussed SEUT model for representative choice.

To separate the two groups, each subject i in the sample is labeled either as PT type ($\tau_{i,SEUT} < 0.5$) or as SEUT type ($\tau_{i,SEUT} \geq 0.5$) after the estimation of the finite mixture model. After such a separation by type, Figure 5 and 6 show the median observed relative risk premia sorted by p for the Swiss and Chinese data, respectively. The observed relative risk premia of the participants classified as SEUT types are indeed close to zero over p's entire range, which reflects an almost risk neutral behavior, as illustrated in the lower panels of Figure 5 and 6. Furthermore, according to Bruhin et al. (2007), the shares of nearly risk neutral participants amount to 22.4% in Zurich 2006 and 20.1% in Beijing 2005 when a mixture model of two different PT types is estimated, instead of assuming one SEUT and one PT type. With the exception of only 8 and 3 subjects, respectively, the individual classifications found here coincide with the ones reported by Bruhin et al. (2007). So, assuming two behavioral types, one SEUT and the other PT, reproduces previous findings by Conte et al. (2007) and Bruhin et al. (2007) that about one fourth of the individuals can, on average, essentially be characterized as expected value maximizers.

Given the observed relative risk premia as shown in Figure 3, it comes at no surprise that the majority of participants, labeled as PT types, exhibit a pronounced fourfold pattern of risk attitudes, as depicted in the upper panels in Figures 5 and 6. In Zurich as well as Beijing the PT types are estimated to consitute 77.7% and 71.2% of the population, respectively. Their behavioral parameters are qualitatively equivalent to the ones estimated in the PT model for representative choice: The Swiss value functions are only slightly curved ($\alpha = 0.902$, $\beta = 1.167$) whereas, at least for gains, Chinese marginal valuation changes at a steeper rate ($\alpha = 0.377$). Analogous to the case of representative choice, the estimates of γ and δ translate into a probability weighting function exhibiting the characteristic inverse S-shape. And again, when considering small-probability gains, the Chinese participants seem to be more optimistic, as their probability weights are more elevated ($\delta = 1.316$) and less sensitive to changes in p ($\gamma = 0.293$).

Thus, estimating a finite mixture model to account for individual heterogeneity instead of modeling representative choice does not only lead to a better fit to the data but also consistently identifies two distinct behavioral types with a neat economic interpretation: A minority of about 25% behave in an almost risk neutral way, and a majority of about 75% exhibit strong probability distortions best described by a sign-dependent model such as PT. Even though being well suited for describing representative choice, in a finite mixture context SEUT does neither deliver any additional insights nor does it simplify the model's interpretation. In spite of the mixed results for aggregate choice, SEUT is a tempting option if the researcher wants to mildly extend standard microeconomic theory and to parsimoniously model a representative agent's choices. But if markets are imperfect, she wants to avoid aggregation bias and take individual heterogeneity into account (Fehr and Tyran, 2005) and, therefore, may opt for a finite mixture specification where SEUT offers barely any advantages over PT.

5 Conclusion

This study compared PT's and SEUT's performance at describing individual decision making under risk in two experimental data sets, one Swiss the other Chinese. On the aggregate level the results are mixed: In conformity with the findings reported by Blavatskyy (2007) for various data sets from other Western countries SEUT clearly outperforms PT in the Swiss data set. In China, however, subjects weight probabilities for gains on average more optimistically and exhibit stronger curvature in their value function. Since SEUT imposes a rigid pattern for deviations from expected utility maximization and cannot cope with behavioral asymmetries between gains and losses, it fits the Chinese data inferiorly when being compared to a more flexible sign-dependent specification such as PT. Furthermore, the finding that both PT and SEUT superiorly describe the choices of a consistent fraction of subjects each calls a representative agent approach into question.

Indeed, the finite mixture regressions, which control for individual heterogeneity by assuming a mix of PT and SEUT types, reveal a coherent picture: In both data sets the mixture model cleanly segregates the subjects into an SEUT and a PT group. Roughly 25% of the individuals are identified as SEUT types and behave essentially risk neutrally, whereas the choices of the remaining 75% are best described by PT. Recent studies estimating finite mixture models based on PT and expected utility theory only report a segregation into two behaviorally similar types (Conte et al., 2007; Bruhin et al., 2007). Moreover, the individual classification found in this study by and large coincides with the one reported in Bruhin et al. (2007). This supports the notion that about one fourth of the subjects can be characterized basically as expected value maximizers.

Despite its parsimony SEUT shows good descriptive power when fitting aggregate choices and, as a modest extension to expected utility theory, molds well into standard microeconomic theory. However, as soon as the often unrealistic assumption of one single representative agent is relaxed, its rigidity causes SEUT to fall short of PT's performance in describing decision making under risk for the majority group of subjects violating expected utility theory. Consequently, its parsimony may make SEUT an elegant option to model aggregate outcomes on perfect markets, but when individual heterogeneity has to be taken into account a flexible sign-dependent specification based on PT is the superior choice.

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