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# Losses on Asset Returns Caused by Perception Gaps of Fundamental Values: Evidence from laboratory experiments<sup>1</sup>

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## Abstract

A large number of studies have tackled the question of asset bubbles, in which whether or not market participants are able to calculate fundamental values is considered to play a key role in reducing bubbles. Contrary to the existing literature on uncertainty, this study conducts a series of laboratory experiments, wherein subjects cannot calculate objective expected returns with certainty. In such cases, gaps between objective and subjective expected returns (perception gaps) arise. The purpose of this study is to clarify (i) how asset prices fluctuate and (ii) if perception gaps lead to inefficient transactions. Moreover, (iii) we estimate the losses caused by perception gaps. Our estimation results indicate that perception gaps linger across rounds, and, accordingly, these gaps may generate earnings losses. Moreover, we find that the greater a perception gap of a subject, the greater is the inefficiency from his/her transactions. Traders now are using artificial intelligence (AI) for decision making. We also discuss policy implications on the introduction of AI into asset markets.

*Keywords:* Uncertainty, Artificial intelligence, Laboratory experiments, Asset markets.

*JEL classification:* C91, G12, G41.

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## **1. Introduction**

People face uncertainty in their daily lives. For example, when the news predicts rain in the morning, they have to decide whether or not to bring umbrellas. Market participants face uncertainty when they transact goods, services, insurance, and other assets. Economists have been focusing on financial and asset markets when considering the effect of uncertainty on prices and the behavior of market participants.

In the field of experimental economics, many studies tried to clarify asset bubble mechanisms and factors that increase or decrease their respective sizes (Caginalp, et al., 2000; Lei, et al., 2001; Dufwenberg, et al., 2005; Hussam, et al., 2008; Lugovsky, et al., 2014; among others). In laboratory experiments, several subjects participate in a single market and carry out asset trading. If they hold their assets, they obtain a dividend at the end of each round. On the other hand, if they sell their assets, they gain from the sale. In most studies, assets are assumed to be risky, in the sense that subjects do not know the value of dividends in future rounds with certainty. However, the probability that a certain value of dividend arises is public information, which is given to subjects in advance. Thus, subjects can calculate the expected value of a dividend per asset unit and the expected fundamental value (FV) in each round. Because FVs become smaller as time passes, trading prices also are expected to decline. However, many experiments found that actual trading prices tend to remain high in the latter half of the experiment and decline sharply only in the final few rounds. As a result, many subjects were not able to sell their assets for a gain: bubbles arise and crash in asset markets. Factors that influence bubbles have been clarified in the literature. For example, it has been demonstrated that insufficient knowledge about FVs and slow learning of transactions influences the occurrence of bubbles (see Huber and Kircher (2012), among others).

In the real world, market participants do not know the probabilities for dividends to arise with certainty. Therefore, this study examines the factors that influence the deviation of asset-

trading prices from FVs in such a situation. In particular, we focus on the perception gap, which is the difference between objective and subjective expected FVs. A few articles examined the relationship between this type of uncertainty and behavior in the purchase of insurance (Hogarth and Kureuther, 1989; Bajtelsmit, et al., 2015). Several articles also examined the effect of the degree of ambiguity aversion on asset prices and trading behavior (Füllbrunn, et al., 2014; Alonso and Prado, 2015). However, as far as we know, few articles focused on perception gaps.

The purpose of this study is to clarify (i) how asset prices fluctuate, and (ii) if perception gap leads to inefficient transactions. Moreover, (iii) we estimate losses caused by uncertainty. Our estimation results, using experimental data, indicate that perception gaps of subjects linger across rounds and generate return losses. We also found that the greater is a perception gap of a subject, the greater is inefficiency from his/her transactions. Traders now are using artificial intelligence (AI) for their decision-making. Thus, we also discuss policy implication on the introduction of AI into asset markets.

The structure of the paper is as follows. Section 2 describes the experimental design. Section 3 first overviews the results of experimental sessions and then demonstrates the estimation results. Section 4 discusses policy implications, in particular, in terms of the introduction of AI into asset markets. Section 5 provides concluding remarks.

## **2. Experimental Design**

Each experimental session consisted of three steps. Subjects filled out a questionnaire on risk preference in the first step. They played an asset-transaction game in the second step, and they filled out a second questionnaire about perceptions and behavior for the asset-transaction game in the third step. We explain the details of each step below.

## **2.1 Risk Preference**

The questionnaire about risk preference consisted of 10 questions.<sup>2</sup> Subjects chose either Choice A or Choice B for each question. For example, the meaning of each choice for Question 1 is as follows. A lottery will be drawn after subjects finish answering questions: (i) 10 cards with a number from 1 through 10 on each card are placed in a bag; then (ii) the experiment's organizer or an assistant will blindly picks one card. When a subject has chosen Choice A, if card 1, 2, 3, or 4 is picked, the subject will receive JPY 400, while if card 4, 5, 6, 7, 8, 9, or 10 is picked, the subject will receive JPY 100. On the other hand, when a subject has chosen Choice B, if card 1 is picked, the subject will receive JPY 680, while if card 2, 3, 4, 5, 6, 7, 8, 9, or 10 is picked, the subject will receive JPY 50. The meaning of other questions is the same, although prizes of Choice B are different across questions. For all questions, Choice A is less risky than Choice B. Thus, the more risk averse a subject, the greater times the subject selects Choice A.

In the sessions, subjects were told that only one of 10 questions would be chosen for real payments although which question is for real payments would be determined by lottery after all of the three steps are finished.

## **2.2 The Asset-Transaction Game**

The second step is the main step in our experiment. In each session, all the subjects participated in a single asset market. They were able to buy and sell their assets based on their decisions while the market was open. In each round, the market was open for 80 seconds, and 15 rounds were played.

At the beginning of the first round, each subject was given eight units of assets and 2,400 units of cash. The cash was called experimental dollars, which was converted into real money

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<sup>2</sup> See Figure 1 for details.

after the session was finished. When each subject bought or sold his/her assets, his/her portfolio, a combination of assets and cash, changed.

At the end of each round, the dividend per asset unit became known to all subjects. The dividend was the same for all assets in each round. Total dividend is equal to the dividend per asset unit times the number of assets held at the end of the round. Dividend values changed across rounds.

We adopted a double auction mechanism for asset trading. As in real asset trading, subjects were able to bid or ask whenever the market was open. They are also able to determine to sell or buy anytime. Figure 2 shows the screen of the trading stages. All bids and asks were public information to all subjects. Subjects were not allowed to carry out short sales or to buy an asset whose price was greater than their cash holdings.

Subjects faced an uncertain situation on dividend values, which means that subjects did not know the probability that each possible value of dividend realizes.<sup>3</sup> It was announced that the dividend in each round would be determined by lottery. The details of the lottery are as follows: There are several blue, several yellow, and several red balls in a bag. An assistant will pick one ball from the bag without looking inside it after the transaction stage finishes in each round. If a blue, yellow, or red ball represents, respectively, a dividend of 40, 20, or 0. The point is that subjects did not know how many blue, yellow, and balls were in the bag. Once a ball was picked and the dividend was determined, the ball was returned to the bag.<sup>4</sup> The numbers of balls remained the same in each session, while they were different among sessions.

In each round, after the transaction stage finished, subjects proceeded to the recording

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<sup>3</sup> This situation is often referred to as “ambiguous” in the literature. However, “ambiguity” has different meanings in different academic fields. Thus, we primarily use “uncertainty” in this study to avoid misunderstandings. More precisely, ambiguity incorporates situations with no information. When referring to the literature, we follow the authors of the literature and may use “ambiguity.”

<sup>4</sup> In the experimental sessions, subjects got to know their dividend values in the result-recording stage in each round instead of seeing the color of a ball.

stage, in which they wrote down their results. They saw their cash (experimental dollars) holdings, asset holdings, dividends per asset unit on the screen. Cash holdings included revenue from dividends. This recording stage continued for 20 seconds, after which subjects proceeded to the next round. Cash and asset holdings at the end of a certain round were carried over to the next round.

Acquired experimental dollars for each subject in each round is the sum of revenue from asset sales and total dividends, minus purchasing expenses of assets. The important point is that an asset's value becomes zero after the fifteenth round finishes, although dividends may realize after the last round' trading stage. Thus, total acquired experimental dollars for each subject from the asset-trading game is the sum of acquired experimental dollars for all 15 rounds and the initial cash holdings. As noted above, initial cash holdings was 2,400 for all subjects.

### **2.3 Perceptions and Behavior**

After the asset-trading game was finished, subjects answered another questionnaire that queried their perceptions about probabilities and behavior in the asset-trading stage. Details of the questionnaire are shown in Figure 3. This questionnaire consisted of three questions. The first and second questions asked subjects about their perceptions regarding dividend probabilities. Because they did not know the numbers of balls in the bag, they could not have known the probabilities with certainty. Thus, we can extract the perception gap of each subject. The third question queried subjects about their behavior on asset trading. Because an asset's value became zero after the fifteenth round finished, it was important for them to consider asset values in each round. Thus, we consider that whether subjects considered asset values influences the difference between the actual trading prices and FVs.

## 2.4 Sessions and Procedures

We conducted 11 sessions in total. In each session, the number of subjects, were nine, ten, eleven, or twelve, and the total number of subjects were 117. Subjects were undergraduate students of either Kwansei Gakuin University or Musashi University<sup>5</sup>. Because we did not exclude students by academic department, our sample includes students from various fields, including business, economics, law, literature, and social studies. Each student participated in only one session. We paid a reward to each subject based on the result of the experiment. The reward was calculated as follows:

$$\begin{aligned} & \text{Reward} = \text{The Prize from the Risk Questionnaire} \\ & \quad + (\text{Acquired Experimental Dollars in the Asset Trading Game}) \times 0.45 \\ & \quad + \text{JPY1000} \end{aligned}$$

The last term is the fixed payment, which is the same for all participants. The maximum overall payment was JPY 4,400, the minimum was JPY 1,200, and the average was JPY 3,166.95. Each session took approximately 90 minutes to complete all steps.

We included more than eight subjects in each session, because we needed to ensure anonymity. In other words, we did not want any subject to identify his/her trading partner. The literature indicates that at least four subjects should be included in a market to ensure anonymity and to establish a competitive market. However, it is also pointed out that a bilateral oligopoly may emerge with four market participants,<sup>6</sup> which implies that prices may deviate from those under conditions of perfect competition because of pricing power. Since we focus on perception gaps, other factors that may influence efficiency should be excluded. Thus, to exclude the bias caused by imperfect competition, we included more than eight subjects.

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<sup>5</sup> See Table 1 for session details. The objective probabilities, or the numbers of blue, yellow, and red balls, are shown in this Table.

<sup>6</sup> See Matsukawa et al. (2015), for an example.



In each session, we first explained the outline of the experiment, and subjects signed consent forms. Then, they answered the questionnaire on risk preference. After all subjects finished the questionnaire, the instruction for the asset-trading game was distributed. Subjects read it silently for approximately 10 minutes, and then, the organizer read it out loud again. Then, the subjects proceeded to the asset-trading game.

In this paper, we use technical terms specific to asset markets to describe the experimental design and results. However, in the experiment, the subjects were shown more neutral terminologies. We conducted the experiment using the University of Zurich's Z-tree program (Fischbacher, 1999).

### **3. Results**

#### **3.1 Indices for Inefficiency**

The purpose of this study is to clarify the relationship between perception gaps and degrees of efficiency. To this end, we first develop two indices to represent the degree of efficiency for each subject in each round.

The definition of inefficiency in this study is losses from transactions, caused by a deviation of trading prices from the expected FVs based on the objective probabilities of dividends. For example, suppose that the probability that dividend is 0 (resp. 20, 40) is 30 percent (resp. 30 percent, 40 percent). Then, the expected dividend value in each round equals 22. Then, the objective FV can be obtained by multiplying 22 by the remaining number of rounds. In round 3, the FV is 286, which is equal to 22 times 13. If a subject buys an asset at a price of 306, we consider that the loss of earnings is 20. Also, if a subject sells an asset at a price of 270, we consider that the loss of earnings is 16. On the other hand, if a subject buys an asset at a price lower than 286, or if a subject sells an asset at a price higher than 286, we consider that the subject gains from the trade. Thus, efficiency is given by

$$Efficiency_{i,r,se} = \sum_{ts=1}^n (Sell_{i,ts,r,se} - FV_{r,se}) + \sum_{tb=1}^m (FV_{r,se} - Buy_{i,tb,r,se}), \quad (1)$$

where *Sell* and *Buy* denote the selling and buying prices of each transaction, respectively<sup>7</sup>. *FV* denotes the objective FV of each round in each session. Moreover, subscripts *i*, *ts*, *tb*, *r*, and *se* are indices for subjects, selling transactions for *i*, buying transactions for *i*, rounds, and sessions, respectively.

Equation (1) represents the degree of efficiency for each subject in each round. The greater is this value of a subject, the more efficient are his/her transactions. Note that speculative transactions may increase efficiency, defined by (1), when subjects gain profits margins. Efficiency, though, declines when loss margins arise.

As the number of speculative transactions increases, efficiencies and inefficiencies may be magnified because of repeating transactions. Thus, we also adopt the average of efficiency, which is the degree of efficiency per unit of transaction, for each subject in each round:

$$Ave\_Efficiency_{i,r,se} = \frac{Efficiency_{i,r,se}}{Trade_{i,r,se}}, \quad (2)$$

where *Trade* denotes the number of trades for subject *i* in round *r*. Because cash and asset holdings are carried over to future rounds in this experiment, transactions can have two purposes. Subjects trade assets to gain long-term benefits from dividends in some cases, while they trade assets to gain profit margins by speculation in the other cases. However, both types of transactions are influenced by perception gaps. Therefore, we consider that inefficiency

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<sup>7</sup> The term rationality may be more suitable than efficiency to represent these losses and gains. However, the definition of rationality depends on the context and field. Thus, we use efficiency in this study.

caused by gains and losses from speculation should also be included in our definition of efficiency ((1)).

### **3.2 Overall Picture of Inefficiency**

First, we report the overall picture of the degree of efficiency. The differences between the expected objective FVs and actual trading prices are shown in Figure 4. Note that efficiency in this figure is that of each transaction, which is different from the sum of the differences defined by (1). Note also that the horizontal axis measures the number of seconds after the beginning of the first round, and that the time is not separated by rounds. This graph indicates that degrees of inefficiency are distributed around zero. Thus, it is possible that subjects carried out asset trading taking FVs into consideration on average. An interesting trend is that the degree of inefficiency becomes smaller until the middle of the session (i.e., 600 seconds after the transaction game begins) and increases as the session approaches the final round. The trend in the latter half was also found in the literature, implies that trading prices reflect FVs imperfectly and that subjects may not be able to sell their assets at prices greater than the purchasing prices. In other words, loss margins arise, in particular, for part of subjects in the last few rounds.

However, because Figure 4 does not identify which type of trading, selling or purchasing, generates the inefficiency, we create Figure 5, in which selling and purchasing transactions can be distinguished. Figure 5 indicates that inefficiencies are generated by sellers in the first half and by buyers in the second half. This result implies that the trading prices are too low in terms of FV in the first half, possibly because subjects tried to avoid uncertainty. Even when subjects face a risky situation, in which probabilities for possible events are public information, they often tried to avoid risks. However, when subjects face uncertainty with no information about probabilities for possible events, they underestimate the value of assets or stop

purchasing them. This preference is referred to as ambiguity aversion in the literature. Ambiguity aversion was observed by Alonso and Prado (2015), and this effect likely is the cause of low prices in the first half of the sessions of our experiment.

Now let us turn to average inefficiency of subjects. The averages of *Ave\_efficiency* of subjects for each round in each session are shown in Figure 6, which indicates that *Ave\_efficiency* did not converge to zero in all sessions. Even if the objective probabilities of dividends are the same for certain two sessions, the trends of *Ave\_efficiency* are different from each other. For example, the probabilities are the same for Sessions 1 and 2. Also, the probabilities are the same for Sessions 7 and 10. However, in both cases, the trends of *Ave\_efficiency* are different between the corresponding two sessions. Moreover, there are significant differences among sessions, in particular, in the first few rounds.

It should be noted that Figure 6 cannot take into consideration the difference in FVs across rounds. FVs become smaller as time passes. Thus, the averages of *Ave\_efficiency* may be large when FVs are large, and they may be small when FVs are small. Thus, Figure 6 does not verify if the learning effect works, more rigorous analyses are needed. These are described in the next two subsections.

### 3.3 Estimation Equation

To clarify the effect of perception gaps on the degrees of efficiency defined in Subsection 3.1, we conduct ordinary-least-squares and panel-data estimations. We adopt a random effect model for the latter, because personal attributes that are constant through rounds may be important factors that influence inefficient transactions. The estimation equations are given by

$$Ave\_efficiency_{i,r,se} = \beta_1 \cdot Pgap_i + \beta_2 \cdot Risk_i + \beta_3 \cdot Trade_{i,r,se} + \beta_4 \cdot Asset_{i,r,se} + \beta_5 \cdot Round_{se} + \beta_6 \cdot Ave\_price_{r,se} + c + \epsilon.$$

*Pgap* represents a perception gap, which is the absolute value of the difference between the objective and subjective expected values of dividends. Subjective expected values for subjects are derived using the answers of a questionnaire carried out after the asset-transaction game (see Subsection 2.3). The coefficient of *Pgap* is expected to be negative, which implies that the greater a subject's perception gap, the greater the inefficiency of the subject's transactions.<sup>8</sup>

We also adopt five other variables as independent variables. *Risk* is the degree of risk loving of each subject. It is equal to the number of questions which a subject chooses Choice B in the first questionnaire (see Subsection 2.1 for details). As explained in Subsection 3.1, *Trade* is the number of each subject's transactions in each round, *Asset* is the asset holdings of each subject at the end of each round, and *Round* is the number of rounds that a subjects has played including the present round. The former variable may be able to reflect the asset effect, and the latter reflects the learning effect on market transactions through rounds. Moreover, *Ave\_price* is the average trading price of each round in each session, which reflects the effect of other unobservable personal attributes.  $c$  and  $\epsilon$  represent constant and error terms, respectively. Cross terms of *Pgap* and other independent variables are also included. Summary statistics are shown in Table 2.

### **3.4 Results of Estimations and Simulations**

Estimation results are shown in Table 3. The most important variable for our purposes is the perception gap (*Pgap*), which is the difference between the objective and subjective expected FVs in each round. The coefficients for both OLS and panel estimations are significant and

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<sup>8</sup> We obtained subjective expected values only after 15 rounds were completed. Thus, this variable also measures the effect of the speed of learning on expected values.

negative. This result is as expected and implies that a greater perception gap leads to greater average inefficiency. In other words, the greater a subject's perception gap, the more likely that the subject experiences trading losses.

There are two more interesting results. First, the larger the number of trades by a subject in a certain round, the greater the subject's inefficiency in the round. This result indicates that inefficient transactions can be repeated. Second, inefficiency may increase through rounds, which indicates that a greater number of inefficient transactions occurred in later rounds than in earlier ones.

Finally, we investigate the loss of earnings caused by perception gaps using simulations. The distribution of perception gaps is shown in Figure 7. It seems that perception gaps of most subjects are relatively small, while those of some subjects are large. Because the transaction game is a type of zero-sum game, we first divide the subjects into two groups, one who gains from transactions and one who loses. The perception gaps of the former subjects are relatively small, while those of the latter subjects are relatively large. First, we assume that all subjects carry out the average number of transactions in each round. Then, using the coefficient of  $Pgap$  in the estimation result, we find a border value of perception gaps so that the sum of gains of subjects whose perception gaps are smaller than the border value is equal to the sum of losses of subjects whose perception gaps are larger than the border value. As a result, the number of subjects who lose from transactions is 26, while the number of subjects who gains from transactions is 91.

Next, we define the reference perception gap to calculate the sum of the 26 subjects' losses. We use the average of perception gaps of subjects who gains from transactions, which is 2.161. Finally, assuming that all subjects carried out the average number of transactions in each round, we calculate the ratio of the sum of losses to the expected earnings when their perception gaps are equal to the reference perception gap. According to our simulation, the ratio is 6.010

percent.

In our estimations and simulations, the subjective expected FVs are derived from answers to the second questionnaire, carried out after the fifteenth round was finished. Subjective evaluations about each round's probabilities are not available. Thus, the perception gap used in the analysis may be either overestimated or underestimated. However, it can be said that subjects whose perception gaps were relatively large experienced lower earnings, and that losses may increase with the size of the perception gaps.

#### **4. Discussion**

In this section, we discuss policy implications, in particular, in terms of introduction of AI into asset markets.

Our experimental results demonstrate that there is a possibility that inefficiency arises for asset trading when market participants cannot predict expected FVs with certainty or if it takes long time to predict them, when they face uncertainty without precise information on the probabilities for possible events. Our simulation indicates that perception gaps generate inefficient transactions and a loss of efficiency for some market participants. If it is difficult for human participants to predict the expected FVs by learning, it is important to introduce systems that improve the efficiency of transactions. One candidate is AI.

At present, almost 50 percent of asset market transactions are alleged to be automatically carried out using computer algorithms and/or robots. In this sense, efficiency has been improved. However, human traders create those algorithms and adjust them day after day. If AI can learn transactions and predict FVs more quickly than existing computer algorithms, efficiency of transactions will be improved by establishing the system using AI. AI can also reduce the frequency and degree of bubbles, which stabilizes asset prices. Observing serious market inefficiencies in both experiments and in the real world, AI is a worthwhile investment.

However, AI's weak point is that it cannot cope with uncertainty which it has not experienced at all. This type of drawback is alleged to take place in actual trading. Recently, sharp decreases in stock prices were sometimes observed, which were possibly caused by automated and high-speed transactions that suddenly increased sell orders. Computer algorithms may over-respond to current news and information. Although the importance of this type of problem has not been discussed sufficiently so far, it is possible that diversity of traders will be lost because of an increase in AI traders, which may lead to sudden drastic fluctuations of asset prices.

Moreover, AI traders may incorrectly revise their perceptions in the wrong direction if they revise perceptions based on the realized dividends in the past periods. It is also possible that AI traders will mimic the behavior of human traders whose perceptions are not correct. Both factors could exacerbate the inefficiency of asset markets.

While several studies have examined the effects of introducing algorithms or robots into asset markets (Harrison, 1992; Duffy and Ünver, 2006; Miller, 2008; Collins and Brink, 2016), their results are not the same. This fact implies that introduction of AI can both positively and negatively affect the efficiency of transactions. Consequently, it is indispensable to introduce AI into asset markets so that perception gaps of both AI and human traders shrink.

## **5. Conclusion**

This study has extended the existing literature about uncertainty of asset markets by assuming that subjects cannot calculate the probabilities for possible dividends with certainty. Having conducted a series of laboratory experiments, we examined (i) how asset prices fluctuate, and (ii) if perception gaps lead to inefficient transactions. Moreover, (iii) we estimated losses caused by perception gaps.

Our estimation results indicate that subjects' perception gaps linger across rounds, and that



they generate losses of earnings. Moreover, these losses of earnings may be large when perception gaps are large.

We have not yet compared human and AI traders. However, our experimental design could accomplish this comparison and possibly shed light on a better structure of asset markets.

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**Table 1. Details of Sessions and Ambiguity**

Session ID	Date (Year2017)	Venue	# of Subjects	Number of Balls (Blue, Yellow, Red)
1	Jun 13	Musashi.	12	(5, 5, 5)
2	Jun 15	Kwansei Gakuin.	10	(5, 5, 5)
3	Jun 15	Kwansei Gakuin.	12	(4, 4, 7)
4	Jun16	Kwansei Gakuin.	11	(5, 7, 3)
5	Jun16	Kwansei Gakuin.	11	(4, 5, 6)
6	Jun 20	Musashi.	10	(3, 7, 5)
7	Jul 10	Musashi.	9	(4, 4, 7)
8	Jul 11	Musashi.	10	(4, 5, 6)
9	Oct 10	Musashi.	11	(5, 5, 5)
10	Oct 11	Musashi.	9	(4, 4, 7)
11	Oct 18	Musashi.	12	(7, 5, 3)

**Table 2. Summary Statistics**

Variable	Observation	Mean	SD	Min	Max
Ave_efficiency	1755	4.516	85.478	-700	700
Pgap	1755	3.402	2.882	0	17.333
Risk	1755	3.932	2.435	0	10
Trade	1755	3.528	3.017	0	26
Asset	1755	8.000	5.585	0	37
Ave_price	1755	184.634	74.001	20	380.571
Dividend	1755	17.644	15.961	0	40

**Table 3. Estimation Results**

	OLS	Panel
Ex_gap	-9.961*** (2.856)	-7.783** (3.258)
Risk	-0.174 (79.079)	-76.866 (0.056)
Trade	-1.964* (1.028)	-1.350 (1.118)
Asset	-0.236 (0.563)	-0.373 (0.662)
Round	-1.448* (0.803)	-1.223 (0.794)
Ave_price	-0.174*** (0.051)	-0.150*** (0.056)
Ex_gap×Trades	0.099 (0.210)	0.060 (0.233)
Ex_gap×Asset	-0.153 (0.148)	-0.400** (0.181)
Ex_gap×Average price	0.035*** (0.009)	0.033*** (0.011)
Ex_gap×Risk	22.110 (30.287)	25.588 (44.436)
Ex_gap×Period	0.444** (0.172)	0.390** (0.168)
c	59.117*** (13.822)	53.712*** (15.541)
R2	0.013	0.016
F	3.06	-
Wald	-	34.24

i) The value in the parentheses are standard errors.

ii) \*\*\*, \*\*, \* indicate the significancy at 1, 5, and 10 percent level.

iii) R2 in the OLS estimation is adjusted R square and that in the panel estimation is overall R square.

Date: \_\_\_\_\_

ID \_\_\_\_\_

Name \_\_\_\_\_

	ChoiceA		ChoiceB	
	Card	Prize	Card	Prize
1	①、②、③	JPY 400	①	JPY 680
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50
2	①、②、③	JPY 400	①	JPY 750
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50
3	①、②、③	JPY 400	①	JPY 830
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50
4	①、②、③	JPY 400	①	JPY 930
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50
5	①、②、③	JPY 400	①	JPY 1060
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50
6	①、②、③	JPY 400	①	JPY 1250
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50
7	①、②、③	JPY 400	①	JPY 1500
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50
8	①、②、③	JPY 400	①	JPY 1850
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50
9	①、②、③	JPY 400	①	JPY 2200
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50
10	①、②、③	JPY 400	①	JPY 3000
	④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 100	③、④、⑤、⑥、⑦、⑧、⑨、⑩	JPY 50

Answer

I have chosen Choice A from Q1 through

I have chosen Choice B from  through Q10.

Figure 1. Questionnaire on Risk Preference

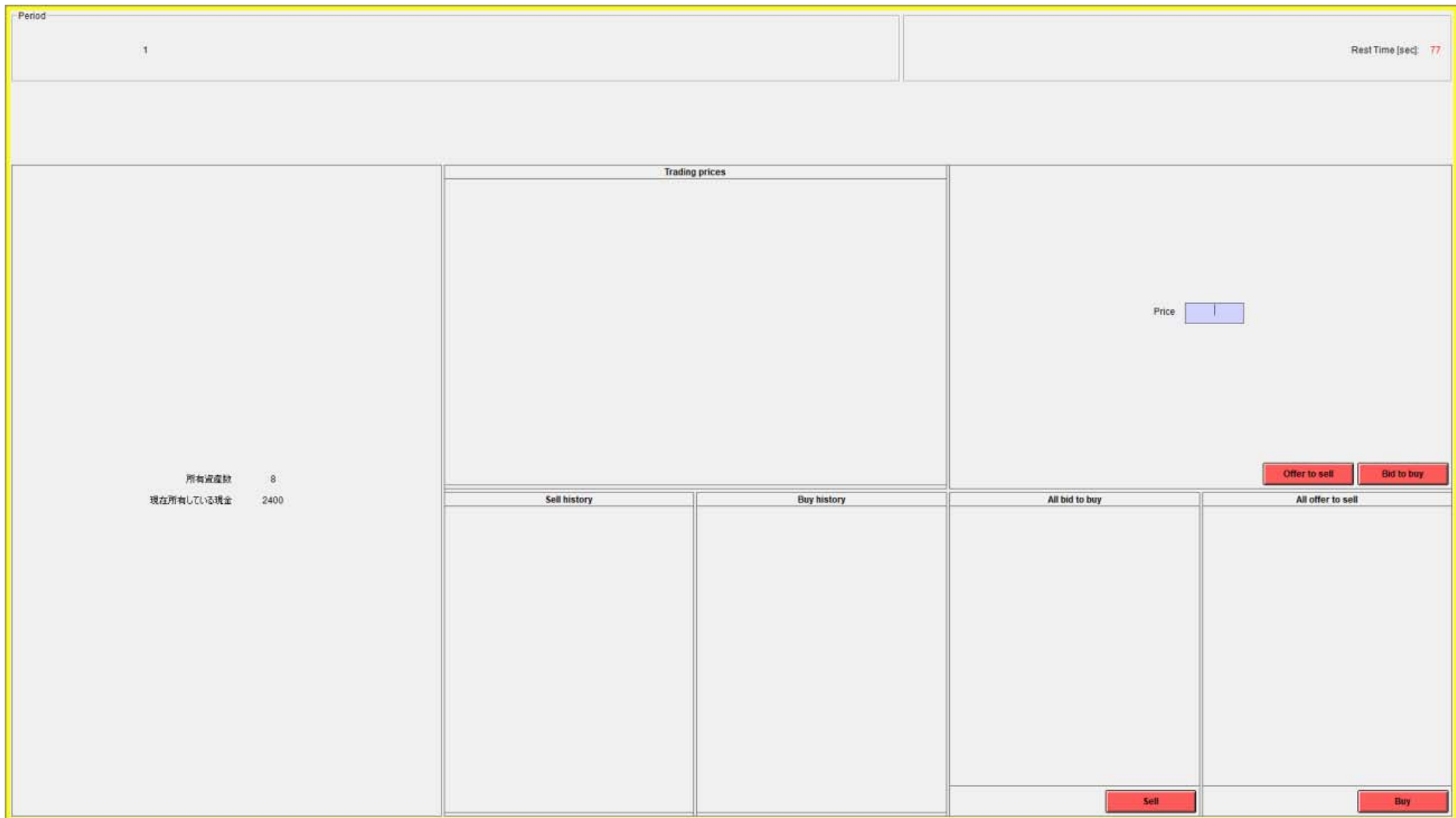


Figure 2. Screen for the Trading Stage

### Questionnaire after Asset-transaction Game

Date: \_\_\_\_\_

ID : \_\_\_\_\_

Name : \_\_\_\_\_

Q1. Could you predict the probability that each value of dividend (0, 20, or 40) realizes?

YES • NO

Q2. What do you think is the probability that each dividend realizes?

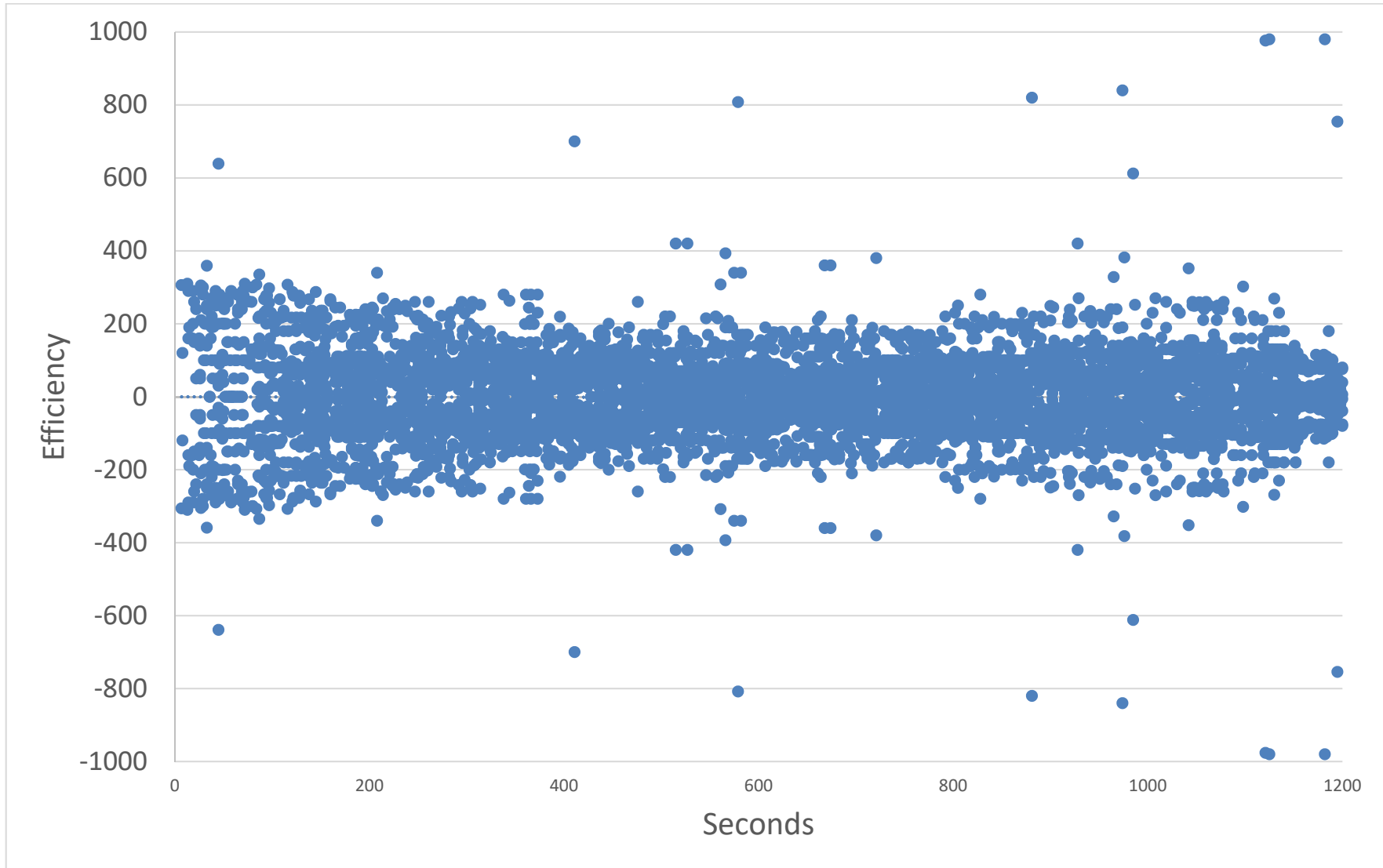
Dividend	Probability
0	%
20	%
40	%

Q3. Did you take into consideration carry the asset values when carrying out transactions?

YES • NO

**Figure 3. Questionnaire on Perceptions and Behavior**





**Figure 4. Inefficiency of Transactions**

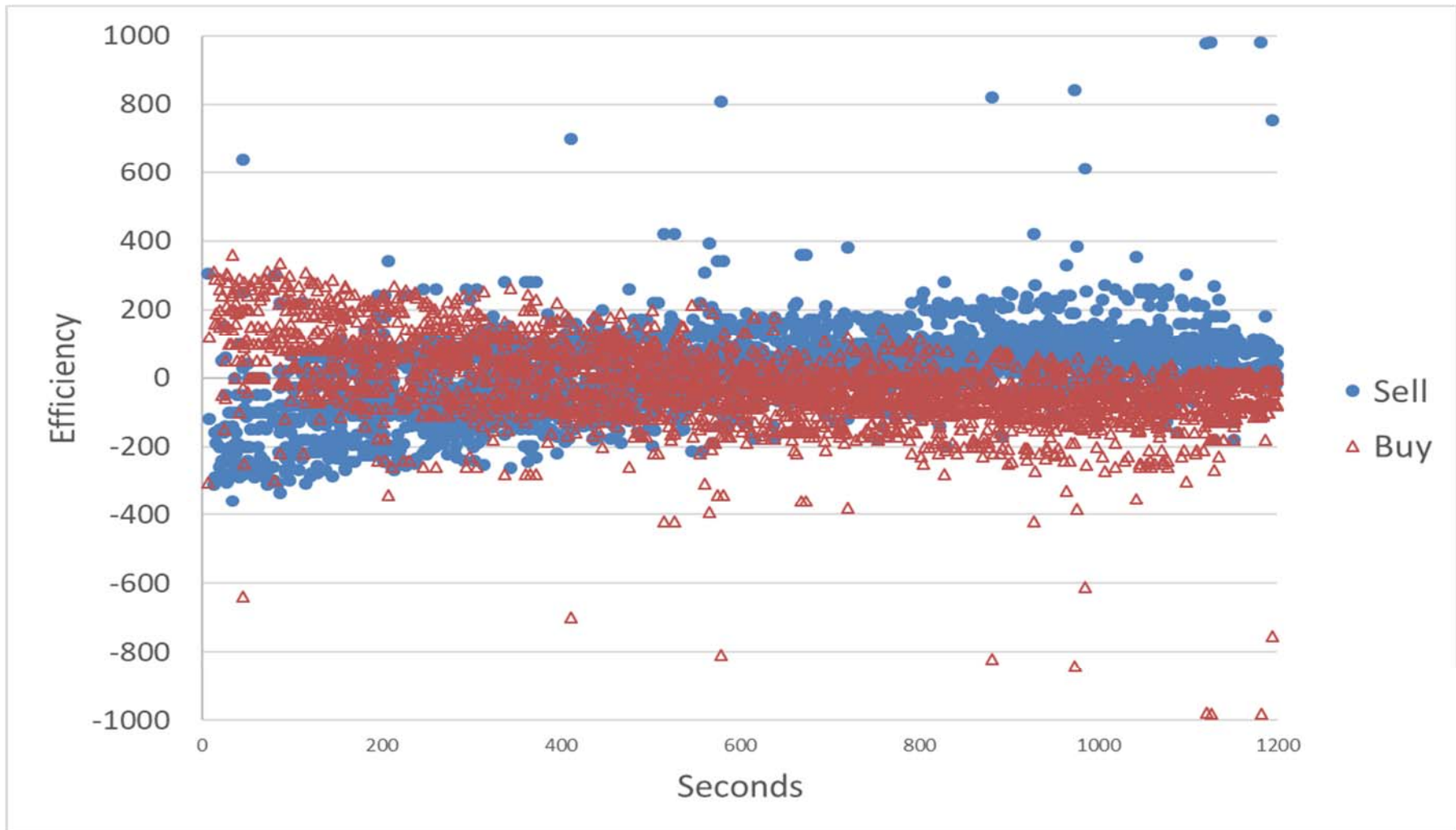


Figure 5. Efficiency of Buy and Sell Transactions

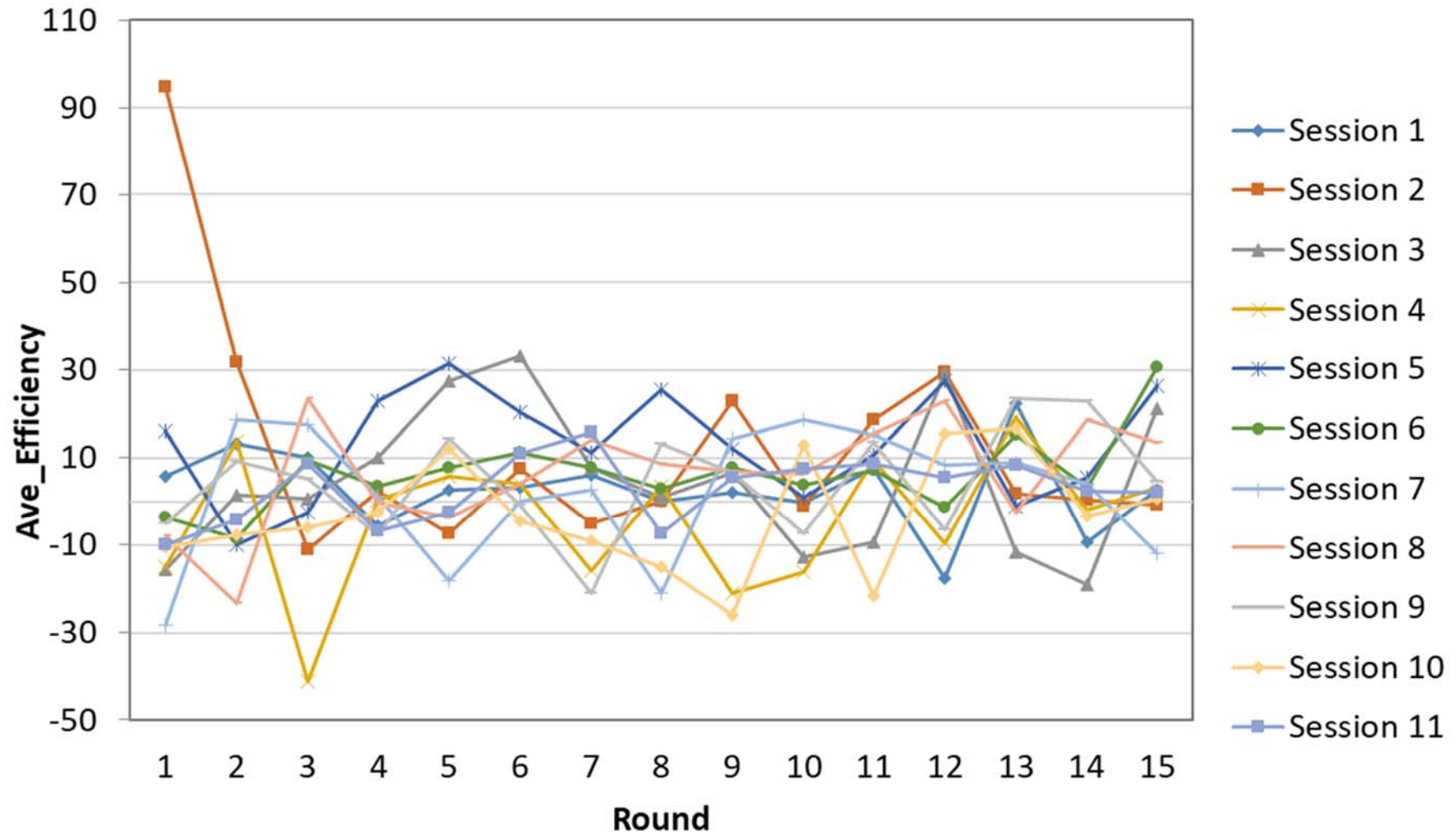
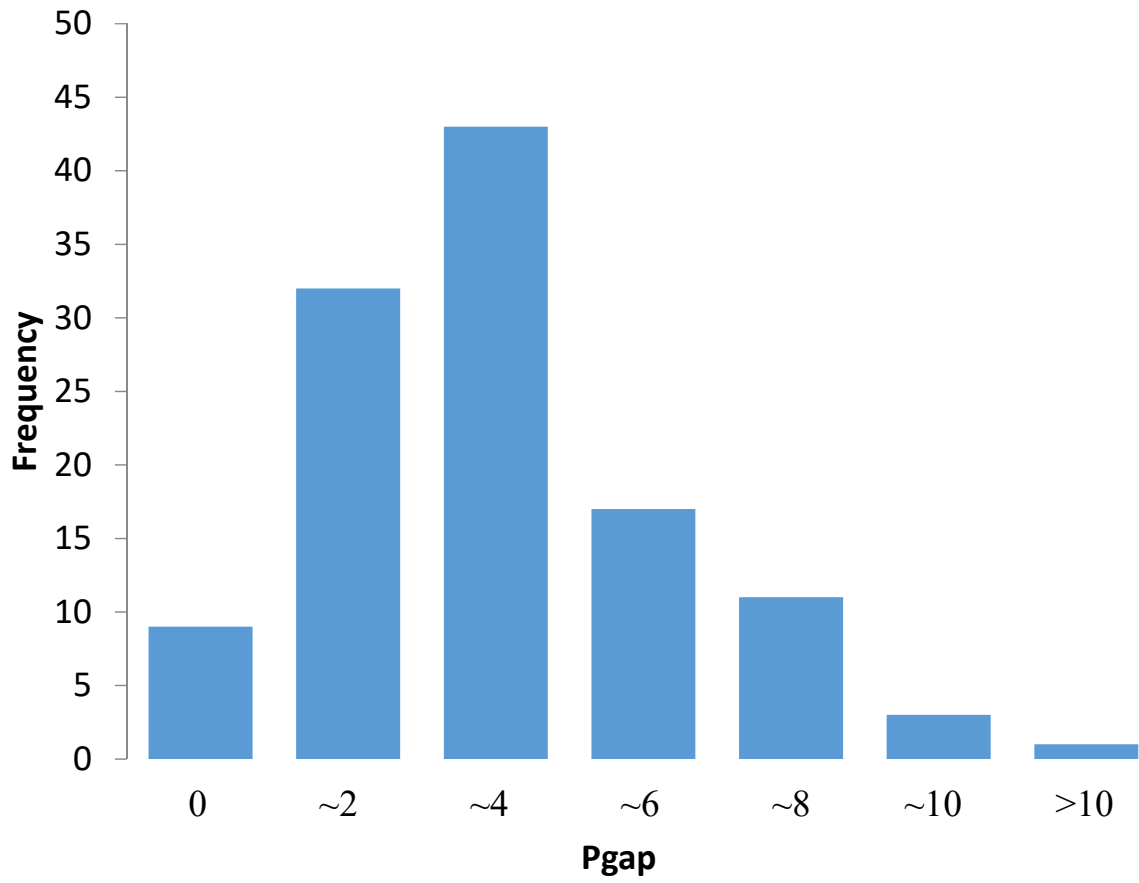


Figure 6. Average Efficiency



**Figure 7. Distribution of Perception Gaps**