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AGENT-BASED MODELING TO INVESTIGATE THE DISPOSITION EFFECT IN FINANCIAL MARKETS

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Abstract

One of the behavioral patterns that deviate from what is predicted by traditional financial theories is the disposition effect. Although most empirical studies have reported a significant disposition effect, researchers have yet to conduct a conclusive test of this effect because a competing hypothesis or confounding effects might explain the documented significance. Thus, we use the tools of computational intelligence, instead of empirical approaches, to explore market behavior. In particular, we allow agents with different investment strategies to interact and to compete with each other in an artificial futures market. We found that the S-shaped value curve proposed by prospect theory may be one of the causes of the observed behavior of the disposition effect. However, rational expectation such as short-term mean reversion can even be more decisive.

Key words: agent-based model, disposition effect, behavioral bias, prospect theory, futures market

1. INTRODUCTION

While the rationality assumption posits that an investor makes a decision on the basis of his or her expected utility, the decision maker's real action usually deviates from what is predicted by the theory. One of the behavioral patterns arising from this line is the propensity of traders to hold losing investments too long and to sell winning investments too early. Shefrin and Statman (1985) labeled this phenomenon the "disposition effect."

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According to Shefrin and Statman (1985), the main theoretical basis of the disposition effect is prospect theory, developed by Kahneman and Tversky (1979). With a view different from that of traditional expected utility theory, prospect theory posits that most investors are loss averse. In other words, investors are risk seekers when facing a loss (and thus will try to hold losing investments) and risk avoiders when facing a gain (and thus will tend to realize winning investments).

In the two decades since Shefrin and Statman (1985), researchers have conducted many studies concerning the disposition effect. Some researchers empirically study disposition effects in the housing market and disposition effects associated with stock markets and mutual fund investors (see, for example, Ferris, Haugen, and Makhija, 1988; Garvey and Murphy, 2004; Genesove and Mayer, 2001; Odean, 1998; Shapira and Venezia, 2001). Recently, a few studies have focused also on this behavioral bias in the futures markets (Coval and Shumway, 2005; Frino, Johnstone and Zheng, 2004; Heisler, 1994; Locke and Mann, 2005; Locke and Onayev, 2005).

Compared to other financial markets, futures markets provide an ideal setting for testing the disposition effect. For example, the cost of trading in a futures market is usually much lower than the cost of trading other securities, and this low cost might help rule out the possibility that a trader, to avoid higher fractional trading costs, would refrain from selling securities whose value is declining. Also, most of the positions in futures contracts expire before the end of the financial year, so this feature rules out the possibility that a trader's desire to maximize tax benefits would motivate the trader to ride losses and to realize gains in a specific period of a year.

Although futures markets provide an ideal testing site for examining the disposition effect and although most empirical studies have reported a significant disposition effect, a conclusive test of it has yet to be conducted because the statistical significance might derive from competing hypotheses or confounding effects. Thus, we use the tools of computational intelligence to explore the market behavior. In particular, we allow the computer agents with different investment strategies to interact and to compete with each other in an artificial futures market.

We found that the S-shaped value curve proposed by prospect theory may be one of the main causes of the observed behavior of the disposition effect, and this finding is consistent with the findings of empirical studies. However, when exploring the relationship between disposition effects and traders with various trading strategies, we found that the traders' rational expectations can play an even more important role than the aforementioned curve. Future studies might further clarify this issue.

In Section 2 of this article, we first review the various theories for explaining disposition effects. We then review some of the important empirical studies regarding the disposition effect in futures markets. In Section 3, we present the methods for our agent-based simulation. In Section 4, we state our results. In Section 5, we discuss conclusions and future directions.

2. LITERATURE REVIEW

2.1 Prospect Theory and the Disposition Effect

Traditionally, investors' behaviors are built on the foundation of the Capital Asset Pricing Model (CAPM) and the Efficient Market Theory (EMT). Many financial models are then derived from the CAPM and the EMT. However, in the late 1970s, many researchers found that their studies' empirical findings such as the size effect, the January effect, and the weekend effect were not consistent with the assumptions attributable to the CAPM and the EMT. While traditional finance scholars considered these phenomena just temporary market anomalies, a group of researchers began to challenge the traditional finance theories, which, themselves, rested mainly on expected utility theory. In their seminal work, Kahneman and Tversky (1979) proposed prospect theory for explaining decision makers' various behavior biases that utility theory cannot explain. The disposition effect, which was named by Shefrin and Statman (1985), derives from prospect theory, as well.

Prospect theory, as developed by Kahneman and Tversky (1979), concerns decision making under uncertainty. Because the behavior of most participants in the researchers' study differed from what was expected according to utility theory, Kahneman and Tversky substituted a value function for the utility function to explain a decision maker's behavior. The prospect theory posits that investors are loss averse. In other words, investors are risk seekers when facing a loss (and thus will try to hold losing investments) and are risk avoiders when facing a gain (and thus will tend to realize winning stocks or investments). To explain the disposition effect, Shefrin and Statman (1985) also proposed other theories, such as those concerning mental accounting, regret aversion, and self-control. Andreassen (1988) related the disposition effect to investors' belief in short-term mean reversion. Similar points also received treatment in Lakonishok and Smidt (1986).

Our literature review in the remainder of this section will focus only on the papers most relevant to our study on the disposition effect in futures markets. There are several studies that explore the disposition effect of futures traders. Heisler (1994) investigated the off-floor traders who traded US Treasury Bond Futures on the Chicago Mercantile Exchange (CME). According to the study's findings, the round-trip trade for positions that initially showed paper loss was significantly longer than the round-trip trade for positions that initially showed paper gain. Similarly, Locke and Mann (2005) concluded that even the professional traders exhibited the disposition effect (i.e., they tended to hold the loss positions longer). Using the same data set, Locke and Onayev (2005) investigated the relationship between trade duration and profitability and found that the duration for unprofitable trades is significantly longer than it is for profitable trades. This finding is also evidence of the disposition effect. Frino et al. (2004) compared different types of traders to one another and concluded that non-local traders exhibited a stronger disposition effect than the on-floor professional traders. Recently, Coval and Shumway (2005) have approached this issue from a different angle and used regression to investigate the relationship between traders' morning-trading performance and traders' afternoon-trading behavior. The researchers found that the traders were loss averse—that they became more risk-seeking when the morning-trading performance was poor.

It is critical that researchers study futures markets, which can yield significant information about the disposition effect. And it is equally critical to note that most empirical studies have reported a significant disposition effect. However, a conclusive test of it remains both difficult and, indeed, unrealized because the significance, as we mentioned earlier, might be attributable to competing hypotheses or to confounding effects. For this reason, our present study explores market behavior by using the tools of computational intelligence.

2.2 Agent-based Computational Finance

Rather than analyze the empirical data obtained from the activities of a real market, agent-based computational finance uses a different approach to study market behavior. Usually, an artificial market hosts multiple agents of multiple types who, by interacting dynamically with one another, determine the price of a financial product and other aggregate properties of the market. As Tsang and Martinez-Jaramillo (2004) mention, researchers in the field can learn important lessons from the work by LeBaron (2001), Farmer et al. (1999), and Tesfatsion (2001). With regard to computer-platform implementation, the Artificial Stock Market (ASM) developed by the Santa Fe Institute opened a new direction for much important work in this field.

However, according to LeBaron (2007), little work in agent-based financial modeling directly or indirectly deals with the issue of behavioral finance, although the concept of bounded rationality in behavioral finance is considered one of the key characteristics of any agent-based model. LeBaron argued that, because the development of agent-based computational finance is still in its early stage, most researchers may refrain from entering too many complications into the models, and the number of studies concerning loss-averse agents is thus small. Takahashi and Terano (2003) considered agents whose value function was similar to the one suggested by prospect theory. In the same study, the researchers also considered over-confident agents. The purpose of the study was to determine how investors with behavioral biases affect asset price, and the researchers found that if there are considerable numbers of non-fundamentalists, the non-fundamentalists will survive and the traded price might significantly deviate from the fundamental value. Using a similar approach, Takahashi et al. (2004) discussed how passive investment strategy affects asset price.

While it is justifiable that we should refrain from using overly complicated agents, as suggested by LeBaron (2007), we found that the study by Takahashi and Terano (2003) and the study by Takahashi et al. (2004) open up a new direction for investigating behavior biases in financial markets and answer some of the most fundamental questions regarding irrational agents. However, we also notice that there are many modeling techniques that need to undergo refinement and many questions that await rigorous answers. In our study, we use a value function similar to that of Takahashi and Terano (2003) to formulate the investors' preference. However, the overall focus of our investigation concerns whether or not the value function suggested by prospect theory really leads to the observed disposition effect. We also want to see whether or not other trading strategies—not the S-shaped value function—can drive the disposition effect. Finally, we plan to examine the spot price and the futures price to determine how biased investors affect the CAPM.

3. DESIGN OF THE VIRTUAL FUTURES MARKET

U-Mart is a virtual futures market developed as a test-bed for investigating economic systems of futures markets; we borrowed it and adapted it to our study (Kita, Sato, and Mori, 2003; Ono et al., 2004; U-Mart Project, 2007). U-Mart allows for inputs of both computer-programmed agents and human agents. In our study, however, we consider only computer-programmed agents. U-Mart is also very flexible in parameter settings. It enables researchers not only to change the time-series data of spot price, the basic market settings such as sessions per day, and the agents' properties such as initial cash balance, but also to design new agents who possess specific risk attitudes and trading strategies.

We implemented the virtual futures market on a personal computer with a Pentium 1.81 GHz CPU and 1G RAM. The market consists of 100 investors who are allowed to trade two types of assets: a futures contract and a risk-free asset (cash). In this market, multiple types of investors exist and trade futures contracts according to the rules that both define and govern the specific type of investor. The market operates basically in two steps: the first step is the formation of investors' predictions and the submission of the order (based on the investors' trading strategy), and the second step is the determination of the trading price. In this section, we will explain in detail how the financial market operates.

3.1 Assets Traded in the Market

The results of simulations can sometimes depend on the sequence of the spot price in use. The default spot price of U-Mart is called J30, which contains the actual data of the price index of stocks in Japan's stock market. Rather than use J30, we use a random work to simulate time-series data ranging from 4,000 to 8,000. The original purpose of generating these time-series data was to mimic the spot price of the price index of stocks in Taiwan's stock market. Although Taiwan's futures market is one of the largest 20 in the world, and although a reasonable object for our study would be one of the most important financial products in this market, we believe that the spot price chosen should have little effect on our results or on our conclusion.

3.2 Modeling of Investors' Behavior

There are 10 different built-in agents in U-Mart. Usually, the agents take information such as the time-series data of spot prices, the time-series data of futures prices, current positions, and cash balances and treat this information as input. The agents then submit a limit price order as output. The main differences between various built-in traders center on the traders' strategies for forming (or predicting) the future price of a financial product and on the traders' strategies for submitting either a buy-limit order or a sell-limit order (based on the predicted price). The built-in traders in U-Mart are AntiTrendStrategy, DayTradeStrategy, MovingAverageStrategy, RandomStrategy, RsiStrategy, TrendStrategy, SFSpreadStrategy, SMovingAverageStrategy, SRandomStrategy, and SRsiStrategy. The first six strategies are the strategies that real-world investors often adopt as their decision criteria. On the basis of this naming scheme, we can easily identify the strategies as the anti-trend strategy, the day-trade strategy, the moving-average strategy, the random strategy, the relative-strength-index (RSI) strategy, and the trend strategy. The remaining four strategies (SFSpreadStrategy, SMovingAverageStrategy, SRandomStrategy, and SRsiStrategy) are strategies that mimic the aforementioned traditional investing strategies but that use spot price (instead of futures price) as the calculation basis. Table 1 lists some of the information regarding built-in agents.

Although these built-in agents differ from one another in terms of their price-forming strategies and their order submitting, they hold the same risk-neutral attitude toward the value of the assets. The default setting of U-Mart uses all 10 types of agents, but it also specifies different proportions for various agents (who differ from one another in terms of their strategies). In our simulation experiments, we use a similar proportion.

TABLE 1

U-Mart Built-in Agents

Agent	Long or short term	Against or follow trend
AntiTrendStrategy	short	against
DayTradeStrategy	short	against
MovingAverageStrategy	long	follow
RandomStrategy	both	neither
RsiStrategy	short	against
SFSpreadStrategy	short	against
SMovingAverageStrategy	long	follow
SRandomStrategy	both	neither
SRsiStrategy	short	against
TrendStrategy	short	follow

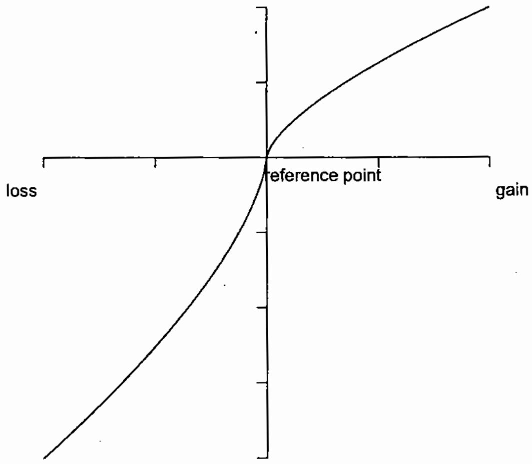
For the traders with the S-shaped value function, we used java code to build a new type of agent. We still partially used the built-in RandomStrategy to predict the futures price. In other words, to determine the predicted price, we randomly drew two values from a Gaussian distribution whose mean was the latest price. The major difference between our agent and the built-in RandomStrategy agents, however, is our use of an S-shaped value function to represent our agent's risk attitude. Although Kahneman and Tversky (1979) did not explicitly specify the function form attributable to the value function proposed in their article, we believe the function forms used in formulating the utility curve in Utility theory is applicable here. Because the power function satisfies the property of decreasing absolute risk aversion and constant relative risk aversion, and because the power function is also relatively easy to manipulate, we use it in our study to formulate the value curve

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -k(-x)^{\alpha} & \text{if } x < 0 \end{cases} \qquad (1)$$

where $0 < \alpha \leq 1$, and $k > 1$. There are three major characteristics of the value function: (1) it contains a reference point that can help determine whether the decision maker is valuing a gain or a loss (where $x > 0$ represents a gain and where $x < 0$ represents a loss); (2) the value function (sketched in Figure 1) passing through the reference point is S-shaped, so the agent is risk-averse when facing a gain and risk-seeking when facing a loss; and (3) the asymmetry of the value function (i.e., with $k > 1$) implies that the effect of losses is greater than the effect of gains.

FIGURE 1

Prospect Theory Value Function



For newly built agents with an S-shaped value function, the average price of their current positions serves as the reference point.

3.3 Determination of Traded Price

The U-Mart artificial futures market uses a double-auction method called "Itayose" to match orders and to determine the price. The Itayose method stores orders for a pre-determined period, and then all the orders are matched. Thus, only one price is settled during each session. This outcome differs from the outcome in the quote-driven trading system, where orders are continuously executed when the price and the numbers of lots match.

3.4 Measurement of the Disposition Effect

Because one of the purposes of this study is to investigate whether or not the S-shaped value function is the major cause of the observed disposition effects, we need a metric to measure the magnitude of a trader's propensity to hold losers and sell winners. We use concepts suggested by Odean (1998). Odean defines the proportions of realized gains and losses, labeled PGR and PLR, by

$$PGR = \frac{\textit{realized gains}}{\textit{realized gains} + \textit{paper gains}}$$
$$PLR = \frac{\textit{realized losses}}{\textit{realized losses} + \textit{paper losses}},$$

where the realized gains (losses) are the number of gain (loss) contracts realized and the paper gains (losses) are the number of contracts that investors could – but do not – realize as a gain (loss). The basic idea behind the PGR measure and the PLR measure is to count the number of contracts wherein an investor faces a gain (loss) and the number of times he or she opts to realize the gain (loss). These ratio metrics help control for the effects of market momentum.

4. RESULTS

4.1 Disposition Effects

We conducted many experiments on U-Mart. For each experiment, the trading period of the virtual market was 90 days, and eight sessions were held a day. Thus, each experiment featured 720 sessions. For the base case, in the value function, α is first set at 2/3 and k is set at 2. For these agents with S-shaped value functions, we found that the average PGR/PLR was 1.36. This finding indicates that the value function might be the main cause for the disposition effect.

4.2 Sensitivity Analysis

We conducted various sensitivity analyses to investigate the effects that model-parameter changes have on observed disposition effects (PGL/PLR ratio). This series of sensitivity analyses also serves as a mechanism for increasing the validity and for widening the inference basis of our simulation model. Analyses discussed in this subsection include those involving parameter changes regarding the prospect theory value function (e.g., α and k in equation (1)) and order-type changes such as changes from market orders to limit orders.

Effect of Changes in α on Disposition Effect

We first tested the effect that changes in α had on the magnitude of traders' disposition effect, and to this end, we systematically changed the value of α, re-ran the experiment, and calculated PGR/PLR again. Table 2 summarizes the results of the experiments. When α is close to 1, the value function is close to a straight line, a finding that suggests that agents become more risk-neutral (regardless of whether they are facing a loss or a gain). On the other hand, a smaller α makes the value function more concave (risk-averse) when agents are facing a gain and more convex (risk-seeking) when agents are facing a loss. This effect did show up in their trading behavior. For example, the proportion of realized gains was not significantly higher than the proportion of realized losses when α equals 1 and 11/12. This finding indicates that agents with a flatter value curve will behave like a build-in agent who follows a random investing strategy. While this finding might reveal some of the constraints that characterize our newly built agents (because, by our default setting, they do not use an investing strategy more sophisticated than random strategy), the findings can also verify the correctness of the setting of the new agents.

TABLE 2

The Effect of Changes in α on PGR/PLR (Market Order)

α / PGR/PLR	1	11/12	4/5	2/3	1/2	1/8
Max.	1.18	1.17	1.93	2.07	2.26	2.08
Min.	0.81	0.82	0.85	0.79	0.78	1.02
Mean	1.01	1.03	1.21	1.36	1.43	1.46
Median	1.04	1.08	1.12	1.29	1.35	1.36
Sd. Dev.	0.11	0.12	0.34	0.52	0.57	0.40
PGR/PLR > 1*	No	No	Yes	Yes	Yes	Yes

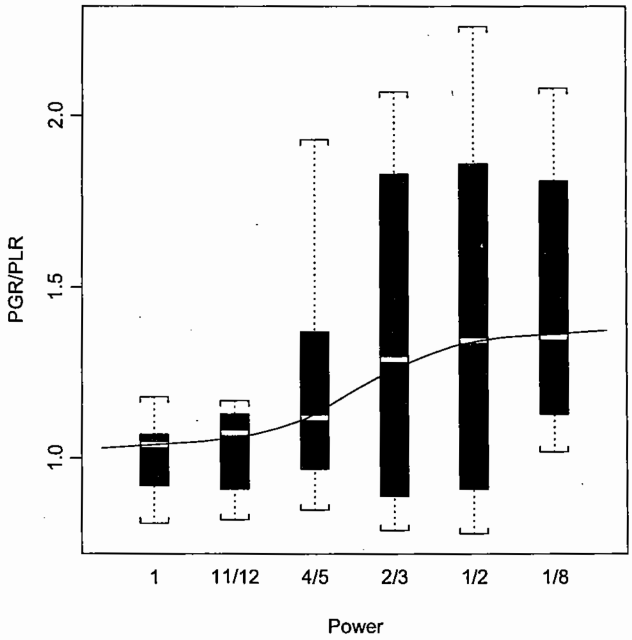
* level of significance = 0.05

On the other hand, when α became smaller (i.e., the value curve became more concave or more convex), we observed a negative correlation between α and PGR/PLR. In other words, relatively significant non-neutral risk attitudes will lead to relatively large disposition effects. This result makes intuitive sense and provides us a way to straightforwardly verify the connection between the prospect theory value function and the disposition effect. After agents dynamically interacted with one another, the bottom-level risk attitudes and the fundamental value systems that were built into the agents held up in output behavior and led the agents (traders) to realize gains more often than realize losses.

However, we also found that when α became smaller, the variation of PGR/PLR between agents became larger. This phenomenon is easily detectable in Figure 2. Because traditional statistical analyses (such as analysis of variance) usually require the homoscedasticity assumption regarding their random components, the seeming violation of the equal-variance assumption might hinder additional analyses and weaken the power of our inferences. More simulations and experiments need to be conducted for clarification of the issue.

FIGURE 2

The Effect of Changes in αon PGR/PLR (Market Order)

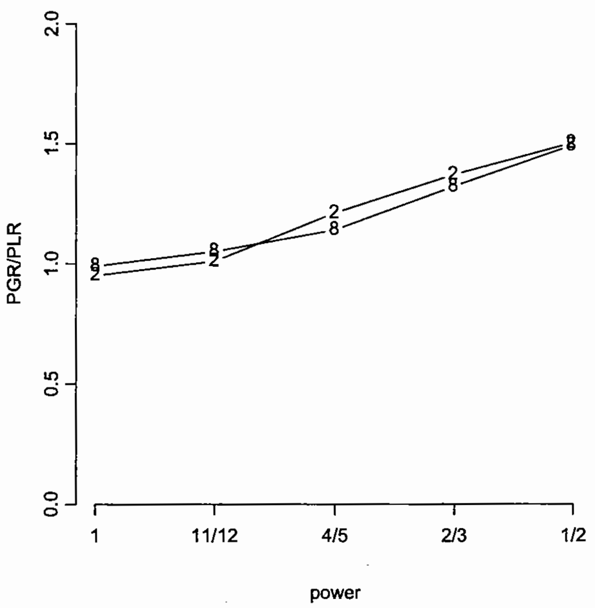


Effect of Changes in k *on Disposition Effect*

We then tested the effect that changes in k had on the magnitude of traders' disposition effect, and to this end, we systematically changed the value of k, re-ran the experiment, and calculated PGR/PLR. Parameter k is a measure of the magnitude of asymmetry (between gain and loss) of a value function. A larger k implies that the effect of losses (the aggravation that one experiences in losing a specific amount of money) is much greater than the effect of gains (the pleasure that one experiences in obtaining the same amount of money). Figure 3 summarizes the results for the simulations with $k = 2$ (base case) and $k = 8$.

FIGURE 3

The Effect of Changes in *k* on PGR/PLR (Market Order)



For various α values, we found that changes in *k* do not create significant effects on traders' PGR/PLR ratios. While intuitively people may think that a larger *k* will generally lead to stronger disposition effects, our simulation results do not support this proposition. One possible reason is that the changes in *k* will affect a trader's behavior only when the forecasted distribution of a (futures) price contains values that fall on both sides of the reference point (i.e., when a trader believes that the futures price in the next session has both a considerable chance of being higher and a considerable chance of being lower than his or her average purchasing price). If the center of the distribution of the predicted price is far away from the reference point, and if thus the whole distribution falls almost on one side of the value curve, then the effects will be minimized because a linear transformation (i.e., multiplication of a different *k* in equation (1)) will not affect a trader's risk attitude.

Effect of Order-type Changes on Disposition Effect

In analyses discussed so far, we allow the newly built agents to use a market order when they buy or sell futures contracts. However, in futures markets, limit orders might be more common owing to the high leverage. We thus tested the effect that changes in order types have on disposition effect. At the same time, we also tested the effect that changes in α had on the magnitude of traders' disposition effect. Table 3 summarizes the results of the experiments.

TABLE 3

The Effect of Changes in α on PGR/PLR (Limit Order)

PGR/PLR \ α	1	11/12	4/5	2/3	1/2
Max.	1.04	1.12	0.98	1.08	1.79
Min.	0.32	0.45	0.48	0.56	0.63
Mean	0.67	0.75	0.73	0.86	1.02
Median	0.68	0.76	0.76	0.84	0.90
Sd. Dev.	0.19	0.22	0.17	0.23	0.40
PGR/PLR < 1*	Yes	Yes	Yes	Yes	No

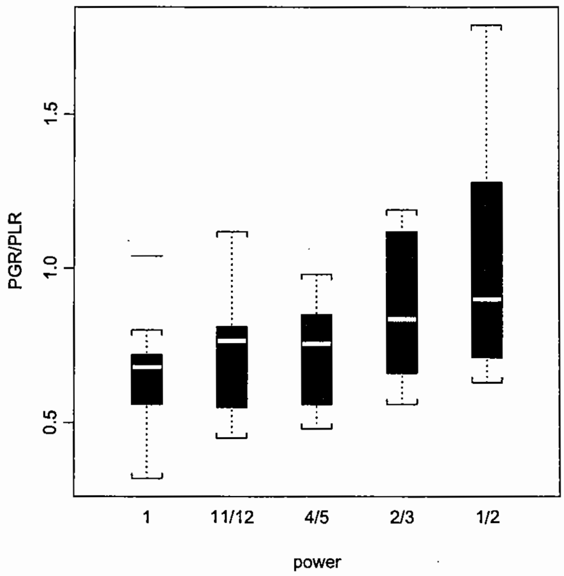
* level of significance = 0.05

Similar to what we obtained from the market-order case, when limit order is the primary order type used by the agents who correspond to the S-shaped value curve, the PGR/PLR ratio is still negatively correlated to the value of α. A flatter value curve exhibits much weaker disposition effects. Thus, we can conclude that the S-shaped value curve significantly affects traders' propensity to hold losers and to sell winners regardless of the order type. However, we also found that the mean PGR/PLR ratios are significantly smaller than 1 for various α when the limit order is the primary buy-or-sell option used by the traders. In other words, the trading behaviors attributable to even traders reflective of the S-shaped value curves do not reveal the disposition effects suggested by Shefrin and Statman (1985).

The above findings might have important implications for investors' behaviors in relation to futures markets. First, the findings might indicate that some other factors (such as a trader's private information or the specific trading strategy used) instead of the value function can be the main cause driving the disposition effects. The findings might also suggest that the PGR/PLR metric that underlies most measurements of the disposition effect might need some improvement for obtaining a more accurate measurement. Feng and Seasholes (2005) showed that the metrics of PGR and PLR, because they examine only an investor's portfolio on a trading day, might neglect the value of holding-time information. Further studies should address the issues discussed here.

FIGURE 4

The Effect of Changes in α on PGR/PLR (Limit Order)



4.3 Is Disposition Effect Really a Behavioral Bias?

The next issue investigated in this study is the link between the magnitude of the disposition effect and the cumulated profit level of the agents. According to normative decision theory, the bounded rationality (or the biases) in humans' judgments will lead to inferior decisions (and usually to inferior outcomes). However, previous empirical studies argued that rational investment strategies can drive the disposition effect, which can thus sometimes lead to better performance (see, for example, Locke and Onayev, 2005).

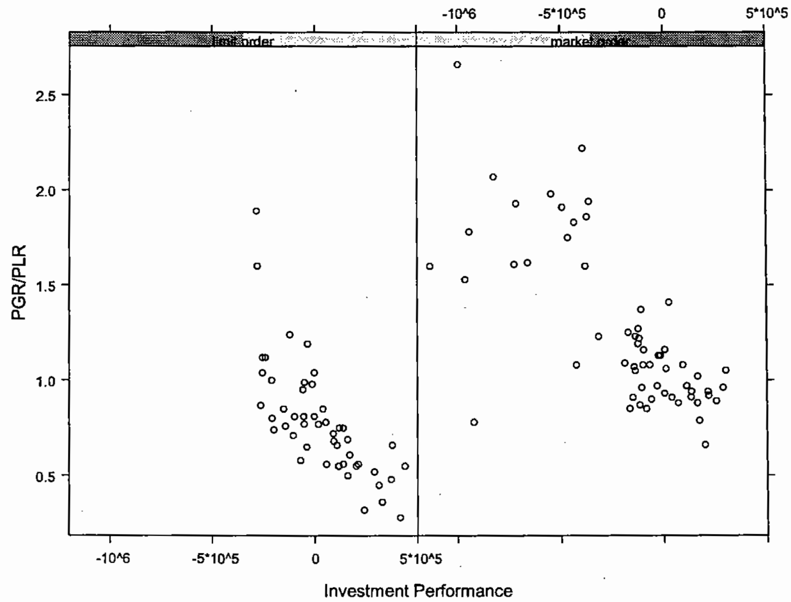
Figure 5 is the multi-panel plot that we used to investigate the relationship between traders' disposition effects and the traders' investment performances. The vertical axis of this figure is the PGR/PLR ratio, representing the magnitude of the disposition effect. The horizontal axis is the investment performance. Results obtained from simulations that featured different order types are separated into left and right panels. We found that there exists a significant negative correlation between PGR/PLR and investment performance. In other words, traders' propensity to sell winners more (frequently) than losers will lead to inferior return on investment.

We also found that a trader can break even when his or her PGR/PLR ratio is approximately 1. As discussed before in our sensitivity analyses, for the traders who use primarily the market-order buy-or-sell mechanism, their loss aversion leads to higher PGR/PLR (i.e., a stronger disposition effect), and the stronger disposition effect leads to inferior return on investment. However, for the traders who use primarily limit buy-or-sell orders, the PGR/PLR ratios are usually less than 1. This indicates that the traders with S-shaped value curves can out-perform other (built-in) traders. Thus, in our experiments, we were not able to reach the conclusion that the agents with a prospect theory value function made an average profit that was lower than the market average.

Although some of the earlier empirical studies showed that the disposition sometimes positively correlated to the discipline of market professionals (i.e., floor traders), such a finding did not surface in our case because our agents did not possess the semi-fundamental information possessed especially by floor traders. Thus, more experiments (using different spot prices and different proportions of built-in traders) might further clarify this issue.

FIGURE 5

The Relationship Between PGR/PLR and Investment Performance



4.4 Performance of Built-in Agents

Because the empirical studies indicate that the disposition might rest on the semi-fundamental information possessed by specific types of investors or on the rational expectations of investors (such as the short-term mean reversion), we investigated the trading behaviors of built-in agents – those who possess a different trading strategy but who do not possess prospect theory value functions). We used the setup of the base case mentioned above to execute the simulation, and found that traders with three built-in strategies (AnitTrendStrategy, RsiStrategy, SRsiStrategy) exhibited significant disposition effects, regardless of order type. Table 4 summarizes the simulation results.

TABLE 4

Disposition Effect and Performance of Built-in Agents

	AntiTrend	Rsi	SRsi
PGR/PLR (Market Order)	2.069	2.136	1.452
PGR/PLR (Limit Order)	2.543	1.424	1.410
Profits (Limit Order)	-209291	-61345	42569

As discussed in the artificial futures market setup, agents who exhibit significant disposition effects use strategies that go against the trend of futures prices. In other words, all these agents expect a short-term mean reversion. Thus, we conclude that rational expectation can easily drive the disposition effect. However, not all agents who strategize in opposition to the trend exhibit significant disposition effects.

When we compared the mean PGR/PLR ratios for built-in agents who had above three investment strategies with the mean PGR/PLR ratios for the newly built agents who reflected the S-shaped value function, we found that these investment strategies triggered even stronger disposition effects than did the prospect theory value function. This finding brings up two additional issues. First, we might need to investigate further the observed disposition effect in the real financial markets to find out if it is driven mainly by the fundamental value system or mainly by specific investment strategies. Second, it would also be interesting to learn how these two factors interact with each other.

When exploring the relationship between observed disposition effects and observed investment performances for three built-in traders who exhibited PGR/PLR > 1, we found that a higher PGR/PLR does not necessarily lead to poor performance. For example, although the traders using relative strength index (RSI) had a comparatively high mean PGR/PLR, they out-performed most of the traders during this simulation period. More experiments using different spot prices and different proportions of built-in traders might clarify this issue.

5. DISCUSSION AND CONCLUSION

In this study, we have used the tools of computational intelligence (instead of empirical analysis) to explore futures-market behavior and the causes of traders' disposition effects. We found that the S-shaped value curve proposed by prospect theory may be one of the causes of the observed behavior of the disposition effect, and this finding is consistent with the results obtained from empirical studies. However, we also found that some of the built-in investment strategies can drive even stronger disposition effects than the prospect theory value function. Furthermore, when exploring the relationship between disposition effects and profitability, we found that the results are not conclusive. Although we can identify a significant negative correlation between PGR/PLR and the investment performance for traders with S-shaped value functions, these traders' performance can sometimes out-perform other (built-in) traders, especially when traders are using limit orders as the primary buy-or-sell mechanism. Other experiments might further clarify this issue.

The contributions of this study are twofold. First, we have applied a new agent-based approach to our examination of the disposition effect. This procedure offers a precious opportunity for us to identify the different causes of the disposition effect and their relative importance. Second, this procedure offers us improved evidence that disposition may stem from rational investment strategy, rather than from the S-shaped value curve.

In the future, it is important to relax some of the constraints on the current agent setting (and, thus, to further solidify the connection between the value function and the disposition effect). For example, we might want to change the form of the value function (e.g., exponential or logarithmic functions) or the proportion of various types of agents to check the robustness of the results. Also, Odean's ratio metrics, the PGR and the PLR used in this study, might benefit from a re-definition. As mentioned in Frino et al. (2004), counting each futures-market transaction as an opportunity for each trader (not just the session in which the trader buys or sells a contract) might be a more reasonable alternative. Finally, it might prove fruitful to implement different price-determination mechanisms (such as a quote-driven market model instead of an order-driven market model) to investigate the effect of institutional factors on our conclusion.

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Resumo

Um dos padrões comportamentais que se desvia do previsto pelas teorias financeiras tradicionais é o efeito disposição. Embora a maioria dos estudos empíricos reporte um efeito disposição significativo, os investigadores conduziram testes ainda não conclusivos deste efeito, dado existirem hipóteses concorrenciais ou efeitos multiplos que podem explicar a significância documentada. Deste modo, neste estudo são utilizadas ferramentas de inteligência artificial como alternativa aos processos empíricos para explorar o comportamento nos mercados. Em particular, permite-se que agentes com diferentes estratégias de investimento interajam e compitam uns com os outros num mercado de futuros artificial. Concluímos que a curva S proposta pela *prospect theory* pode ser uma das causas da observação do comportamento de efeito disposição. No entanto, a expectativa racional, tal como a reversão para a média no curto prazo pode desempenhar um papel ainda mais decisivo.

Palavras-chave: Modelo baseado em agentes, efeito disposição, comportamento enviesado, *prospect theory*, mercados futuros.