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Article

Designing Prediction Markets to Achieve Convergence Speed

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Abstract. The aim of this paper is twofold: to propose the model of artificial prediction markets that capture the characteristics of real prediction markets and to study the impact of key parameters on the performance of the proposed markets. In the experiments, the artificial markets are implemented and the market performance in terms of convergence speed is measured. Our experimental results show that the number of traders and the mean value of initial belief have no significant impact on the convergence speed. However, the trader's memory size impacts negatively on the convergence because of its delay in adjusting to the true value. Finally, the external information transmission rate and the ratio of smart traders have positive impacts on the convergence of the prediction markets. The insights can assist a market maker in designing and constructing more efficient prediction markets.

Keywords: Prediction markets, artificial markets, agent-based simulation, aggregation of beliefs, trading mechanisms, logarithmic market scoring rules.

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1. Introduction

Predicting outcomes of the future events with high accuracy is always an interesting and challenging problem. Several techniques have been developed to achieve this goal, such as opinion poll, Delphi method, and traditional assessment of experts. Prediction markets are recent methodology, where speculative markets are created to predict an outcome by trading contracts in the markets. Trading behavior of the traders determines the market price, and the price yields certain information on the outcome, such as the probability that the specified outcome is true. For example, in the prediction markets with the winner-takes-all contract, participants may receive $1 if and only if a specified candidate wins an election and $0 otherwise. Thus, participants who believe with 80% certainty that the candidate will be elected should be willing to buy the contract at the price of 80 cents or lower. Various experiments have shown that the accuracy of this technique is at least equivalent to other techniques with similar pool of participants [1]. Many well-known international firms use prediction markets for their internal decisions. Hewlett-Packard Corporation uses this technique to forecast sales [2]. Eli Lilly uses markets to predict the chance of new drugs passing the product test [3-4]. Google has run a number of prediction markets to forecast company performance and industry trends [5]. Apart from prediction results, prediction markets also show the flow of information within the organization [6].

In general, two main approaches exist to study prediction markets. One is to create and experiment on real prediction markets. The other is to study via artificial prediction markets, which are virtual markets implemented on a computer where trading is done by computer-generated agents. The first option faces numerous problems, such as whether the prediction markets are against the law of that country, how to control participants, the magnitude and certainty of cost to the market maker, etc. Therefore, gaining insights on how to design the prediction markets via the latter option offers more control, convenience, and cost effectiveness. This paper proposes the model of artificial prediction markets that capture the characteristics of real prediction markets. The agents in these markets also update their belief towards the specified event according to their prior beliefs, the recently received information, and the market price.

The paper is organized as follows. Section 2 provides the background of the prediction markets and the artificial markets. The proposed market mechanism is thoroughly explained in section 3. Section 4 describes the experimental parameter setting and performance measurement. Section 5 presents analyses on the impact of key parameters, such as the number of traders, the mean value of initial belief, the memory pool size, the transmission rate and the ratio of innovators. Finally, section 6 offers the insights on how to calibrate those parameters in order to optimize the convergence of the markets to the real price.

2. Literature Review

2.1. Prediction Markets

Prediction markets are speculative markets that aim to predict future outcome of interest, such as a presidential election, expected profit, and a project deployment date by gathering information from participants. Iowa Electronic Market (IEM), one of the first prediction markets, has been introduced by University of Iowa, aiming to predict the results of US presidential election [7]. After Berg *et al.* have concluded data from IEM that prediction markets outperformed polling organizations and forecasted very accurately, prediction markets have gained much attention [7]. Researchers have adopted prediction markets as a forecasting tool in many areas, such as politics [7], health care [8], and project management [9]. Ritterman *et al.* [8] have used prediction markets together with Twitter to find the probability that Swine Flu virus will become a plague and this approach had higher accuracy than some baseline methods. Remidez and Joslin [9] have adapted prediction markets to help improve project communication which is a substantial factor for effective project management [10]. Moreover, Prediction markets can also be used for other purposes, such as supporting decision making [11] and assessing information quality [12].

Polgreen [13] have stated four reasons why prediction markets are accurate. First, the knowledge discovered by prediction markets is derived from all participants, each of whom may have different opinions on particular events. Second, prediction markets support intelligent participants to trade frequently through the incentive scheme. Third, this technique provides feedback from other's beliefs to participants. Participants learn from the market price and feel motivated to gain more information. Finally, participants can trade anonymously in the prediction markets; consequently, they tend to share more information that they may not otherwise share publicly.

There exist many contract types but the popular one that will be used in our experiments is called "winner-takes-all" [14]. This contract pays \$1 if the specified event occurs and \$0 otherwise. The traders who believe that the event will occur will buy the contracts, which in turn drives the market price up. On the contrary, the traders believe otherwise will sell the contracts once the market price is too high thus driving the price down. The final market price reflects the probability that the event will be true, according to the belief of the crowd.

2.2. Trading Mechanisms

There are four main trading mechanisms used in the prediction markets: Continuous Double Auction (CDA) [15-16], Market Scoring Rule (MSR) [14, 17-18], Pari-Mutuel (PM) [3, 19], and Dynamic Pari-Mutuel (DPM) [19]. In CDA markets, all bids and offers are maintained in the order book. Trading is executed only when the buyer's bids and the seller's offers are matched. At any time, both buyers and sellers can update their bids or offers. Market operators are free of financial risk because it simply matches corresponding sellers and buyers. MSR is developed to address the liquidity problem in CDA. In MSR markets, buying and selling can be done at any time with the market maker and the market price is adapted automatically due to the number of contracts in the market. In PM markets, participants bet on the fixed outcome pool and participants who bet on a right pool will divide the total proceedings among themselves after management cost is subtracted. One main problem with this mechanism is that many participants will delay buying the contracts until almost near the market closing because new information may arise before the market closes and there is no benefit in buying the contract early. Pennock [19] has developed DPM in order to benefit from limitless liquidity of PM and allow the market price to change as a result of new information. In DPM markets, traders can buy any outcome they want at a certain price but selling can be executed only via CDA mechanism with limited liquidity; therefore, DPM serves as a hybrid between CDA and PM.

In our experiments, we implement MSR markets, as it is highly popular in practice due to its simplicity and liquidity. Klingert and Meyer [20] have compared an impact of CDA and MSR mechanics on the number of trades, the accuracy, and the standard deviation of price. They have concluded that the advantages of MSR over CDA include higher number of trades and less standard deviation of price; however, accuracy is independent of trading mechanisms. MSR facilitates more trades because CDA needs at least two traders to execute a trade, while MSR needs only one trader, thus leading to higher liquidity. Moreover, the mechanism to calculate the market price by considering all past trades of MSR reduces a magnitude of price changes resulting in a lower standard deviation.

2.3. Logarithmic Market Scoring Rules (LMSR)

LMSR [17, 21] originates from logarithmic scoring rule; thus, the cost function and the price function are in logarithmic form. Cost function is a function for calculating the cost of buying or selling a certain number of contracts as shown in Eq. (1). Price function is used to calculate the spot price of the contract as shown in Eq. (2). A spot price will increase if a trader buys a contract and will decrease if a trader sells a contract, following the same logic as in the real market.

<u>Cost Function</u>:

$$C(\vec{q}_t) = b \bullet \ln(\textstyle\sum_{j \in N} e^{q_{j,t}/b}) \tag{1}$$

The amount of money a trader must pay or receive for each trade is $C(\vec{q}_t) - C(\vec{q}_{t-1})$. N is the number of mutually exclusive and exhaustive outcomes. $\vec{q}_t = (q_{1,t}, q_{2,t}, \dots, q_{N,t})$ is the vector of the number of shares on the market for each of the N outcomes after the tth trade in the market. b is the liquidity parameter, which is determined by the market maker.

<u>Price Function</u>:

$$P_i(\overrightarrow{q_t}) = \frac{e^{q_{i,t}/b}}{\sum_{j \in N} e^{q_{j,t}/b}} \tag{2}$$

$P_i(\overrightarrow{q_t})$ is a spot price of i^{th} outcome. $\vec{q}_t = (q_{1,t}, q_{2,t}, \dots, q_{N,t})$ is the vector of the number of shares on the market for each of the N outcomes after the tth trade in the market. b is the liquidity parameter, which is determined by the market maker.

For example, the market maker creates the prediction markets with two choices and sets liquidity parameter (b) to 100. At the beginning, if a trader buys five contracts of the first outcome, then he has to pay $C(5,0) - C(0,0) = [100 \text{ x } \ln(e^{5/100} + e^{0/100})] - [100 \text{ x } \ln(e^{0/100} + e^{0/100})] = \$2.531$. The market price of the first outcome contract will increase from 0.5 to $P_1 = \frac{e^{5/100}}{e^{5/100}+e^{0/100}} = \$0.512$.

2.4. Artificial Markets

Artificial markets are computer-simulated markets with electronic agents acting as traders participating in the markets. This kind of traders can use heuristics, mathematical equations, or machine learning techniques to imitate human's decision process. Artificial markets are popularly used in finance area because artificial markets can model the empirical interactions of traders in financial markets [22]. LeBaron [23] has also explained why artificial markets are frequently used in financial experiments. Financial setting offers clear objectives of agents and information aggregation methods, while financial data is also readily available and can be accessed easily. Moreover, the advancement in experimental financial markets with controlled environments makes a comparison with artificial markets reasonable.

Most research in artificial markets can be divided into two fields [24]. The first field focuses on creating a successful market mechanism and its environment. For example, Qin (2006) has used artificial markets with heterogeneous agents to find the market mechanism that minimize Smith's coefficient of convergence and found Continuous Double Auction (CDA) or English Auction (EA) to be the most appropriate for the given supply-demand schedules. The other field concentrates on the dynamics of price that are generated by these markets in order to replicate some characteristics of real financial markets. For example, Raberto *et al.* [25] have implemented artificial financial markets which are populated with heterogeneous agents and used Genoa market microstructure to capture leptokurtic return distributions and volatility clustering.

On applying artificial markets to prediction markets environment, Toriumi and Ishii [26] have used artificial markets to study the conditions that make prediction markets more effective than opinion polls. They have run a number of artificial prediction markets to analyze the influences of information frequency, innovators, and motivation rate by using the difference between real price and the final market price of prediction markets as a measure. Their results have shown that the important factors are the presence of innovators (intelligent traders) and a low motivation rate, while both prediction markets and opinion polls benefit from high information frequency. This research serves as a framework for our proposed artificial prediction markets.

3. The Proposed Artificial Prediction Markets

Our goal is to propose the design for an artificial prediction markets using MSR and to provides insights on how to calibrate various parameters for market performance. Our proposed markets design is based on Toriumi and Ishii [26] information distribution approach and certain assumptions about traders. Specifically, the information is distributed to traders at a transmission frequency with the information attributes. The traders are modeled with the same five basic attributes, as explained later.

However, this paper takes on several key different assumptions about the trader's belief and trading behavior. First the previous paper has assumed that the agents or participants in the real world come into the markets with no prior beliefs or expectations, but in our proposed model all agents are assumed to possess certain initial beliefs towards the specified event. Second, instead of agents updating their belief solely on an external information, our model incorporates their prior belief and the market price as additional important factors to calculate the predicted price. The third extension is on the trading behavior. Toriumi and Ishii (2011) have assumed that if the predicted price is higher than the market price, the agents will sell the contract because they think that the price will fall soon. Or if the market price exceeds the predicted price, they will buy the contract. However, this paper proposes that the agents execute their transactions based on their beliefs with a goal to generate a profit. Specifically, if the predicted price is higher than the market price, the agents will buy the contracts due to the belief that the market price should rise soon. If the market price exceeds the predicted price, the agents will sell the contracts, as the contracts are currently over-valued.

Our simulation will create automated prediction markets that are populated with traders. The traders will then receive information from the market maker, update their beliefs, and make a decision to buy or sell the contracts until the indicated number of steps is reached. Traders' behavior is a key factor that determines the effectiveness of the markets. Sections below explain the mechanisms of the proposed artificial prediction markets in detail.

3.1. Prediction Goal

The simulation is used to investigate the traders' ability to receive and comprehend information on the real price of the contract, which is a real number between 0.0 and 1.0 inclusive, and also to study the effectiveness of the market mechanism to extract the wisdom of the crowd. For example, given a real price of 0.8, the market price after traders have executed some tradings should eventually reach 0.8.

3.2. Information Distribution Approach

In each step, the information about the real price of the contract will be distributed to every trader at a certain probability called a transmission rate, between 0.0 and 1.0 inclusive. Each piece of information has the following attributes:

1. Type of information (m) is an integer of value 0 or 1 that shows negativity or positivity of the information. For example, if the real price is 0.8, an average 80% of the information will show positivity (m=1) and 20% of the information will show negativity (m=0).

2. Difficulty level (d) is a real number between 0.0 and 1.0 inclusive that represents the difficulty of the information. The difficulty models characteristics in the real world where information is sometimes harder or easier to comprehend by general public.

3.3. Trader Modeling

During the simulation, each trader decides to buy or sell a contract by comparing his belief with the market price. Each trader has the following attributes:

1. Smartness (s) is a real number between 0.0 and 1.0 inclusive that shows trader's ability to comprehend the information. In this experiment, we divide traders by their smartness into two groups. The first group with smartness between 0.8 and 1.0 inclusive represents innovators who can understand almost every received information. The second group represents normal traders whose smartness is between 0.0 and 0.2 inclusive. Traders can comprehend the information if and only if the below inequality is true.

$$s > d \tag{3}$$

2. Trading frequency (f) is a real number between 0.0 and 1.0 inclusive that shows the probability that each trader will trade in this step. This parameter reflects uncertainty in human's behavior. They only trade when they want to do so.

3. Motivation rate (h) is a real number between 0.0 and 1.0 inclusive that shows the motivation to trade. All traders' motivation rate is set to a constant value throughout the experiments. When traders cannot comprehend the information, the trading frequency will be multiplied by the motivation rate in order to lessen the traders' probability to trade as follows.

$$f_{t+1} = f_t \bullet h \tag{4}$$

4. Memory pool (p) is a limited-size FIFO (first in first out) memory used to store the received information type value. When the trader comprehends the information, the information type is put into an empty slot

of this memory pool. When the memory pool is full, new incoming data will replace the oldest data in the memory pool. Similar to human behavior, we can remember only a certain amount of information.

5. Belief (b) is a real number between 0.0 and 1.0 inclusive that shows the trader's belief towards the event or the predicted price of the contract. We propose the trader's belief to depend on his prior belief, previous information and the current market price. Therefore, our proposed belief will be recalculated over time as a weighted average among these factors, as shown in the following equation.

$$b_{t+1} = x_1\ (Belief_t) + x_2\ (Price\ from\ memory\ pool) + x_3\ (Market\ price) \tag{5}$$
$$x_1 + x_2 + x_3 = 1$$

x_i is a weight representing the contribution of each factor in updating the trader's belief.

3.4. Trading Mechanism

First, all traders' beliefs will be initiated from a normal random variable with a certain mean and variance to represent a range of beliefs at a certain mean. Next, information will be distributed to all traders based on a transmission frequency. When the trader receives an information, he will compare his smartness (s) with the information's difficulty level (d). If the inequality (3) is true, the trader can comprehend the information and will put the information's type value into his memory pool. His trading frequency will be set to 1.0 which means that he will trade on the next step because he just received new information. On the contrary, if he cannot comprehend the information, his trading frequency will be decreased by a factor of his motivation rate according to Eq. (4), as receiving unclear information may deter one's action.

Next, he will update his belief based on Eq. (5). He will then decide whether to trade in this step, based on his trading frequency. If he decides to trade, he will compare his predicted price or his current belief with the market price. If his predicted price is higher than the market price, he will buy the contract because he believes that the real price of the contract should be higher than the current price, so the market price will rise. On the other hand, if the market price is higher than his predicted price, he will sell the contract because he believes that the market price is too high, and it will likely decline. We can summarize the inequalities that the traders use to buy, sell, or hold the contract as follows:

Buy if $Predicted\ price > Market\ price$ (6)
Sell if $Predicted\ price < Market\ price$ (7)
Hold if $Predicted\ price = Market\ price$ (8)

Figure 1 shows the flow of the proposed prediction markets. At the beginning, all traders' beliefs are initialized from a random normal distribution with certain mean and variance. At the beginning of each step, information about the outcome will be sent to all traders at a constant transmission rate. Traders then update their beliefs using Eq. (5) before they decide to buy or sell the contracts according to inequalities (6), (7) and Eq. (8). Their trading behavior determines the new market price which is one of the factors used to calculate their beliefs in the next round. This cycle repeats until a specified number of steps is reached.

4. Experimental Parameters And Performance Measurement

We implement artificial prediction markets in JAVA and perform sensitivity analysis on various parameters in order to study the impact of each parameter to the market performance.

4.1. Experimental Parameters

The parameter setting of the base simulation is shown in Table 1. We will analyze the performance of the traders and the market mechanism on its convergence to the real price of 0.8. There are 3000 steps in each simulation. A step is a cycle when all traders are given information, decide whether to trade, transact if appropriate, and lastly update their beliefs. In the real world, a step can be a day or half a day. The model simulates 100 traders, 50 normal traders and 50 innovators, participating in the markets. This mix reflects existence of people who understand most of information they receive and people who may not in the real world. Each trader's initial belief is drawn from a normal random distribution with mean = 0.6 and variance = 0.04. Trader's memory pool size is 100 and the transmission rate and the motivation rate are 0.5. The liquidity parameter (b) of the market is set to 100. This parameter determines the liquidity of the markets, the cost to the market maker, and adaptability of the price.

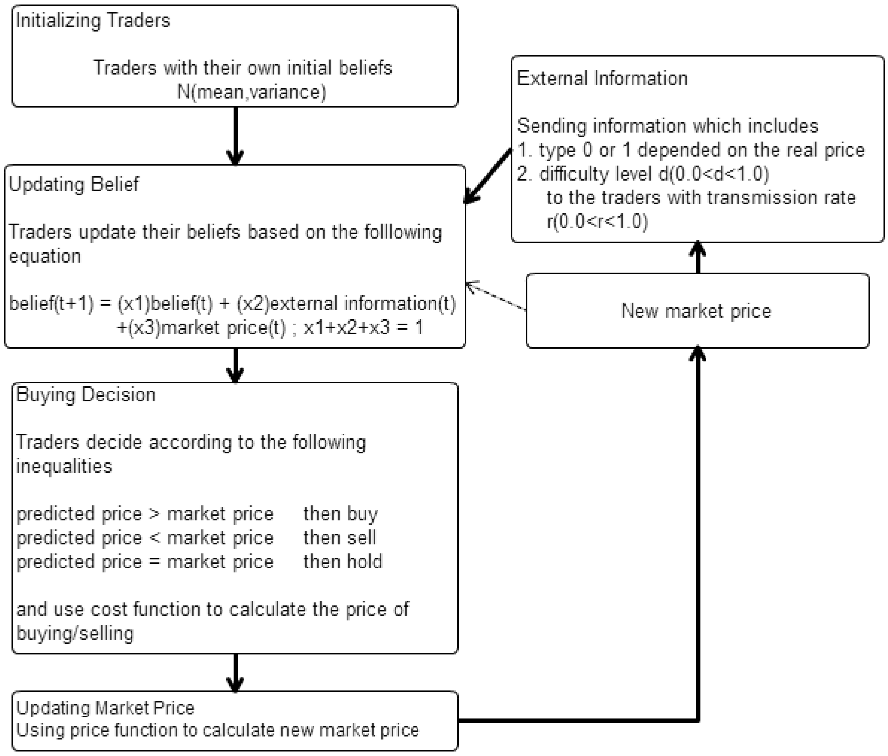

Fig. 1. Flow of the proposed artificial prediction markets.

Table 1. Base-case parameter setting.

Parameter	Value	Parameter	Value
Real price	0.8	Mean	0.6
Number of steps	3000	Variance	0.04
Number of traders	100	Memory pool size	100
Ratio of innovators	0.5	Transmission rate	0.5
Liquidity parameter (b)	100	Motivation rate	0.5

4.2. Performance Measurement

In this simulation, the market performance is measured by the steps to convergence. We define the steps to convergence as the number of steps it takes until the market price changes within one percent of the real price for ten consecutive steps. Given that the markets open only on weekdays, ten consecutive steps can be interpreted as two weeks, which represents a reasonable period to conclude its convergence to the real price. This value is averaged over 100 simulations. Measuring the market performance using speed to convergence is appropriate because in practice time to open the prediction markets is often limited. Therefore, the market price's fast convergence to the real price is highly beneficial practically.

5. Experimental Results

In this section, we explore the impact of each parameter on the performance of the artificial prediction markets. Five key parameters that we analyze includes the number of traders, the mean value of initial belief, the memory pool size, the ratio of innovators, and the transmission rate. By understanding the impact of these parameters, the market creator can design more effective prediction markets that can forecast the real price efficiently.

5.1. Number of Traders

Figure 2 shows the relationship between the number of steps to convergence and the number of traders over 100 simulations. We observe that the number of traders participating in the prediction markets has no significant impact on the convergence speed. Figure 3 illustrates the price dynamics for various numbers of traders. During the first few steps, a higher number of traders leads to a faster approach to the real price because starting with a relatively low market price, every trader buys the contract until the price approaches the true value. Nonetheless, regardless of how many traders participate in the markets, it must take a certain amount of time for the traders to absorb the external information and adjust to the true value. We can observe from Figs. 2 and 3 that the market price converges to the real price at almost the same time (over 200 steps from the beginning to reach within one percent from the true value).

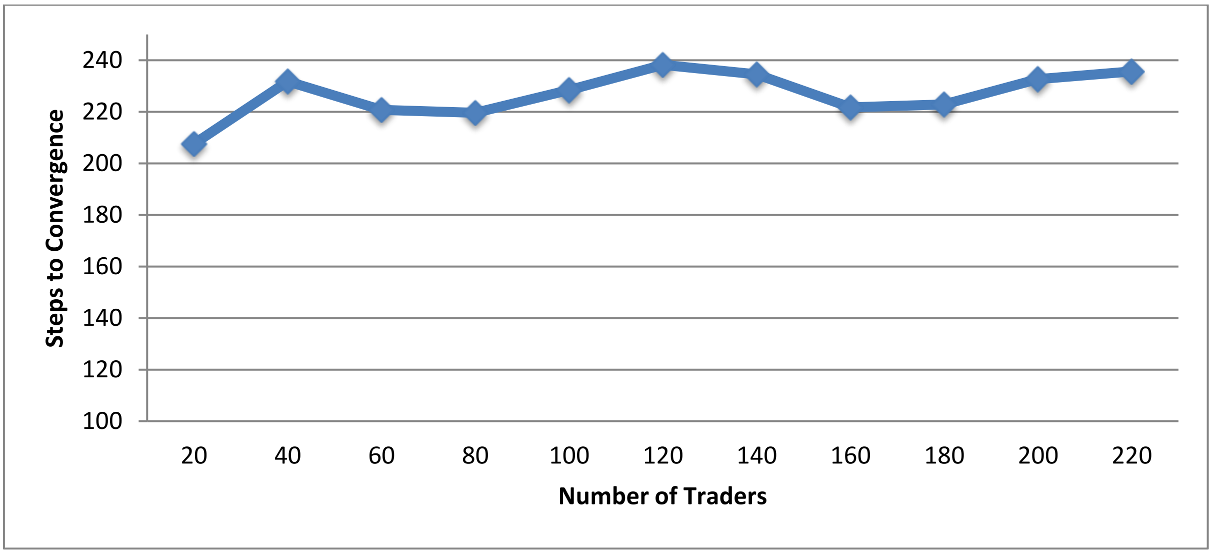

Fig. 2. Number of steps to convergence at various numbers of traders.

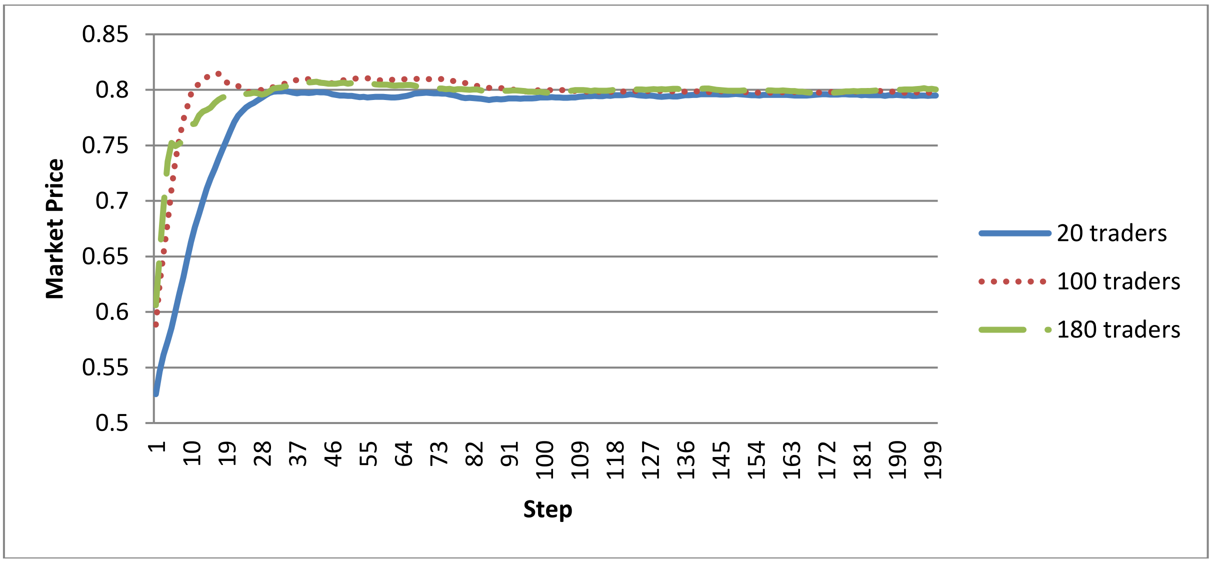

Fig. 3. Market price over time with 20, 100, and 180 traders.

5.2. Mean Value of Initial Belief

The relationship between the number of steps to convergence and the mean value of initial belief is shown in Fig. 4. This mean value represents an average of traders' belief coming into the prediction markets. The mean value of the initial belief has no significant impact on the convergence. Figure 5 illustrates the price dynamics for various mean values. Regardless of the initial value, the market price approaches the real value almost at the same time because this initial belief quickly changes over time according to the belief update model (Eq. (5)).

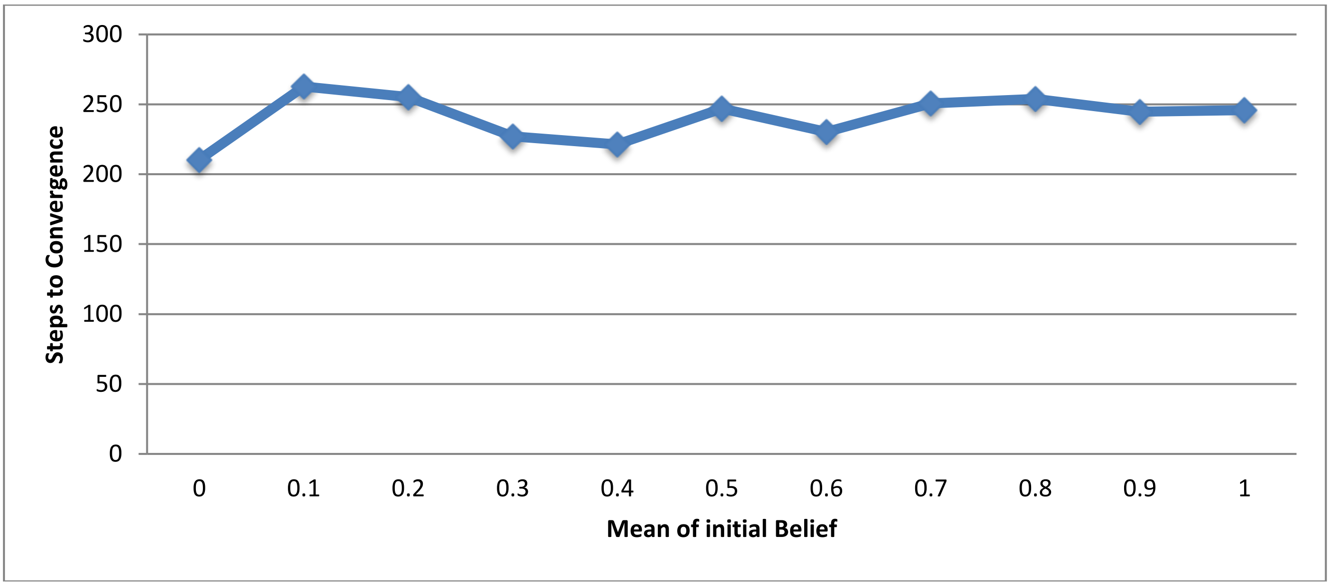

Fig. 4. Number of steps to convergence at various means of initial belief.

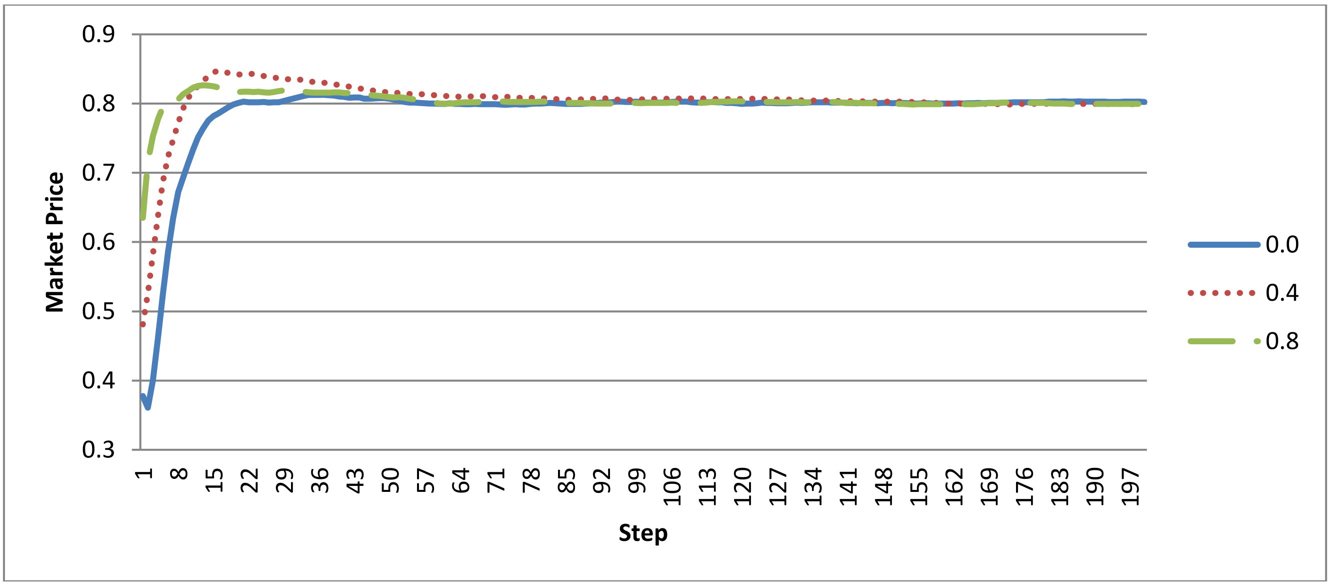

Fig. 5. Market price over time when the mean of initial belief is 0.0, 0.4, and 0.

5.3. Memory Pool Size

As illustrated in Fig. 6, the bigger the memory pool size, the larger the number of steps to convergence. This phenomenon can be explained by Fig. 7. With a smaller pool size of 100, the price can adapt to the external information quickly and approach the real price. On the contrary, with a larger pool size of 600, mixed behaviors can be observed. In one case, if the external information happens to lead the market in the right direction, the market price will converge quickly within a few hundred steps. On the contrary, should the first set of external information lead the market in the wrong direction, the larger memory pool size will delay the trader's belief update, leading to slower convergence. Overall, a small memory pool size leads to a faster convergence.

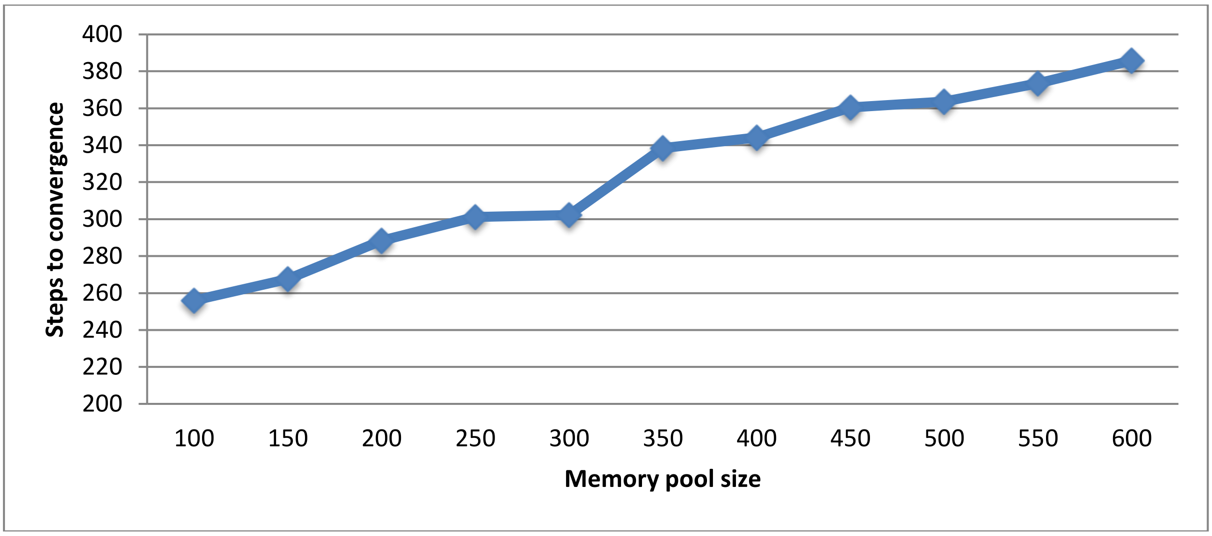

Fig. 6. Number of steps to convergence at various memory pool sizes.

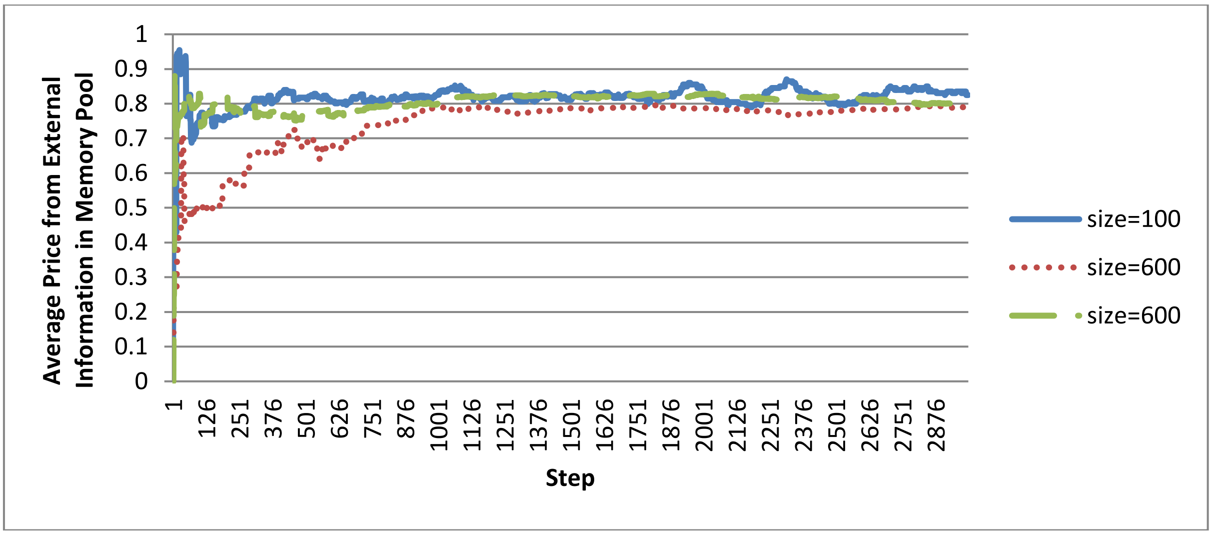

Fig. 7. Price calculated from external information over time at memory pool size of 100 and 600.

5.4. Ratio of Innovators

To show the impact of having smart people in the crowd on the convergence speed, we alter the ratio of innovators from 0.0 to 1.0 in Fig. 8. We can observe that the higher ratio of innovators, the faster the market converges to the real price because a higher ratio of innovators means that more traders can comprehend the information. Figure 9 also emphasizes that the presence of innovators is an important factor to reach the true value. The more traders comprehend the information, the more people update their beliefs to correspond to the real price. The number of steps to convergence decreases dramatically when the ratio of innovators is low (less than 0.5). As the ratio of innovators increases beyond 0.5, the convergence speed improves but not substantially. Therefore, increasing the proportion of smart people when very few exist offers a large impact. Increasing the proportion of smart people when most are already smart only provides incremental benefits as shown at the tail end of the graph in Fig. 8.

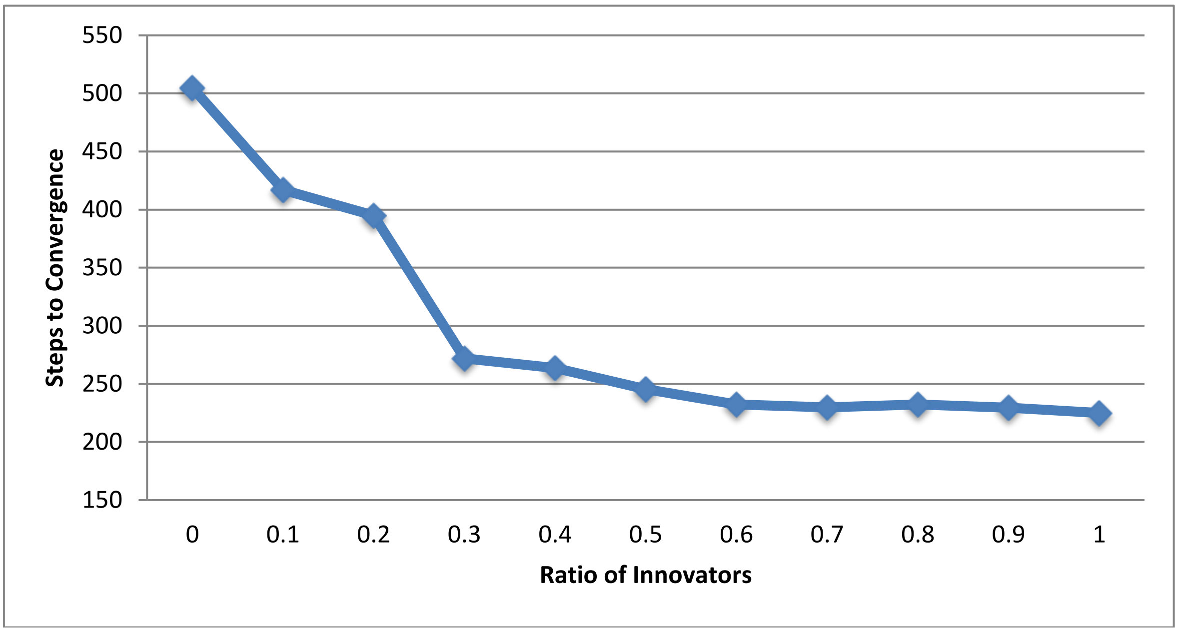

Fig. 8. Number of steps to convergence at various ratios of innovators.

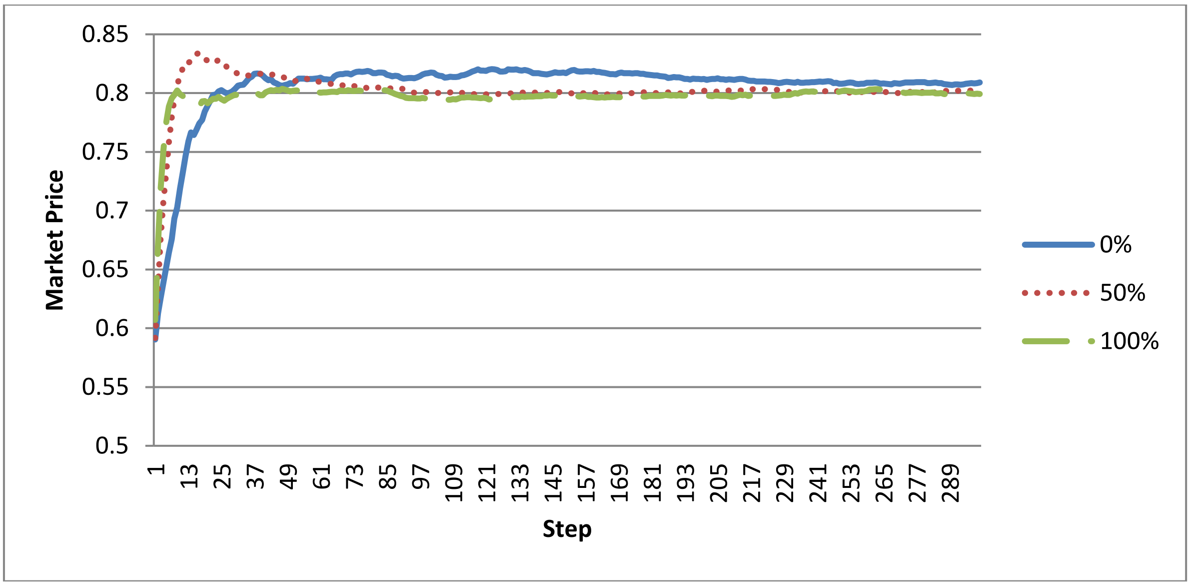

Fig. 9. Market price over time at the ratio of innovators of 0.0, 0.5, and 1.0.

5.5. Transmission Rate

Finally, we show the relationship between the number of steps to convergence and the transmission rate in Fig. 10. When we increase the transmission rate from 0.1 to 1.0, we can observe that the higher the transmission rate, the faster the market converges to the real price. For example, from Fig. 11 with the transmission rate of 0.9, the market price quickly approaches the real price because the traders can receive more information. On the contrary, with the transmission rate of 0.1 the market price takes a long time to approach 0.8 since the traders rarely receive information related to the real price. Therefore, the transmission rate has a strong positive impact on the prediction markets. The more information (on the true value) the participants receive, the faster the market converges. Thus, it is vital to construct the prediction markets in the real world that allows for efficient and effective communications.

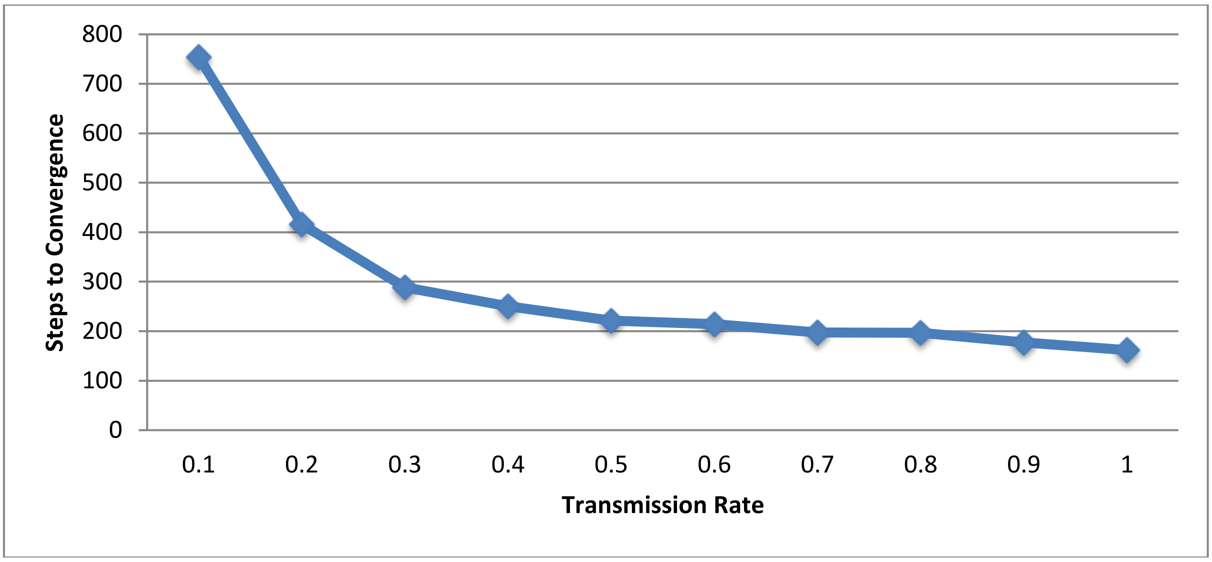

Fig. 10. Number of steps to convergence at various transmission rates.

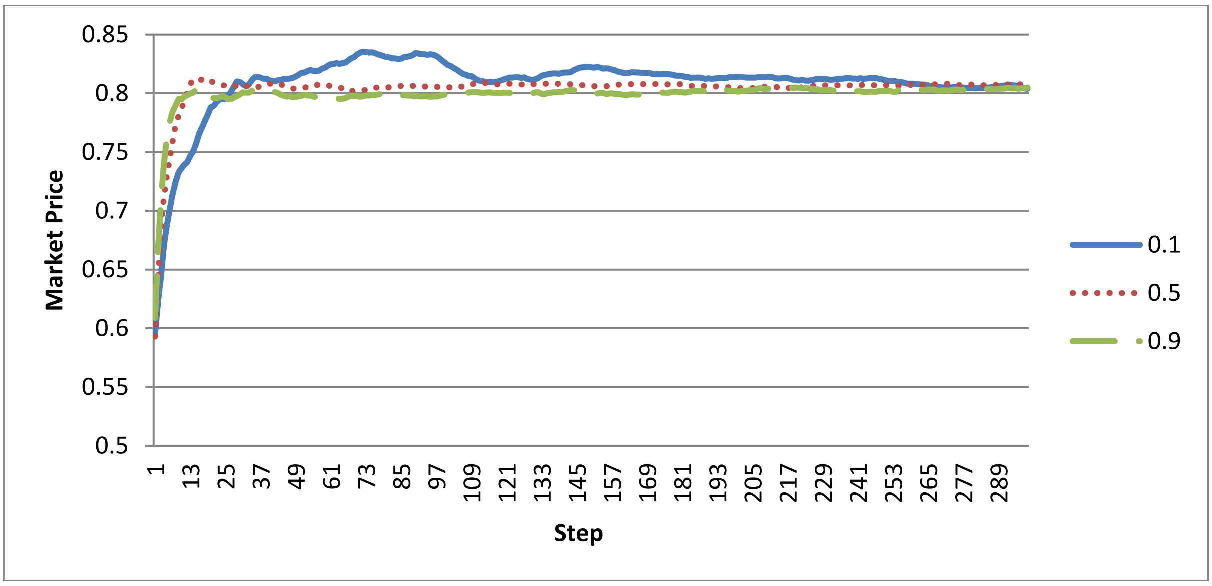

Fig. 11. Market price over time at the transmission rate of 0.1, 0.5, and 0.9.

6. Insights and Conlclusion on Optimizing Market Parameters

Prediction markets are widely used by many large organizations all over the world. Creating an effective prediction market depends on many factors. Our study of the market performance through the artificial prediction markets offer many insights relating to the impacts of key parameters in the market design. Since most of the events we want to forecast have limited time for market opening; these guidelines lead to a better market design that can forecast accurately within the time limit.

First of all, the experimental results have shown that the price convergence benefits from the ratio of innovators or smart traders. Moreover, the number of traders has no obvious effect on the convergence speed. In other words, regardless of the number of traders participating in the market; the market price converges to the real price at a relatively similar speed. Hence, we can conclude that, given the true and accurate information is being disseminated, the market maker should focus on incorporating smart participants that can grasp this new information and trade accordingly instead of aiming for a large number of participants.

Second, the traders' initial beliefs have no significant impact on the market performance. These initial values will be used during the first period and then replaced by the new beliefs which are calculated from the current beliefs together with the external information and the market price. Thus, the market maker should aim to recruit smart people with ability to learn instead of people with initial correct beliefs but unwilling to learn or adapt to the new information.

Third, from our analyses the memory pool size has a negative impact on the convergence because a large memory pool size tends to delay the traders in adjusting their predicted price to the real price. In other words, remembering too much can be damaging if earlier information is not accurate.

Last but not least, the higher the transmission rate, the faster the market price converges to the real price. When we increase the transmission rate from 0.0 to 0.5, the number of steps to convergence decreases dramatically; however, after the transmission rate reaches 0.5, the incremental gain slows down. Therefore, it is important for the market maker to encourage information related to the real price to be distributed as frequently as possible because information is the key knowledge that allows the traders to move in the right direction.

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