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Acknowledgements

I would like to thank my advisor Ji-Hsuan Liu, he guided and supported me of the research and the writing of this thesis. Special thanks to Yuang-Hsiang Cheng, as a free-software advocate, he shared his insights of Latex with us, this thesis wouldn't be so elegant without Latex. I also like to thank Hseng-Yang Peng, Gang-Long Linand Wen-Che Wen, they provide unique prespectives toward my research.

Greatest thanks to my father and mother, for not only being parents but also friends.

This thesis is dedicated to my beloved grandmother, may her soul be with our family, always.

ABSTRACT

In this research, we proposed two variables that could be incorporated with prediction markets: Reputation and Risk. Instead of attracting new players, The reputation system could stop losing bankrupted player, Player willing to help bankrupted player will gain reputation, and bankrupted player will lose reputation. Previous works suggest longshot bias is related to the risk-neutrality of players. Our approach is to experiment different risk distribution. We observe the impact of these variables in an agent-based model of prediction markets. We use zero-intelligence agents, where human qualities such as maximizing profit, learning or obeserving are missing. We further discuss the result, and the impact of risk and reputation.

CHAPTER 1
Introduction

1.1 Background

There is a growing need for predicting future event, for example, estimating stock price, outcome of political election, and the winner of sport games. Knowing the possible outcome in advance is crucial for decision making. However, the information related to future events usually exists as personal opinions, ideas, or instinctions. These valuable information is dispersed into crowds, thus we need to aggregate these information.[6]

To cope with the problem, several approach had been developed. Prediction markets (a.k.a. information markets, decision markets, electronic markets, virtual markets) is developed as an information aggregation model.[22] Its price instantly summarized the information related to certain event, with its accuracy usually outperform other approaches, like predictions from experts, poll results, and questionnaire results.[23]

Many successful prediction market systems are developed. To name some, Yahoo Buzz Game,[4] Intrade,[2] Iowa Electronic Market (IEM),[3] Hollywood Stock Exchange (HSX).[1] These systems have been producing precise results, attracting researchers, companies and governments.

1.2 Issues of Prediction Market Systems

Studies had found some questions about prediction markets:

Attract uninformed traders. The number of bids and asks mostly depends on the number of active players, It is not possible to match bids and asks if there aren't enough players,[24] or the lack of participation makes the player not expecting to find a match.[19] The price of market then fails to summarize the information. This is also known as the thin market problem. This problem could be specific to certain kind of contracts which informed traders are rare, or could be system-wide. Another aspect is that prediction markets only attract specific kind of audiences which is familiar of markets.[11]

Interest and contractibility. The possible outcomes of real-world events is infinite, but it is not possible to enumerate every possibility into contracts. As a trade-off, only options that most likely to happen are put into contracts. When the event progresses, the possibilities of every option changes. If any option becomes likely to happen, but is not put into the contract set initially, the current set of contracts might become unfeasible.[24]

Intervention from players. Studies showed that players might influence the outcome.[24] For instance, In a contract predicting whether a policy would be made, It happens that the decision maker is also a player, using prediction market as a decision supporting tool. In an extreme case, players will try to influence the outcome if there are enough incentives, like real money.

Manipulation. It is obvious that markets should fight against manipulation, otherwise the outcome could be biased. A wealthy player could put an enormous bids in order to change the price, and profit from a later price. Some works have shown that the impact is only temporary and short-lived, it is hard to manipulate prediction market[12], but when the market is thin, Manipulation might be possible to impact the market significantly.

Calibrate on small probabilities. Dealing with a low probability outcome, Manski[15] studied that prediction markets might have some difficulties in Prediction markets. In a market setting that two mutually exclusive securities exists, a less likely outcome is often overpriced and the more likely outcomes are underpriced. This is known as the longshot bias. Works from Gjerstad[8] and Wolfers and Zitzewitz[25] showed that if the players were risk-averse, results would be more precise.

1.3 Agents and Prediction Markets

Many works had been devoted to agent-based modeling in economics. However, it was hard to simulate a complex economic system until recently, the computational power grows, more and more scalable and affordable solutions are on our disposal. Agent-based modeling is not meant to replace the real-world experiments, but to simulate models prior to the experiment at relatively low costs.

The merits of agent system in economic model are many: Compared to human subject experiments, there are less constraints on prediction markets. For example, human subjects need to learn "how to play the game" before the experiment actually take place, as such issue doesn't exist in agent systems. Ceteris paribus, an important prerequisite not only in economics but most of the experiments, means "all other things being equal". While other systems might have uncertainties upon ceteris paribus, It is easier to achieve in computational approaches, such as multi-agent systems.

Combining prediction market with agent system is a novel approach, though the nature of prediction markets seems collide with multi-agent systems, the results of recent research is promising. The agent system is a perfect solution for modeling, with its scalable and repeatable feature, multi-agent systems attract many related studies, and we believe the combination is the pavement to further development of prediction markets.

1.4 Research Problem

Previous studies suggests that risk could be an important factor in prediction markets, that risk-averse players produced more accurate results. Since there are very few works that put risk variable into simulation experiments, we will try different risk distributions in our experiments.

Thin market is a phenomenon that will make prediction perform poorly, because there is too few transactions to make the price converge. Our proposed reputation variable could make those bankrupt players obtain credits and rejoin market, This could increase the chance of successful transactions, and may reduce the impact of thin market.

We try to simulate these two variables in a zero-intelligence agent prediction market, and observe how these two variables affect prediction market.

1.5 Thesis Organization

In chapter 2, we review the recent work of the models of prediction markets, thin market problem and prediction markets with agent simulation. Chapter 3 introduces a new mechanism which brings back bankrupted players in prediction market, the experiment design and settings. We compare the simulation results, with and without the mechanism in chapter 4. We conclude the results in chapter 5, discuss the possibility of prototyping prediction market models with multi-agent system.

CHAPTER 2
Literature Review

2.1 Prediction Markets

The concept of prediction market systems mainly comes from two competiting hypotheses, **Hayek Hypothesis** and **Efficient Market Hypothesis**.[6] The former states that the price of the market could be a decentralized mechanism to aggregate information among crowds, the latter claims that the price will instantly summarized all relevant information in an efficient market. We could associate the price of a particular security with the outcome of real-world event. By observing the relevant information, it is possible to estimate the outcome of real-world event in real-time.

The event we try to predict in prediction markets is like a security, for example, if we like to predict the winner of an election, the securities would be the candidates, plus a draw security. The price of each security, say, from 0 to 100, denotes the possibility of each event. If the price of candidate A security is 40, it means the predicted possibility of candidate A winning is 40 percent.

After the securities have been decided by the system operator, players then trade these securities. In a given timespan, they could bid and/or ask at any price, matching bids and asks makes the price rise or fall. After the trade timespan passed, no more bids and asks could be made. The security will expire according to the real outcomes, in previous example, if candidate A wins, the price of candidate A will expire at 100, any player holding a security of candidate A will recieve 100 credits. and all other securities will expire at 0, any player holding other security will not receive any credits. Above example is a winning-losing event, we could even predict the vote precentage where candidate A recieves. The price then denotes the percentage of vote candidate received.

2.1.1 Evolution of Prediction Markets

Iowa electronic Marketplace (IEM) is one of the earlist prediction markets, In 1988, IEM have already outperformed poll results in predicting elections, political events and military crises. Compared with statistical forecasting methods, the main advantage of prediction market is real-time information aggregation, and no historical data required.[6]

Continuous Double Auction (CDA) is the most broadly used design of prediction markets. The market price of security fluctuates as players participate in the system. The system either sells the security to the player at market price, or match the buy requests (bids) and sell requests (asks) with the same price.

However, CDA suffers from thin market problem: When there is a significant price gap between of bids and asks, It is hard to match them. This problem severely reduced the liquidity of prediction markets, resulting less accurate results.[13] To cope with this problem, Continuous double auction with market maker (CDAwMM) could alleviate this problem with built-in liquidity induction, a centralized market maker willing to accept bids and asks at specific price. Since it poses significant risk to monetary losses. it is risky to implement it in a real-money system.

Pennock[18] proposed the Dynamic Pari-Mutuel Market (DPM) for prediction market, which lowered the risk existed in CDAwMM. Unlike the CDA market design, DPM models have infinite liquidity effectively since bets are not matched. Players could bet at any price, any quantity. Winning players just redistribute total bets. However, the nature of pari-mutuel market model prevents the market reveal the aggregated information under some circumstances.

2.1.2 Implementations and Experiments

Current prediction markets in operation mainly choose CDA or CDAwMM as its main model. It requires a lot of investments operating a prediction market, whether it's real money or play money. The most important issue of operating prediction market is to attract players. The high cost hinders large-scale real-subject experiments and verifications of new models. In the past few decade, several works provided computational model verification and prototyping, and the results justified their approach. As computing resource becomes more cheaper, it is economic to introduce simulation models prior to real systems.

2.2 Multi-Agent System for Simulating Prediction Markets

Many works discussed the computational approach for specific market models, Feigenbaum et al.[7] found that the price converges to equilibrium in a distributed environment, Pennock and Sami[19] further studied specifically on prediction markets. In both works, agents are myopic, risk neutral, and bid truthfully, similar settings are found in other related works.

Recent studies have shown that accuracy of prediction market models could be verified by simulated results. [14][17] Several experiments with different agent settings are performed, we divided them into two types of agent, **Zero-Intelligence (ZI) agents** and **non-ZI agents**.

2.2.1 Zero-Intelligence Agents in Prediction Markets

Gode and Sunder[10] devoted to the early works of ZI Agents. In their experiments, ZI Agents has no intelligence, do not maximize their profit, do not observe the environment, remember or learn. In terms of allocative efficiency of market, budget-constrainted ZI agents have over 95% of mean efficiency in CDA markets, which is very close to human subject experiment results. Othman[17] discussed an implementation of ZI agents in Prediction Markets. He suggests increasing the level of sofistication of ZI agents might produce new results.

2.2.2 Non-ZI Agents versus ZI agents

In prediction market submodels, Gjerstad and Dickhaut[9] developed Gjerstad-Dickhaut (GD) agents, early works of GD agents with double auction are able to achieve competetive equilibrium and market efficiency. Bagnall and Toft had compared results of ZI-Plus (ZIP) agent, a modified version of ZI agent which incorporates an elementary form of machine learning, and GD agents with sealed-bid auctions, GD agents learnt the optimal strategy, and outperformed the ZIP agents.

In prediction market models, Experiments introducing more complex agents in several works produced interesting results. Tseng et al.[21] compared ZIP agents, GD agents and

ZI agents. Their experiments showed that ZI agents outperformed ZIP agents and GD agents.

It is hard to say which one is superior, both approach has its strength and weaknesses. Despite its simplicity, ZI agents had much performance, We try to use ZI agents to construct a prediction market, following Othman's ZI model. This model will be used to experiment our prediction model, we believe ZI agent could be a powerful tool for modeling innovative systems without incurring large costs.

CHAPTER 3
Methodology

Our experiment implements Othman's work[17] in a simulation manner, As our model is different from Othman's model, We propose a modified model incorporates two variables into simulated prediction markets, **Reputation** and **Risk**. By replicating a working model, we could justify our methodology. We use similar simulation settings derived from Jie-Jun Tseng, et al.[21]

3.1 Prediction Market Modeling

Chen[6] proposed a generic model of prediction markets, as shown in figure 3.1. We will discuss our model in this context, Table 3.1 below is an overview of parameters.

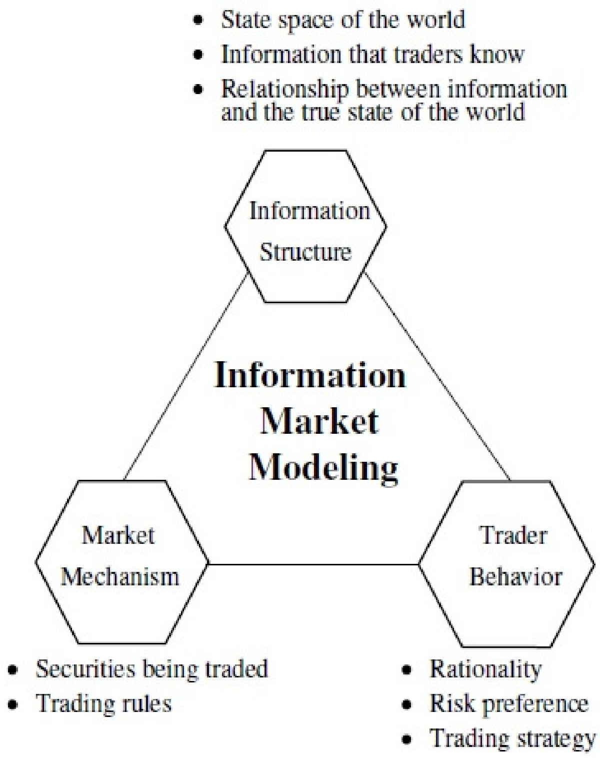

Figure 3.1: Main components of Prediction Market Modeling

Table 3.1: An overview of simulation parameters

Parameter	Value
Simulation days in an experiment	100
Rounds in a day	1250
Number of agents	2500
Belief regime	Beta distribution
Distribution mean of belief	0.6, unless stated otherwise
Risk attitude	Skew normal distribution
Distribution mean of risk	0.5, when $\alpha = 0$
Initial endowment	100000 credits
Inactive threshold T	2000 credits
Reputation penalty R_p	50000 credits

3.1.1 Information Structure

The information structure of prediction market denotes the state space of the world, how much world state information that traders hold, and how traders relate that information to the world state. The state space of the world consists every possible option probability S_i, where $\sum S_i = 1$. For example, the state space of "will it rain tomorrow" would be the probability of "it would rain" and "it would not rain".

We use zero-intelligence agents to simulate the traders. In each experiment, a prior belief $B_i \in [0, 1]$ is assigned to each agent. In our experiment, we use a virtual event E, If an agent is assigned $B_i = 0.7$, the agent believe that the probability of E happening is 70 percent. The belief is chosen from a predefined beta distribution, with the exception of control experiment, which belief is randomly assigned (uniform distribution). The parameter of the belief distribution is identical to the middle accuracy belief regime in figure 3.2, as Othman suggests that real-world belief won't be as diffuse as low accuracy belief regime, we choose middle accuracy belief regime (denoted by green line) with .6 mean.

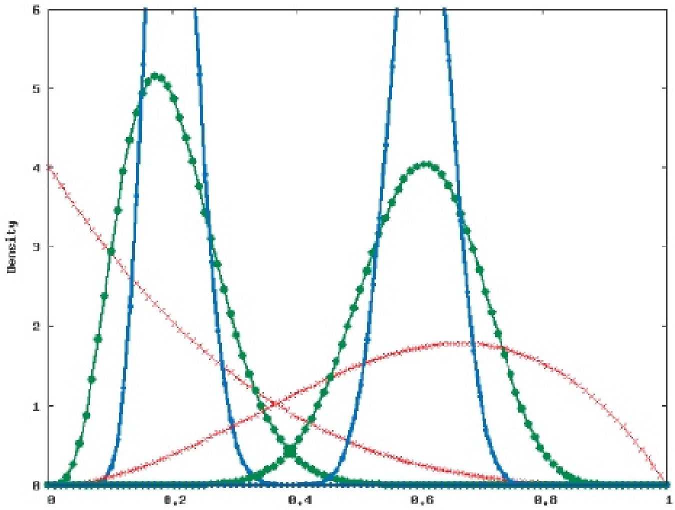

Figure 3.2: Belief regimes proposed by Othman

3.1.2 Market Mechanism

There are exactly two securities in the state space of our model, and they are mutually exclusive: when the probability of one security increases, the probability of the other security decreases. Since the two securities are mutually exclusive, only one security is traded in our model. This could be regarded as a one dimensional state space.[6] Our system diagram is shown in figure 3.3.

In each of our experiments, 2500 agents are populated, the market proceeds in 100 virtual days, and each day is consisted of 1250 rounds. Note that there is no relationship between real days and virtual days, nor rounds, It only represents the iteration count of the simulation. In each round, a bidder and an asker is randomly chosen from the agent

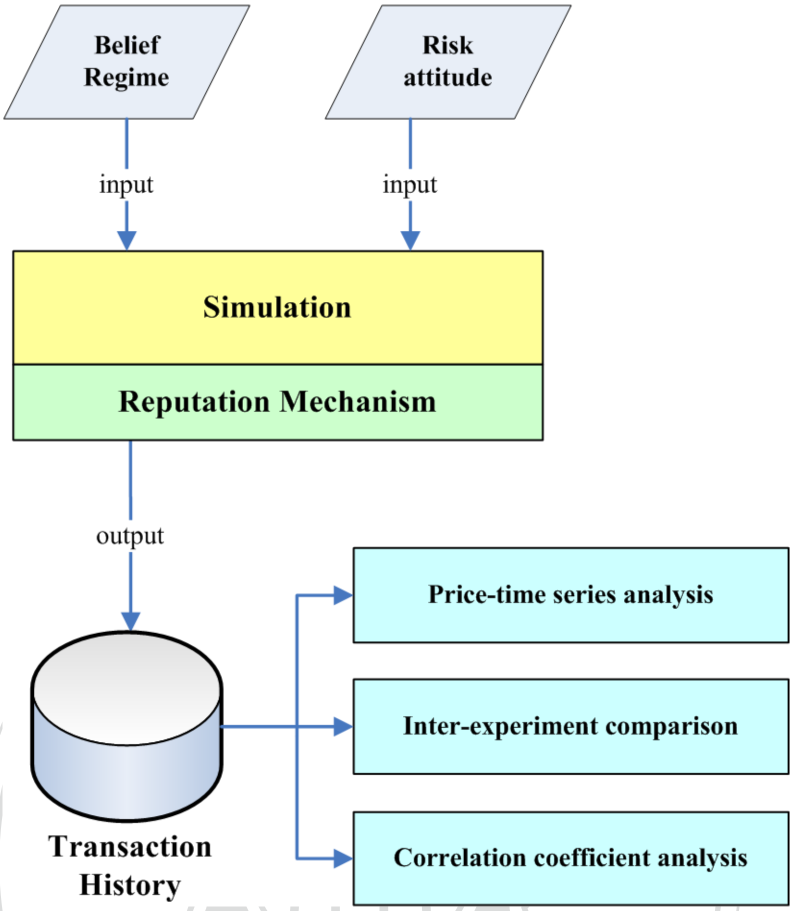

Figure 3.3: System diagram

pool. Their price upon the security is $P_i = B_i \times 100$, where B_i is their assigned belief. if the bidding price P_b is less than of equal to the asking price P_a , a transaction occurs at the bidding price, bids and asks not matching will expire immediately. The quantity of the transaction Q_i would be the asker's risk attitude R_a times its credit C_a, divided by the matching price P_b:

$$Q_i = \frac{R_a \times C_a}{P_b}$$

At the end of each day, every matched agent will earn or loss credit according to their bids or asks, Our assumption is that the distribution mean could represent the objective probability of the event,[17] therefore, the security is always expired at value of 60. For example, if an agent bids the security at $P_i = 40, Q_i = 300$, the agent will earn $(60 - P_i) \times Q_i = 6000$ credits. After this, any agent that their holding credit is less than the participation threshold T will be marked as inactive, these agents will not be able to trade further.

3.1.3 Trader Behavior

The traders are homogeneous agents, their belief is assigned from Beta distribution mentioned previously, the agents will always reveal their belief truthfully. In the zero-intelligence model,[17][5] the agents do not observe market price, do not remember any information of their earlier transactions, and do not react to the results of any transactions.

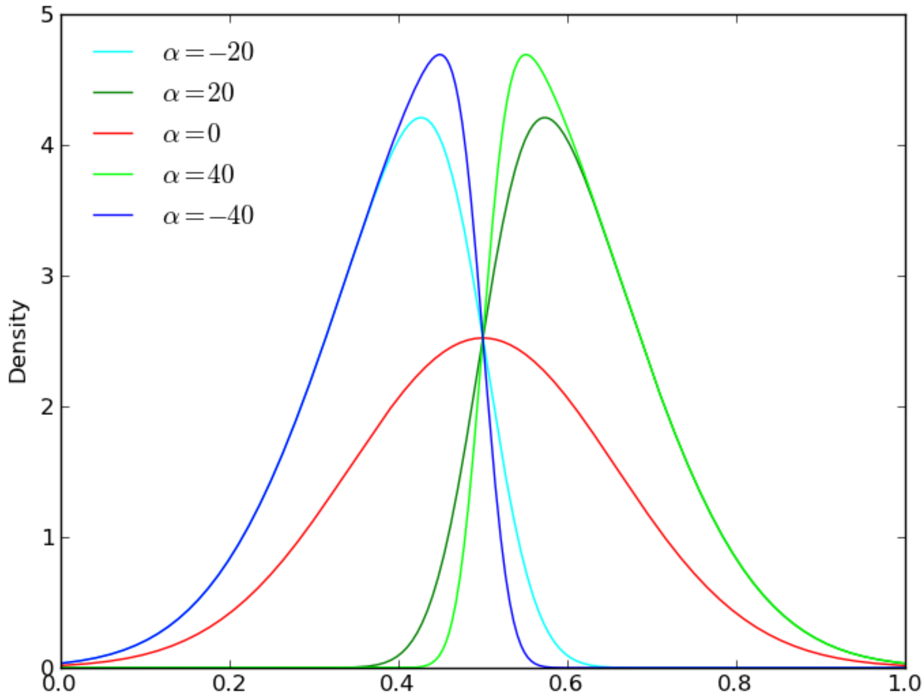

Figure 3.4: Skewed Normal Distribution

Risk attitude are assigned from specific skew normal distributions, it represents the portion of credit could an agent risk. It is assigned to each agent and it will not change during the simulation, the distribution of risk parameter varies among experiments, shown in figure 3.4, Choosing different skew normal distributions let us change the number of risk-aversion and risk-seeking agents, then we observe the simulation results.

3.2 Reputation

In a real-world prediction market, when a player loses all of his money, he can not participate in the market anymore. In real-money prediction markets, he could deposit real-money and continues to play. In play-money prediction markets, it depends on how the market is designed. Some system let players gain credits by logging in daily, post comments or share opinions with other players.

However, A bankrupt player might just create a new account, gain another initial endowment and continues to play. This prevents us to keep track on individual players, We could study their playing history, their belief and risk preferences only if they keep playing on their original account. Our assumption is that if we bring these bankrupt players back to the market, it may reduce the impact of thin market, and the price might be more accurate. Therefore, we introduce a new mechanism which brings players back.

We try to help bankrupt players with reputation variable. The name **reputation**, is a score denotes the fiscal status of an agent. The idea is from the real world, the bank will check the financial status, the credit history of a person to determine whether the credit card should be issued. A higher score represents a better credit history, thus a better reputation.

Just like real world, when a player bankrupted, he could ask other players for help. The reputation of a player will increase if he chooses to help, and the reputation of the bankrupt player decreases. An amount of virtual money, **Reputation penalty** R_p, is transferred from the helping player to the bankrupt player, making them possible to participate again. After that, the helping player gained reputation, and the bankrupt player loses reputation.

In our simulation, agents won't really bankrupt because they will only use a portion of their holding credit to trade. So we set a threshold T, agents holding credit below T would not be able to trade in significant volume, We call these agents "inactive agents" because they are not really bankrupt.

3.3 Risk Parameter

Previous studies of prediction market lack of risk attitude experiments, most of them are risk-neutral[17][14][21][16][15], which means agents will use all its credit to trade.

However, Gjerstad argues that the longshot bias is related to the risk parameter, if the players are risk-averse, the price would be more precise[8][25]. We try to manipulate the impact of longshot bias by using different risk settings.

Putting risk variable in our model is challenging, because risk is related to profit-maximizing nature of rational human. Zero-intelligence agents don't maximizing their profits by design, we could take an alternate approach. In our model, we define risk attitude $R_i \in [0, 1]$ as agent's willingness to risk its credit. For example, an agent with 0.65 risk attitude would trade with 65 percent of his total credit. We offset the risk-neutral trade ratio to 50 percent, in order to describe risk-seeking and risk-aversion scenario.

3.4 Populating Agents

Throughout the experiments, we need to generate pseudo-random numbers based on distributions we prefer. We use the inverse transform sampling method to achieve this. First, we pick a random number $u \in [0, 1]$. Next, let $F(x)$ denotes the cumulative distribution function of the desired distribution, solve x in $F(x) = u$, and x is the output. Repeating these steps will produce a sample of the desired distribution.

3.5 Experiments

We describe four sets of experiments below, To eliminate finite size effect [21], we will run 30 passes for each set. The price of each day is calculated from the average of 30 passes.

3.5.1 Control set

In each of control experiments, The risk parameter among agents is all the same, as shown in table 3.2. Every agent will receive an initial endowment at the beginning of each experiment, each experiment runs 100 simulation days. At the beginning of each simulation day, We randomly pick two agents from the agent pool that haven't trade in the market yet, one as the bidder, and the other as the asker. The agents then makes their bids and asks. After 1250 rounds, all agents have participated, The agent will earn or lose credits according to their transactions. The next simulation day then begin. Any inactive agents will not be able to put bids and asks further.

Table 3.2: Experiments in Control set

Symbol	Description	Belief regime	Risk attitude
Ctrl-1	Control experiment	Randomly assigned	Risk neutral (0.5)
Ctrl-2	Control experiment, risk attitude of agents is 0.3	Beta distribution	Risk-aversion (0.3)
Ctrl-3	Control experiment, risk attitude of agents is 0.5	Beta distribution	Risk neutral (0.5)
Ctrl-4	Control experiment, risk attitude of agents is 0.7	Beta distribution	Risk-seeking (0.7)

3.5.2 Risk only set

In risk only experiments, The settings are identical to the control experiments, except we changed the distribution of risk attitude parameter, shown in table 3.3. As figure 3.4 depicts, left-skew normal distribution experiments are the risk-seeking agents, and vice versa.

3.5.3 Reputation only set

In reputation only experiments, The settings are identical to the control experiments, and at the end of each simulation day, the most poor inactive agent will receive credit of half the amount of initial endowment, the process repeats until there is no inactive agents. Every agent has the chance to trade in every simulation day.

Table 3.3: Experiments in Risk only set

Symbol	Description	Risk attitude
Risk-0	Risk only experiment, baseline	Standard Normal distribution
Risk-L5	Risk-seeking experiment	Left-skewed Normal distribution, $\alpha = 5$
Risk-L10	Risk-seeking experiment	Left-skewed Normal distribution, $\alpha = 10$
Risk-L20	Risk-seeking experiment	Left-skewed Normal distribution, $\alpha = 20$
Risk-L40	Risk-seeking experiment	Left-skewed Normal distribution, $\alpha = 40$
Risk-R5	Risk-aversion experiment	Right-skewed Normal distribution, $\alpha = -5$
Risk-R10	Risk-aversion experiment	Right-skewed Normal distribution, $\alpha = -10$
Risk-R20	Risk-aversion experiment	Right-skewed Normal distribution, $\alpha = -20$
Risk-R40	Risk-aversion experiment	Right-skewed Normal distribution, $\alpha = -40$

3.5.4 Reputation and Risk set

In the reputation and risk experiments, we choose several risk-seeking and risk-aversion distributions, and the inactive agents will return to market as in the reputation only experiments.

Table 3.4: Experiments in Reputation only set

Symbol	Description	Risk attitude
RP-Ctrl-1	Reputation experiment	Standard Normal distribution
RP-Ctrl-2	Reputation experiment, risk attitude of agents is 0.3	Risk-aversion (0.3)
RP-Ctrl-3	Reputation experiment, risk attitude of agents is 0.5	Risk neutral (0.5)
RP-Ctrl-4	Reputation experiment, risk attitude of agents is 0.7	Risk-seeking (0.7)

Table 3.5: Experiments in Reputation and Risk set

Symbol	Description	Risk attitude
RR-L5	Reputation, risk-seeking experiment	Left-skewed Normal distribution, $\alpha = 5$
RR-L10	Reputation, risk-seeking experiment	Left-skewed Normal distribution, $\alpha = 10$
RR-L20	Reputation, risk-seeking experiment	Left-skewed Normal distribution, $\alpha = 20$
RR-L40	Reputation, risk-seeking experiment	Left-skewed Normal distribution, $\alpha = 40$
RR-R5	Reputation, risk-aversion experiment	Right-skewed Normal distribution, $\alpha = -5$
RR-R10	Reputation, risk-aversion experiment	Right-skewed Normal distribution, $\alpha = -10$
RR-R20	Reputation, risk-aversion experiment	Right-skewed Normal distribution, $\alpha = -20$
RR-R40	Reputation, risk-aversion experiment	Right-skewed Normal distribution, $\alpha = -40$

CHAPTER 4
Simulation Results

4.1 Performance metrics

We will discuss the results of each set of experiments, and the differences between experiment sets. Our comparison method of results includes Absolute Error, Quadratic score, Logarithmic score, price-time series figures,[21] standard deviation, and simple linear regression analysis of mean price, We use simple linear regression analysis to observe the price trend, combined with the price-time series figures, price fluctuations are measured by standard deviation, a higher standard deviation means the price fluctuates more wildly.

When evaluating the prediction accuracy of the experiments, the metrics of Absolute Error, Quadratic score, Logarithmic score is used. Chen[6] used these metrics introduced by Serven-Schreiber et. al.[20] Chen compares the median of the prediction, the work stated a prediction more accurate in a difference of 0.02 median value.

Absolute Error is the estimated probability of **the other** security, which in our model is:

$$Absolute\_Error = |1 - Price_{estimated}|$$

It is commonly used in evaluating the accuracy of forecast, a prediction is more accurate with lower absolute error.

Quadratic score is a linear transformation of squared absolute error,

$$Quadratic\_Score = 100 - (400 \times Absolute\_Error^2)$$

A prediction is more accurate with higher quadratic score.

Logarithmic score is another scoring rule used:

$$Logarithmic\_Score = log(Price_{estimated})$$

A prediction is more accurate with higher logarithmic score. We will only compare absolute error in our discussion.

Serven-Schreiber use these metrics to measure the differences between real-money and play-money prediction markets, It turns out there is no significant difference in forecasting ability of real-money and play-money prediction markets. That leads to another analysis metric, **correlation coefficient**, correlation coefficient could evaluate whether two variables are statistically related.

Correlation coefficient $R \in [-1, 1]$ could tell the difference between two experiments, this was used in Serven-Schreiber et. al.[20]. If $R = 1$, there is a strong positive linear relationship between two experiments, if $R = -1$, there is a strong negative linear relationship between two experiments. If R is close to zero, there is no linear relationship between two experiments, but that does **not** imply there is no relationship between two experiments.

4.2 Experiment results

4.2.1 Control experiments

Experiment **Ctrl-1** is identical to zero-intelligence simulation from Tseng et al,[21], As the literature missing the performance metrics we used, we could only compare the result side by side. In figure 4.1 and 4.2, the scatter plot seems persistent.

Table 4.1: Simulation Results: Control experiments

Symbol	Risk Attitude	Distribution mean of belief	Mean	Median	Standard deviation	Absolute error
Ctrl-1	0.5	0.5	33.696	33.368	6.203	0.6630
Ctrl-2	0.3	0.6	54.189	54.193	2.101	0.4581
Ctrl-3	0.5	0.6	54.185	54.187	2.097	0.4581
Ctrl-4	0.7	0.6	54.164	54.165	2.108	0.4584
Oth-1	1	0.8	76.6	N/A	N/A	0.3340
Oth-2	1	0.2	23.4	N/A	N/A	0.3340

Table 4.2: Correlation coefficient: Control experiments

	Ctrl-1	Ctrl-2	Ctrl-3	Ctrl-4
Ctrl-1	1			
Ctrl-2	0.131	1		
Ctrl-3	-0.018	0.999	1	
Ctrl-4	0.064	0.999	0.999	1

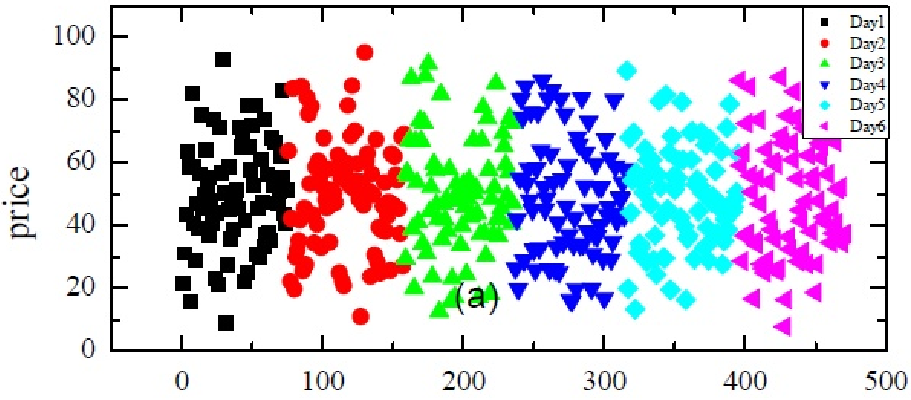

Figure 4.1: Price-time series from Tseng et al.

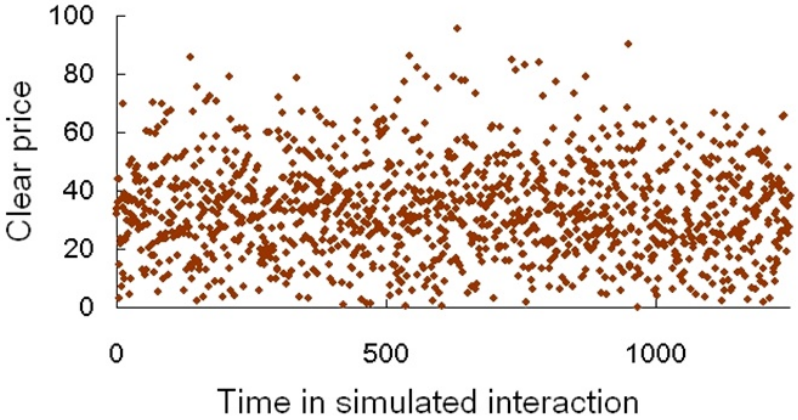

Figure 4.2: Price-time scatter plot of experiment Ctrl-1

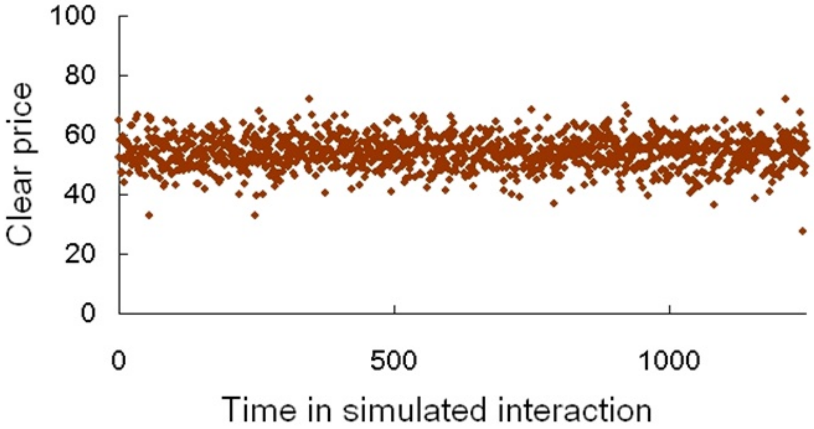

Figure 4.3: Price-time scatter plot of experiment Ctrl-3

We include original results of the middle accuracy regime, from Othman's work,[17] the values are adjusted in order to fit our metrics. When we changed the belief regime

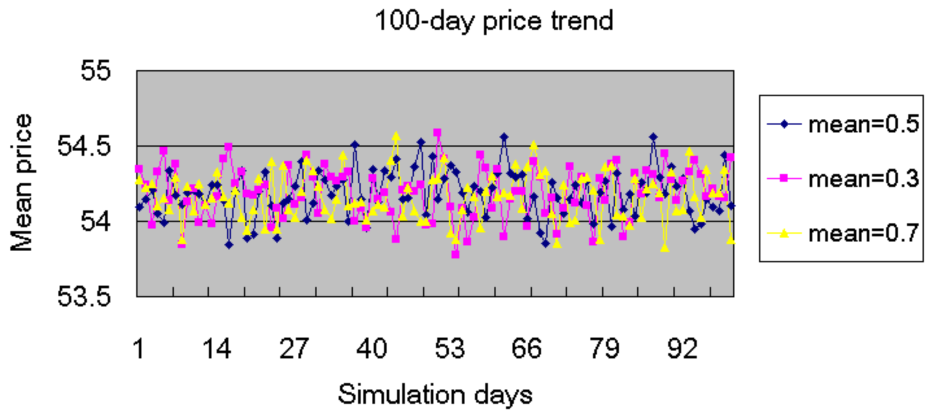

Figure 4.4: Combined price-time series of control experiments

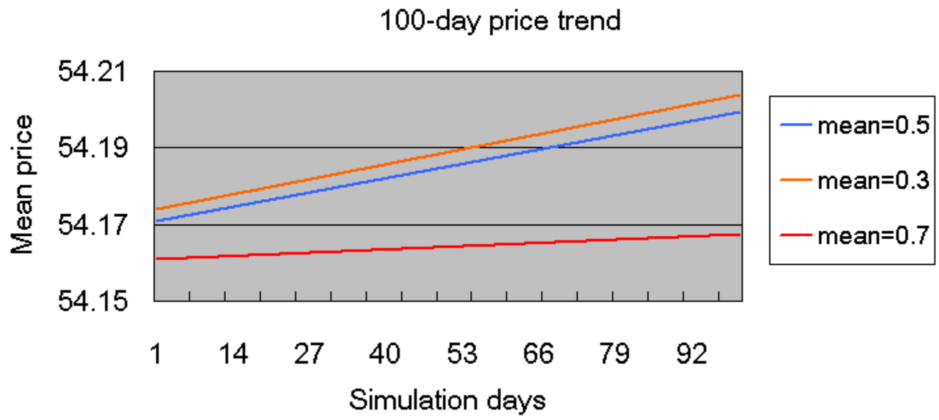

Figure 4.5: Regression analysis of control experiments

to Beta distribution, we could see that the fluctuations narrowed in figure 4.3, and the mean price moves closer to the mean belief. Table 4.1 showed that belief regime affects prediction market accuracy,

The price-time series and the regression analysis are shown in figure 4.4 and figure 4.5, Ctrl-1 experiment is omitted, because it is hard to see the slope differences between other experiments. Even we enlarged the scale, we could only observe the slight differences in the regression analysis between experiments. It is obvious that price are more fluctuated in randomly assigned belief than our chosen belief regime, and price fluctuation seems affected by belief regime rather than the mean of risk attitude. The absolute error declines when the risk attitude rises, but we don't observe a strong relationship between them.

We also found that the slope of Ctrl-1 and Ctrl-2 are almost the same, shown in the regression analysis in figure 4.5. The correlation coefficients between same belief regime experiments are close to 1, which means there is slight difference in changes of mean of risk attitudes.

4.2.2 Risk-only experiments

As we can see in control experiments, there might be a connection between risk attitude and the prediction accuracy. In risk-only experiments, we change the skewness α of normal distribution $\mu = 0.5, \sigma = 1$. when $\alpha = 0$, it is standard normal distribution as shown in figure 3.4. Then we populate risk attitude accordingly. This is to observe how risk attitude affects the longshot bias mentioned by Gjerstad.[8]

Table 4.3: Simulation Results: Risk-only experiments

Symbol	Skewness α	Mean	Median	Standard deviation	Absolute Error
Risk-0	0	54.193	54.182	2.103	0.4581
Risk-L5	5	54.187	54.187	2.097	0.4581
Risk-L10	10	54.157	54.163	2.094	0.4584
Risk-L20	20	54.158	54.143	2.100	0.4584
Risk-L40	40	54.207	54.157	2.110	0.4579
Risk-R5	-5	54.172	54.160	2.101	0.4583
Risk-R10	-10	54.192	54.189	2.103	0.4581
Risk-R20	-20	54.191	54.188	2.110	0.4581
Risk-R40	-40	54.171	54.157	2.093	0.4583

Table 4.4: Correlation coefficient: Risk-seeking experiments

	Risk-0	Risk-L5	Risk-L10	Risk-L20	Risk-L40
Risk-0	1				
Risk-L5	0.068	1			
Risk-L10	-0.097	-0.058	1		
Risk-L20	-0.224	0.017	0.041	1	
Risk-L40	-0.014	-0.024	0.028	-0.201	1

Table 4.5: Correlation coefficient: Risk-aversion experiments

	Risk-0	Risk-R5	Risk-R10	Risk-R20	Risk-R40
Risk-0	1				
Risk-R5	0.109	1			
Risk-R10	0.083	-0.106	1		
Risk-R20	0.017	0.128	0.075	1	
Risk-R40	0.097	0.117	0.162	-0.012	1

Since there is too much data points in one figure, The figures and tables are separated as high-risk (left skewed) and low risk (right skewed). In table 4.3, the mean price does not change significantly with the skewness, so is the accuracy. The differences between standard error is small, therefore the change in price fluctuations is not obvious, either. The correlation coefficient shown in table 4.4 and table 4.5 suggests there might be little linear relation between changes in skewness α.

We can see that, in regression analysis of control experiments, Generally, the slope of risk-seeking price trend lines are negative, and the slope of risk-aversion price trend lines are positive. That means risk-aversion experiment tends to move closer to mean belief, while risk-seeking experiment deviates from mean belief. Though the difference

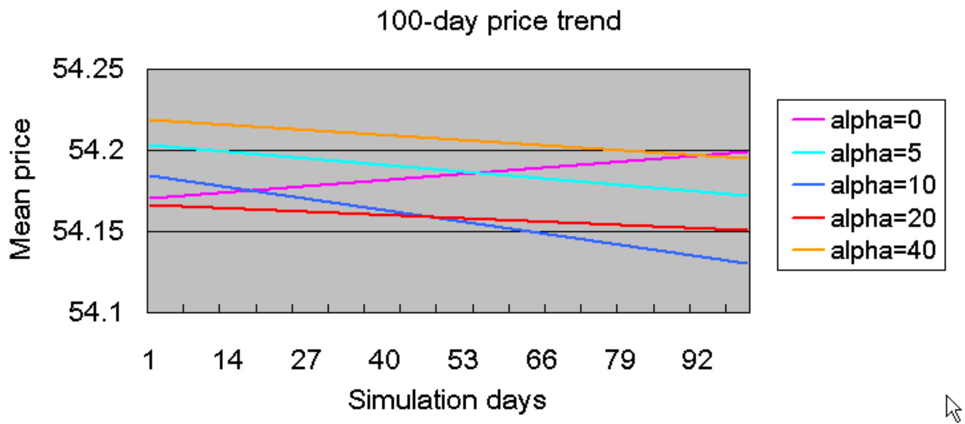

Figure 4.6: Regression analysis of risk-seeking experiments

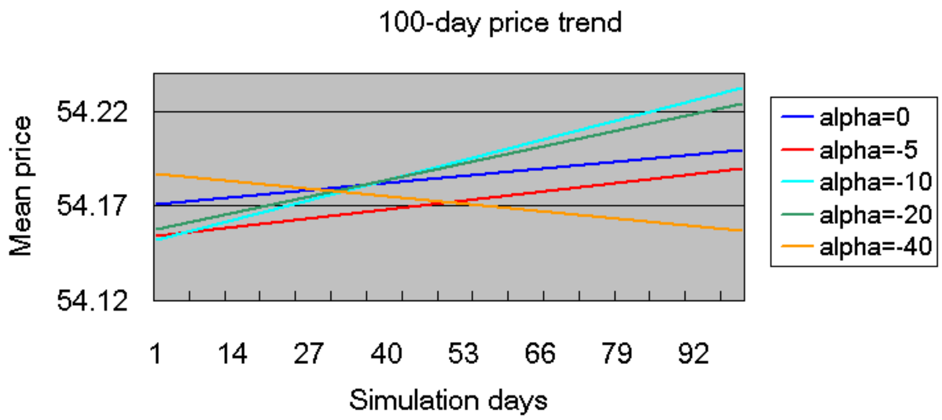

Figure 4.7: Regression analysis of risk-aversion experiments

is small, this result fits the theory from Gjerstad,[8] lower risk attitude leads to better accuracy. The trend is also observed in risk-only experiments, especially in risk-aversion experiments.

4.2.3 Reputation-only experiments

In reputation-only experiments, we try to make those inactive agents re-enter the market, We keep track on how many agents are inactive in each simulation day, before they will be put back to the market. Figure 4.9 clearly showed that the number of inactive agents decreased significantly. The impacts of these returning agents are interesting.

Compared with control experiments, It seems that reputation variable makes risk-seeking experiment perform more accurately, and makes risk-aversion experiments deviate from mean price.

Table 4.6: Simulation Results: Comparison of Reputation-only and control experiments

Symbol	Risk Attitude	Mean	Median	Standard deviation	Absolute Error
RP-Ctrl-2	Risk-aversion (0.3)	54.188	54.204	2.093	0.4581
RP-Ctrl-3	Risk-neutral (0.5)	54.170	54.176	2.106	0.4583
RP-Ctrl-4	Risk-seeking (0.7)	54.191	54.207	2.111	0.4581
Ctrl-2	Risk-aversion (0.3)	54.189	54.193	2.101	0.4581
Ctrl-3	Risk-neutral (0.5)	54.185	54.187	2.097	0.4581
Ctrl-4	Risk-seeking (0.7)	54.164	54.165	2.108	0.4584

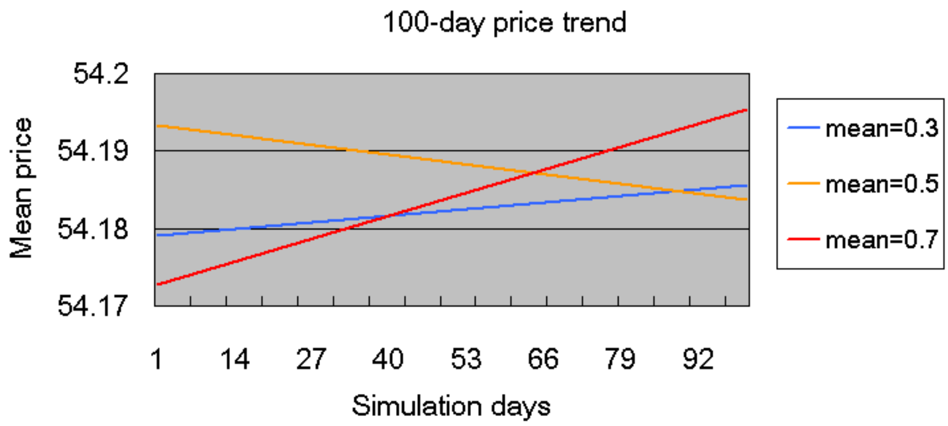

Figure 4.8: Regression analysis of reputation-only experiments

It is hard to interpret results with such minuscule change, the correlation coefficient table is omitted because the value is very close to 1, which means there is no significant differences between reputation and control experiments. We will continue to reputation and risk combined experiment.

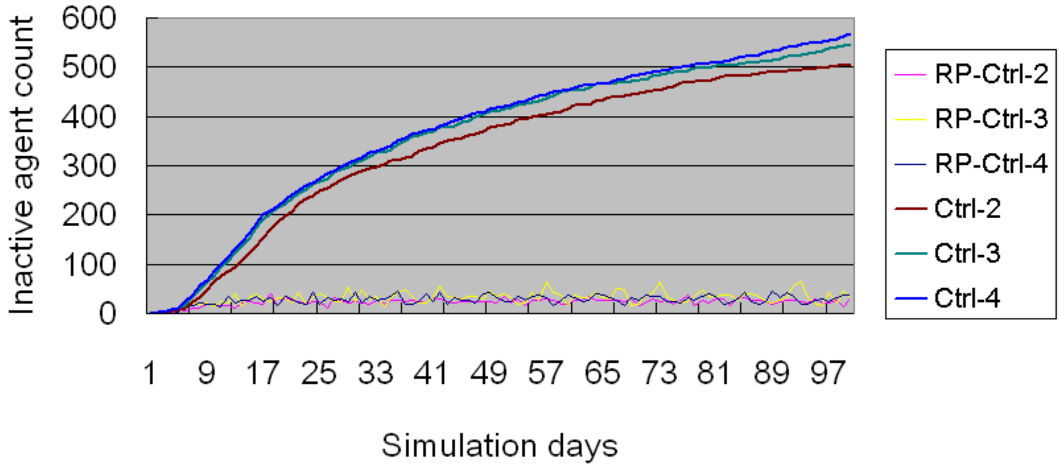

Figure 4.9: Comparison of inactive agent count

4.2.4 Risk and Reputation experiments

We compare the risk and reputation experiments with risk-only experiments, the correlation coefficients are very close to 1, meaning there is only slight differences between them. The inactive agent count is significantly lower than control experiments, shown in figure 4.9. The total amount of credit in market does not change might be an explanation that reputation did not affect the prediction accuracy.

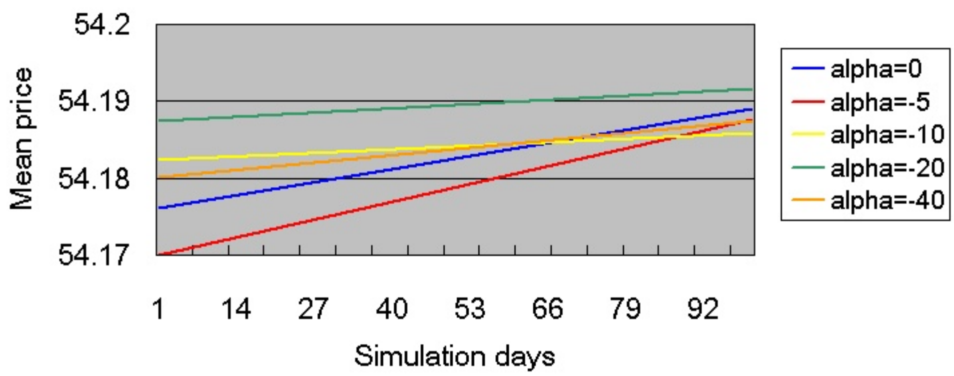

Figure 4.10: Regression analysis of risk and reputation experiments, risk-seeking

In table 4.7, compared with risk-only experiments, risk-neutral and risk-aversion experiments are less accurate in terms of absolute error. On the other side, risk-seeking experiments are more accurate.

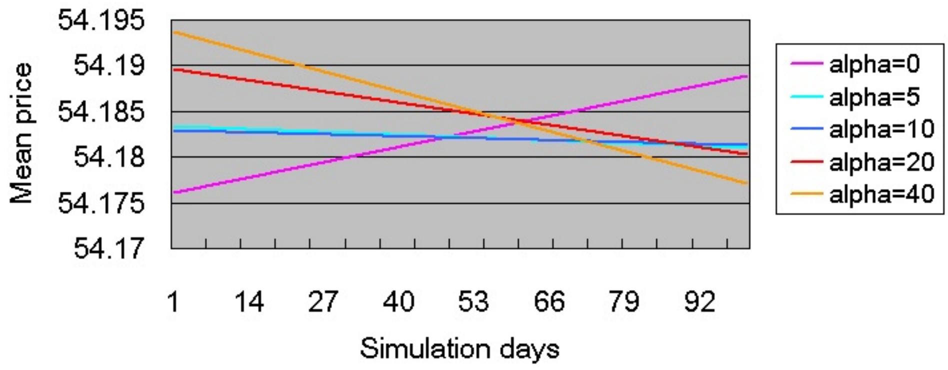

Figure 4.11: Regression analysis of risk and reputation experiments, risk-aversion

In regression analysis shown in figure 4.10 and figure 4.11, we could see that risk-aversion experiments generally approach the mean belief, and risk-seeking experiments generally deviate from mean belief. We observed the same trend Gjerstad[8] suggested, mean price approaches mean belief when the risk is lower, It is consistent with the reputation only experiments.

Interestingly, while some risk-seeking experiments deviate from mean belief in the risk-only experiments, In risk and reputation experiments, the price trend is approaching mean belief. Based on our observation, we could made a strong assumption that reputation might increase the accuracy of prediction markets with risk-seeking players, but might decrease the accuracy of risk-aversive one.

Table 4.7: Simulation Results: Comparison of Risk and reputation experiments and Risk-only experiments

Symbol	Skewness α	Mean	Median	Standard deviation	Absolute Error
RR-0	0	54.146	54.156	2.108	0.4585
RR-L5	5	54.197	54.200	2.089	0.4580
RR-L10	10	54.186	54.200	2.097	0.4581
RR-L20	20	54.169	54.178	2.107	0.4583
RR-L40	40	54.182	54.173	2.101	0.4582
RR-R5	-5	54.173	54.190	2.107	0.4583
RR-R10	-10	54.168	54.171	2.112	0.4583
RR-R20	-20	54.169	54.156	2.098	0.4583
RR-R40	-40	54.210	54.213	2.099	0.4579
Risk-0	0	54.193	54.182	2.103	0.4581
Risk-L5	5	54.187	54.187	2.097	0.4581
Risk-L10	10	54.157	54.163	2.094	0.4584
Risk-L20	20	54.158	54.143	2.100	0.4584
Risk-L40	40	54.207	54.157	2.110	0.4579
Risk-R5	-5	54.172	54.160	2.101	0.4583
Risk-R10	-10	54.192	54.189	2.103	0.4581
Risk-R20	-20	54.191	54.188	2.110	0.4581
Risk-R40	-40	54.171	54.157	2.093	0.4583

4.3 Summary

Our model builds on prior work in modeling prediction markets, problems of prediction markets and agent-based simulation. The overall performance analysis seeks to prove that we could prototype an zero-intelligence agent-based prediction market, and we have observed longshot bias among experiments.

Our design of risk variable does not change the mean price significantly, however, we observed the same trend mentioned in previous works[8][25]. Our intepretation is that, risk is closely related to the profit-maximizing trait of real-subject, while zero-intelligence agents lacks of almost every human trait. We might need a more sophiscated risk variable design to see much radical changes.

Reputation variable does not change the mean price in risk-neutral and risk-aversion experiments, but reputation could help risk-seeking prediction markets perform more accurately. We believe the diversity of belief affects the performance of prediction markets, There are some preliminary results in othman's work[17] about how diversity affects accuracy of prediction markets, and our experiments may justify that.

CHAPTER 5

Conclusions

5.1 Summary

Prediction markets is a very powerful forecasting tool, Many real-world systems have provided accurate results, whether it is operated with real-money or play-money. The growth of internet usage increased rapidly in the past decades, play-money based prediction markets even break the barrier of country, distance and time. Prior to establishing an online prediction market, we proposed a modeling approach with ZI-agent.

We have successfully constructed a ZI agent based prediction market model, with considerable high accuracy. In our model, The longshot bias is observed in our model as well as in othman's model.[17] we conclude that it is statistically insignificant between the skewness of risk attitude and the prediction accuracy. We think this may be caused by the very nature of zero-intelligence model, to be specific, is that agent will not maximize their profit. Risk attitude studied in real prediction market is closely related to the profit maximization. Profit maximization is a assumption of rational human subjects, while almost every human traits are missing in zero-intelligence model.

We observed that reputation may make risk-seeking experiments perform more accurately. However, the quantitative analysis in reputation variable showed it is statistically insignificant between the reputation variable and the control experiments. We argue that this might be caused by our ineffective design of risk variable.

We are not able to fulfill the assumption that naive player will increase the performance of prediction market. Maybe making inactive agents re-enter the market is considered as manipulating prediction market. It is proved very hard to manipulate prediction market.[12]

5.2 Future Works

Our approach may have no significant changes in zero-intelligence model, but we could use another agent model such as ZIP agents, GD agents and other simulation frameworks which could possibly reflect the impact of our proposed variables.

Rank-order is a strong incentive in real-world prediction markets, It is possible to include reputation as a rank-order in addition to the credit, and it may affect the performance of real-world prediction markets.

We have found the belief regime affects accuracy significantly, if we acquire belief regimes by questionnaires, polls, or any other quantitative sources. We could implement the belief regime and simulate with our model. This could augment the usage of other prediction tools, and provide second opinion.

We have not discussed thin market in our model since we didn't reproduce a scenario. But it may be possible to construct a hybrid prediction market, where ZI-agents and real subjects coexist. This may be helpful alleviating the thin market problem.

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Appendix

A Figures of experiments

A.1 Control experiments

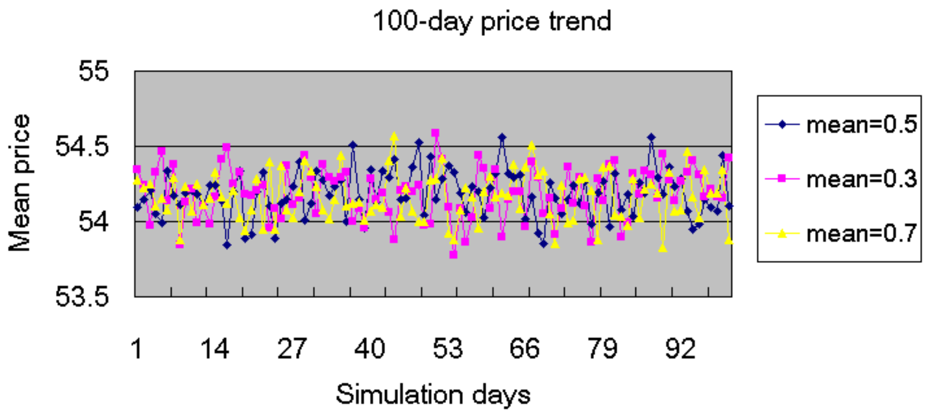

Figure A.1: Combined price-time series of control experiments

A.2 Risk-only experiments

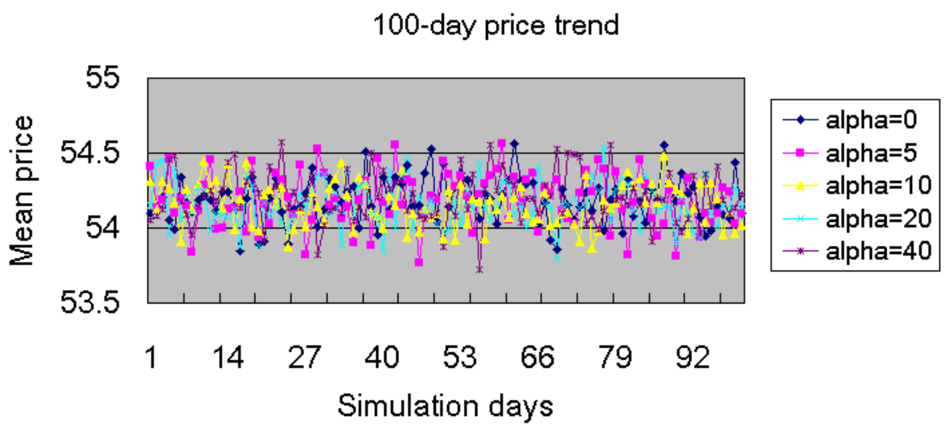

Figure A.2: Combined price-time series of risk-seeking experiments

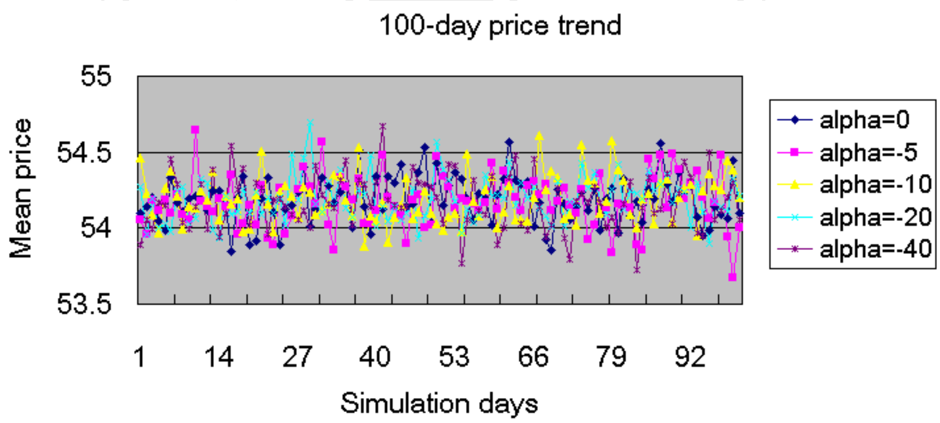

Figure A.3: Combined price-time series of risk-aversion experiments

A.3 Reputation-only experiments

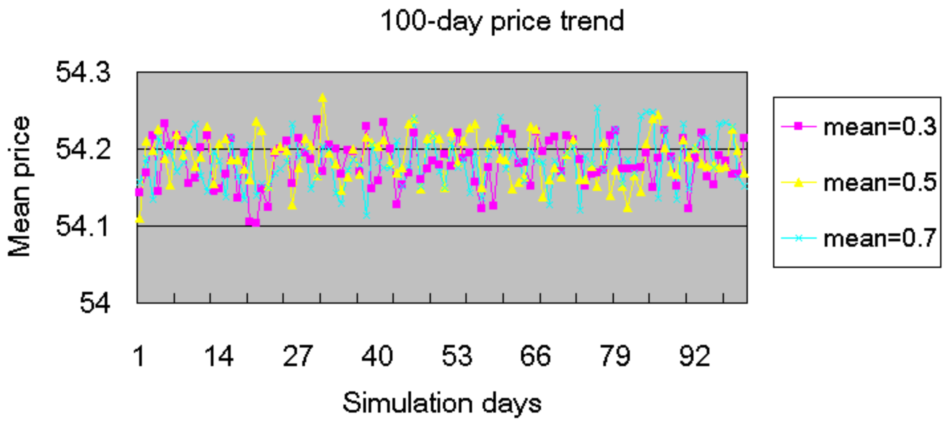

Figure A.4: Combined price-time series of reputation-only experiments

A.4 Risk and reputation experiments

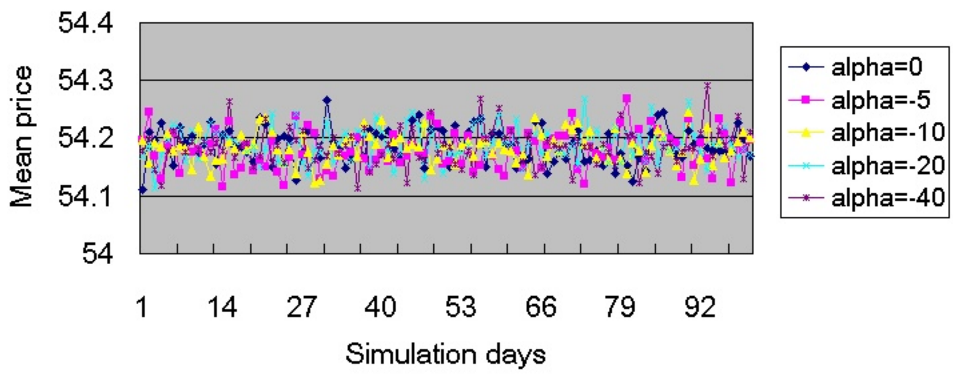

Figure A.5: Combined price-time series of risk and reputation experiments, risk-seeking

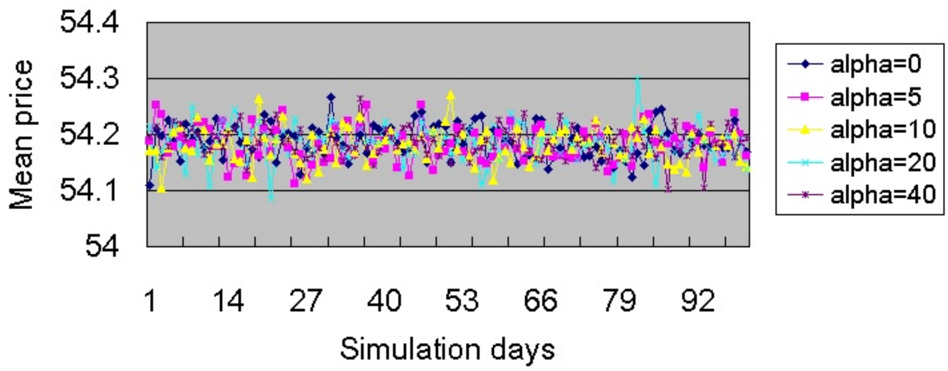

Figure A.6: Combined price-time series of risk and reputation experiments, risk-aversion