

A METHODOLOGICAL NOTE ON ELICITING PRICE FORECASTS IN ASSET MARKET EXPERIMENTS

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A methodological note on eliciting price forecasts in asset market experiments*

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Abstract

We investigate (a) whether eliciting future price forecasts influences market outcomes, and (b) whether differences in the way subjects are incentivized to submit “accurate” price forecasts influence the market outcomes as well as the forecasts submitted by subjects in an experimental asset market. We consider three treatments: one without forecast elicitation (NF) and two with forecast elicitations. In one of the latter treatments, subjects are paid based on both their performance of forecasting and trading (Bonus), while in the other, they are paid based only on one of the two that is chosen randomly at the end of the experiment (Unique). While we found no statistical differences in terms of mispricing, trading volumes, and trading behavior between NF and Unique treatments, there were some statistically significant differences between NF and Bonus treatments. Thus, if the aim is to avoid influencing the behavior of subjects and the market outcomes by eliciting price forecasts compared to NF treatment, then the Unique treatment seems to be better than the Bonus treatment.

Keywords: Price forecast elicitation, Experimental asset markets

JEL Codes: C90, D84

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1 Introduction

Expectations play a central role in modern macroeconomics and financial economics. Furthermore, recently, various policies, both monetary and fiscal, have been described increasingly as policies that influence the expectations of people, in particular, market participants (see, for example, Campbell et al., 2012; Yellen, 2012). However, there is still large room for research on the dynamics of expectation formations to understand better how such policies influence the expectations and behavior of market participants.

In studying the dynamics of expectation formations, laboratory experiments provide a powerful tool. This is because unlike the case of field data, which rarely provide researchers with full knowledge of the information people base their expectations on, in a laboratory experiment, it is the researchers who decide what kind of information subjects have access to. For example, recent studies on “learning-to-forecast experiment” (Hommes et al., 2005; Heemeijer et al., 2009; Sonnemans and Tuinstra, 2010; Bao et al., 2012; Bao and Hommes, 2014) have been very successful in demonstrating under what kind of market environments the price expectations of subjects quickly converge to those under rational expectations equilibrium (REE). In addition, these experimental studies demonstrate complex dynamics of expectations in the case that expectations do not converge to those under the REE. These experimental studies contribute to the construction of new types of models of expectation formation/dynamics by providing them with the data against which proposed models can be tested (Anufriev and Hommes, 2012).

The importance of studying expectation dynamics in other experimental paradigms is increasingly a shared concern among researchers. For example, in a recent survey of a significant body of experimental literature that emerged after the seminal study by Smith et al. (1988), Palan (2013) discusses the scarcity as well as great need for more research investigating the dynamics of expectations regarding future prices in these multi-period asset markets.

A potential obstacle for future development in this direction is that there is not yet consensus regarding the methodology for forecast elicitations. For example, it is not yet very well known how eliciting forecasts influences such market outcomes as de-

gree of mispricing or trade volumes.¹ One recent study that investigates this issue is Bao et al. (2013) in the framework of “learning-to-forecast experiment.” These authors study cobweb economies in which subjects undertake (1) only forecasting, and computers implement optimal trading behavior based on the submitted forecasts, (2) only trading, and thus, no elicitation of price forecasts, and (3) both forecasting and trading. Bao et al. (2013) find that the market prices all converge to REE, but with significantly different speed. The convergence is the fastest in (1) and the slowest in (3), suggesting that when subjects need to engage in multiple tasks, they need longer time to learn “optimal” trading behavior.

Furthermore, researchers use different ways of incentivizing subjects for their performances in forecasting and trading when subjects engage in both activities. In some studies, subjects are rewarded for both their performance of forecasting and trading. In these studies, typically, performance for forecasting is rewarded in the form of bonus payments in addition to rewards from performance in trading (Haruvy et al., 2007; Akiyama et al., 2014, 2015; Bosch-Rosa et al., 2015). In other studies, subjects are rewarded based on their performance of only one of the two activities and not both, and which one will be used is determined randomly at the end of the experiment (Bao et al., 2015). In comparing the two incentive schemes, researchers often discuss possibilities of subjects hedging between forecasting and trading when subjects are incentivized for both (see, e.g., Bao et al., 2015). While the observed trading behavior may well be different between the two incentive schemes discussed above, to the best of our knowledge, there is no systematic experimental study investigating how exactly this difference in the way subjects are rewarded influences their behavior and forecasts.

In this note, we aim to fill this gap in the literature. We investigate, in the experimental asset market paradigm pioneered by Smith et al. (1988)² (a) whether and how eliciting future price forecasts influences the market outcomes, and (b) whether and how differences in the way subjects are incentivized for their performance in forecasting and

¹Lack of methodological consensus was also clear in a discussion held among prominent scholars in the field, such as Vernon Smith, Charles Noussair, and Bruno Biais, during the June 2015 annual meeting of the Society for Experimental Finance held in Nijmegen, NL. Vernon Smith noted that in analyzing the data from their first experiments related to Smith et al. (1988) with one-period-ahead forecast elicitation, eliciting a forecast seemed to influence the trading behavior of subjects and thereby market outcomes, and thus, they stopped eliciting forecasts in the subsequent sessions.

²See Palan (2013) and Powell and Shestakova (2015) for a survey of this rapidly growing literature.

trading—that is, whether they are rewarded for both forecasting and trading or either for forecasting or trading but not both, as well as which one of those used will be determined randomly at the end of the experiment— influence the market outcomes as well as the forecasts they submitted.

We find some statistically significant differences in terms of the direction of mispricing, trading volumes, and the orders submitted by subjects across the treatments we consider. On one hand, the treatment with forecast elicitation in which subjects were paid based only on either the forecasting or trading performance, and which is determined randomly at the end of the experiment, generated market outcomes that were not statistically different from those in the treatment without forecast elicitation. On the other hand, the treatment in which subjects were paid based on both trading and forecasting performance showed statistically different outcomes, in some dimensions, from that without forecast elicitation. Thus, if anything, if the aim is to avoid influencing the behavior of subjects and the market outcomes by eliciting price forecasts compared to the benchmark case without forecasts elicitation, rewarding subjects based on either the forecasting or trading (to be determined randomly at the end of the experiment) seems to be better than rewarding them based on both forecasting and trading.

The remainder of this note is structured as follows. Section 2 presents the experimental design. The results are reported in Section 3. Section 4 offers a summary and concluding remarks.

2 Experiment

We consider asset market experiments, a la Smith et al. (1988), with and without forecast elicitation. In total, we consider three treatments: one without forecast elicitation (No-forecast treatment) and two with forecast elicitation. The two treatments with forecasts elicitation, which we call Bonus and Unique treatments, differ in the way subjects are incentivized.

In the Bonus treatment, subjects receive bonus payments for the accuracy of their forecasts in addition to payments based on their trading performance. This type of incentive scheme has been employed by Haruvy et al. (2007) as well as Akiyama et al.

(2014, 2015); Bosch-Rosa et al. (2015).

In the Unique treatment, on the other hand, subjects receive payments based on *either* the accuracy of their forecasts or their trading performance, but not both. Which one is used for payment is determined randomly at the end of the experiment. To the best of our knowledge, this type of incentive scheme has not been employed in the experimental framework a la Smith et al. (1988), but has been employed in other asset market experiments called “learning-to-forecast and learning-to-optimize” experiments by Bao et al. (2015).

Below, we first describe our experimental markets that are common in all the three treatments. We then illustrate the way forecasts were elicited and how subjects were incentivized in the two treatments with forecasts elicitation. See Appendix for English translation of the instructions.

2.1 Markets

In all the treatments, each group of six subjects trades an asset for a life of 10 periods. As their initial endowment, all the traders receive 4 units of assets and 520 experimental currency units (ECUs), which we called Marks in our experiment. Each unit of the asset pays dividend of 12 ECUs at the end of each period, and after the final dividend payment at the end of period 10, the asset loses its value. Thus, the fundamental value of the asset at the beginning of period t , FV_t , is $12(11 - t)$ ECUs. We employ a call market structure in organizing trading among subjects as in van Boening et al. (1993); Haruvy et al. (2007); Akiyama et al. (2014, 2015); Bosch-Rosa et al. (2015). In call markets, unlike in continuous double auctions, there is one market-clearing price for the asset in each period. Having only one price per period is an advantage for experiments with future price forecasts because the future prices to be forecasted are defined very clearly.³

In our call market experiment, subjects can submit, in each period, a buy as well as a sell order by separately specifying a pair of price and quantity for each type of order. Therefore, if a subject decides to submit a buy order in a period, he has to specify the maximum price at which he is willing to buy a unit of asset (PD), and the maximum units of asset he is willing to buy (QD) in the period. Similarly, to submit a sell order

³Our experimental set-up is based on that by Akiyama et al. (2014, 2015).

in a period, a subject has to specify the minimum price at which he is willing to sell a unit of asset (PS), and the maximum units of asset he is willing to sell (QS) in the period. Of course, subjects can decide to submit neither buy nor sell orders by setting the quantities of both buy and sell orders to zero. We impose three constraints to the orders that subjects can submit: the admissible price range, a budget constraint, and the relationship between PD and PS in the case of a subject submitting both buy and sell orders. The admissible price range is set so that, when $QD \geq 1$ ($QS \geq 1$), PD (PS) must be an integer between 1 and 2000, that is, $PD \in \{1, 2, \dots, 2000\}$ ($PS \in \{1, 2, \dots, 2000\}$). The budget constraint simply means that neither borrowing of cash nor short-selling of an asset is allowed.⁴ The final constraint is such that when a trader is submitting both buy and sell orders, the maximum buying price must not be greater than the minimum selling price, that is, $PS \geq PD$. We imposed a 60-second, non-binding time limit for submitting orders. When the time limit was reached, the subjects were simply informed, through a flashing message in the upper-right corner of their screens, to submit their orders as soon as possible.

Once all the traders in the market have submitted their orders, the price that clears the market is calculated,⁵ and all transactions are processed at that price among traders who submitted a maximum buying price no less than, or a minimum selling price no greater than, the market-clearing price.⁶

2.2 Forecast elicitation

In addition to the trading assets in the call market, in the Bonus and Unique treatments, subjects were asked, at the beginning of each period, and thus, before submitting their orders, to submit their forecasts for the prices in all the remaining periods. This allowed us to study the evolution of long-run as well as short-run price forecasts of subjects. This elicitation method was first introduced by Haruvy et al. (2007) and has been used in more recent works (Akiyama et al., 2014, 2015; Bosch-Rosa et al., 2015). Because,

⁴Thus, the budget constraint implies (i) $QD \times PD \leq \text{cash holding at the beginning of the period}$, and (ii) $QS \leq \text{units of asset on hand at the beginning of the period}$.

⁵When there are several such prices, the lowest one is chosen as the market-clearing price. This is important to ensure the price does not jump up in the absence of transactions at the market-clearing price.

⁶Any ties among the last accepted buy or sell orders are resolved randomly. It is possible that no transaction will take place given the computed market-clearing price.

in period t , each subject submitted $11 - t$ forecasts, subjects submitted a total of 55 price forecasts over the 10 periods. We imposed a 120-second, non-binding time limit for submitting price forecasts. When the time limit was reached, the subjects were simply told, through a message flashing in the upper-right corner of their screens, to submit their forecasts as soon as possible.

2.2.1 Bonus treatment

In the Bonus treatment, subjects were informed that they would receive the following bonus payment based on how accurate their forecast prices were:

$$\begin{aligned} \text{Bonus (in ECUs)} &= 0.5\% \times \text{number of "accurate" forecasts} \\ &\quad \times \text{final cash holding in period 10.} \end{aligned}$$

An “accurate” forecast is defined as a forecast that was within 10% of the realized price. Therefore, if all 55 forecasts were “accurate,” the subject would receive 27.5% of his/her final cash holding (which results from trades and dividends) as a bonus payment. This is the incentive scheme used in Akiyama et al. (2014, 2015).

2.2.2 Unique treatment

In the Unique treatment, subjects were told that they would be rewarded (paid) based on *either* their trading performance (i.e., based on their final cash holding that results from trades and dividends), or the number of “accurate” forecasts. The one used for payment is determined randomly at the end of the experiment. The subjects were informed that in the case in which they would be paid according to the accuracy of their forecasts, they would receive 40 ECUs for each “accurate” forecast. An “accurate” forecast is defined in the same way as in Bonus treatment, that is, a forecast that was within 10% of the realized price. Thus, if all the 55 forecasts of a subject were “accurate,” the subject would receive 2,200 ECUs.

40 ECUs per “accurate” forecast in the Unique treatment may seem high given the total value of the initial endowment (4 units of asset and 520 ECUs of cash) is 1,000 ECUs. We chose this value based on the average number of “accurate” forecasts for

subjects in the data reported in Akiyama et al. (2014). Akiyama et al. (2014) repeated the same experiment three times with the same group of subjects and the same market condition. The average number (and their standard deviation) of “accurate” forecasts for 168 subjects were 11.7 (11.08), 25.71 (15.99), and 39.02 (16.47) for the first, second, and third rounds, respectively. Thus, the overall average number of “accurate” forecasts per subjects per round of a 10-period market was approximately 25. By setting the reward for an “accurate” forecast at 40 ECUs, we aim to equate the expected reward from the final cash holding (1,000 ECUs) with those from the number of “accurate” forecasts. We did not, however, tell our subjects our reasoning behind setting the reward for an “accurate” forecast to be 40 ECUs.

In all three treatments, the same group of traders, with identical initial endowments of cash and assets, repeated the same 10-period market three times as one experiment. We call a 10-period market a round. Thus, the experiment consisted of three rounds of a 10-period market with identical initial endowments and an identical group of subjects.⁷ In the Unique treatment, the payment method (either based on the forecasting performance or the trading performance) for each round was determined independently (independent across rounds but the same across subjects) at the end of the experiment. Subjects were paid based on the exchange rate 1 ECU = 1 JPY in addition to the show-up fee (500 JPY $\approx$ 4 USD).

3 Results

The experiment was conducted at the University of Tsukuba, Japan between May 2013 and November 2015.⁸ The data for the Bonus treatment are taken from Akiyama et al. (2014, 2015), which were gathered between May and November 2013. The data for the No-forecast and Unique treatments were gathered between July and November 2015, with a total of 96 subjects (two sessions of 24 subjects each for the two treatments). These subjects had never participated in a similar experiment before and each subject

⁷Before entering Round 1, there was a practice period to allow subjects to familiarize themselves with the user interface of the software. Subjects were given their initial endowments of cash and assets, and asked to enter their price forecasts (only in the treatments with forecasts elicitation) and their orders for period 1. Information regarding the resulting market-clearing price and so on, however, was not shown to the subjects.

⁸The experiment was computerized with z-Tree Fischbacher (2007).

participated in only one experimental session.

In the dataset of Akiyama et al. (2014, 2015), there are a total of 168 subjects (seven sessions of 24 subjects each) participating in the Bonus treatment. Because these sessions were conducted 2 years prior to the other two treatments, we needed a way to guarantee the comparability of the subjects participating in the two other treatments. Recent studies have demonstrated the relationship between the subjects' scores of a cognitive reflection test (CRT, Frederick, 2005) and the experimental outcomes in this type of experiment, both at individual level (Breaban and Noussair, 2015; Corgnet et al., 2015; Akiyama et al., 2015) and at the market level (Breaban and Noussair, 2015). Since CRT was conducted as a part of a post-experimental questionnaire in our experiment, we have decided to control for average CRT scores of subjects in the three treatments. While the two-sample permutation test⁹ did not reject the equality of CRT scores among subjects between No-forecasts and Unique treatments, the same test rejected the equality of CRT scores between the full sample (seven sessions with 168 subjects) of Bonus treatment and No-forecast or Unique treatments. The average CRT scores of the subjects who participated in Bonus treatments were significantly lower. Because the average CRT scores of subjects in all the sessions for No-forecasts and Unique treatments were no less than 2.0, we decided to keep only two out of the seven with average CRT scores no less than 2.0 for the Bonus treatment. The CRT scores in the three treatments with this restricted set of sessions for the Bonus treatments were not significantly different from each other, according to two-sample permutation tests. Thus, our analyses below are based on a total of 144 subjects, that is, 48 subjects (eight markets of 6 subjects each) for each of the three treatments.

The experiment lasted about 2 to 3 hours (longer with forecast elicitation), including instructions and the post-experimental questionnaire. Subjects were paid, in addition to the show-up fee, on average, 3,000 JPY in the No-forecast treatment, and 3,420 JPY and 3,350 JPY in the Bonus and Unique treatments, respectively.

Below, we first summarize the market-level outcomes, prices, and volumes from the three treatments. We then compare the orders submitted by subjects in the three treatments, and then, the price forecasts in the Bonus and Unique treatments.

⁹Permutation tests are carried out using the STATA package by Kaiser (2007).

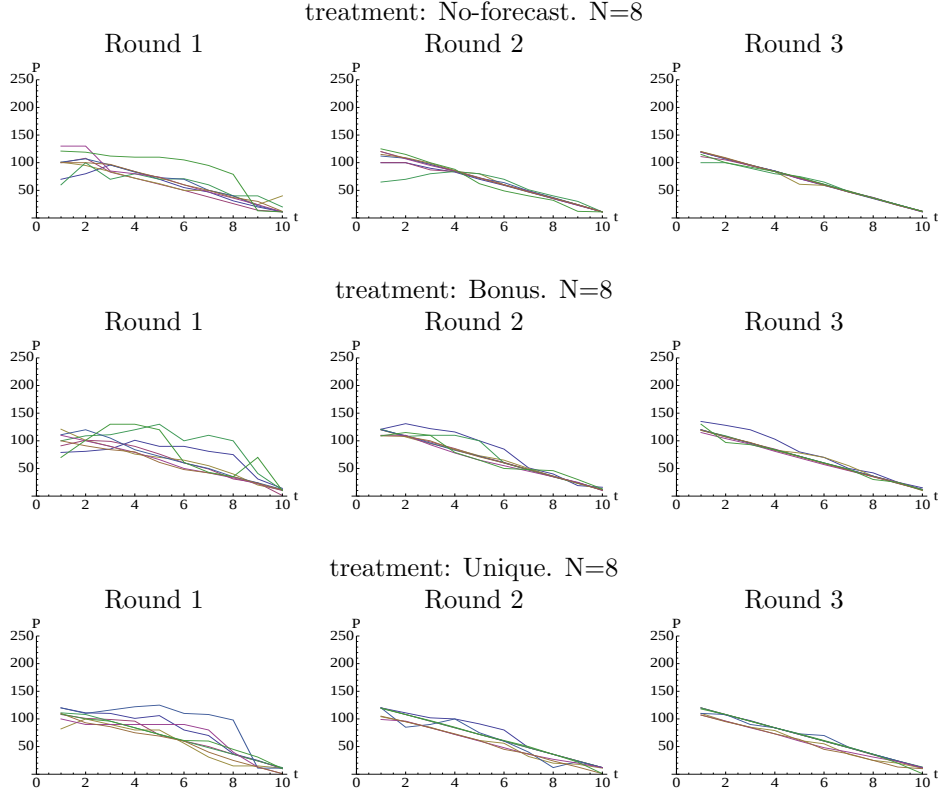


Figure 1: Price dynamics in three rounds. Top: No-forecast treatment. Middle: Bonus treatment. Bottom: Unique treatment. .

3.1 Market outcomes

3.1.1 Prices

Figure 1 shows the dynamics of prices over 10 periods across three rounds in three treatments. Results of the three treatments are shown separately in the three rows of the figure: No-forecasts (top), Bonus (middle), and Unique (bottom).

If anything, a smaller tendency for over pricing in the No-forecast treatment compared to the Bonus and Unique treatments is observed. To compare the magnitude of mispricing observed in the three treatments better, we compute the relative absolute deviation (RAD) and the relative deviation (RD) proposed by Stöckl et al. (2010). For

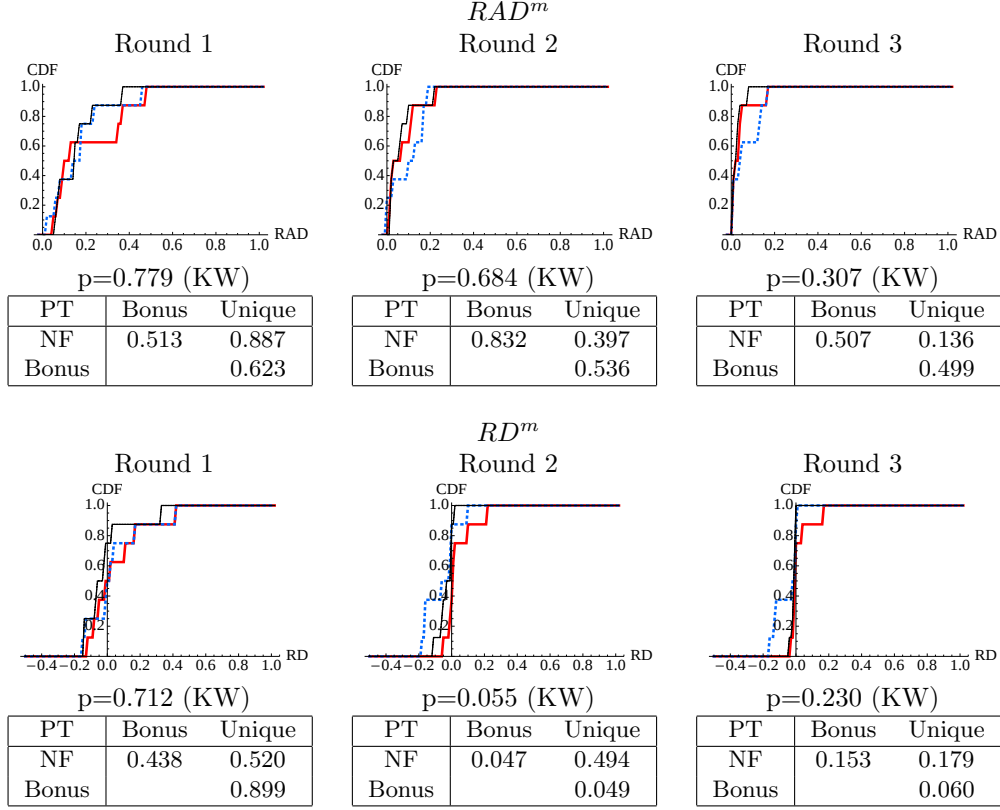


Figure 2: Distributions of RAD^m (top) and RD^m (bottom) in No-forecast (NF, thin, black), Bonus (red), and Unique (blue, dashed) treatments over three rounds. The p-values for a Kruskal–Wallis (KW) test for the multiple comparison, as well as two-sample permutation tests (PTs) for pair-wise comparisons (two-tailed) are also reported.

each market m , RAD^m and RD^m are defined as

$$RAD^m = \frac{1}{T} \sum_{p=1}^T \frac{|P_p^m - FV_p|}{|\overline{FV}|} \quad (1)$$

$$RD^m = \frac{1}{T} \sum_{p=1}^T \frac{P_p^m - FV_p}{|\overline{FV}|} \quad (2)$$

where $T = 10$, and P_p^m is realized price in period $p \in \{1, 2, \dots, 10\}$ in market m . FV_p is the fundamental value of asset in period p . $|\overline{FV}| = |\frac{1}{T} \sum_{p=1}^T FV_p|$.

Figure 2 shows the empirical cumulative distribution (CDF) of RAD^m (top) and RD^m (bottom) for three rounds of No-forecast (NF, thin, black), Bonus (red), and Unique (blue, dashed) treatments. The p-values for a Kruskal–Wallis (KW) test for

the multiple comparison, as well as two-sample permutation tests (PTs) for pair-wise comparisons (two-tailed) are also reported.

The top panel of Figure 2 shows no significant differences in the distribution of RAD across three treatments in all three rounds. The Kruskal–Wallis (KW) test as well as permutation tests (PTs) do not reject the null hypothesis of equality of RAD across treatments in any of the three rounds. The same result is obtained for RD in the first round. In the second round, however, RD in the Bonus treatment is significantly larger than that in the No-forecast and Unique treatments. There is no significant difference between RD for the latter two treatments. Thus, for Round 2, the Bonus treatment generated relatively more markets with over-pricing of the asset compared to the other two treatments, which generated relatively more markets with under-pricing.

3.1.2 Trading volumes

Figure 3 shows dynamics of observed trading volumes in the three rounds for the three treatments. One may notice a larger volume in the last period of Round 1 of the Bonus treatment compared to the other two treatments. Other than this, it is difficult to observe any differences across the three treatments.

To analyze the possible differences in the trading volumes across the three treatments better, we compute the measured called *turnover* (TO), which is the share of outstanding assets that are traded over 10 periods. For market m , turnover, TO^m is defined as follows:

$$TO^m = \sum_{p=1}^{10} \frac{Q_p^m}{24} \quad (3)$$

where Q_p^m is the units of asset traded in period p of market m , the 24 in the denominator is the total number of outstanding assets (recall that each of the six traders had 4 units of the asset to begin with).

Figure 4 reports the empirical cumulative distribution of TO^m across the three rounds in the three treatments: No-forecast (NF, thin, black), Bonus (red), and Unique (blue, dashed). The p-values for a Kruskal–Wallis (KW) test for the multiple comparison, as well as two sample permutation tests (PTs) for pair-wise comparisons (two-tailed) are reported.

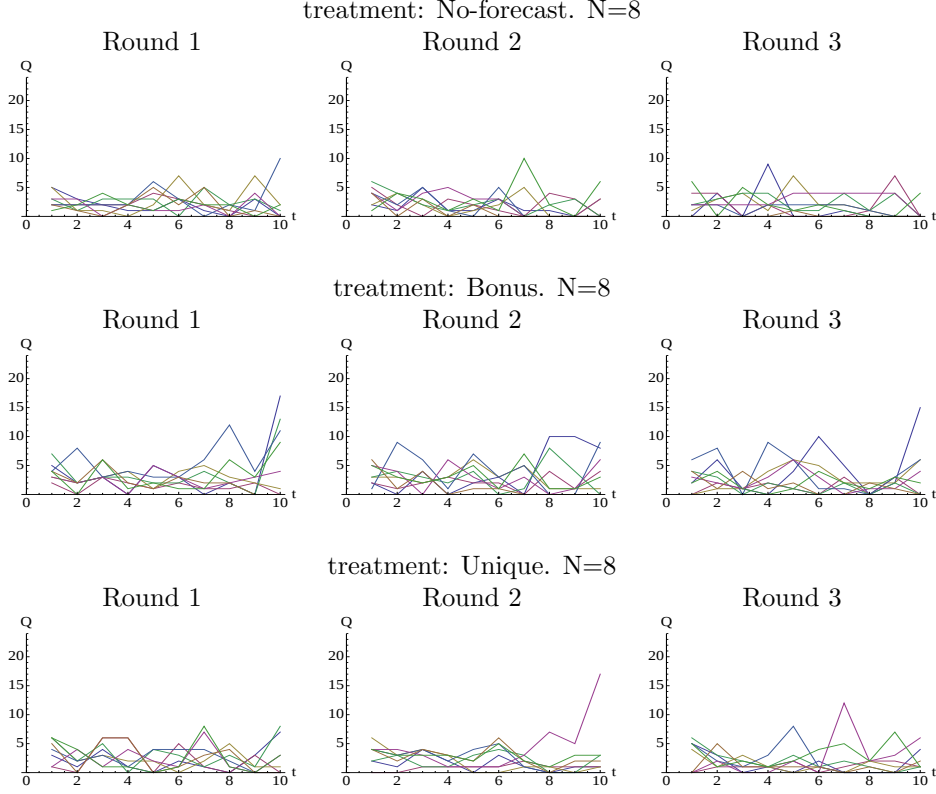


Figure 3: Trade volume dynamics in three rounds. Top: No-forecast treatment. Middle: Bonus treatment. Bottom: Unique treatment

The figure shows, as observed from the time-series figure, that TO tends to be larger in the Bonus treatment than in the other two treatments. The results of permutation tests show that indeed, TO of the Bonus treatment is significantly larger than that of the No-forecasting treatment in the first two rounds.

3.2 Orders

We now analyze the orders submitted by subjects to go beyond the mispricing and trading volume. To summarize the orders submitted by subjects across 10 periods in a market, we employ a measure of the potential loss that can be generated by these orders. Akiyama et al. (2014) define the potential loss for subject i in market m , $PL^{i,m}$, as:

$$PL^{i,m} \equiv \frac{1}{1000} \sum_t \left(d_t^{i,m} \max(pd_t^{i,m} - FV_t, 0) + s_t^{i,m} \max(FV_t - ps_t^{i,m}, 0) \right) \quad (4)$$

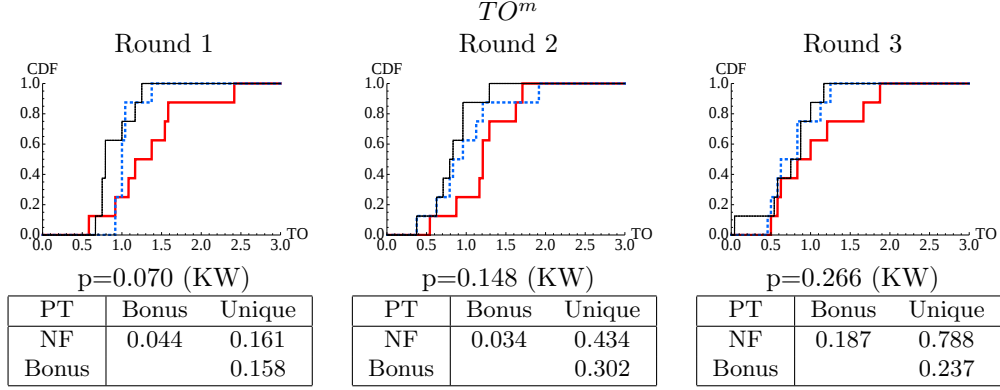


Figure 4: Distribution of turnover TO^m in No-forecast (NF, thin, black), Bonus (red), and Unique (blue, dashed) treatments over three rounds. The p-values for a Kruskal-Wallis (KW) test for the multiple comparison, as well as two sample permutation tests (PTs) for pair-wise comparisons (two-tailed) are also reported.

where $pd_t^{i,m}$ and $ps_t^{i,m}$ are the maximum price at which i is willing to buy and the minimum price at which i is willing to sell an asset, respectively, specified in subject i 's orders submitted in period t . $d_t^{i,m}$ and $s_t^{i,m}$ are the maximum quantities demanded or supplied, associated with $pd_t^{i,m}$ and $ps_t^{i,m}$, respectively. The potential loss is normalized by the value of the initial endowment ($=1,000$) so that $PL^{i,m}$ denotes the share of the initial endowment subject i would potentially lose if his orders were executed at the prices submitted.¹⁰

Based on the individually computed $PL^{i,m}$, we define, for each market, the average potential loss of the traders in the market, PL^m , and use them as independent observations. Figure 5 shows the empirical cumulative distribution of PL^m across the three rounds in the three treatments: No-forecast (NF, thin, black), Bonus (red), and Unique (blue, dashed). The distributions of PL^m are not significantly different across the three treatments across the three rounds (p-values are 0.183, 0.594, and 0.599 for Rounds 1, 2, and 3, respectively, based on the KW test). In Round 1, however, we observe that PL^m tend to be larger in the Bonus treatment than the No-forecast treatment, just as in the case of turnover observed above. This significantly larger PL^m in the Bonus treatment is likely to be a result of subjects in this treatment submitting orders with larger quantities, which results in larger trading volumes, than in the No-forecast treatment.

¹⁰It should be noted that submitting such orders may not result in any losses in our experiment because the actual trading prices can differ from those submitted by the subjects.

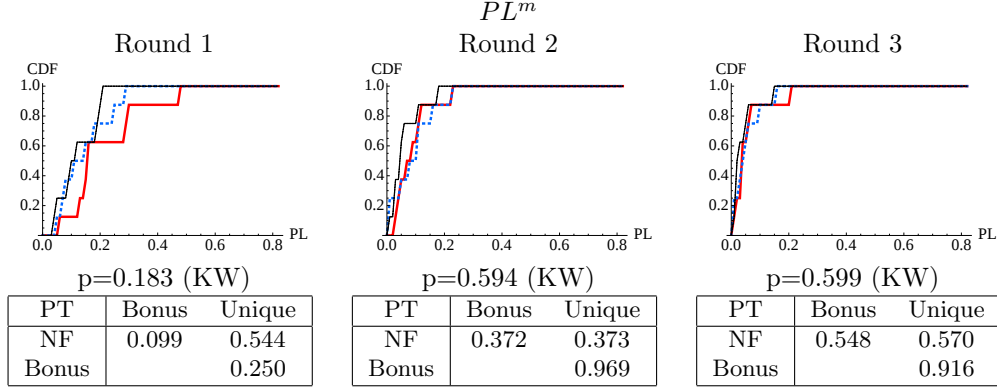


Figure 5: Distribution of the within-market average potential loss, PL^m , in No-forecast (NF, thin, black), Bonus (red), and Unique (blue, dashed) treatments over the three rounds. The p-values for a Kruskal–Wallis (KW) test for the multiple comparison, as well as two sample permutation tests (PT) for pair-wise comparisons (two-tailed) are also reported.

3.3 Forecasts in Bonus and Unique treatments

We now move our attention to the two treatments in which price forecasts were elicited. We are interested in whether the differences in the way subjects were incentivized to submit “accurate” forecasts influenced their forecasts.

The average number of “accurate” forecasts in the Bonus and Unique treatments in our sample were 13.69 and 14.5, respectively, in Round 1, 28.33 and 33.60, respectively, in Round 2, and 41.06 and 41.83, respectively, in Round 3. There was no statistically significant difference between the two treatments in any of the three rounds (p-values are 0.846, 0.473, and 0.885 for Rounds 1, 2, and 3, respectively, based on a two-sample PT (two-sided) using within-group averages as an independent observation).¹¹ Thus, in terms of forecasting performance according to which subjects are rewarded, our two treatments with forecast elicitations generated similar outcomes. Below, we investigate in more detail the dynamics of price forecasts, deviations of the forecasts from the fundamental value, as well as how forecasts are related to the past realized prices and fundamental value.

¹¹The number of “accurate forecasts” between the two treatments is not statistically significantly different, even using individual as an independent observation. P-values are 0.762, 0.136, and 0.784, for Rounds 1, 2, and 3, respectively, based on the two-sample PT (two-tailed).

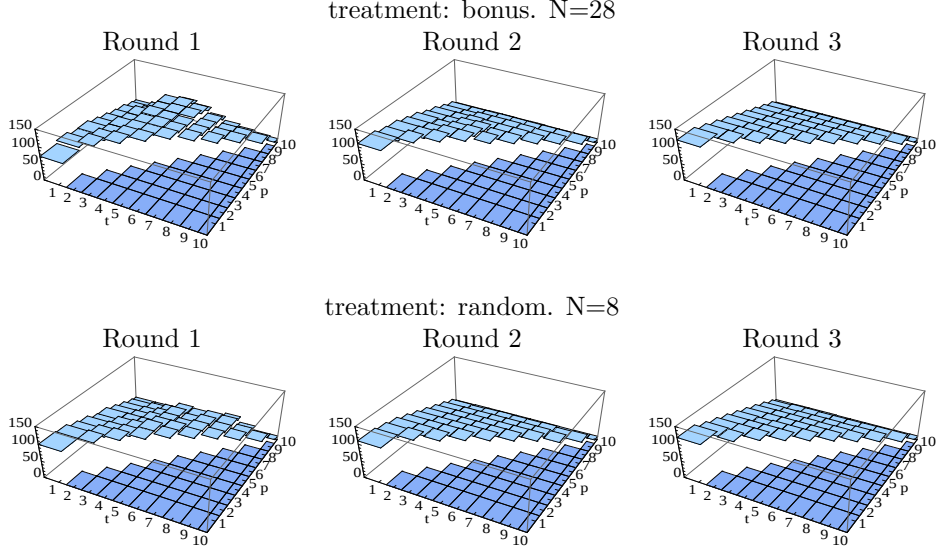


Figure 6: Dynamics of mean forecasts in three rounds. Top: Bonus treatment. Bottom: Unique treatment

3.3.1 Forecast dynamics

Figure 6 shows the dynamics of the median forecasts in the Bonus (top) and Unique (bottom) treatments in three rounds. In each panel, the median forecast for period p price elicited at the beginning of period t is shown by the height. While the dynamics of median forecasts in Rounds 2 and 3 are very similar in the two treatments, they are slightly different for Round 1. That is, in the Bonus treatment, the median forecasts for the later periods' prices submitted in period 5 or so tend to be higher than those submitted in the Unique treatment. Below, we investigate this by computing the magnitudes of forecast deviations.

3.3.2 Forecast deviations

We follow Akiyama et al. (2014, 2015) in measuring the magnitude of the deviations of forecasts submitted by subject i in market m in period t from the fundamental values by the relative absolute forecast deviation ($RAFD_t^{i,m}$) as well as the relative forecast deviation ($RFD_t^{i,m}$). These two measures are very similar to the two measures of mispricing, RAD^m and RD^m , we used above. That is, $RAFD_t^{i,m}$ and $RFD_t^{i,m}$ are defined

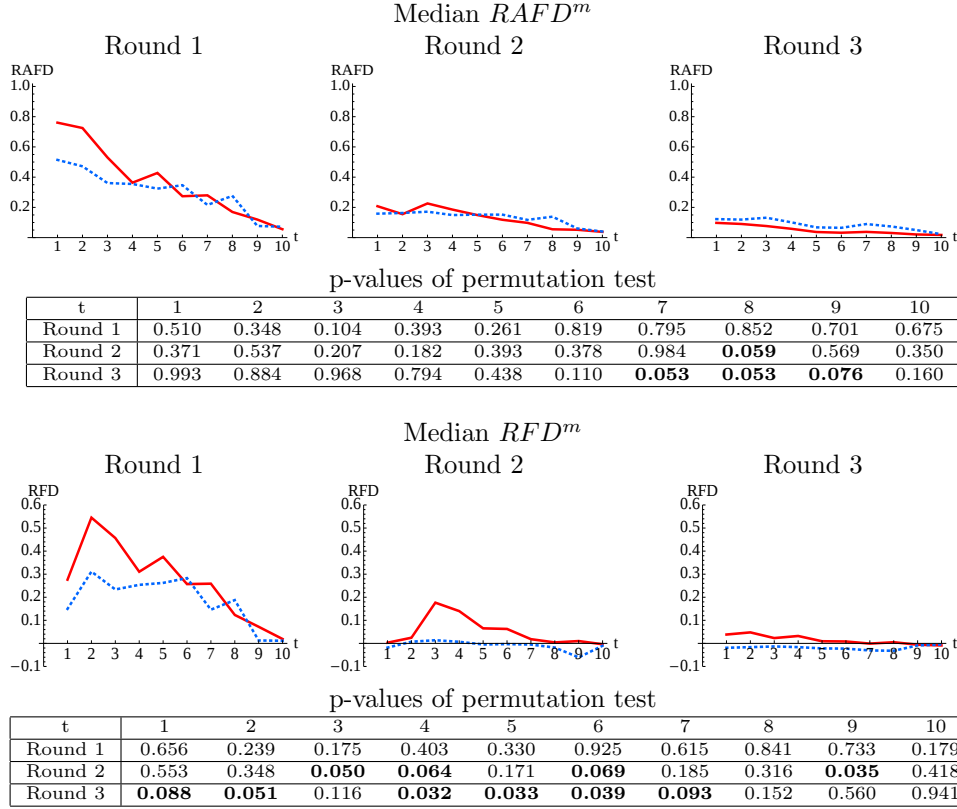


Figure 7: Dynamics of the median $RAFD_t^m$ (top) and RFD_t^m (bottom) in the Bonus (red, solid) and Unique (blue, dashed) treatments over three rounds. P-values from the two-sample permutation test (PT) are reported for each period.

as:

$$RAFD_t^{i,m} = \frac{1}{T-t+1} \sum_{p=t}^T \frac{|f_{t,p}^{i,m} - FV_p|}{|\overline{FV}|} \quad (5)$$

$$RFD_t^{i,m} = \frac{1}{T-t+1} \sum_{p=t}^T \frac{f_{t,p}^{i,m} - FV_p}{|\overline{FV}|} \quad (6)$$

where $f_{t,p}^{i,m}$ is the forecast of asset price in period p submitted by subject i at the beginning of period t of market m .

By taking an average of $RAFD_t^{i,m}$ and $RFD_t^{i,m}$ across traders within a market, we obtain the average $RAFD_t^m$ and RFD_t^m , respectively, for forecasts submitted by traders in period t in market m . Below, we use this within-market average across subjects in a market as an independent observation.

Figure 7 shows the dynamics of median $RAFD_t^m$ and RFD_t^m for the Bonus (red, solid) and Unique (blue, dashed) treatments in three rounds. In addition, p-values from two-sample PTs (two-tailed) are shown for each period.

In early periods of Round 1, the median $RAFD_t^m$ as well as RFD_t^m tend to be larger for the Bonus treatment than for the Unique treatment. They are, however, not statistically significantly different. In fact, $RAFD_t^m$ s are not significantly different between the two treatments for most of the 30 periods of the experiment. The exceptions are period 8 in Round 2 and periods 7–9 in Round 3.

On the other hand, RFD_t^m becomes significantly different between the two treatments (at 10% significance level) in several periods (periods 3, 4, 6, and 9) of Round 2, and the majority of periods in Round 3. This is in line with the significant differences in the relative deviation, RD^m , between the Bonus and Unique treatments for Rounds 2 and 3 observed above. Since the expectations tend to be driven by the realized prices in the market (Haruvy et al., 2007), this difference in the RFD_t^m may be driven by the differences in the direction of mispricing between the two treatments in these two rounds. Below, we attempt to clarify this issue by estimating how forecasts are related to past realized prices to observe whether these relationships differ between the two treatments.

3.3.3 Relationships between forecasts and realized prices

We follow Haruvy et al. (2007) in estimating the following simple forecast adjustment model.

$$f_{t,p}^{i,r} = \alpha^i + \beta_1 MT_{t,p}^{i,r} + \beta_2 PT_{t,p}^{i,r} + \beta_3 FV_p \quad (7)$$

where $f_{t,p}^{i,r}$ is the forecast of period p price submitted by subject i at the beginning of period t of round r , and FV_p is the fundamental value of the asset in period p .¹² $MT_{t,p}^{i,r}$ and $PT_{t,p}^{i,r}$ are what Haruvy et al. (2007) called market-trend and period-trend,

¹²Haruvy et al. (2007) do not include FV_p in their basic model, but estimate its relationship with $f_{t,p}^{i,r}$ separately, from $MT_{t,p}^{i,r}$ and $PT_{t,p}^{i,r}$, to be defined below.

respectively, and are defined as follows:

$$MT_{t,p}^{i,r} = f_{t,p-1}^{i,r} \left(1 + \frac{P_p^{r-1} - P_{p-1}^{r-1}}{P_{p-1}^{r-1}} \right) \text{ for } t > 1 \quad (8)$$

$$PT_{t,p}^{i,r} = f_{t,p-1}^{i,r} \left(1 + \frac{f_{t,p-1}^{i,r} - f_{t,p-2}^{i,r}}{f_{t,p-2}^{i,r}} \right) \text{ for } t > 2 \quad (9)$$

where P_p^{r-1} is the period p market-clearing price in Round $r - 1$. In case $p = t$ or $p = t + 1$, $f_{t,p-1}^{i,r}$ and $f_{t,p-2}^{i,r}$ are not defined. Haruvy et al. (2007) set $f_{t,t-1}^{i,r} = P_{t-1}^r$ in defining $MT_{t,p}^{i,r}$. Similarly, in defining $PT_{t,t}^{i,r}$ or $PT_{t,t+1}^{i,r}$, $f_{t,t-1}^{i,r} = P_{t-1}^r$ and $f_{t,t-2}^{i,r} = P_{t-2}^r$ are used. Note that $MT_{t,p}^{i,r}$ is not defined for $r = 1$, and $MT_{t,p}^{i,r}$ is only defined for $t > 1$ for $r \in \{2, 3\}$. Similarly, $PT_{t,p}^{i,r}$ is defined only for $t > 2$ for all r .

This simple forecast adjustment model assumes that subjects adjust their forecasts based on three types of information: (1) the observed price dynamics in the previous round (for $r > 1$), (2) the way prices (or their own forecasts in the case of predictions of $p \geq t + 2$ periods) have changed from the two previous periods to the current round, and (3) the fundamental value of the asset in the relevant future period.

We are interested in whether the estimated coefficients β_1 , β_2 , and β_3 are significantly different between the two treatments. For this reason, we define a dummy variable, D , that takes values 0 and 1 for Bonus and Unique treatments, respectively, and estimate the above regression with terms interacting the dummy with MT , PT , and FV , that is, with $D \times MT$, $D \times PT$, and $D \times FV$.

Table 1 shows the results of individual fixed-effect regressions. Robust standard errors that correct for the within-group correlations are used. The estimated coefficients for PT and FV are both positive and statistically significant for all the three rounds. The estimated coefficients of MT are also positive, but are not statistically significantly different from 0 in Round 2.

The treatment effects are captured by the estimated coefficients of $D \times MT$, $D \times PT$, and $D \times FV$. The estimated coefficients of $D \times MT$ are not significantly different from zero in either Rounds 1 or 2. Thus, the effects of market-trends on the forecasts are not significantly different between the two treatments. However, the effects of period-trends and fundamental values are significantly different between the two treatments. That is,

Table 1: Result of individual fixed-effect regressions

	Round 1	Round 2	Round 3
constant	17.42** (9.03)	-11.263*** (2.085)	-9.573*** (1.373)
MT		0.098 (0.060)	0.159** (0.073)
PT	0.721** (0.251)	0.475*** (0.0898)	0.449** (0.107)
FV	0.355** (0.124)	0.543*** (0.093)	0.427*** (0.110)
$D \times MT$		0.105 (0.0622)	-0.047 (0.079)
$D \times PT$	-0.621** (0.271)	-0.394*** (0.0924)	-0.434*** (0.111)
$D \times FV$	0.317* (0.155)	0.263** (0.099)	0.439*** (0.114)
R^2	0.403	0.828	0.880
No. Obs.	4896	4896	4896

Robust standard errors adjusted for within-group correlation are reported in parentheses.

***, **, and *: Significant at 1, 5, and 10% significance levels, respectively.

the estimated coefficients of $D \times PT$ are significantly negative. Indeed, in Rounds 1 and 3, the estimated coefficients of PT and $D \times PT$ are jointly not significantly different from 0 (p-values for testing $PT + D \times PT = 0$ are 0.350, 0.002, and 0.597, for Rounds 1, 2, and 3, respectively), which suggests the period-trends do not have systematic impact on the forecasts in the Unique treatment while they are positively related to the forecasts in the Bonus treatment. For the fundamental value, the effect is stronger in the Unique treatment than in the Bonus treatment, as demonstrated by the positive and significant estimated coefficients of $D \times FV$.

4 Summary and conclusion

In this study, we investigated whether (a) eliciting future price forecasts influences the market outcomes, and (b) differences in the way subjects are incentivized for performance in forecasting and trading—that is, whether they are rewarded for both forecasting and trading or only on either forecasting or trading but not both—influence the market

outcomes as well as the forecasts they submit in the experimental asset market paradigm pioneered by Smith et al. (1988).

We considered three treatments: one without forecast elicitation (NF treatment), and two with forecast elicitations. In one of these latter treatments, subjects were rewarded based on both their forecasting and trading performances in the form of bonus payments for the forecasting performance in addition to the payment based on the trading performance (Bonus treatment). In the other treatment with forecast elicitations, subjects were paid based on either their forecasting performance or their trading performance, but not both. The treatment selected for payment was determined randomly at the end of the experiment (Unique treatment).

While we found no statistically significant differences in terms of mispricing, trading volumes, and potential losses that can be generated by the orders subjects submit between NF and Unique treatments, there were some statistically significant differences between the NF and Bonus treatments. Thus, if the aim is to avoid influencing the behavior of subjects and market outcomes by eliciting price forecasts compared to NF treatment, the Unique treatment seems to be better than the Bonus treatment.

However, in designing experiments with an incentive scheme similar to what we have considered in the Unique treatment, one may wish to have some idea about the average forecasting performance in setting the piece-rate for an “accurate forecast” so that the expected rewards from forecasting and from trading are comparable. An interesting topic for future research may involve investigating the importance of this “ex-ante” comparability of reward from two activities in providing a good monetary incentive for forecast performance without distorting trading behavior, and thereby market outcomes.

In this study, we decided the piece-rate for an “accurate” forecast based on the average forecast performance observed in the Bonus treatment, which was conducted prior to the other treatments to make them comparable. When there is no such dataset to compute an appropriate piece-rate, it may be necessary to run enough pilot experiments just in order to find one. A possible solution for finding an appropriate piece-rate without engaging many subjects in the pilot would be to conduct a set of “forecasting only” experiments in which subjects are asked to forecast the prices observed in a market under the NF treatment without themselves engaging in trading (see, e.g., Section 4 of

Akiyama et al., 2014). There, of course, remains a question about whether forecasts collected in this way are comparable to forecasts subjects submit when they are engaged in both trading and forecasting. We leave this for future research as well.

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Appendix: English translation of the instructions

Instructions for the Stock Trading Experiment

Please do not turn over a page until instructed to do so. Before the experiment begins, we kindly request that you:

- confirm that you are seated in your designated seat;
- do not log in to the computer until you are instructed to do so;
- inform us immediately if your computer is not working correctly.

Please turn to the next page.

[Today's schedule]

Today we will be conducting an experiment consisting of three games by following the four steps outlined below.

1. Explanation of the experiment (games) and a practice round
 2. Games 1, 2, and 3 (each game has ten time periods)
 3. Questionnaire and quizzes
 4. Payment: The attendance fee (500 yen) plus any profit that you earn in the games will be paid out in cash at the end.
- The questionnaire and quizzes do NOT affect the games' results.
 - Games are independent of each other. The result of one game does not affect the other games.
 - If you need to go to the toilet, please inform an instructor at the end of a game.

[Today's experiment]

Today you will participate in stock trading games in which you trade stocks in an artificial stock market. Please listen to the instructions carefully and if you do not understand any part of an instruction, ask for clarity by raising your hand. Moreover, if you have any questions during the experiment, raise your hand and an instructor will come to you and answer your question.

Throughout the experiment, please respect the following rules:

1. Do not talk to the other participants during the experiment or the breaks.
 - ✓ This may affect the results of the experiment.
2. Use your mouse or keyboard only when instructed to do so by the instructor; otherwise, it may cause a problem.
 - ✓ If any malfunction occurs, all participants will have to restart the game.

Please turn to the next page.

[Outline of stock trading game]

- You buy and sell dummy stocks in an artificial market in which six traders are active.
- Each market consists of 6 human traders.

[Objectives of the game]

Your objective in this game is to make as much profit as you can. We use Mark as the currency for the experiment. At the end of the experiment, 1 Mark will be converted into 1 Yen and paid out to you.

There are 2 ways of making a profit:

[NF]

- First, you can earn a profit margin through buying and selling stocks;
- Second, you can earn dividends on your stock holdings.

[Bonus/Unique]

- First, you can earn a profit margin through buying and selling stocks, and dividends on your stock holdings.
- Second, you can make a profit by accurately predicting the future prices of the stocks.

Please turn to the next page.

[Earning a profit margin]

You will be given four stocks + 520 Marks at the beginning of each game.

To earn a profit margin by trading, you need to buy stocks at a lower price and sell these at a higher price. For example, suppose you buy a stock for 100 Marks, and then the price of the stock increases to 120 Marks. If you sell the stock, you will earn $120 \text{ (selling price)} - 100 \text{ (purchase price)} = \underline{20 \text{ Marks profit}}$. In contrast, suppose you buy a stock for 100 Marks, and then the price of the stock decreases to 80 Marks. If you sell the stock, you will make $80 \text{ (selling price)} - 100 \text{ (purchase price)} = \underline{20 \text{ Marks loss}}$. We will explain later how the prices are determined.

Now we will explain how to use the experimental program interface. We will also explain how to earn a profit margin. Please do not perform any operations other than those which you are instructed to carry out; otherwise, it may jeopardize our experiment.

Please double-click on the indicated icon on the computer screen.

[Order entry screen]

The following screen will appear, through which you can enter your orders for each time period.

The screenshot shows a web-based order entry interface. At the top right, a red box indicates '残り時間 [秒] 57' (Remaining time [seconds] 57), labeled with a red circle 1. Below this, the interface is divided into several sections. On the left, '現在の所持金' (Current cash balance) is 520 (labeled 2) and '現在の保有株数' (Current stock holdings) is 4 (labeled 3). In the center, there are two input fields: '最高購入希望価格' (Maximum purchase price) labeled 4 and '買い注文数' (Buy order quantity) labeled 5. On the right, there are two input fields: '最低売却希望価格' (Minimum sell price) labeled 6 and '売り注文数' (Sell order quantity) labeled 7. A red 'OK' button is located below these fields, labeled 8. Below the input fields, a line of text reads: '売り・買い注文の価格と注文数を入力してください。売り注文をしないときは売り注文数に「0(ゼロ)」を入力してください。(買い注文も同様)' (Please enter the price and order quantity for sell/buy orders. When you do not want to place a sell order, enter '0 (zero)' for the sell order quantity. (The same applies to buy orders)). Below this is a section for '株取引ゲーム 1回目 (全3回)' (Stock trading game 1st round of 3), labeled 9, showing '第 1 / 10 Period' (Period 1 / 10) and '取引価格の履歴' (History of transaction prices). At the bottom, there is a table with 11 columns: 'Game', 'Period 1', 'Period 2', 'Period 3', 'Period 4', 'Period 5', 'Period 6', 'Period 7', 'Period 8', 'Period 9', and 'Period 10'. The first row shows 'Game 1' and the rest of the cells are empty.

- (1) This shows the remaining time for entering your orders. The time limit to enter your order is 60 seconds. When the time has elapsed, a red warning message will flash at the top right corner of your screen. A period ends once everyone has pressed “OK”; note that this could be within the 60 second time limit.
- (2) This indicates your cash balance or the amount of money at your disposal; you may buy stocks up to this amount.
- (3) This shows the number of stocks you have. You may sell a maximum of this number of stocks.
- (4) This is where you enter the maximum price you are willing to pay to buy a stock in this period. You must enter a whole number between 1 and 2000.
- (5) Here you need to enter the maximum number of stocks that you want to buy in this period. If you do not want to purchase any stocks, enter 0. The product of (4) and (5) must be no greater than your cash balance shown in (2). An error message will appear if (the number of stocks you wish to buy) × (the maximum price you are prepared to pay for these) exceeds your cash balance.

In practice, the price you actually pay for a stock may not be the same as the maximum price you are willing to pay. This is because the market price is set based on all the orders placed by market participants. If the market price is greater than the maximum you are willing to pay, your order will not be processed. This will be further clarified at a later stage.

Please turn to the next page.

- (6) Here please enter the minimum price at which you would be prepared to sell your stocks in this period. You must enter a whole number between 1 and 2000. The price you enter here should not be greater than that given in (4).
- (7) This is where you should enter the number of stocks you want to sell in this period. If you do not want to sell any of your stocks, enter 0. The maximum number of stocks you can sell is the number of stocks you hold, as shown in (3). If the number of stocks you want to sell exceeds the number of stocks you hold, an error message will appear.

In practice, the price at which you sell a stock may not be the same as the minimum price at which you are willing to sell. This is because the market price is set based on all the orders placed by market participants. If the market price is lower than your minimum price, your order will not be processed. This will be further clarified at a later stage.

- (8) After entering appropriate values in (4)~(7), press the “OK” button. Once all market participants have pressed this button, the current period ends.
- (9) This table gives a history of the market prices. Thus, the cells after the current period are blank.

Before proceeding, the most important points in buying and selling stocks are summarized below.

- You can simultaneously place buy and sell orders, or you can place only a buy or a sell order. It is also possible not to submit any orders at all.
- If you do not want to submit a buy order, please enter 0 as the quantity to buy. If you do not want to submit a sell order, please enter 0 as the quantity to sell.
- The screen displays an error message, if any of the following conditions are violated:
 1. The maximum quantity to sell must be less than or equal to the number of units you hold.
 2. The maximum purchase price multiplied by the quantity to buy must be less than or equal to the cash you have available at the time.
 3. If you simultaneously place buy and sell orders, the maximum price at which to buy must be less than or equal to the minimum selling price.

Please turn to the next page.

[End of each period screen]

- (1) Market prices

The price is set according to the order book within your market. There is a single price for all stocks in each period. The price is set so as to equate the number of buy orders and sell orders.

We will explain how the market prices are set by using the following two examples.

[Example 1: how the market price is determined]

Consider the following buy/sell orders placed by four traders:

- Trader 1: One sell order, which can be executed at 10 Marks or higher
- Trader 2: Two sell orders, which can be executed at 40 Marks or higher
- Trader 3: One buy order, which can be executed at 60 Marks or lower
- Trader 4: One buy order, which can be executed at 20 Marks or lower

A graph summarizing these orders is shown below:



A seller is willing to sell at the price requested or higher. A buyer is willing to buy at the price specified or lower. As shown above, there is only one stock supplied at 10 Marks or higher. If the price rises to 40 Marks, the number of stocks supplied increases to three. On the other hand, only one stock is demanded at 60 Marks. If the price falls to 20 Marks, the quantity demanded increases to two. Therefore, the quantity demanded is equal to the quantity supplied at prices between 21 Marks and 39 Marks. The market price is set to the minimum price of this interval, i.e., 21 Marks.

Now let us consider the second example.

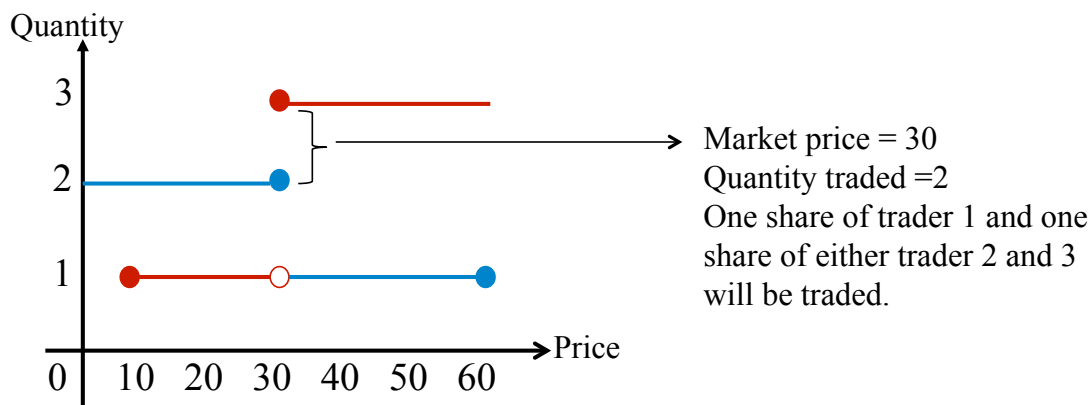
Please turn to the next page.

[Example 2: how the market price is determined]

Consider the following buy/sell orders placed by five traders:

- Trader 1: One sell order, which can be executed at 10 Marks or higher
- Trader 2: One sell order, which can be executed at 30 Marks or higher
- Trader 3: One sell order, which can be executed at 30 Marks or higher
- Trader 4: One buy order, which can be executed at 60 Marks or lower
- Trader 5: One buy order, which can be executed at 30 Marks or lower

A graph summarizing these orders is shown below:



As shown above, only one stock is supplied at 10 Marks or higher as in the previous example. If the price rises to 30 Marks, the number of stocks that are supplied increases to three. However, there is only one stock demanded at 60 Marks or lower. If the price falls to 30 Marks, the quantity demanded increases to two. As a result, two transactions can be completed at 30 Marks. In this case the market price is set to 30 Marks. Which orders will be fulfilled is determined as follows.

Priority is given to Trader 1, because he/she requested a price less than the market price. In addition to the order of Trader 1, the order of either Trader 2 or Trader 3 will be fulfilled. Which order is chosen is determined randomly by a computer.

[End of each period screen]

At the end of each period, the following screen is displayed, with the information described below.

⑦ 残り時間 [秒] 24

① 取引価格

0

② 今期(Period)購入した株の数

0

現在の所持金

392

③

④ 現在の保有株数

1

Next Value

108

⑤

取引価格の上下10%以内に入っていた予測の総数

0

⑥

⑧
CONTINUE

- (1) This shows the market price as explained previously.
- (2) A positive value denotes the number of stocks you have purchased in the current period, while a negative value denotes the number of stocks you have sold in the current period.
- (3) This shows your cash holding after the transactions and dividend payments have been processed for the current period.
- (4) This is the number of stocks you currently hold.
- (5) An explanation of *Next Value* is given on the next slide.

[Bonus/Unique]*

- (6) This is the number of predicted prices in the range between 90% and 110% of the market price. An explanation of this is given in the slide entitled: “Earning a profit by predicting future prices correctly”.
- (7) The remaining time (maximum of 30 seconds) that this screen will be visible is displayed here. After observing the information on the screen, press the “Continue” button (8). Once all of the participants have pressed this button, the computer will display the next screen.

Please turn to the next page.

[Earning returns from dividends]

In each game, there are ten periods in which you can submit your buy/sell orders and trade with other traders in your market. You will also be offered a dividend of 12 Marks per stock based on the number of stocks you have at the end of each period. Dividend income at the end of each period is calculated as: $12 \text{ Marks} \times (\text{number of stocks you hold})$.

[Next value]

As mentioned above, at the end of each period an amount is displayed as the “Next Value”. This amount depicts **the sum of the dividends** per stock that will be offered in the remaining periods. For example, consider *Next Value* at the end of the second period. There are 8 periods left. A dividend of 12 Marks per stock will be offered 8 times. Thus, *Next Value* is $12 \times 8 = 96$ Marks.

After period 10, a dividend is also paid according to your stock holdings. Your cash balance after payment of the dividend for period 10 is the final amount you will earn in the game.

Turn to the next page to see a table of *Next Values*. A copy of this table will be handed out separately from the instructions. You should refer to this copy during the experiment as necessary.

[<Jump to \[Summary of ways to make a profit\] in the instruction of NF treatment>](#)

* Since this item does not appear in NF treatments, the referred number of the remaining times in NF treatments is adjusted.

[Bonus/Unique]

[Earning a profit by predicting future prices correctly]

Before each period begins, you will be asked to predict the market prices in all the remaining periods. The following screen will appear. The time limit is 120 seconds. When the time limit is reached, a warning message to complete your prediction will flash in red in the upper right corner of your screen. The next period will begin when everyone has finished entering their predicted prices and has pressed “OK”; note that this may occur within the 120 second time limit.

Please turn to the next page.

[Prediction of future prices]

You will be asked to predict the prices for all the remaining periods before each period begins. In other words,

- before the beginning of period 1, there are ten remaining periods and therefore you must predict ten prices;
- before the beginning of period 2, there are nine remaining period and therefore you must predict nine prices;
- . . .
- before the beginning of period 10, only one period remains and therefore you must predict one price.

Thus, in total you will be making 55 predictions regarding market prices.

[Earning a profit by predicting future prices]

The computer will keep a record of the number of accurate predictions (that is, your predicted prices that were between 90% and 110% of the realized market price for each period).

At the end of each game you will be offered a bonus based on the number of accurate predictions according to the following formula: (your final cash balance) $\times$ 0.5% $\times$ (the number of accurate predictions). The maximum bonus percentage is $0.5\% \times 55 = 27.5\%$. Please be aware that since your final cash balance depends on earnings made from profit margins and dividends, the amount of the bonus decreases as earnings from profit margins and dividends decrease.

[NF]

[Summary of ways to make a profit]

There are two ways of making a profit: (1) earning a profit margin, and (2) earning returns from dividends. At the end of the experiment, your holdings of Mark in all the three games will be equivalently converted to Yen, and paid out to you.

[Bonus/Unique]

Please turn to the next page.

[Summary of ways to make a profit]

There are two ways of making a profit: (1) earning a profit margin and returns from dividends, and (2) predicting market prices.

[Bonus]

At the end of the experiment, your holdings of Mark in all the three games will be equivalently converted to Yen, and paid out to you.

[Unique]

At the end of each game, you are randomly given EITHER (1) earning a profit margin and returns from dividends, or (2) earning from prediction of market prices.

At the end of the experiment, your holdings of Mark in all the three games will be equivalently converted to Yen, and paid out to you.

In addition to the aforementioned rewards, you will be offered 500 yen as a payment for participating in the experiment.

[Finish instruction]

[Practice]

Now we will conduct a practice round so that you can familiarize yourself with the software. In particular, you will learn how to enter the required information. The first screen displayed is for the prediction of future prices. Press the “OK” button after you have entered all your price forecasts. The computer will display the order entry screen once everyone has pressed “OK”.

The practice round ends when everyone has pressed the “OK” button after entering their orders. Results of the practice round will not be displayed. Rewards do NOT take into consideration the practice round.

Let us get started with the practice round.

[Finish the practice round]

Now we will begin the experiment. You will participate in stock trading games with members from your group in an artificial stock market. Each group consists of six traders. 5 of 6 traders except you are the participants in this room. You will be given four stocks + 520 Marks at the beginning.

Let us begin the experiment!

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