HUMAN BEHAVIOR AND PERFORMANCE:

AN EMPIRICAL INVESTIGATION OF LOSS AVERSION

by

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Abstract

Empirical research in experimental and behavioral economics suggests that actual decision makers value losses significantly higher than objectively commensurate gains -- a behavior commonly referred to as *loss aversion* or the *endowment effect*. The prevalence of such "irrational" behavior raises pertinent issues with respect to the validity and reliability of normative economic theory and applied economic analysis. We report the results of three distinct empirical investigations intended to provide a better understanding of valuation asymmetries *per se* and to shed light on the relation of loss averse behavior and human performance in the market place.

The first study provides both within- and between-subject tests of the endowment effect and investigates the presumption that people's disparate valuations of willingness to pay (WTP) and willingness to accept (WTA) is an artifact of substitutability between commodities. A within-subject, real exchange market experiment providing for a high degree of substitutability in the exchange commodities was conducted. The results indicate that large and significant between-subject and, more importantly, within-subject valuation disparities prevailed despite the closeness of the substitution between goods.

The second study is comprised of an empirical investigation of the performance of asymmetric valuation patterns in comparison to the normatively presumed and prescribed symmetric valuations. We simulate a finite decision environment and compare payoffs and survival rates of populations of artificial agents adhering either to loss averse or normative valuation characteristics. The results suggest that even for perfectly stylized but finite problem domains, loss averse agents perform at least at par with their normative counterparts in terms of returns over a series of risky prospects and population survival rates for loss averse agents is significantly higher than that of normative benchmark agents.

The third and final study investigates the emergence of valuation and preference structures. Simulation experiments employing evolutionary methodology were conducted for both routine and non-routine decision contexts. The results of these experiments suggest asymmetric valuation patterns to be a robust emerging preference and valuation property for maximizing, adaptive decision makers.

Dedication

To my mother.

Acknowledgments

The studies and work that preceded this dissertation goes back many years and started during the later semesters of my undergraduate studies. Along this way several people have been repeatedly extremely knowledgeable, supportive, and helpful and I would like to thank them.

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Introduction

An important aspect of economic (decision) theory concerns the notion of agents' valuation characteristics providing the foundation to such critical aspects of economic theory such as utility and expected utility theories. Agents' valuations, i.e. the transformation of objective outcomes to some agent-specific subjective value, have a long history in economics dating back to early empirical work by Bernoulli (1738).

Empirical evidence from the areas of experimental economic and behavioral decision research, however, portrays a picture vastly different from the conventional prescriptive course of action. That is, actual agent valuations are seemingly asymmetric valuing losses much heavier than objectively commensurate gains (e.g., Kahneman, and Tversky, 1979; Thaler, 1980; Knetsch and Sinden, 1987). The pervasive nature of this "irrational" valuation behavior, generally termed *loss aversion* or the *endowment effect* (Kahneman and Tversky, 1979; Thaler, 1980) has several nontrivial implications. First, the existing, descriptive literature strongly suggests that even if the actions chosen by bounded rational agents was suboptimal, the collective force of such "suboptimal" action nonetheless significantly undermines the predictive validity and reliability of economic (decision) theory. Pertinent staples of neoclassical theory, such as the irreversibility of indifference curves (Knetsch, 1989, 1992), the efficiency of Coasian allocations (Knetsch and Sinden, 1984; Kahneman, Knetsch, and Thaler, 1990), the opportunity cost criterion (Borges and Knetsch, in press), the Pareto-efficiency of market exchanges (Borges and Knetsch, 1995), and the validity of expected utility theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), have all been called into question.

Second, agents' "deviation" from the normative, prescriptive behavior do not necessarily have to suffer the effects of the asserted suboptimality. Axelrod (1984, 1987; also, Axelrod and Hamilton, 1981), for example, not only demonstrated in the context of the Prisoner's Dilemma game that irrational and allegedly suboptimal cooperative strategies, i.e. tit-for-tat strategies, indeed outperform rational, and thus "optimal", non-cooperative strategies but also that adaptive (i.e., learning) behavior results in the emergence of such cooperative strategies within the bounds of neo-Darwinian evolution. Axlerod presented several reasons why the tit-for-tat strategy outperformed rational non-cooperative strategies and several of these reasons distinctly highlight the problems associated with the well-structured, artificially transparent problem domains commonly "assumed" for theoretical work. The assumption of well-defined problem domains employed for armchair theorizing constitutes a problem plaguing normative, reductionist theories in general and economic theory in particular as real-world problem domains are generally ill-structured, noisy, complex, and computationally intensive. This problem-specific translucence often prevents the required transformation of real problems into the well-structured problem space necessary to apply traditional optimization methodology.

This paper is concerned with some of the fundamental issues associated with the existence of loss averse valuation characteristics as well as an investigation of both the asserted suboptimality resulting from this behavior and the conditions allowing for such behavior to emerge as the result of decision makers' adaptation to their environments.

The first experiments address a recent criticism that questions the existence of loss aversion. Recently, Hanemann (1991) has shown that if a large substitution effect is underlying valuations at hand, asymmetric valuation patterns may ensue that are explainable by and consistent with the normative model. Unfortunately, the normativist community at large has come to an understanding that substitution effects *per se* account for observed valuation disparities. Evidently, if decision makers' observed asymmetric valuations of gains and losses were in fact solely attributable to substitution effects, a prevalent but erroneous interpretation of Haneman's work, the implications suggested to undermine normative theory and analysis would be rendered irrelevant and merely constitute a meaningless artifact of ill-designed experimental investigation. Furthermore, descriptive theories, such as Prospect Theory (Kahneman and Tversky, 1979), Cumulative Prospect Theory (Tversky and Kahneman, 1992;

Tversky and Wakker, 1995), and Regret Theory (Loomes and Sudgen, 1982) would be shown invalid. To test for the dependence relation between observed valuation disparities and the substitution effect, an empirical test of people's valuation patterns was conducted. The experiment employed a within-subject design and controlled for substitution effects for two exchange commodities. The experimental results strongly suggest that agents' valuation patterns adhere to the asymmetric valuations inherent in loss aversion even under conditions of highly substitutable exchange commodities effects.

The second empirical investigation reports the results of a simulation experiment that tests and compares the performance of loss averse behavior relative to normative (benchmark) behavior. To this end, a decision environment closely mirroring the transparent world of normative theory, although assuming a finite time horizon, was simulated and the performance of populations of artificial economic agents were compared on the basis of their objective decision criteria. The experiments indicate not only that loss averse agents perform at least at par with their normative counterparts on an individual basis of comparison but also that the population of loss averse agents outperforms the normative population of decision makers in exhibiting a higher survival rate.

The third and final empirical investigation assumed an evolutionary perspective posing the question of what type of valuation pattern, i.e. symmetric or asymmetric valuations, would emerge as the result of agents' adaptive response to their decision making and decision context. In order to investigate agents' valuation patterns as adaptive, emergent structures, a series of simulation experiments was conducted. Starting with a generalizable, unparameterized valuation function, evolutionary modeling techniques were employed to investigate this issue. Specifically, the evolution of the parameters defining agents' valuation preferences was modeled as an adaptive, outcome-dependent process over a portfolio of pairs of risky gambles. The results obtained suggest a strong tendency for both individual and populations of artificial decision makers to evolve toward a suit of parameter values resembling loss averse valuation preferences.

Overall, the experiments reported in this paper suggest that a) loss aversion is alive and well acting independent of substitution effects, b) loss averse agents even in finite, transparent decision environments outperform normative benchmark agents for large numbers of routine decisions, and c) evolutionary processes foster the emergence of loss averse valuation patterns for finite, although large, numbers of iterated decisions. Consequently, the results support earlier evidence documenting the existence of loss aversion and further suggest that loss averse decision makers are by no means operating within the mires of asserted suboptimality.

Chapter 1:

The Prevalence Of Valuation Disparities

1.0 Introduction

A fundamental assertion of consumer choice theory is that, in the absence of income effects, an individual's maximum willingness to pay for a commodity is to equal the minimum amount he or she is willingness to accept to give it up (Willig, 1976; Randall and Stoll, 1980). Empirical research, however, suggests the disparity between these two valuations is a pervasive phenomenon even if income effects and transaction costs are eliminated. Such valuation disparities have been demonstrated in a variety of settings and survey and real exchange experiments [see, for example, Kahneman, Knetsch and Thaler (1990) and Hoffman and Spitzer (1993)]. Although most of the real exchange market experiments provide controls for income effects and transaction costs, essentially all of the reported real exchange experiments used between-subject comparisons, with notable exceptions as those reported by Kachelmeier and Shehata (1992). While between-subject designs allow comparisons of the buy and sell values of a representative of each group, a within-subject design provides the much stronger test of any buy and sell disparity for each individual.

One recent explanation for some observed disparities is the degree of substitutability, or the lack thereof, between the commodities to be exchanged. Hanemann (1991) demonstrated that WTA-WTP differentials due to a lack of substitutability among the exchange commodities are a likely occurrence and reconciled this finding with existing theory showing that such valuation disparities are consistent with and explainable by Randall-Stoll bounds (1980).[1]

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[1] Hanemann is quite clear, however, that valuation disparities due to a lack of substitutability are different from the behavioral argument, i.e. that (within-subject) valuation disparities may arise due to agents' loss aversion. This is made explicit in Hanemann (1991, p.645, *note* 25): "This [loss aversion] is a different phenomenon from that involved in the Randall-Stoll

This paper reports the results of a real exchange experiment that provided a combination of both a between- and within-subject test for exchange commodities with a high degree of substitutability.

2.0 Experimental Methods And Design

A discrete-choice variant of the Becker-DeGroot-Marschak (1964), or BDM, random price auction was employed for a two-stage experiment eliciting WTA and WTP values [2]. Money and "scratch & win" tickets issued by the British Columbia Lottery Corporation were chosen as the experimental exchange commodities. These lottery tickets retail for $1 and are widely available at gas stations, convenience stores, shopping malls and the like[3].

The use of these (unscratched) lottery tickets and money as the exchange commodities explicitly introduces high substitutability to the real exchange market as first, there is a high degree of substitutability between money and a ticket as these tickets are widely and easily available and their going market price is well known and printed on each ticket, and

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bounds: it [loss-aversion] concerns the disparity between WTP to obtain a change from q^0 to q^0+D (for some D > 0) and the WTP to avoid a change from q^0 to q^0-D, which is not the same as the disparity between WTP and WTA for the same change from q^0 to $q^1 = q^0 + D$." While Hanemann makes this distinction, the substitutes possibility has sometimes been thought of as a somewhat simpler explanation than possibly warranted, as seemingly implied in the observation "[H]anemann showed that one would expect convergence of WTP and WTA value measures when the good in question has a very close substitute" (Shogren, Shin, Hayes, and Kliebenstein, 1994, p. 255).

[2] The BDM auctioning process is extremely well suited for valuation elicitations. A stochastic procedure, BDM-driven bidding is optimal because subjects' reported valuations affect the likelihood of selling or buying the object under consideration. Subjects' bids, however, have no bearing on the distribution and closing prices (see, for example, Davis and Holt, 1993). The experimental design reported above implements the BDM auction for each subject individually, which should further enhance this desirable property.

[3] Although irrelevant to the value elicitation at hand, as Ss were not allowed to scratch their tickets until the end of the experiment, the maximum payout of such a lottery ticket is $10,000. The expected payout ratio of these tickets is approximately 50 cents on the dollar and Ss were made aware of this value.

second, one unscratched lottery ticket is a perfect substitute for another (unscratched) lottery ticket.

A total of 110 third and fourth year undergraduate students enrolled in small Business Administration seminars (up to 25 students per session) at Simon Fraser University, volunteered to participate in the experiment. All subjects (Ss) were randomly assigned to either a group of sellers or buyers. Each subject received a lottery ticket before the actual value elicitation experiment started and was given the opportunity to exchange this ticket for another one, if so desired.

The real exchange market was designed as a two-group, two-stage experiment (illustrated in Figure 1a and Figure 1b). Ss in one group (hereafter G_{WTA}) were initially endowed with a (second) lottery ticket[4] and asked to state their minimum WTA to give up (sell) the ticket. Ss assigned to the second group (hereafter G_{WTP}) were not given a (second) ticket but were asked to state their maximum WTP to obtain (buy) such a ticket. Depending on the experimental group, Ss were instructed to state their minimum WTA, or maximum WTP, values according to a scale ranging from \$0 to \$4 spaced in \$0.25 increments (see Appendix 1 for a sample of the survey forms). For each sum, Ss indicated whether they would be willing to sell, or to buy, a ticket. Upon the completion of this task, a BDM auction was carried out for each subject individually by drawing game chips (from a black bag) marked with amounts corresponding to the different values provided on the survey forms. Sellers (G_{WTA}) traded their ticket for money if the chip drawn indicated an amount equal to or greater than the maximum WTA. Buyers (G_{WTP}), on the other hand, exchanged money for a ticket if the randomly drawn chip indicated an amount equal to or less than the minimum WTP stated.

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[4] An additional experimental control was implemented to assure subjects' revealed values would not be influenced by the illusion of control bias. Langer (1975) demonstrated people's tendency to treat chance events as a controllable activity, with subjects who were given their choice lottery ticket demanding a higher price for it than those who were not given a choice. In order to control for this undesirable bias, subjects were handed their ticket(s) by the experimenter, rather than having individuals select their own.

Depending on the outcome of the random-price auction, some Ss in G_{WTA} received money in exchange for their tickets, whereas other Ss kept their tickets. Similarly, some Ss in G_{WTP} bought a ticket from the experimenter, whereas others did not. Only those Ss in G_{WTA} who sold their tickets and those Ss in G_{WTP} that bought a ticket advanced to the second round of the experiment.

The second round of the experiment, now comprised by a reduced sample size, reversed the value elicitation procedures employed. Those Ss in G_{WTA} that had sold their tickets in the first round (see Figure 1a) were now asked to state their maximum WTP to buy a lottery ticket, whereas those Ss of G_{WTP} that had bought a ticket in the first round (see Figure 1b) were asked to state their minimum WTA to sell the ticket. The second round of the experiment was again concluded with the same BDM auction for each individual. Ss were not told about this second round of the experiment until the first stage had been completed.

*** Insert Figure 1a and 1b Approximately Here ***

The two-stage value elicitation process allowed for the observation of within-subject, as well as between-subject, WTA and WTP valuations.

3.0 Results

Fifty of the 110 participants were randomly assigned to the G_{WTA} group and the remaining 60 Ss comprised the G_{WTP} group. In total, 45 Ss advanced from the first round to the second round of the experiment - 23 Ss from G_{WTA} and 22 Ss from G_{WTP} (see Figure 2a and 2b below). A total of 42 of those 45 individuals indicated a WTA value higher than their WTP value.

*** Insert Figure 2a and Figure 2b Approximately Here ***

Subjects assigned to the group in which they were first asked to state their WTA (G_{WTA}) revealed WTA values averaging $2.42 (median $2.00). The average WTP for Ss assigned to the group asked to state their WTP in the first round of the experiment (G_{WTP}), on the other hand, was $0.96 (median $1.00). The average between-subject valuation disparity was $1.46 for all Ss[5].

*** Insert Table 1 Approximately Here ***

The results from the first round of the experiment suggest that subjects' valuation of tickets (from G_{WTP}) was not significantly different from the market price (see Table 2). That is, subjects' WTP values were closely anchored to the going market price of $1.00.
The second round of the experiment was comprised of only those Ss that had either sold their tickets or bought tickets during the first round. Those Ss initially assigned to the group that was asked to state their WTA (G_{WTA}), and subsequently sold their tickets, indicated an average WTA of $1.88 (median $1.875) when they were then required to disclose their WTP for a lottery ticket. The average WTP for this group amounted to $1.02 (median $1.00) -- see Figure 2a -- an amount significantly less than they had previously demanded to give up a ticket. The resulting, average within-subject valuation disparity amounted to $0.85 ($1.87 less $1.02) or a WTA-to-WTP ratio of 1.83. Not unlike the Ss from G_{WTP}, these Ss valued the tickets not significantly different from the going market price of $1 (see Table 2).

Subjects assigned to the group that was initially asked to reveal their buying price and who had bought tickets in the first round of the experiment indicated an average WTP of

[5] The average WTP for those Ss who stated amounts less than or equal to the individually determined auction price amounted to $1.14 (median $1.00), whereas those Ss who did not purchase a ticket disclosed an average WTP of $0.84 (median $1.00). The mean valuation differential for those Ss who either bought or sold a ticket and thus, had advanced to the second round of the experiment, was $0.74.

$1.14. Their average WTA valuation was $2.38 (median $2.50) -- $1.24 in excess of the average WTP revealed earlier for a WTA-to-WTP ratio of 2.09.

Both rounds of the experiment revealed very large and highly significant preference reversals consistent with the endowment effect for both the initial buy and the initial sell groups. Even though the exchange commodities at hand displayed a high degree of substitutability, significant within-subject valuation disparities ensued.

Between-group comparisons (initial buyers versus initial sellers) do not suggest any significant differences for either the WTA and the WTP elicitations or the valuation disparity[6] (see Table 2). The lack of any significant differences between the two experimental groups is rather interesting and suggests the sequence in which agents enter the market does not have an effect on either their WTP or WTA valuations.

*** Insert Table 2 Approximately Here ***

The results of the experiment reported above indicate strong within- and between-subject valuation disparities despite the fact that the real exchange market controlled for the normative presumptions, i.e. income effects and substitution effects, on both within- and between-subject levels. Even though the average and median WTP amounts between groups were not significantly different from the $1 retail price of the lottery tickets, the corresponding WTA values were significantly higher on both a within-subject and between-subject level. These disparate valuations lead to a significant, sizable disparity, even though the correspondence of valuations across groups as well as subjects' strong calibration on the going market price for

[6] The between-subject difference in WTA amounts for Ss having engaged in trades is attributable to the different amounts entering the comparison and do not indicate any significant differences between these two groups *per se* as indicated by the non-significant difference between the overall WTA values for both groups. The G_{WTA} value is the mean of the realization of the BDM auction, whereas the G_{WTP} value is the mean of the actual valuations submitted by Ss.

tickets suggests a high degree of substitutability between cash and (unscratched) lottery tickets.

4.0 Discussion And Conclusion

In light of the experimental controls employed, the results of the experiment reported above lend further support to the descriptive hypothesis that the endowment effect, or more generally loss aversion (Kahneman et al., 1991), is a pervasive preference characteristic that heavily influences people's market behavior. The experimental results further confirm Hanemann's suggestion that valuation disparities attributable to loss aversion represent a causal phenomenon different from valuation differentials stemming from the "substitution effect." That is, even if goods do or do not have substitutes, the endowment effect is a separate, different source of large, significant disparities between WTA and WTP values. Specifically, valuation disparities driven by the endowment effect can occur independent of other causal effects, such as the substitution effect, transaction costs, and/or income effect.

Future research, then, should not only investigate the plausible causes, and their possible interactions, underlying people's differential valuations, but also attend to the consequences of disparate valuations.

Chapter 2:

Loss Aversion, Market Profits, And Economic Survival

1.0 Introduction

Although agents' preferences *per se* do not enter economic theory and are commonly assumed an exogenous variable, the underlying construct representing agents' preferences, in form of valuation patterns, play a fundamental and important role in economic theory and analysis (e.g., Stigler and Becker, 1977) providing the foundation for utility theories. Specifically, neoclassical economic theory asserts that people symmetrically value gains and objectively commensurate losses (e.g., Willig, 1976; Randall and Stoll, 1980).

Empirical research in experimental economics and behavioral decision theory, however, strongly suggests decision makers' propensity to value losses significantly more than objectively commensurate gains. These findings portray a robust and systematic attribute of (human) judgment and decision making commonly referred to as *loss aversion* or *endowment effect* (Kahneman and Tversky, 1979; Thaler, 1980). The pervasiveness of loss aversion suggests it to be a fundamental valuation characteristic favoring the status quo (Samuelson and Zeckhauser, 1988) and the avoidance of risk when valuing gains but to display risk-seeking preferences when valuing losses (Kahneman, and Tversky, 1979; Kahneman, Knetsch, and Thaler, 1991; Tversky and Kahneman , 1991).

Under the assumption of perfect and well-structured problem domains, the rigors of deductive theory lead to the unambiguous prescription that those who accept and follow the axioms of rational, and thus by definition optimal, behavior will be rewarded and those who do not follow this behavior will be taken for "suckers" (e.g., Hirschleifer and Riley, 1992:34). Given the prevalence of irrational agents, at least by normative standards, displaying loss averse valuation patterns, the question arises of how poorly loss averse market traders would fare as opposed to how well they would have fared had they instead conformed to prescriptive behavior.

This paper empirically investigates the performance of loss averse behavior relative to normative (benchmark) behavior in the context of a market that is perfect in all respects except that the number of repeated trades is restricted to a large but finite number rather than the commonly assumed infinite number. Simulation experiments testing both loss averse and normative valuation characteristics over a portfolio of risky decisions were conducted and the results compared. The introduction of finite time horizons, or trials, rather than assuming an infinite number of trials which reduces the problem to choosing the completely transparent greater expected value, appears to favor choices maximizing utility by taking account of the different valuation of gains and losses.

2.0 On Valuations And Valuation Patterns

Loss averse behavior displays itself in form of a two-part, S-shaped valuation function explicitly delineating between positive and negative outcomes relative to a neutral reference position (Figure 3). The reference position is critical to decision makers' valuation of outcomes in terms of gains and losses as decision makers value outcomes of their decisions as changes relative to a reference state, which is commonly their current position (i.e., the status quo), rather than employing an aggregate view of attainment. The differential valuations, or weighing, of losses and gains are the behavioral key differences between loss averse decision behavior and prescriptive decision theories, such as utility theory (UT) and expected utility theory (EUT).

*** Insert Figure 3 Approximately Here ***

Formally, Tversky and Kahneman (1992) propose a two-part power function to capture agents' loss aversion. That is,

$$\text{Equation 1:} \qquad v(x_i) = \begin{cases} x_i^{\alpha}, & x \geq 0 \\ -\lambda(-x_i)^{\beta}, & x < 0 \end{cases} \qquad \text{where}$$

$v(x_i)$ defines the loss-gains preserving valuation function over outcomes, or consequences, such that

$x \equiv (x_1, x_2, \ldots, x_S)$,

λ represents the loss aversion parameter governing the asymmetric weighting of gains and losses, and

α, β are preference scaling parameters over outcomes.

The ensuing valuation function v(•) is distinctly different from the notational similar elementary utility function, or preference scaling function, commonly encountered in expositions of EUT. It should be noted that v(•) is defined over outcomes, or consequences, and that the valuation of the reference position results in a fixed valuation of v(0) = 0 (Kahneman and Tversky, 1979). That is, the behavioral valuation function resembles measurement on a ratio-scale, whereas EUT is measured on an interval scale. The primary "technical" incompatibility between the descriptive function v(•) and the elementary utility function employed in EUT[7], i.e. the ensuing downward transformation voids the notion of a reference position and the distinction between gains and losses is lost. Of course, this difference in measurement scales is more than a mere technicality as it reflects the fundamental difference in how agents value consequences as described by the endowment effect versus how agents value consequences as assumed by conventional normative theory.

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[7] Unlike EUT, UT requires only an ordinal measurement scale simply preserving the rank-order of preferences. As a rank-order scale is subordinate to an interval scale, however, the above discussion also applies to UT.

The prevalence of loss aversion among expert and naive decision makers alike raises the question of how well general optimization behaviors perform in "real world" problem domains. Normative theory is deductive in nature and takes place in well-defined, transparent problem domains. In reality, however, most problem domains are translucent demanding specialized problem solving approaches often deviating from the normative approaches guaranteeing optimality (e.g., Garey and Johnson, 1979, in the context of NP-completeness and computational intractability).

A very realistic complexity encountered in many judgment and decision making contexts concerns finite time horizons as opposed to the traditionally infinite time horizons employed in many analytical analysis. Even mundane imperfections in the unfolding of the problem space, such as falling short of the large number of iterations, or trials, required to attain an expected distribution, may undermine the effectiveness of generalized optimization methodology (e.g., Baumol and Quandt, 1964; Wall, 1993; Cosmides and Tooby, 1994).

3.0 On The Comparative Performance Of Loss Averse Preferences

The frequently encountered "imperfection" in the analysis and modeling of problem space concerns the mundane, but nevertheless nontrivial, issue of the number of trials required to attain the probabilistic expected long-run value(s), or equilibrium. Even if we focus our attention exclusively on routine decision problems, it is hard to envision a decision maker encountering the identical problem, or problem set, without any changes in or of the problem domain[8]. Of course, the number of iterations required to attain the expected distribution for problems with larger outcome spaces and/or multi-attribute properties increases exponentially. Shackle (1970, 1979) critiques neoclassical economic (decision) theory on exactly this issue

[8] The price of my regular toothpaste at my favorite supermarket, for example, has changed seven times over the past two weeks, whereas the price of milk has changed "only" four times. Overall, all items of my regular basket of purchases were subject to at least two prices changes over the two week time period.

arguing on philosophical grounds that the probability concept is concerned with relative frequencies of outcomes, whereas choices are essentially unique acts.

Under finite conditions, loss averse behavior may be an effective valuation characteristic that minimizes the variance over the array of realizable gains but maximizes the variance over the corresponding array of losses. Borrowing from Roy (1952), a loss averse decision maker would employ a "safety first" approach to gains, but accept the risk (coupled with a high variance) of incurring higher losses (relative to the certainty equivalent) in order to minimize or avoid losses at all. Given the boundedness of the amount of (cumulative)losses a decision maker can incur before succumbing to bankruptcy and the unconstrained amount of gains an agent can accumulate, asymmetric valuation behavior may in fact prove an effective, possibly even efficient, decision behavior for decision making marked by finite time horizons.

3.1 Methods

In order to explore the efficiencies and inefficiencies of behavioral valuation patterns, simulation experiments comparing the performance of artificial decision makers adhering to loss averse behavior and decision makers following neoclassical, rational valuation behavior were conducted. Specifically, the experiments took the form of a market "tournament" pitting loss averse decision makers against normative agents. Cumulative (objective) payoffs and (population) survival rates were used as the criteria to measure the performance of each.

The decision making context was comprised of a portfolio of eight pairs of gambles[9] (Table 3). Each artificial decision maker was repeatedly confronted with the decision to choose between a randomly selected pair of gambles. Depending on agents' "hard-coded" expected valuation functions, which reflected either loss averse or normative preferences as discussed below, agents made their choice among the alternatives for the pair of gambles at hand. Upon an agent's decision, the outcome of the chosen gamble was determined on the basis of a randomly generated probability determining the consequence of the chosen gamble and the artificial agent was credited, or debited, with the realized payoff.

*** Insert Table 3 Approximately Here ***

The artificial agents employed for the purpose of this investigation were fitted with a static valuation function reflecting either gain-loss neutral or loss averse behavior. Formally, we define the expected valuation function V such that

Equation 2: $$V(x,p) \equiv \sum_{s=1}^{S} p_i v(x_i), \text{ where}$$

V(x,p) is the valuation function defined over the gambles with x again denoting the vector of consequences and p the vector of probabilities associated with x, such that $p \equiv (p_1, p_2, \ldots, p_S)$, of course summing to unity, and

v(x) is the loss-aversion preserving preference scaling function of Equation 1.

The valuation function of Equation 2 was parameterized to reflect four population preferences – risk-neutral (RN), risk-averse (RA), risk-seeking (RS), and loss averse (LA). The chosen set of parameters (Table 4) reflect the normative notion of symmetric valuation of gains and losses for RA, RN, and RS, and the asymmetric valuation preferences for LA agents[10].

*** Insert Table 4 Approximately Here ***

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[9] These gambles were originally employed by Kahneman and Tversky (1979:268) in their laboratory experiments with human subjects underlying the formulation of Prospect Theory.
[10] Due to the fact that only pure gambles, i.e. all alternatives for each gamble were either positive or negative payoffs, were employed, the loss aversion parameter, i.e. λ, had no impact on loss averse agents choices. As can be easily seen in the valuations of the prospects for the chosen parameter values (Table 3a and 3b), setting $\lambda > 1$ merely increases the valuations symmetrically across alternatives but does not impact on the choice pattern.

The expected valuation function defined by Equation 2 is uncharacteristic of prescriptive and descriptive decision behavior. Normative theory applies a linear probability weighting function to an interval-scaled elementary utility function, whereas descriptive theory incorporates the empirically observed nonlinear probability weighting function to a ratio-scaled preference-scaling function. Nevertheless, V(•) is very suitable for the experimental investigation at hand as it allows the separation of behavioral characteristics in probability judgment from the valuation of outcomes. Furthermore, V(•) allows the comparison of normative and descriptive decision behavior despite the difference in the measurement scales, while implementing rational, maximizing agent behavior in all respects but valuation asymmetry in the case of loss averse agents.

The parameterized valuation functions for both loss averse and normative agents allow an *ex ante* determination of the choices that each agent will make for each of the eight pairs of gambles. Also, the differential choice patterns allow the *a priori* calculation of the expected outcomes for both the loss averse and normative types of artificial agents (Table 5a and Table 5b). Over the chosen set of preference parameters all four types of agents would make choices that would result in an expected value of $250 over the portfolio or $31.25 per gamble although agent-specific choice patterns differ.

*** Insert Table 5a And Table 5b Approximately Here ***

3.2 Experimental Design And Variations

Two simulation experiments were conducted to provide two separate measures pertaining to the individual and aggregate levels of outcomes to compare the performance of the four populations of artificial agents. The first performance measure concerns' agents cumulative payoffs as the result of repeated decision making. Each population's average cumulative values allow for inter-population comparisons. In addition, the maximum (i.e., best-of-population) and minimum (i.e., worst-of-population) cumulative payoff values for each of the four populations are assessed to give an indication of and allow for the comparison of agents' individual performance over multiple decision periods.

The second measure takes into account the very common "real world" phenomenon that agents' financial resources are limited. Decision makers face a lower bound the amount of losses they can incur before financial failure, i.e. bankruptcy, occurs. To provide this second measure, another simulation experiment constraining agents' financial resources was conducted such that cumulative payoffs falling short of a pre-set survival threshold, Ω, lead to the elimination of the underachieving, or "bankrupt", agents. The ensuing performance measure is a measure of population survival

The first simulation experiment focused solely on the comparative performance of the normative and the behavioral populations in terms of their cumulative payoffs over 500 decision periods. To this end, the two populations were each seeded with 400 artificial decision makers and subjected to 500 decision making periods. As the experiment was extensively governed by random numbers for both the pick of a gamble and the outcome probabilities, fifty repetitions, or samplings, of the simulation run were implemented to guard against undue random fluctuations.

The second experiment was essentially identical to the first one. However, this time "ill-performing" agents were culled from their respective populations. Both populations were equally seeded with 750 agents and the maximum number of decision periods was fixed to 200[11]. The threshold amount of accrued payoffs was set to zero, i.e. $\Omega = 0$, and periodically applied after every 10th decision period. Thus, agents received some "reprieve" from the rig-

[11] Pre-tests revealed that population comprised of lower number of agents, such as the 400 employed for the first experiment, were eliminated too quickly to allow for the desired comparisons.

ors of the resource constraints allowing for the accumulation of (expected) payoffs. Again, 50 repetitions of the simulation experiment were conducted.

3.3 Results

For programming purposes, the payoff values of the gambles (Table 3) were scaled by a factor of 1/1000. Thus the expected (long run) outcomes for the first experiment are $0.25 per eight iterations for the average agent resulting in a cumulative expected payoff over 500 generations (i.e., 62.5 expected portfolio selections) of $15.625.

3.3.1 Experiment 1 – Decision Making With Unconstrained Resources

This simulation experiment allows the investigation of two distinctly different types of information. First, the performance of the best and worst individual performances over the fifty trials can be compared for each of the four types of agent valuation and preference scaling characteristics. These best-of and worst-of-generation performances, i.e. the performances of those individual agents that attained the highest, or lowest, payoffs for each of the fifty trials, essentially provide an indication of the realization of the extreme payoff values realized by the different types of agents. Second, the performances of the four different populations of agents, i.e. an aggregate, central measure, over the fifty trials can be compared.

Best-Of-Generation Performance: The highest average payoffs for the best-of-generation performance was obtained by RS agents amounting to $193.52 followed by LA agents ($187.60), RN agents ($182.36), and RA agents ($177.56). The same ranking also holds for the highest and the lowest individual best-of-generation performance (Table 6), where individual RS agents attained high and low values of $280 and $155, respectively. LA agents again followed suit ($275 and $142) only trailed by RN agents ($252 and $141) and RA agents ($234 and $126). Not unexpectedly the best-performing individuals came from the RS population, although it is noteworthy that LA agents outperformed both RN and RA agents in this best-of category.

In order to test for the significance of the (mean) differences, a one-way ANOVA was conducted, which proved highly significant (Table 7). Furthermore, Scheffe *post-hoc* tests were employed suggesting a significant performance difference only between RS and RA agents (Table 8) indicating a better performance of RS over RA agents.

Worst-Of-Generation Performance: As much as RS agents dominated the best-of-generation performances, this population also harbored the worst performers. Specifically, RA agents sported the highest worst-of-generation average of -\$144.54 followed by RN agents (-\$154.22) and LA agents (-\$155.34) and a distant last RS agents with an average of -\$161.00 (Table 6). In terms of the individual extreme values, the same ranking holds with the exception of the worst individual minimum performance, which was attained by a RN agent (-\$280) trading place with the worst RS agent (-\$216). Again, one-way ANOVA suggests a highly significant difference between the four populations (Table 7). The only significant (mean) difference between performances, however, was again recorded for the RA and RS populations (Table 8). This time, however, RA agents command a significant mean-difference advantage over their RS counterparts.

Traditional empirical and analytical research would have predicted both the best and worst performances of individual RS and RA agents, respectively, with RN agents falling in between. Most interestingly, LA agents performed rather well – showing no significant (mean) difference between the high-performing RS agents in the best-of-performance category and the highest performers, i.e. RA agents, in the worst-of-performance category. The minimization of variances over gains and the maximization of variances over losses seemingly shelters LA agents on an aggregate level from the weaknesses of both RA and RS behavior.

Average Population Performance: This level of comparison appears the most important source of comparative information allowing the comparison of populations of agents, thus shielding against the outliers of individual agent performance. The highest population performance was obtained by LA agents with an average payoff of $16.21 followed by RA agents ($14.66), RN agents ($14.54), and RS agents ($14.48). Again, this order holds for the high-low (average) values, where the highest ($21.61) and the lowest ($12.24) LA averages obtained dominated those of the other population types.

One-way ANOVA comparing the performances of these four populations proved once more highly significant (Table 7) and the corresponding Scheffe *post-hoc* tests for significant mean differences were conducted. These tests revealed that LA agents, on average, significantly outperformed RN, RA, and RS agents (Table 8). However, no significant mean difference between the average payoffs of the normative populations was observed.

*** Insert Table 6, Table 7, And Table 8 Approximately Here ***

The results of this first experiment suggest that loss averse agents were not outperformed by any of the normative, symmetrically valuing agents. Although the general statistical expectations with respect to symmetric, normative agent preference patterns hold, i.e. RA agents, as a population, outperform RS agents with RN agents falling in between, LA agents performed extremely (and significantly) well on both the individual and average range-measures, i.e. best-of-generation and worst-of-generation payoffs, and outright dominated normative populations on an aggregate population level of comparison. Again, the straddling of no/low risk exposure to gains and risk-seeking behavior for losses appears to be an effective decision pattern under conditions of relatively large but finite decision periods.

3.3.2 Experiment 2 – Decision Making With Constrained Resources

The second experiment focuses on agents' performance under the imposition of a resource constraint, Ω. The rationale for this experiment is that in most realistic environments resource constraints play a very pertinent role acting as a "natural" lower bound to the cumulative losses an agent can incur. Again, under the conditions of finite, but large number of trials, the loss averse valuation pattern of banking the sure gains but gambling on the losses may prove effective. As briefly discussed above, the expected value of the losses are lower than the maximum loss but much higher than no loss. Loss averse agents seem to successfully exploit this fact on the basis of the comparatively high variance, which coupled with the limited number of trials seems to work in favor of loss averse agents. While this exploitation of the mean-variance may work well in unconstrained environments, the high variance in the payoffs to loss averse agents may prove "deadly" in resource constrained environments.

LA populations had the highest average number of agents surviving the application of the Ω threshold resulting in an average number of 178.90 agents who survived the risky choices without falling below the threshold (Table 9). The second highest average survival rate was produced by the RN population (168.46) followed by RS (114.92) and RA agents (114.92). Furthermore, LA agents had both the highest maximum and the highest minimum number of agents surviving (222 and 153, respectively), whereas RA agents claimed the lowest maximum and minimum survival rates (131 and 95, respectively).

A one-way ANOVA proved highly significantly (Table 10) prompting another round of Scheffe *post-hoc* tests for mean differences (Table 11). LA agents significantly outperformed, or out-survived, all three types of normative valuation and preference-scaling patterns. Furthermore, RN agents significantly fared better than RA and RS agents, whereas no significant difference was recorded for the survival of RA and RS agents.

*** Insert Table 9, Table 10, And Table 11 Approximately Here ****

The results of this experiment are somewhat surprising, especially in lieu of the ill-performance of RA agents which counters common normative wisdom. A closer review of the descriptive statistics concerning agent survival indicates two interesting observations. First, the level of survival, as reflected in the mean and the range of the number of agents surviving, of the LA populations did not even overlap with those of any normative type of agent. Second, the standard deviation measuring the dispersal of agent survival was almost twice as high for LA agents, i.e. approximately 14 agents, than for any of the normative populations. Thus, the variance of agent survival for LA agents appears much higher than for normative agents, although the base-rate of survival is also (significantly) higher for this type of valuation and preference-scaling structure than for normative types, making LA valuations a rather attractive choice pattern. Again, this pattern furthers our earlier speculation that LA's asymmetric straddling of risks is an effective strategy.

3.4 Summary And Discussion Of Results

Both simulation experiments over the given decision portfolio do not suggest that asymmetric valuations of gains and losses constitute suboptimal behavior. The first experiment, comparing the market performance of agents following symmetric valuations to agents employing asymmetric valuations, provides a strong indication that LA agents performed at least at par, if not better, than their normative counterparts for the simulated routine decision context. The probabilistic range of the expected average payoffs for both individual and repeated trials (Table 12) indicate that both the average payoffs per trial and the grand mean (i.e., the average payoffs for the fifty trials) fall within the two or three standard deviations expected for such random events. Of course, these calculations only serve as a check for the simulation experiments. The issue to be investigated, however, was the comparative performance of the different valuation and preference patterns **given** identical environmental conditions, i.e. the random numbers governing the prospect selection and outcome determination were identical for all types of agents.

*** Insert Table 12 Approximately Here ***

The results for the second, constrained experiment mirrored the trend of the results to the unconstrained simulation experiments with LA agents significantly outperforming the symmetric valuation patterns. A sensitivity analysis that reduced the periodicity from ten to five and one periods, resulted in a dramatic relative improvement (of course, the overall number of surviving agents decreased dramatically) in RA agents survival with respect to RN and RS agents. LA agents, however, still dominated RA agents.

A critical aspect to the experiments concerns the selection of the parameter values driving the generalized expected valuation function defined by Equation 2. For the first four prospects, the expected values of the two alternatives was not identical, whereas this identity prevailed for the remaining four prospects. The critical value of the exponent equation the first four prospects' expected values amounts to 0.7757 and had the α and β values been chosen accordingly, distinct changes in agents' choice patterns would have occurred. Specifically, agents' choice patterns for these prospects would have been different across the different preference structures for RA, RS, and LA agents, although no changes would have transpired for RN agents. Of course, the expected value of the portfolio would also change with RN agents remaining at an expected value of $250, RA and RS agents' expected value falling to $0, and LA agents' expected value dropping to -$250. Such a change in the parameter values merely a reflects a change in value preferences and does not allow for a meaningful, objective comparison of cumulative payoffs as the expected valuation function defined above does not allow for the inter-personal comparison of value, or utility.

Overall, the results of the simulation experiments suggest that loss aversion is not only an effective but also an efficient decision heuristic outperforming the normative benchmark, even though the latter decision rule was highly favored on the basis of its expected value. We attribute the effective performance of LA agents to the min-max management of variances over gains and losses implicit in the asymmetric valuation pattern. Although this comparative effectiveness of loss aversion only holds for finite time horizons, it is exactly this "limitation" that is most prevalent in real world decision making environments.

4.0 Discussion And Conclusion

Neoclassical economic theory operates on the basis of two fundamental postulates: rationality and selfishness. With respect to the latter postulate, Axelrod (1984, 1987), for example, has shown that cooperative behavior, in the form of tit-for-tat strategies, not only outperforms "greedy" behavior but also proves evolutionary feasible and stable (Axelrod and Hamilton, 1981).

Employing a similar, although static, approach, the simulation experiments conducted for this study demonstrated that a simple, intuitively appealing valuation pattern, i.e. loss aversion, has proven to be a rather effective, if not efficient, alternative to the rational, reference-independent normative method. Furthermore, reference-independence, as reflected in the interval measurement scale, of EUT has been a source for discontent long before the issue of loss aversion arose. As renowned game theorist Anatol Rapoport (1962:118) notes:

> *"I have seen many research proposals and listened to long discussions of how hot and cold wars are zero sum games (which they are not!), the assignment of "utilities" to outcomes must be made on an interval scale. There is the problem. Of course, this problem can be bypassed, and the utilities can be assigned one way or another, so that we can get on with the gaming, which is the most fun. But of what practical use are results based on arbitrary assumptions?"*

The minimal but realistic degree of imperfection injected into the simulated decision environment furthers the perception that the purely mathematical expected value principles driving economic theory lack the robustness to effectively and efficiently deal with "noisy" decision environments -- even if the introduced bias is solely based on the (relatively) low number of trials. Surely, neoclassical decision theory provides a basis for improved decision making in the absence of alternatives and are preferable to erratic *ad hoc* decision processes. However, behavioral research has provided alternative approaches that justify rigorous tests of and comparisons to the traditional optimization principles for decisions governed by risk and uncertainty.

Chapter 3:

On The Emergent Properties Of Valuation Patterns

1.0 Introduction

Neoclassical economic theory provides an extensive and comprehensive framework for prescriptive and predictive decision analysis building on a minimal set of behavioral assumption, which in turn provide the basis for the axiomatic, deductive modeling of agent behavior (e.g., Stigler & Becker, 1977). Recently, however, these fundamental behavioral maxims, i.e. the presumptions that economic agents behave in a selfish and rational manner, have been shown to be in significant discrepancy with empirically observed judgment and decision behavior for both naïve and expert decision makers alike (e.g., Axelrod, 198?; Kahneman, Slovic, & Tversky, 1982; Neale & Bazerman, 1991).

An exceptionally disturbing and far reaching discrepancy between normative and descriptive decision theory concerns agents' valuation of the consequences of a course of action. Agents' valuations, i.e. the transformation of observed consequences by means of subjective weighting of these consequences resulting in some form of utility, constitute a behavior critical to economic theory. In particular, economic theory postulates valuation behavior leading to the symmetric valuation of negative and objectively commensurate positive consequences as reflected in the presumed CV and EV equivalence (e.g., Willig, 1976; Randall & Stoll, 1980). Providing the basis for utility and expected utility theories, this behavioral maxim has wide and far reaching implications with respect to most economic and decision theoretic prescriptions and predictions.

Empirical research in experimental economics and behavioral decision theory, however, suggests a vastly different valuation behavior than the one presumed by normative theory. In fact, countless research accounts report a robust and systematic two-fold valuation pattern suggesting agents value losses much heavier than objectively commensurate gains -- a behavior commonly referred to as *loss aversion* or *endowment effect* (Kahneman & Tversky, 1979; Thaler, 1980).

Although asymmetric valuations of gains and losses have been shown to be a prevalent and pervasive aspect of agents' decision making, this behavior is still widely deemed irrational and, by definition, suboptimal. Given this concern, we employ evolutionary modeling techniques building on the notion of artificial adaptive agents (Holland & Miller, 1993) and artificial economic agents (Arthur, 1991, 1993) to investigate the emergent properties of maximizing agents' fundamental valuation preferences. Specifically, we implement populations of artificial decision makers making choices over pairs of risky gambles. The results of these experiments suggest asymmetric valuations to be a dominant, emergent choice pattern for adaptive, maximizing decision makers.

2.0 Background

Neoclassical economic theory has developed into a highly reductionist, axiomatic discipline relying extensively on the virtues of mathematical and statistical optimization techniques. Selfishness and rationality comprise the two principal behavioral maxims underlying economic theory. The selfishness postulate essentially allows for use of the maximization principle and the rationality postulate assures economic agents have the necessary cognitive capacity to carry out the optimization processes. These behavioral maxims allow for the thorough and elegant expression of high-powered theory in a highly parsimonious, mathematical notation generally leaving the behavioral details of the model as exogenous details (e.g., Becker, 1976; Stigler & Becker, 1977).

Recent empirical evidence in experimental economics and behavioral decision theory suggests, however, that even fundamental normative presumptions regarding decision behavior, such as the symmetric weighing of gains and losses, do not adequately capture actual behavior. Instead, naïve and expert decision makers alike seemingly adhere to loss averse behavior, i.e. the asymmetric weighing of positive and objectively commensurate negative payoffs relative to some reference position (Kahneman & Tversky 1979; Thaler, 1981). Loss aversion has been documented in a wide variety of contexts as well as both certain (e.g., Thaler, 1980; Knetsch & Sinden, 1987; Kahneman, Knetsch, & Thaler, 1990; Borges, 1995) and risky and uncertain conditions (e.g., Kahneman & Tversky, 1979; Kachelmeir & Shehata, 1992; Tversky & Kahneman, 1992) and culminated in descriptive alternatives to expected utility theory models such as Prospect Theory (Kahneman & Tvekrsy, 1979) and Cumulative Prospect Theory (Tverksy & Kahneman, 1992; Tversky & Waaker, 1995).

As a result of agents' observed valuation disparities, staples of economic (decision) theory, such as the irreversibility of indifference curves (Knetsch, 1989, 1992), the efficiency of Coasian allocations (Knetsch and Sinden, 1987; Kahneman, Knetsch, and Thaler, 1990), the opportunity cost criterion (Borges and Knetsch, in press), the Pareto-efficiency of auctions (Borges and Knetsch, 1995), and the validity of expected utility theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), have all been called into question. Furthermore, recent simulation studies (Borges, 1996) comparing the performance of artificial decision makers with respect to both payoff maximization and population survival criteria indicate that loss averse agents performed at least at par with normative agents and displayed higher population survival rates than normative agents.

Kahneman & Tversky (1979) suggest a two-piece power function to describe loss averse valuations. That is,

Equation 1: $$v(x_i) = \begin{cases} x_i^{\alpha}, & x \geq 0 \\ -\lambda(-x_i)^{\beta}, & x < 0 \end{cases}$$ where

$v(x_i)$ defines the loss-gains preserving valuation function over outcomes, or consequences, such that

$$x \equiv (x_1, x_2, \ldots, x_S),$$

λ represents the loss aversion parameter governing the asymmetric weighting of gains and losses, and

α, β are preference scaling parameters over outcomes.

The function v(•) is distinctly different from the notational similar elementary utility function, or preference scaling function, commonly encountered in expositions of EUT. It should be noted that v(•) is defined over outcomes, or consequences, and that the valuation of the reference position results in a fixed valuation of $v(0) = 0$ (Kahneman & Tversky, 1979). That is, the behavioral valuation function resembles measurement on a ratio-scale, whereas EUT is measured on an interval scale. Kahneman & Tversky (1992) empirically determined a paramterization of v(•) where $<\lambda = 2.0, \alpha = 0.8, \beta = 0.8>$. Of course, this function also allows the expression of symmetric valuation patterns, such as traditional risk-aversion, which would require a parameterization such that $\{\lambda = 1.0, \alpha < 1.0, \beta > 1.0\}$.

Advances in research in Prospect Theory and Cumulative Prospect Theory (Kahneman & Tversky, 1992) further suggest a fourfold decision pattern over outcomes and probabilities (Table 13). In particular, decision makers seemingly tend to behave risk-seeking over choices combining low probabilities and gains or high probabilities and losses but to act risk-averse for payoff-probability combinations that either promise positive payoffs with high probabilities or negative outcomes governed by low probabilities.

*** Insert Table 13 Approximately Here ***

Although the rigorous use of mathematical analysis unambiguously corroborates the superiority of the highly axiomatic, normative decision theory, such as EUT, it is puzzling how a significant number of (human) decision makers relying on "irrational" valuation preferences have, by and large, performed reasonably well in their (economic) environments. If loss aversion, as a guiding decision preference, was indeed inferior to the normative approach, one would expect "rational tricksters and confidence men" to take advantage of such vulnerable prey (Hirschleifer & Riley, 1992:34). Of course, the (finite) supply of decision making agents relying on inferior judgment and decision making strategies would, over time, eventually be decimated to the point of extinction (e.g., driven into economic ruin or converted to "rational" agents) and only rational agents would survive.

The remainder of this paper investigates this issue by means of evolutionary modeling. Employing a genetic algorithm (GA) governing the survival of populations of maximizing artificial agents, we empirically investigate the emergent valuation patterns of parameter values for a generalized expected valuation function under conditions of finite time horizons.

3.0 Emergence Of Adaptive Valuation Patterns

Although there exists no explicit reason for decision makers to symmetrically value gains and losses, normative economic (decision) theory presumes and prescribes such behavior. If irrational deviations from the symmetric valuation behavior was truly inferior to the prescribed behavior, the market should correct for such erroneous conduct and allow only rational agents to prosper and survive. The wide observation of loss aversion as documented in empirical laboratory and field studies seems to refute such corrective market action, even if market imperfections and general dynamics masking asymmetric valuation behavior providing pockets of survival are taken into consideration. Furthermore, the success of loss aversion compared to symmetric valuation behavior, as reported by Borges (1996), further casts doubt on the presumed superiority of symmetric valuation patterns.

The existing literature with respect to (asymmetric) valuation behavior is comprised of accounts of empirical work aimed at uncovering valuation asymmetry as a robust and systematic decision behavior, reports documenting the implications of such behavior on the validity and reliability of normative theory, and recently the comparative market performance of agents adhering to either normative or descriptive valuation patterns. Little, if any, research, however, documents the emergence of valuation behavior for maximizing, adaptive agents. The experiments reported below address the issue of what type of valuation pattern maximizing agents learning from market feedback, such as payoffs, would develop.

3.1 Experimental Methods And Design

The simulation experiments conducted are grounded in the notion of neo-Darwinian evolution asserting that the vast majority of life is fully accounted for by a minimal set of statistical processes (i.e., reproduction, mutation, competition, and selection) acting on and within populations and species (Fogel, 1995). Thus, the experimental methodology employed for the purpose of our investigation leans strongly on the notion of artificial adaptive agents (AAAs) proposed by Holland & Miller (1991) and the design of artificial economic agents (Arthur, 1991).

We implement a population of adaptive agents optimizing parameters governing valuation and preferences for a generalized expected valuation function. This optimization process was governed by a genetic algorithm (Holland, 1975). Artificial adaptive decision makers (ADM) are exposed to pairs of gambles, i.e. prospects, and required to make a choice among the gambles' alternatives. These choices, which are a direct reflection of agents' valuation and preference parameters optimized by the GA, are then played out and agents are credited, or debited, with the appropriate payoffs. Agents' payoff values functioned as the fitness measure for the GA.

Portfolio of Gambles

The experimental environment was comprised of a total of eight pairs of gambles (Table 14). These eight prospects, originally employed by Kahneman & Tversky (1979:268), are either strictly positive or strictly negative with respect to the outcomes where the negative gambles are simply the negations of the positive gambles. Thus, the probabilistically expected values of the positive gambles are mirrored by their negative counterparts. If an ADM was presented with G1, for example, the agent had to choose between a gamble paying $4,000 with an 80% chance or nothing with a 20% chance, i.e. Alternative 1, or $3,000 for certain, i.e. Alternative 2.

*** Insert Table 14 Approximately Here ***

It should be noted that the sets of gambles differ in the expected values across alternatives. The first four prospects, i.e. G1 through G4, do not have equal expected values leading to an indifference exponent, γ, of less than unity, whereas the remaining sets of gambles have equal expected values resulting in $\gamma^* = 1.0$. That is, an agent relying on a valuation function as outlined in Equation 2 below would be indifferent between the two alternatives of G1, if the corresponding preference scaling parameter was less than $\gamma^* = 0.7757$[12]. Thus, traditional risk-aversion leading to a preference for the sure payoff of $3,000 if attained with a scaling parameter value of $\gamma < 0.7757$. Of course, a risk-averse agent with a preference scaling parameter of, say, 0.8, would choose the distinctly a risk averse first alternative for G5 (i.e., the gamble that promises to pay either $3,00 with probability 0.9 or nothing otherwise) but choose the risky gamble, i.e. the first alternative, over the sure gain for G1.

Agent Representation

A population of adaptive artificial decision makers governed by evolutionary principles, i.e. a GA, was created and repeatedly subjected to an environment requiring decision making and responding with outcomes to these choices. Each ADM was comprised of a bit string, i.e. a

[12] The value of γ^* is determined by solving the exponential equation $(0.8 * 4{,}000)^{\gamma} = 3{,}000^{\gamma}$ resulting in $\gamma^* = \ln(0.8)/\ln(3/4) \approx 0.7757$.

chromosome, representing the values of the parameters driving an expected valuation function, which in turn governed agents' choices. The outcome of each decision made by ADMs resulted in a payoff to the agents and the (accumulated) payoff of each agent, relative to all the other agents in the population, determined the entity's fitness. After each decision period, or generation, the GA ensured that reproduction of the agents was conducted according to agents' proportional fitness. That is, fitter agents reproduced more than less successful members of the population. Hence, "successful" parameter values, or decision patterns, diffuse quickly into the next generation.

In order to facilitate agents' decision process, we define an expected valuation function (Equation 2) that employs the linear probabilistic weighting suggested by normative decision theory but allows for the asymmetric weighting of positive and negative outcomes in the manner introduced by Equation 1 above. Formally, we define an expected valuation function V such that

Equation 2: $$V(x,p) \equiv \sum_{s=1}^{S} p_i v(x_i), \text{ where}$$

V(x,p) is the valuation function defined over the gambles with x again denoting the vector of consequences and p the vector of probabilities associated with x, such that $p \equiv (p_1, p_2, \ldots, p_S)$, of course summing to unity, and

v(x) is the loss-aversion preserving preference scaling function of Equation 1.

The above function, combining the normative linear weighting of probabilities and the possibility of descriptive valuation asymmetry, facilitates the specific investigation of outcome valuations allowing the derivation of both symmetric and asymmetric valuations depending on agents parameter selection. Consider an ADM facing the choice between a gamble paying $3,200 for sure or $4,000 with an 80% chance (and $0 with a 20% chance). If the agent had an α value in excess of unity, i.e. $\alpha > 1.0$, the ADM could be considered risk-seeking and would choose the \$4,000, 80% or \$0, 20% gamble. Conversely, if the ADM had an α value less than unity, i.e. $\alpha < 1.0$, it would choose the gamble paying \$3,000 for sure. Now consider an agent facing a choice between the negated version of this pair of gambles. That is, the agent has a choice between a \$3,200 loss for sure or a \$4,000 loss with an 80% chance (or no loss with a 20% chance). Hence, an agent with a β value in excess of unity, i.e. $\beta > 1.0$, would choose the \$3,000 loss for sure, whereas an agent with a β value of less than unity, i.e. $\beta < 1.0$, would choose the risky gamble incurring either a \$4,000 loss with an 80% chance or no loss with a 20% chance (regardless of the value of the loss aversion parameter λ).

In general, a normative agent adhering to the symmetric valuation pattern should either have parameter values such that $<\lambda = 1.0, \alpha > 1.0, \beta < 1.0)$, $<\lambda = 1.0, \alpha < 1.0, \beta > 1.0)$, or $<\lambda = 1.0, \alpha = 1.0, \beta = 1.0)$. That is, an agent should be either risk-averse (RA), risk-seeking (RS), or risk-neutral (RN) over both gains and losses. A loss averse agents, on the other hand, with RA in the gains and RS in the losses would have a parameter set such that $<\lambda \geq 1.0, \alpha < .0, \beta < 1.0>$. As it can be seen on hand of this example, the loss aversion parameter, λ, can be fixed at unity if, and only if, the prospects employed are pure, i.e. either strictly positive or negative in payoffs.

GA Configuration And Simulation Parameters

The variant of the GA implemented was based on a single binary chromosome either accommodating α and/or β depending on the experimental variation. A deterministic selection procedure was employed and coupled with a weakest replacement algorithm and single-point crossover. Although this configuration makes for an extremely accurate GA, its major drawback lies in the computational expense incurred. That is, this GA configuration is extremely slow. Since each agent in the population of the genetic algorithm in fact represents a solution in the solution space and the number of discrete solutions facilitating the choice process was very small, it was decided to operate with a small population of twenty agents operating on a real number range for both the α and β parameter of [0.0, 1.75].

The convergence criterion for the GA was based on the α and β parameter in the population simultaneously reaching values that fell within 0.05 standard deviations of the respective population means after at least 100 generations up to 500 generations and 0.075 standard deviations afterwards. To guard against the pitfalls of premature convergence and random fluctuations in general, each GA run was repeated 24 times.

Applying descriptive statistics to the actual parameter values evolved by the GA for agents is of little value as only the action following the parameter values matters as agents' actual choices are discrete states. That is, for a strictly positive gamble with equal expected value, values less than $\gamma^* = 1.0$, is risk-averse regardless of whether the derived parameter value is, say, 0.8 or 0.1. Instead of reporting agents' actual parameter values, we report the corresponding preference structure. Thus, an α parameter of less than the γ^* associated with the respective gambles is reported as a RA preference, whereas a value exceeding γ^* is reported as a RS preference. Of course, this pattern reverses for the β values, i.e. $\beta < \gamma^*$ is reported as a RS preference and a $\beta > \gamma^*$ is reported as a RA values.

3.2 Experiment 1 – Evolving Individual Preference Parameters

The first experiment investigated the emergence of valuation either for gambles strictly dealing with gains or gambles strictly dealing with losses. Of course, agents employed only the appropriate portion of the piece-wise valuation function to these gambles and thus, only the α or β parameter was evolved. Gambles were individually presented to agents for either 10 or 200 decision periods facilitating a comparison between a short-term and long term time horizon.

3.2.1 Preference Structures For Strictly Positive Gambles

The first prospect, G1, offered agents either the alternative to gain \$4,000 with an 80% probability (or nothing with a 20% probability) or to gain \$3,000 for sure (A2). The expected values for these alternatives are \$3,200 and \$3,000, respectively. Thus, a decision maker with a preference scaling value $\alpha < 0.7757$ will choose the second alternative paying \$3,000 for sure, whereas decision makers with α values equal to 0.7757 would be indifferent between the two alternatives, and agents with an $\alpha > 0.7757$ would choose the first alternative with the higher expected payoff of \$3,200. The GA results for the first gamble were unanimous for both the short, i.e. 10 trials, and the long, i.e. 200 trials, variants. That is, the evolved α values exceeded the γ^* for every trial suggesting evolved preferences favoring the risky A1 , i.e. \$4,000 with an 80% chance, over the sure alternative.

G3 presented the decision makers with a choice of a again of either \$4,000 with a 20% chance or nothing otherwise or \$,3000 with probability 0.25 or nothing otherwise. Although not unanimous, the GA solutions converged 75% (short time horizon) and 92% (long time horizon) of the time to an RS preference. Thus, ADM's developed a strong preference for A1 promising to pay \$4,000 with a 20% chance.

The remaining positive prospects, i.e. G5 and G7, differed from the previous prospects as the corresponding expected values of the alternatives were equal, i.e. $\gamma^* = 1.0$. Distinct preferences were observed for the remaining two positive prospects, G5 and G7. While the solutions for G5 converged 78% of the time (sort run) and 58% of the time (long run) to a preference for A2, a dominant convergence of 83% and 92% for the short-run and long-run, respectively, was attained for G7.

In summary, these results suggest that for the prospects with unequal expected values, agents choose in a manner resembling risk-seeking (or risk-neutral) behavior preferring the payoffs with the higher expected value but in disregard for lower risk, lower expected payoff gambles. For the prospect with the low probability event , i.e. G7, agents opted to pursue a distinctly risk-averse course of action. Only for the third positive prospect, i.e. G5, did the GA not produce a predominant choice pattern. Instead, agents seemingly were indifferent between the two alternatives.

3.2.2 Preference Structures For Strictly Negative Gambles

The second set of individually played out gambles were the negations of their positive counterparts leading to strictly negative in outcomes. Thus, agents were now required to adapt with respect to the β parameter driving the expected valuation function of Equation 2.

G2, the negated version of G1, promises choosers either a $4,000 loss with an 80% probability or nothing otherwise (A1) or a $3,000 loss for sure (A2). The converged solutions were nor very dominant, with agents preferring the sure loss with the higher expected value 63% of the time for the short-run and 58% for the long-run. Similarly, the convergence rates for the fourth prospect, G4, resulted in approximately an even split between the two alternatives for both variants.

These results are in contrast to the unanimous preferences that emerged for these prospects' positive counterparts. While agents clearly chose the prospect with the higher positive payoffs for the positive variants of these prospects, a valuation reversal occurred leading agents to be indifferent between the gambles with low-risk, lower expected loss payoffs and the higher-risk, higher expected value losses. That is, ADM's seemed to predominantly favor a RS valuation for the gains but reverse, at the least half of the time, to the asymmetric, RS preference for the corresponding loss variants.

The remaining two sets of gambles, again differing from G2 and G4 by virtue of equal expected values for the two alternatives, displayed more pronounced convergence patterns. For G6, 62% and 75% of the runs converged to a pattern preferring A1 over A2, whereas 92% and 88% of the runs for G8 resulted in patterns valuing A2 more than A1.

The evolved pattern for G8 reflects a direct valuation reversal from its positive counterpart, i.e. G7, switching from a RA pattern to a RS pattern. Although only directional in dominance, ADMs were approximately indifferent for the two alternatives of G5, the positive prospect, but leaned toward a RA valuation for G6, the negative variant.

*** Insert Table 15 Approximately Here ***

Although the simulation runs for this experiment do not allow for intra-personal, or intra-agent, valuation and preference patterns, it has become apparent that ADM's recognize the higher positive expected values for the positive prospects G1 and G3 and choose in accord with these payoffs even though the risk associated with these alternatives was higher than that associated with the low-payoff alternatives. This pattern did not carry symmetrically into the valuation of losses, where valuation symmetry would required a distinct preference for the low-risk, lower loss alternatives. Instead, ADM's leaned toward indifference between the alternatives indicating at least a partial valuation reversal. Furthermore, an outright valuation reversal was obtained for the low probability, equal expected value prospects G7 and G8. While agents dominantly preferred the RA alternative, A1, for G7, they switched to the RS alternative of the negated version of this prospect, G8. A somewhat indifferent choice pattern was observed for agent behavior for G5, although agents leaned strongly toward the RA alternative for G6. Overall, it appears that valuation reversals have taken place and that valuations were rather stable over both the short-run and the long-run time horizons.

3.3 Experiment 2 – Evolving Valuations Over Pairs Of Prospects

The simulations conducted for the first experiment individually evolved gain and loss preference parameters and provided interesting insights with respect to the choice patterns of adaptive, maximizing agents. However, the first experiment lacked an intra-agent, or "within-subject", perspective. This second experiment extends the scope of the investigation presenting agents with pairs of prospects allowing for the observance of truly intra-agent preference patterns.

Once again, we employed the above gambles but instead of having AAAs separately evolve the α and β parameters for gambles, α and β were co-evolved over the two sets of gambles. That is, over the set number of trials, i.e. 10 or 200, agents were randomly presented with either Gamble 1 or Gamble 2 (or Gamble 7 or Gamble 8) and in accordance with Equation 2 both α and β parameters were evolved. Given the two basic parameter values, i.e. RA and RS (excluding RN), we anticipate the emergence of four different combinations of valuation/preference patters: RA/RS, RA/RA, RS/RS, and RS/RA. An $\alpha < \gamma^*$, then, would be again considered RA and RS otherwise. Analogously, a $\beta < \gamma^*$ would indicate RS behavior, whereas a $\beta > \gamma^*$ would suggest RA behavior.

The first tuple of prospects, comprised of G1 and G2, was presented to agents and led to a convergence of 96% of the long runs favoring a RS/RA preference pattern. That is, the majority of the runs for the long-run variant produced a behavior preferring the risky gamble A1 ($4,000 with an 80% chance) over the sure payoff ($3,000) of A2 for G1 and the sure loss of $3,000 (A2) over the risky loss of $4,000 with probability 0.8 (A1) for G2. This result indicates a strong, symmetric valuation of payoffs with respect to the expected valuation principle. For the short-run variant, however, no distinct pattern was evolved with approximately half of the solutions leading to the asymmetric RA/RA or RS/RS valuations. Thus, only the long-run produces the expected valuation pattern.

A similar but much less pronounced decision pattern emerged for the second set of prospects, i.e. G3 and G4. The dominant valuation pattern was again the RS/RA combination (58% of the time for the long-run variant) preferring the alternatives with the higher expected gain and the lower expected loss, although almost one quarter of the solutions led to an asymmetric valuation pattern showing a preference for the higher expected gain and the higher expected loss. A similar pattern was observed for the shortOrun variant.

The third and forth set of prospects again operated on the basis of equal expected values. The third tuple, comprised of G5 and G6, converged 75% (short-run) and 54% (long-run) of the time to a RA/RS solution. Given the equivalence of expected values, this choice pattern constitutes a distinct asymmetric valuation in the traditional sense of loss aversion.

The last set of prospects, G7 and G8, dominantly converged to a loss averse valuation pattern in form of a RA/RS solution (83%) for the long-run variant, whereas the short-run variant produced only a 46% RA/RS valuation and followed by a strong 33% RS/RS pattern.

*** Insert Table 16 Approximately Here ***

In summary, the simulation runs over tuples of prospects including both a gain and a loss variant suggest that with the exception of the first set of prospects, G1 and G2, ADM's showed strong signs of valuation asymmetry and preference reversals. Specifically, the solutions to those prospects with equal expected values over the alternatives converged to the commonly reported loss averse valuation pattern.

3.4 Experiment 3 – Evolving Generalized Valuations

This last experiment requires artificial gents to generate preference parameters over the decision portfolio. The previous experiments were geared toward the local preferences for either individual or tuples of prospects. This experiment investigates the global, generalized valuation preferences of ADM's in the context of a relatively large and diverse portfolio of decisions. Due to the long runs required to expose ADM's to the portfolio we limit simulation runs to only one time horizon comprised of 500 decision periods.

The GA results for this experimental variant suggests that 54% of the solutions favored a RA/RS valuation pattern, 33% a RS/RA pattern, 13% a RS/RS pattern, and no RA/RA pattern (Table 17). Due to the difference in expected values over alternatives for the first four prospects, a close examination of the actual parameter values was required to account for the degree of risk-aversion, or risk-seeking, as reflected in parameter values relative to the minimum γ^*, i.e. $\gamma^* = 0.7757$. The majority (76%) of the RA/RS valuation pattern was driven by both $\langle\alpha,\beta\rangle$ values in excess of γ^*. Thus, the majority of the loss averse solutions preferred the higher-risk/higher expected gains alternatives and the lower-risk/lower expected loss alternatives for the first four prospects but preferred the high-probability, risk-averse alternatives for gains and the low-probability, risk-seeking alternatives for the remaining four prospects (governed by equal expected payoffs over alternatives).

*** Insert Table 17 Approximately Here ***

In summary, the generalized decision valuation and preferences for the entire portfolio mirrored our earlier results. The dominant, emerged valuation and preferences pattern was such that the solution recognized the expected payoff difference among gambles and generate parameter values to take advantage of this payoff differential. That is, agents essential developed preference parameters that simultaneously allowed for the pursuit of an essentially risk-neutral choice pattern for the prospects with unequal expected values and a loss averse choice pattern otherwise. Overall, it appears that agents tend to be favor asymmetric valuation patterns with respect to gains and losses but adjust those parameter in a manner allowing the exploitation of "skewed" gambles.

4.0 Conclusion

This paper introduced evolutionary modeling to investigate the viability of asymmetric valuation patterns of maximizing agents. The results to the simulation experiments conducted strongly indicate hat maximizing artificial agents indeed respond with asymmetric valuation patterns reminiscent of those obtained with human subjects. In conjunction with the existing literature on loss aversion, it seemingly appears to be an effective choice pattern – at least under conditions of finite time horizons.

Future research should extend the approach outlined above and investigate the evolutionary feasibility of a complete, descriptive expected value model including the evolution of probability weighting parameters commonly reported in studies concerning natural decision makers. The most challenging and interesting use for the developed simulation approach concerns the investigation and modeling of dynamic economic systems. Calibrating maximizing agents in accordance with the methodology introduced above constitutes an effective and novel way to seed systems with bounded rational, but maximizing agents. We are convinced that such modeling will play a major role in the development and testing of economic models particularly in the area of public policy and business strategy.

Conclusion

Simon's work on bounded rationality has widened the interest and perceived relevance of human behavior. Especially in the decision sciences, the advent of the bounded rationality paradigm has had a profound impact and human behavior has taken once more the center stage. Although the prescriptive behaviors emanating from the decision sciences have been tremendously helpful and successful, and will continue to be so, in providing analytical aids to improve decision making, the human mind and behavior got somewhat lost in the search for better, faster, and more elegant algorithms and decision aids.

A fundamental precursor underlying human decision behavior concerns humans' judgment of probabilities and valuation of outcomes. Even if a decision maker employed the correct decision tools for a particular problem at hand, deviations from the assumed judgment and valuation behavior underlying these decision tools may prove the analysis flawed.

The three studies comprising this paper focus on people's valuations of outcomes. As discussed above, human valuation structures are best expressed in form of a reference-preserving ratio scale rather than the normatively presumed interval scale. Although reference-dependent behavior, as reflected in loss aversion, is widely documented, little, if any, information pertaining to the effectiveness and efficiency of such behavior is available. The second and third study conducted investigated the performance of asymmetric valuation behavior.

The first study documents the manifestation of loss aversion, or an endowment effect, under conditions of highly substitutable exchange goods, i.e. money and lottery tickets, and weakens the assertion that uncontrolled substitution effects are the source of valuation disparity reported in earlier work. Although the investigation of the dependence relation between the endowment and substitution effect was the primary motivation for the experiments, two other results obtained in the course of this investigation are also noteworthy. First, the observed valuation disparity was observed in the context of both a within- and a between-group design, whereas the majority of documented valuation disparities (in the context of real exchange markets) are based on between-subject designs. Second, decision makers displayed a strong anchoring on the going market price for their willingness to pay (WTP)measure, rather than an anchoring on the intrinsic value of the lottery ticket, i.e. the expected value of the ticket. While the observation of disparate valuations on a within-subject level further strengthens the support for the endowment effect hypothesis, agents' anchoring on going market prices, rather than intrinsic values, provides an opportunity for further research of asymmetric, reference-dependent valuations. Specifically, the relation between procedural fairness and reference values, as employed in arbitration processes, may prove an important avenue for further investigations. Moreover, an interesting extension of the experimental design employed above entails the implementation of an experimental control for purchasers and non-purchasers of lottery tickets.

The establishment of an endowment effect independent of the substitution effect provided the *rosetta stone perceived necessary* to proceed with investigations concerning the effectiveness and efficiency of asymmetric valuation behavior as implemented in the second study. The results of the experimental tests with respect to artificial agents' comparative performance and relative survival over a portfolio of risky, routine decisions suggest not only that loss averse behavior performs favorable compared to the normative, symmetric valuation patterns but outperformed these benchmark behaviors under conditions of resource constraints.

Although the results of this second study are confined to the contextual constraints of the experiments, several important issues warranting further research have arisen. Most importantly, perhaps, is the observation of the different directions and speeds of convergence to the limit. If this observation comprises a robust, systematic phenomenon, it could and should play an important role in the formal optimization toolbox of decision theory. The investigation of different valuation structures' convergence to the limit, then, warrants future research.

Furthermore, research with respect to agent survival, and particularly the rate of attrition, also requires more investigation. Specifically, a relationship between actual length of time horizon and the corresponding survival rates should be established in the context of a real-time simulation study and actual longitudinal data.

Having established a favorable performance account for loss averse agents, a logical progression regarding the investigation of loss aversion, at least in our mind, concerned the investigation of the formation of valuation patterns and preference structures. Although tastes and preferences are commonly regarded exogenous variables in economic (decision) theory, they are not exogenous to the decision maker. Decision makers' tastes and preferences must have some place of origin -- be it of genetic or environmental origin as, for example, reflected in individual learning and adaptation processes.

The third study addressed this issue and reports on the investigation of agents' valuation and preference formulations assuming the perspective of agents adapting to, or leaning from, their environment as the result of the decision-outcome feedback loop. Employing evolutionary modeling techniques allowed the "construction" of unencumbered, maximizing agents and the exploration of truly emergent properties of adaptive artificial agents' valuation structures and preference patterns.

The results of this study suggest that maximizing, adaptive decision makers favor the prototypical , asymmetric valuation pattern inherent in loss aversion for individual and paired low probability prospects as well as for the comprehensive, complex portfolio. It is of particular interest that agents' valuation preferences significantly favored the asymmetric valuation structures for the complex decision context. Furthermore, the preference parameters evolved for the portfolio were such that the ensuing choice pattern isomorphically corresponded to the choice patterns deployed in the second study. Hence, the performance of the emerged asymmetric valuation structures is identical to the results obtained for loss averse agents in the second study.

This third study provides several opportunities for further investigation. First, the methodology employed appears suitable for economic research concerned with emergent and adaptive agent behavior -- a research thread most prominent in the field of game theory. Second, the context-driven evolution inherent in the methodology developed may prove an excellent supplement to reinforcement learning algorithms and valuable for the development of high-level cognition in autonomous agent research. Third, the methodology may be a useful tool in portfolio optimization, especially in the area of finance.

In summary, the three studies conducted document the manifestation of loss aversion as a cause of valuation disparities independent of substitution effects, indicate that the performance of individuals using asymmetric valuations may not be inferior to the normative, symmetric behavior, and suggest that asymmetric valuation structures are a feasible and viable valuation response of maximizing, adaptive decision makers.

As a final note, a "classification" issue deserves attention. Much of the research concerning valuation behavior, especially observed valuation behavior, has been classified as "bounded rationality research." In fact, asymmetric valuation behavior, as reflected in loss aversion and the endowment effect, seems to be viewed as the result of humans' bounded cognition. This appears to be an erroneous conclusion as asymmetric valuation behavior reflects a decision maker's fundamental preferences for gains and losses. The very emergence of such behavior in the context of maximizing, "rational" agents, as discussed in Chapter 3, furthers this notion.

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TABLES

Table 1: Descriptive Statistics

	n	Mean	Median	Std.Dev.	Min, Max
Group 1 – G_{WTA}					
WTA - All Ss	50	$2.42	$2.00	$0.96	$1.00,$ 4.00
WTA - Ss with no trade	28	$2.85	$3.00	$0.92	$1.25, $4.00
WTA - Ss with trade only	22	$1.88	$1.875	$0.71	$1.00, $3.25
WTP - Ss with trade only	22	$1.02	$1.00	$0.59	$0.00, $3.00
Valuation Disparity (WTA,WTP)	22	$0.85	$0.875	$0.92	$-1.00, $2.25
Group 2 – G_{WTP}					
WTP - All Ss	60	$0.96	$1.00	$0.46	$0.00,$ 2.00
WTP - Ss with no trade	37	$0.84	$1.00	$0.41	$0.00, $2.00
WTP - Ss with trade only	23	$1.14	$1.00	$0.49	$0.25, $2.00
WTA - Ss with trade only	23	$2.38	$2.50	$0.99	$0.75, $4.00
Valuation Disparity (WTA,WTP)	23	$1.24	$1.25	$0.46	$-0.25, $3.00

Table 2: Within and Between Group Comparisons

Comparison	Analysis	Statistics	Significance
Within-Group -- G_{WTA}			
WTP to market price of ticket	Paired t-test	$t = 2.09$, $df = 20$	$p = 0.42$
Valuation Disparity (WTA,WTP)	Paired t-test	$t = 4.35$, $df = 21$	$p = 0.000$
Within-Group -- G_{WTP}			
WTP to market price of ticket	Paired t-test	$t = 2.00$, $df = 59$	$p = 0.48$
Valuation Disparity (WTA,WTP)	Paired t-test	$t = 6.6$, $df = 22$	$p=0.000$
Between-Group: G_{WTA} vs. G_{WTP}			
WTA -- all Ss	ANOVA	$F_{ratio} = 0.0264$, $df = 1, 71$	$p = 0.8715$
WTA -- Ss with trade	ANOVA	$F_{ratio} = 3.8547$, $df = 1, 43$	$p = 0.0562$
WTP -- all Ss	ANOVA	$F_{ratio} = 0.2702$, $df = 1, 80$	$p = 0.6046$
WTP -- Ss with trade	ANOVA	$F_{ratio} = 0.5399$, $df = 1, 43$	$p = 0.4665$
Valuation Disparity (WTA, WTP)	ANOVA	$F_{ratio} = 2.0374$, $df = 1, 43$	$p = 0.1607$

Table 3: Decision Portfolio 1

Gamble	Alternative 1 (A1)	Alternative 2 (A2)
1	$4,000.00, 0.800; $0.00, 0.200	$3,000.00, 1.000; $0.00, 0.000
2	-$4,000.00, 0.800; $0.00, 0.200	-$3,000.00, 1.000; $0.00, 0.000
3	$4,000.00, 0.200; $0.00, 0.800	$3,000.00, 0.250; $0.00, 0.750
4	-$4,000.00, 0.200; $0.00, 0.800	-$3,000.00, 0.250; $0.00, 0.750
5	$3,000.00, 0.900; $0.00, 0.100	$6,000.00, 0.450; $0.00, 0.550
6	-$3,000.00, 0.900; $0.00, 0.100	-$6,000.00, 0.450; $0.00, 0.550
7	$3,000.00, 0.002; $0.00, 0.998	$6,000.00, 0.001; $0.00, 0.999
8	-$3,000.00, 0.002; $0.00, 0.998	-$6,000.00, 0.001; $0.00, 0.999

Adapted from Kahneman & Tversky (1979), p. 268.

Table 4: Parameter Values For Artificial Agent Preference Structures

Parameter	Loss Averse (LA)	Risk-Averse (RA)	Risk-Seeking (RS)	Risk-Neutral (RN)
λ	1.00	1.00	1.00	1.00
α	0.80	0.80	1.05	1.00
β	0.80	1.05	0.80	1.00

Table 5a: Valuations and Expected Values For Decision Portfolio 1

G	RN Valuation A1, A2		RA Valuation A1, A2		RS Valuation A1, A2		LA Valuation A1, A2	
1	3200.00	3000.00	609.17	604.92	4844.54	4476.90	609.17	604.92
2	-3200.00	-3000.00	-4844.54	-4476.90	-609.17	-604.92	-609.17	-604.92
3	800.00	750.00	152.29	151.23	1211.14	1119.22	152.29	151.23
4	-800.00	-750.00	-1211.14	-1119.22	-152.29	-151.23	-152.29	-151.23
5	2700.00	2700.00	544.43	473.95	4029.21	4171.30	544.43	473.95
6	-2700.00	-2700.00	-4029.21	-4171.30	-544.43	-473.95	-544.43	-473.95
7	6.00	6.00	1.21	1.05	8.95	9.27	1.21	1.05
8	-6.00	-6.00	-8.95	-9.27	-1.21	-1.05	-1.21	-1.05

Table 5b: Preference-Dependent Choices and Expected Values For Decision Portfolio 1

Gamble	RN Choice	LA Choice	RA Choice	RS Choice	E[2]$_{RN}$ ($)	E_{LA} ($)	E_{RA}	E_{RS}
1	A1	A1	A1	A1	3,200.00	3,200.00	3,200.00	3,200.00
2	A2	A2	A2	A2	- 3,000.00	- 3,000.00	-3,000.00	-3,000.00
3	A1	A1	A1	A1	800.00	800.00	800.00	800.00
4	A2	A2	A2	A2	-750.00	-750.00	-750.00	-750.00
5	A1or A2[1]	A1	A1	A2	2,700.00	2,700.00	2,700.00	2,700.00
6	A1or A2	A2	A1	A2	- 2,700.00	- 2,700.00	-2,700.00	-2,700.00
7	A1or A2	A1	A1	A2	6.00	6.00	6.00	6.00
8	A1 or A2	A2	A1	A2	-6.00	-6.00	-6.00	-6.00
				Expected Value over Portfolio	250.00	250.00	250.00	250.00

1: A simulated toss of a fair coin was employed to break ties.

2: E denotes the expected outcome for this pair of gambles.

Table 6: Summary Statistics For Experiment 1

Descriptives

			N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Portfolio 1 Best-Of-Generation	Group	LA	50	187.6000	23.7375	3.3570	180.8539	194.3461	142.00	275.00
		RN	50	182.3600	23.4849	3.3213	175.6857	189.0343	141.00	252.00
		RA	50	177.5600	21.2412	3.0040	171.5233	183.5967	126.00	234.00
		RS	50	193.5200	24.8680	3.5169	186.4526	200.5874	155.00	280.00
Portfolio 1 Worst-Of-Generation	Group	LA	50	-155.340	20.5015	2.8993	-161.166	-149.514	-216.00	-118.00
		RN	50	-154.220	26.9431	3.8103	-161.877	-146.563	-281.00	-115.00
		RA	50	-144.540	18.8628	2.6676	-149.901	-139.179	-188.00	-114.00
		RS	50	-161.000	22.8562	3.2324	-167.496	-154.504	-240.00	-123.00
Portfolio 1 Average	Group	LA	50	16.2148	2.3987	.3392	15.5332	16.8965	12.24	21.61
		RN	50	14.5380	2.1193	.2997	13.9357	15.1402	10.44	18.70
		RA	50	14.6672	2.1832	.3088	14.0467	15.2876	10.90	18.95
		RS	50	14.4816	2.5593	.3619	13.7542	15.2089	6.46	18.95

Table 7: One-Way ANOVAs For Experiment 1

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Portfolio 1 Best-Of-Generation	Between Groups	7070.160	3	2356.720	4.315	.006
	Within Groups	107046	196	546.155		
	Total	114116	199			
Portfolio 1 Worst-Of-Generation	Between Groups	7006.655	3	2335.552	4.615	.004
	Within Groups	99198.2	196	506.113		
	Total	106205	199			
Portfolio 1 Average	Between Groups	103.325	3	34.442	6.389	.000
	Within Groups	1056.518	196	5.390		
	Total	1159.843	199			

Table 8: Post-Hoc Tests For Experiment

Multiple Comparisons

Scheffe

Dependent Variable	(I) Group	(J) Group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Portfolio 1 Best-Of-Generation	LA	RN	5.2400	4.674	.740	-7.9403	18.4203
		RA	10.0400	4.674	.206	-3.1403	23.2203
		RS	-5.9200	4.674	.659	-19.1003	7.2603
	RN	LA	-5.2400	4.674	.740	-18.4203	7.9403
		RA	4.8000	4.674	.788	-8.3803	17.9803
		RS	-11.1600	4.674	.131	-24.3403	2.0203
	RA	LA	-10.0400	4.674	.206	-23.2203	3.1403
		RN	-4.8000	4.674	.788	-17.9803	8.3803
		RS	-15.9600*	4.674	.010	-29.1403	-2.7797
	RS	LA	5.9200	4.674	.659	-7.2603	19.1003
		RN	11.1600	4.674	.131	-2.0203	24.3403
		RA	15.9600*	4.674	.010	2.7797	29.1403
Portfolio 1 Worst-Of-Generation	LA	RN	-1.1200	4.499	.996	-13.8080	11.5680
		RA	-10.8000	4.499	.128	-23.4880	1.8880
		RS	5.6600	4.499	.664	-7.0280	18.3480
	RN	LA	1.1200	4.499	.996	-11.5680	13.8080
		RA	-9.6800	4.499	.205	-22.3680	3.0080
		RS	6.7800	4.499	.520	-5.9080	19.4680
	RA	LA	10.8000	4.499	.128	-1.8880	23.4880
		RN	9.6800	4.499	.205	-3.0080	22.3680
		RS	16.4600*	4.499	.005	3.7720	29.1480
	RS	LA	-5.6600	4.499	.664	-18.3480	7.0280
		RN	-6.7800	4.499	.520	-19.4680	5.9080
		RA	-16.4600*	4.499	.005	-29.1480	-3.7720
Portfolio 1 Average	LA	RN	1.6769*	.464	.005	.3675	2.9863
		RA	1.5477*	.464	.013	.2383	2.8571
		RS	1.7333*	.464	.004	.4239	3.0427
	RN	LA	-1.6769*	.464	.005	-2.9863	-.3675
		RA	-.1292	.464	.994	-1.4386	1.1802
		RS	5.639E-02	.464	1.000	-1.2530	1.3658
	RA	LA	-1.5477*	.464	.013	-2.8571	-.2383
		RN	.1292	.464	.994	-1.1802	1.4386
		RS	.1856	.464	.984	-1.1238	1.4950
	RS	LA	-1.7333*	.464	.004	-3.0427	-.4239
		RN	-5.64E-02	.464	1.000	-1.3658	1.2530
		RA	-.1856	.464	.984	-1.4950	1.1238

*. The mean difference is significant at the .05 level.

Table 9: Summary Statistics For Experiment 2

Descriptives

		N	Mean	Std Deviation	Std. Error	95% Confidence Interval for Mean: Lower Bound	95% Confidence Interval for Mean: Upper Bound	Minimum	Maximum
Portfolio 1 Group Survival	LA	50	78.9400	14.4398	2.0421	174.8363	183.0437	153.00	222.00
	RN	50	68.4600	8.8161	1.2468	165.9545	170.9655	145.00	188.00
	RA	50	10.4000	8.0686	1.1411	108.1069	112.6931	95.00	131.00
	RS	50	14.9200	7.4419	1.0524	112.8050	117.0350	104.00	132.00

Table 10: One-Way ANOVA For Experiment 2

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Portfolio 1 Survival	Between Groups	189551	3	63183.5	621.407	.000
	Within Groups	19928.9	196	101.678		
	Total	209480	199			

Table 11: Post-Hoc Tests For Experiment 2

Multiple Comparisons

Dependent Variable: Portfolio 1 Survival
Scheffe

(I) Group	(J) Group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval: Lower Bound	95% Confidence Interval: Upper Bound
LA	RN	10.4800*	2.017	.000	4.7930	16.1670
	RA	68.5400*	2.017	.000	62.8530	74.2270
	RS	64.0200*	2.017	.000	58.3330	69.7070
RN	LA	-10.4800*	2.017	.000	-16.1670	-4.7930
	RA	58.0600*	2.017	.000	52.3730	63.7'70
	RS	53.5400*	2.017	.000	47.8530	59 270
RA	LA	-68.5400*	2.017	.000	-74.2270	-62.8530
	RN	-58.0600*	2.017	.000	-63.7470	-52.3730
	RS	-4.5200	2.017	.174	-10.2070	1.1670
RS	LA	-64.0200*	2.017	.000	-69.7070	-58.3330
	RN	-53.5400*	2.017	.000	-59.2270	-47.8530
	RA	4.5200	2.017	.174	-1.1670	10.2070

*. The mean difference is significant at the .05 level.

Table 12: Probabilistic Mean Payoff Ranges For Experiment 1

	Exp. Mean	SD	CI (2SD, 3SD)	Observed Mean Range	SD	CI 2SD,3SD	Observed Grand Mean
RN	15.625	2.8393	9.95, 21.30 7.11, 24.14	10.44, 18.70	0.4015	14.82, 16.43 14.42, 16.83	14.5380
RA	15.625	2.6064	10.41, 20.84 7.81, 23.44	10.90, 18.93	0.3686	14.89, 16.36 14.52, 16.37	14.6672
RS	15.625	3.0546	9.51, 21.73 6.46, 24.79	6.46, 18.61	0.4320	14.76, 16.49 14.32, 16.92	14.4816
LA	15.625	2.8393	9.95, 21.30 7.11, 24.14	12.24, 21.61	0.4015	14.82, 16.43 14.42, 16.83	16.2148

Table 13: The Fourfold Decision Pattern

	Gain	Loss
Low Probability	Risk Seeking	Risk Aversion
High Probability	Risk Aversion	Risk Seeking

Table 14: Decision Portfolio 1

G	Critical Value	Alternative 1 (A1)	Alternative 2 (A2)
1	0.7757	$4,000.00, 0.800; $0.00, 0.200	$3,000.00, 1.000; $0.00, 0.000
2	0.7757	-$4,000.00, 0.800; $0.00, 0.200	-$3,000.00, 1.000; $0.00, 0.000
3	0.7757	$4,000.00, 0.200; $0.00, 0.800	$3,000.00, 0.250; $0.00, 0.750
4	0.7757	-$4,000.00, 0.200; $0.00, 0.800	-$3,000.00, 0.250; $0.00, 0.750
5	1.0000	$3,000.00, 0.900; $0.00, 0.100	$6,000.00, 0.450; $0.00, 0.550
6	1.0000	-$3,000.00, 0.900; $0.00, 0.100	-$6,000.00, 0.450; $0.00, 0.550
7	1.0000	$3,000.00, 0.002; $0.00, 0.998	$6,000.00, 0.001; $0.00, 0.999
8	1.0000	-$3,000.00, 0.002; $0.00, 0.998	-$6,000.00, 0.001; $0.00, 0.999

Table 15 : Choice Patterns For Experiment 1

	γ^*	10	200
Gamble 1	0.7757	RA: 0% RS: 100%	RA: 0% RS: 100%
Gamble 2	0.7757	RA: 63% RS: 37%	RA: 58% RS: 42%
Gamble 3	0.7757	RA: 25% RS: 75%	RA: 8% RS: 92%
Gamble 4	0.7757	RA: 54 % RS: 46%	RA: 54% RS: 46%
Gamble 5	1.0000	RA: 79% RS: 21%	RA: 58% RS: 42%
Gamble 6	1.0000	RA: 62% RS: 38%	RA: 75% RS: 25%
Gamble 7	1.0000	RA: 83% RS: 17%	RA: 92% RS: 8%
Gamble 8	1.0000	RA: [illegible] RS: 92%	RA: 12% RS: 88%

Table 16: Choice Patterns For Experiment 2

	γ^*	10	200
Gamble 1, Gamble 2	0.7757	RA/RA: 25% RS/RS: 21% RA/RS: 8% RS/RA: 46%	RA/RA: 0% RS/RS: 4% RA/RS: 0% RS/RA: 96%
Gamble 3, Gamble 4	0.7757	RA/RA: 25% RS/RS: 21% RA/RS: 13% RS/RA: 42%	RA/RA: 8% RS/RS: 21% RA/RS: 13% RS/RA: 58%
Gamble 5, Gamble 6	1.0000	RA/RA: 0% RS/RS: 21% RA/RS: 75% RS/RA: 4%	RA/RA: 4% RS/RS: 33% RA/RS: 54% RS/RA: 8%
Gamble 7, Gamble 8	1.0000	RA/RA: 8% RS/RS: 33% RA/RS: 46% RS/RA: 13%	RA/RA: 0% RS/RS: 4% RA/RS: 83% RS/RA: 13%

Table 17: Choice Patterns For Portfolio

All Prospects	**RA/RS: 54%** **RA/RA: 0%** **RS/RS: 13%** **RS/RA: 33%**

Figures

Figure 1a: Schematic Representation of Experimental Flow for Group G_{WTA}

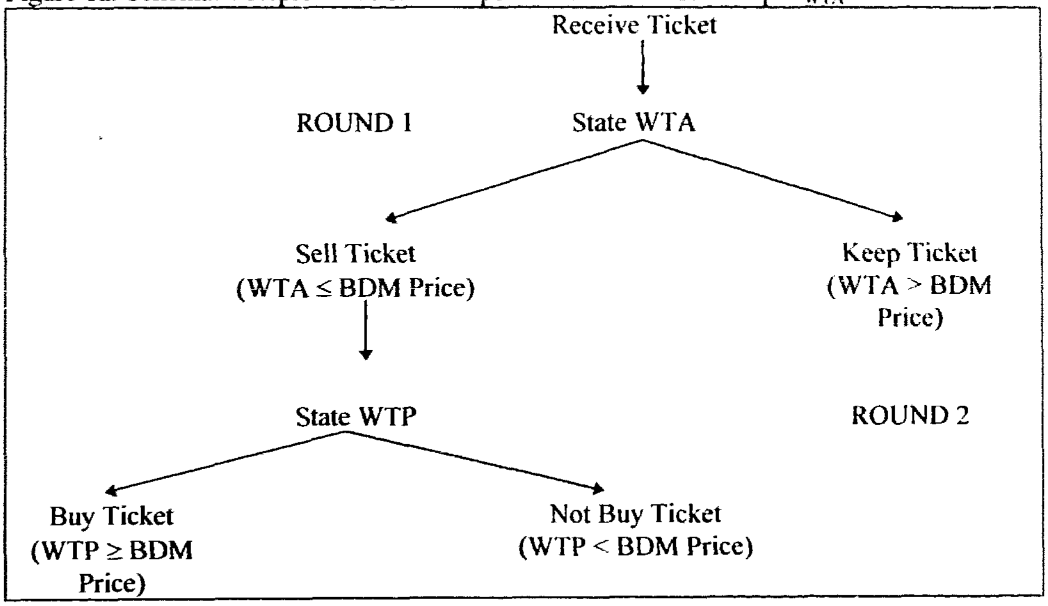


Figure 1b: Schematic Representation of Experimental Flow for Group G_{WTP}

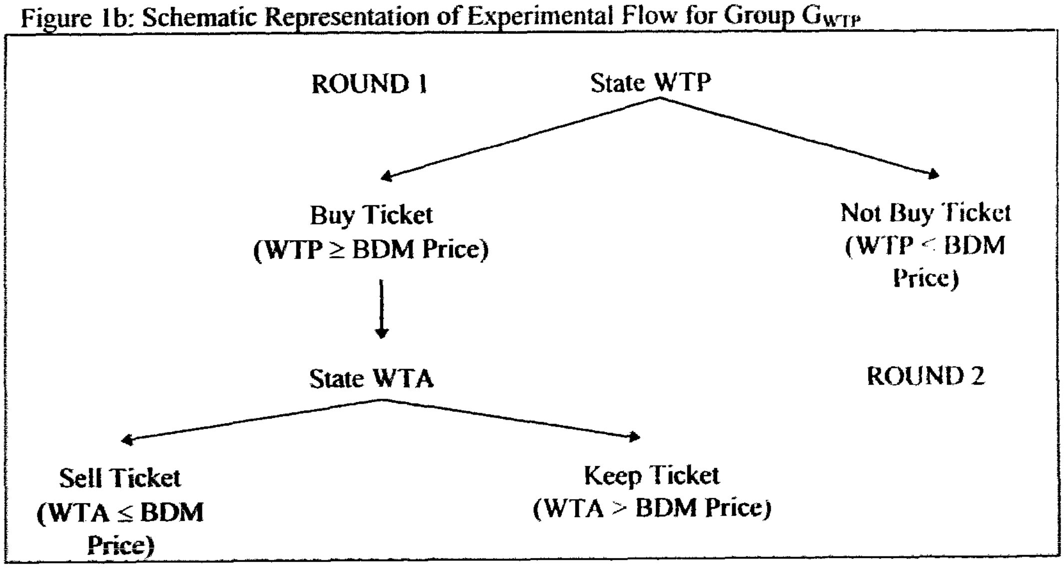


Figure 2a: Mean Valuations for Group G_{WTA}

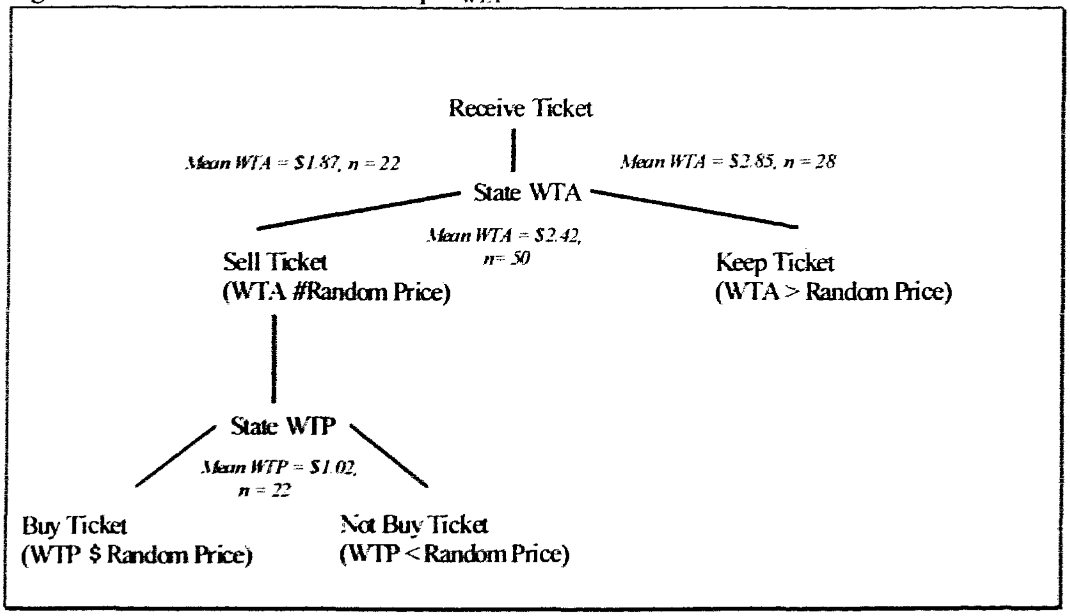


Figure 2b: Mean Valuations for Group G_{WTP}

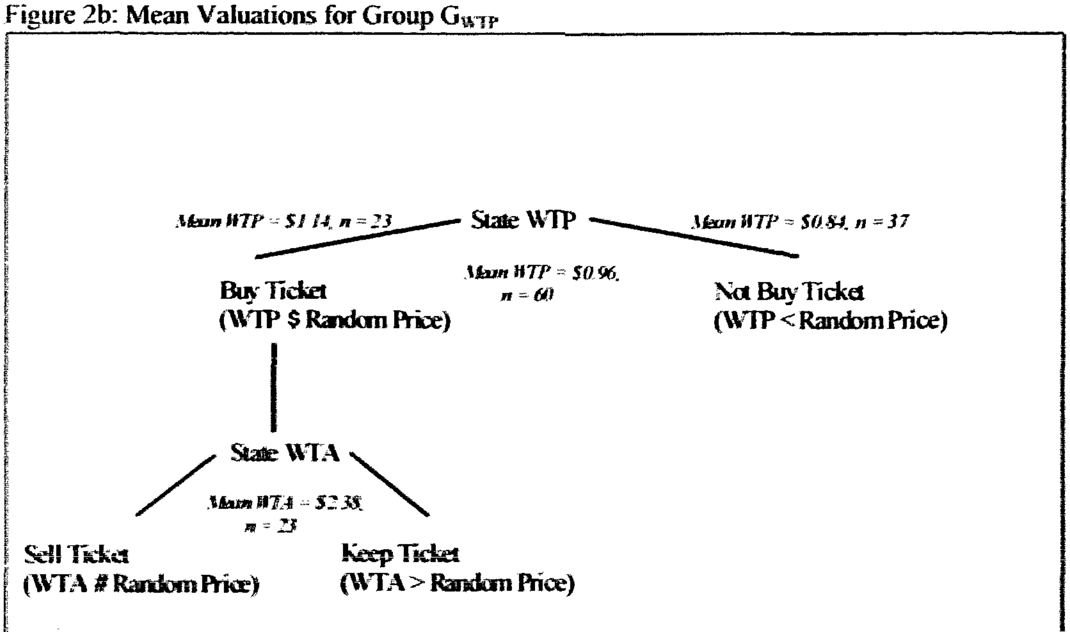


Figure 3: Hypothetical Value Function Displaying Loss Averse Behavior

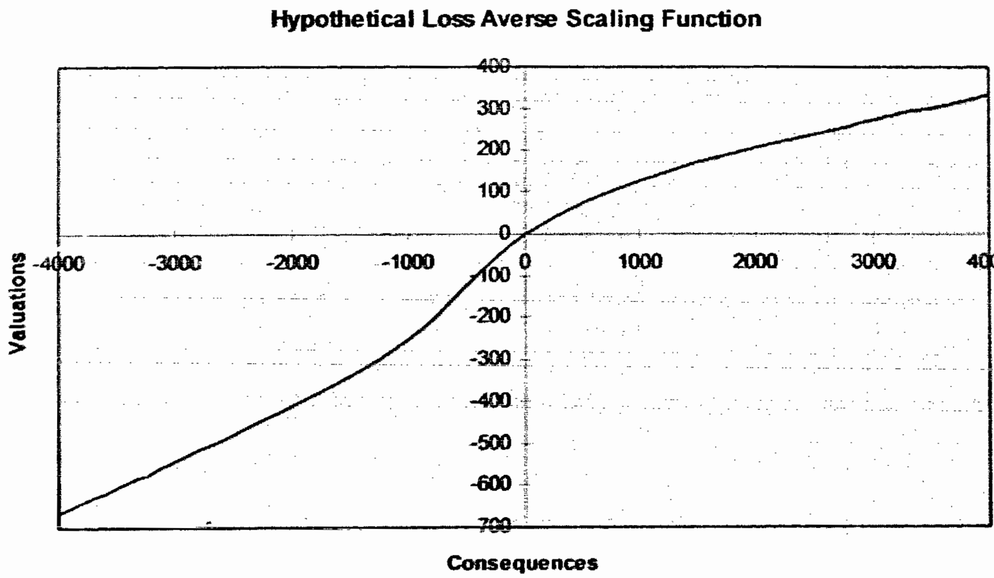
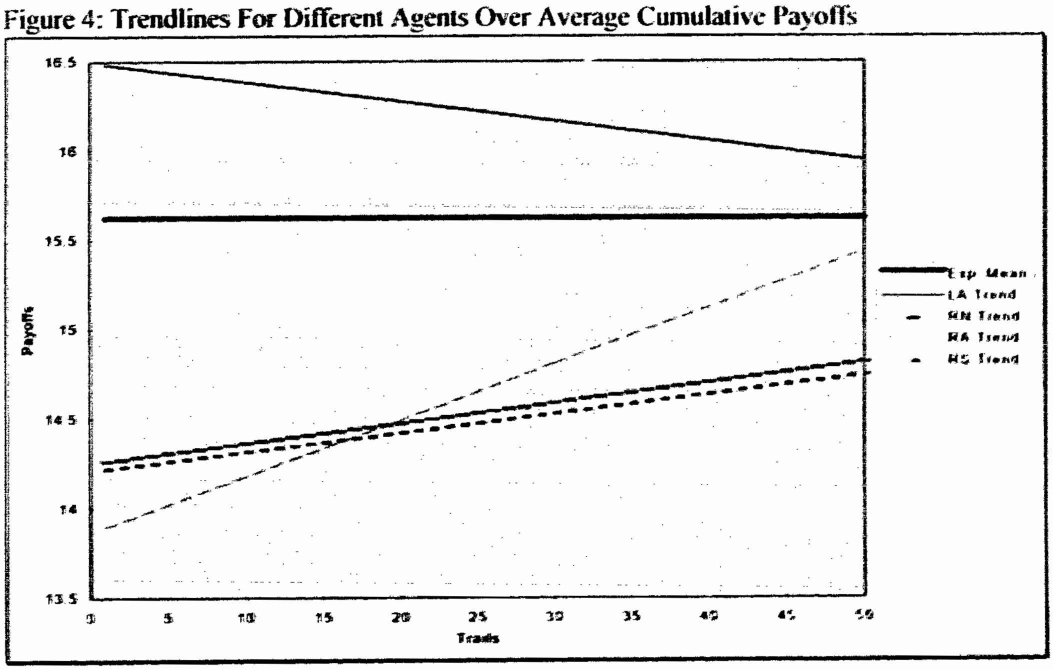


Figure 4: Trendlines For Different Agents Over Average Cumulative Payoffs



APPENDIX: Survey Forms

ROUND 1 :

THIS SURVEY IS PART OF A PH.D. DISSERTATION AND IN PART SUPPORTED BY THE SOCIAL SCIENCES AND HUMANITIES RESEARCH COUNCIL OF CANADA

YOUR PARTICIPATION IS VOLUNTARY AND YOU MAY WITHDRAW FROM THE SURVEY AT ANY TIME.

Instructions
Please answer the following questions before proceeding to the section below. Please do not use pencil.

Please Do Not Scratch The Attached Ticket Until Told Otherwise

Lastname:______________________________ Firstname: ______________________

You have the opportunity to purchase a lottery ticket, which is a typical "win & scratch" ticket issued by the British Columbia Lottery Corp. and retails for $1. The maximum winning prize is $10,000. The payout ratio associated with this type of ticket is approximately 50%. The actual purchasing price for the ticket will be determined by a random draw of prices ranging from $0 to $4.00. As previously explained, you will pay this random price if you indicated that you would be willing to buy the ticket at any price equal to or lower than this amount. Indicate if you will be willing to buy or not to buy for each of the prices below.

If the random price is $	I will buy	I will not buy
0.00	______	______
0.25	______	______
0.50	______	______
0.75	______	______
1.00	______	______
1.25	______	______
1.50	______	______
1.75	______	______
2.00	______	______
2.25	______	______
2.50	______	______
2.75	______	______
3.00	______	______
3.25	______	______
3.50	______	______
3.75	______	______
4.00	______	______

ROUND 2:

Instructions

Please answer the following questions before proceeding to the section below. Please do not use pencil.

Lastname:_______________________ Firstname: _______________________

You have the opportunity to sell your lottery ticket to the experimenter. Again, the actual selling price will be determined by a random draw of prices ranging from $0 to $4.00. As previously explained, you will receive this random price if you indicated that you would be willing to sell the ticket at any price equal to or higher than this amount. Indicate if you will be willing to sell or not to sell for each of the prices below

If the random price is $	I will sell	I will not sell
0.00	______	______
0.25	______	______
0.50	______	______
0.75	______	______
1.00	______	______
1.25	______	______
1.50	______	______
1.75	______	______
2.00	______	______
2.25	______	______
2.50	______	______
2.75	______	______
3.00	______	______
3.25	______	______
3.50	______	______
3.75	______	______
4.00	______	______