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Diversity in cognitive ability and mispricing in experimental asset markets*

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Abstract

Does diversity of cognitive ability among market participants increase mispricing? Does common knowledge of heterogeneity in relation to cognitive ability of market participants further increase mispricing? We investigated these questions by measuring subjects' cognitive ability and categorizing those above median ability as type 'H' and those below median ability as type 'L'. We then constructed three market types, each containing six traders: 6H, 6L, and 3H3L. Subjects were informed of their own cognitive type and, depending on the treatment, that of the others in their market. We found that heterogeneous markets (3H3L) generated significantly larger mispricing than homogeneous markets (6H or 6L) regardless of whether subjects were informed about the cognitive type of others in their market. Thus, diversity of cognitive ability among market participants increased mispricing. However, common knowledge of heterogeneity or homogeneity in the market did not have a significant additional effect.

Keywords: Cognitive ability, Heterogeneity, Mispricing, Experimental asset markets

JEL Code: C90, D84

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1 Introduction

Economic bubbles are often characterized by market euphoria and an inflow of new and possibly naïve investors (Kindleberger and Aliber, 2005). Indeed, Lopez (2015) reports that a non-negligible fraction of new investors in China's stock market is unable to read, and for a majority of these new investors, junior high school is the highest level of education they have completed. Such an inflow of new investors can amplify heterogeneity among market participants regarding their belief about future prices of the asset being traded, as well as their naivety in terms of financial knowledge and trading behavior, and thus may increase mispricing, as noted by Xiong and Yu (2011) in their study of "bubbles" in a subset of China's warrant market.

Furthermore, several theoretical works (Allen and Gale, 1992; Aggarwal and Wu, 2006; Allen et al., 2006) build upon this idea and show how heterogeneity in terms of (strategic) sophistication among traders can lead to significant mispricing. Allen and Gale (1992), for example, show that sophisticated strategic traders try to generate an initial upward price trend to influence the belief of naïve trend followers and later profit from their naïveté.

Recent experimental studies have demonstrated the relationship between the cognitive abilities of subjects and mispricing in asset-market experiments *à la* Smith et al. (1988).[1] Breaban and Noussair (2015) and Cueva and Rustichini (2015) show that the average cognitive skill of subjects in the market is negatively correlated with the degree of mispricing observed in the market. Cognitive skills are measured by the Cognitive Reflection Test (CRT, Frederick, 2005) in the former and by the Raven's progressive matrices (RPM) test (see Raven, 2008, for an overview) and Race to X game (Gneezy et al., 2010; Dufwenberg et al., 2010) in the latter. Corgnet et al. (2015) and Cueva and Rustichini (2015) demonstrate that subjects with higher cognitive skills earn more than their counterparts with lower cognitive skills.

These experimental findings are in line with findings from empirical studies based on large-scale surveys that tend to report that people with high cognitive skills make better financial decisions (see, for example, Korniotis and Kumar, 2010, for a survey of the empirical

[1] See Palan (2013) and Powell and Shestakova (2016) for recent surveys of the literature. However, the body of literature is expanding very quickly, with many new papers being presented each year at the annual meeting of the Society of Experimental Finance. See `http://www.experimentalfinance.org/` for a list of papers presented at recent meetings.

literature).

However, the effect of interactions among traders with varying degrees of strategic sophistication has not been explicitly investigated to any great extent, either empirically or experimentally. The abovementioned experimental studies only relate cognitive skills and market outcomes ex post, and thus do not use cognitive skills as an experimental variable.[2] An exception is the study by Bosch-Rosa et al. (2015), who investigate how the average cognitive ability of market participants influences mispricing in an experimental market by creating markets based explicitly on the subjects' cognitive abilities measured ex ante. Bosch-Rosa et al. (2015) first conduct an experimental session consisting of the CRT, guessing games, and multiple rounds of the Race to 60 game to measure and create a composite index of the cognitive abilities of their subjects. Then, they select subjects from the top 30% ("high sophistication") and bottom 30% ("low sophistication") of their subject pool according to the index and conduct an asset-market experiment using markets consisting only of high-sophistication subjects or those consisting only of low-sophistication subjects. They report significant mispricing in the markets consisting only of low-sophistication subjects but almost no mispricing in those consisting only of high-sophistication subjects.

These experimental and empirical studies lead us to speculate that the mispricing observed in both experimental and real financial markets is primarily due to bad decision-making by naïve market participants, rather than by interactions (both strategic and non-strategic) among traders with varying degrees of cognitive sophistication. However, two recent experimental studies by Cheung et al. (2014) and Akiyama et al. (2015) have demonstrated that this might not be the whole story.

[2] There is an increasing number of experimental studies on games and individual decisions that use cognitive skills as an experimental variable. For example, in game theoretic settings, Gill and Prowse (2016) study a three-player p-beauty contest game by creating three types of groups based on the subjects' relative cognitive ability: an all-high-cognitive-ability group, an all-low-cognitive-ability group, and a mixed group. They find that subjects with higher cognitive ability are faster at learning to choose numbers close to the Nash equilibrium, and thus earn more. They also find that those with high cognitive ability respond to the cognitive ability of their counterparts, while those with low cognitive ability do not. Another recent game theoretic work is that of Proto et al. (2016). They study the evolution of cooperation in repeated games while varying the cognitive ability of groups and find that, although the initial levels of cooperation are similar, groups with high cognitive ability learn to achieve high or full cooperation, while cooperation declines in groups with low cognitive ability. Regarding studies on individual decision-making, Dohmen et al. (2010), in their study using a German sample, find that subjects with higher cognitive ability take more calculated risks and are more patient. Oechssler et al. (2009) study the relationships between CRT scores and various behavioral biases such as the conjunction fallacy and conservatism in updating probabilities, as well as time and risk preferences. They find similar relationships between CRT scores and risk and time preferences to those found by Dohmen et al. (2010), as well as a negative correlation between CRT scores and the incidence of the two biases.

Cheung et al. (2014) investigate the effect of a lack of common knowledge in terms of subjects' understanding of the fundamental value (FV) of the asset being traded. They train some of their subjects extensively about the FV of the asset before the experiment, and then compare the degree of mispricing in three types of markets: (1) everyone is trained and knows that everyone else is also trained, (2) everyone is trained but no one knows that everyone else is also trained, and (3) no one is trained. The results show that the degree of mispricing is small only when everyone is trained and it is common knowledge. When it is not common knowledge that everyone is trained, the mispricing is as large as that in the market where no one is trained.

Akiyama et al. (2015) investigate how the presence of uncertainty about the behavior of others in the market influences long-term price forecasts by comparing the price forecasts in two market environments: one in which one subject interacts with computer traders with known behavior, and another in which subjects interact among themselves. They find that the subjects' initial long-term forecasts deviate further from FV in the former case than in the latter. Furthermore, subjects with a perfect CRT score react more strongly to the presence of uncertainty about the behavior of others in the market (where they interact with other subjects) than those with lower CRT scores by forecasting future prices that deviate further from the FV compared with the market without such uncertainty (where they interact with computer traders with known behavior).

Because diversity (or heterogeneity) in cognitive ability among market participants can be an important source of heterogeneous belief about future prices, as well as behavioral uncertainty in cases where the heterogeneity is common knowledge, these two experimental studies hint at the possibility that such diversity can indeed amplify the mispricing of the asset being traded. Therefore, in this paper, we investigate *whether heterogeneity in cognitive ability among market participants increases mispricing.* In addressing this question, we also investigate the relationship between the average cognitive ability of market participants and the degree of mispricing. Furthermore, we ask *whether common knowledge of heterogeneity (or homogeneity) in cognitive ability among market participants further increases mispricing.* The latter question is motivated by the theoretical literature on strategic manipulation cited above. We conjecture that knowing that naive traders are present in the market creates an opportunity for more sophisticated traders to manipulate prices, and thus increases mispricing.

We approach these research questions by first measuring subjects' cognitive ability using a part of the advanced version of the RPM test,[3] and then grouping subjects based on their relative RPM test scores within an experimental session. That is, subjects with an RPM score above the median are labeled H types and those with an RPM score below the median are labeled L types. We consider three types of markets: those consisting solely of H types, those consisting solely of L types, and those consisting of equal numbers of H and L types. By comparing the outcomes of these three types of markets, we investigate the influence not only of the average cognitive ability of market participants, but also of diversity in cognitive ability on market outcomes. Furthermore, we investigate the impact of subjects being informed about the composition of the market participants on market outcomes by conducting experiments wherein the subjects either are or are not informed about the composition of the market in which they participate. Our main aim is to investigate the effect of heterogeneity of cognitive ability among market participants by creating markets that mix both high- and low-sophistication subjects, which is an aspect that Bosch-Rosa et al. (2015) do not address.

We found that heterogenous markets, i.e., markets consisting of an equal number of H- and L-type subjects, showed a greater degree of mispricing than the two homogeneous markets, i.e., those consisting solely of either H- or L-type subjects, regardless of whether the composition of the market was ex ante known or otherwise. Our results showed that not only the average cognitive ability of market participants but also their heterogeneity, regardless of whether that heterogeneity is ex ante known or otherwise, increases mispricing. However, we did not find any significant difference in terms of mispricing between treatments with and without subjects being ex ante informed about the composition of the market. Thus, we did not observe any significant additional effect of common knowledge of cognitive heterogeneity on mispricing beyond the effect of the existence of cognitive heterogeneity.

[3]The RPM test measures what is called "fluid intelligence," that is, "the capacity to think logically, analyze and solve novel problems, independent of background knowledge" (Mullainathan and Shafir, 2013, p. 48) and its score has been shown to be correlated to the degree of strategic sophistication, which is measured in terms of the number of wins in Race to 5, 10, and 15 games (Carpenter et al., 2013) or the deviation from the equilibrium in a three-player p-beauty contest game (Gill and Prowse, 2016). "Fluid intelligence" should be distinguished from what is called "executive control." The latter is the ability to control one's impulsive behavior or responses. Thus, the CRT score can be interpreted as a measure of one's executive control, not their fluid intelligence.

2 Experiment

In each session involving 24 subjects, we first asked the subjects to complete a part of the advanced version of the RPM test (24 questions to be answered in 15 minutes).[4] We did not tell our subjects why they were required to complete the test (which we termed a quiz during the experiment), nor what kind of experiments would follow. Thus, our subjects were unaware that their scores on the RPM test would be used to place them into different groups in an asset market experiment. In accordance with standard practice in administering the RPM test, we did not offer any monetary incentives to our subjects for answering as many questions as possible correctly.

Following the RPM test, we divided our subjects into two types based on their scores on the RPM test. Those above the median score were termed 'H type' and those below the median score were termed 'L type'. We then created three versions of a 20-period call asset market with six traders in each market: in version one, all six traders were H type (6H markets); in version two, all six traders were L type (6L markets); and in version three, there were equal numbers of H and L types (3H3L markets). In one experimental session using our 24 subjects, we created two 6H markets and two 6L markets, and in another session, we created four 3H3L markets.[5] In all of our treatments, we informed our subjects of their own type (H or L), but not how many quiz questions they had answered correctly.

To investigate the effect of (1) the composition of the market participants (in terms of their relative cognitive ability) and (2) the fact that the composition was known to the market participants, we considered two information treatments. In half of our treatments, we did not inform our subjects of the composition of their market (unknown composition), while in the other half, we informed them of the composition (known composition). Therefore, in the unknown composition treatment, subjects were only informed of their own type, H or L, but not the type of the five other traders in their market.[6] In the known composition

[4]The full advanced version of the RPM test consists of 48 questions to be answered in 30−40 minutes. We used all of the odd-numbered questions from the full test, retaining the original order to ensure that the questions became progressively more difficult.

[5]Groups were created according to the rankings on the RPM test of the participants in that session. In the 24-subject 6H and 6L session, the first 6H market consisted of subjects with rankings of $\{1, 3, 5, 7, 9, 11\}$ and the second consisted of subjects with rankings of $\{2, 4, 6, 8, 10, 12\}$, while the first 6L market consisted of subjects with rankings of $\{13, 15, 17, 19, 21, 23\}$ and the second consisted of subjects with rankings of $\{14, 16, 18, 20, 22, 24\}$. For the 3H3L markets, we established four markets that consisted of subjects with rankings of $\{1, 5, 9, 13, 17, 21\}$, $\{2, 6, 10, 14, 18, 22\}$, $\{3, 7, 11, 15, 19, 23\}$, and $\{4, 8, 12, 16, 20, 24\}$. In cases where subjects had identical scores, rankings were assigned randomly.

[6]We informed our subjects in the unknown composition treatment as follows. At the beginning of the

treatment, if an H-type subject was in a 6H market, s/he was informed that s/he was H type and all of the other five traders in the market were also H type. If an H-type subject was in a 3H3L market, s/he was informed that s/he was H type and that the other five traders consisted of two H-type traders and three L-type traders. Similarly, if an L-type subject was in a 6L market, s/he was informed that s/he was L type and all of the other five traders in the market were also L type.[7]

In all of the markets, traders are initially given four units of the asset and 1040 experimental currency units (ECUs), which they can use to trade over 20 periods. Each unit of the asset pays a dividend of 12 ECUs at the end of each period, which is added to traders' cash holdings and can be used for trading in future periods. After the final dividend payment at the end of period 20, all of the assets lose their value. Under these conditions, the FV of a unit of the asset during period t ($t = 1, 2, ..., T$), FV_t, is the sum of the remaining dividend payments, that is, $FV_t = 12(21 - t)$. For example, a unit of the asset has an initial value of 240 ECUs. Thus, the value of the initial endowment is 2000 ECUs for all of the market participants (1040 ECUs in initial currency plus 960 ECUs for the four units of the asset). We have eliminated uncertainty in dividend payments to minimize the presence of uncertainty beyond that caused by the behavior of market participants. Even with fixed and known dividend payments, mispricing has been observed in these markets (Porter and Smith, 1995; Akiyama et al., 2014, 2015).

We employ a call market mechanism, as in van Boening et al. (1993); Haruvy et al. (2007); Akiyama et al. (2014, 2015), instead of a continuous double auction as used in many

asset-market experiment, we told them that "You have been divided into the top 12 scorers and the bottom 12 scorers out of the 24 people who completed the quiz. Before starting the game, you will know what your rank is, i.e., the top 12 or the bottom 12. The 24 people in the room are divided into four groups of six." We displayed each subject's type (H or L) on the first screen presented to them during the asset-market experiment.

[7]More specifically, we informed subjects in the known composition treatment as follows. (1) At the beginning of the asset-market experiment, we stated, in the 6H and 6L treatments, that "You have been divided into the top 12 scorers and the bottom 12 scorers out of the 24 people who completed the quiz. Before starting the game, you will know what your rank is, i.e., the top 12 or the bottom 12. The 24 people in the room have been divided into four groups of six. Two of the four groups consist of the top 12 scorers and the other two groups consist of the bottom 12 scorers." In the case of the 3H3L markets, the last sentence of the statement read, "Each of the four groups consists of three top scorers and three bottom scorers." (2) At the end of the instruction, we repeated the same information. In the 6H or 6L treatments, we advised subjects that "There are six people in each market. All of those people are in this room. Each group consists entirely of either the top scorers or the bottom scorers in the quiz. Your ranking, in either the top or the bottom half, is shown on the first screen." In the case of the 3H3L treatment, the third sentence was "Each group consists of three people who scored in the top half and three who scored in the bottom half in the quiz." See the Appendix for an English translation of the instructions, as well as examples of the first screen displayed in the asset-market experiment, in which the subjects' type and group composition were displayed.

other studies. In our call market, in each period, each trader can submit at most one buy order and one sell order.[8] An order consists of a pair of values: a price and a quantity. When submitting a buy order in period t, trader i must specify the *maximum price*, b_t^i, at which s/he is willing to buy a unit of the asset, and the *maximum quantity*, d_t^i, s/he is willing to buy at that price. In the same manner, when submitting a sell order in period t, trader i must specify the *minimum price*, a_t^i, at which s/he is willing to sell a unit of the asset, and the *maximum quantity*, s_t^i, s/he is willing to sell at that price. We attach three constraints: the admissible price range, a budget constraint, and the relationship between b_t^i and a_t^i in the case where a subject submits both buy and sell orders. The admissible price range is set so that when $d_t^i \geq 1$ ($s_t^i \geq 1$), b_t^i (a_t^i) must be an integer between 1 and 2000, i.e., $b_t^i \in \{1, 2, ..., 2000\}$ ($a_t^i \in \{1, 2, ..., 2000\}$). The budget constraint simply means that neither borrowing of cash nor short selling of an asset is allowed.[9] The final constraint is that when a trader is submitting both buy and sell orders, i.e., $d_t^i \geq 1$ and $s_t^i \geq 1$, the maximum buying price must not be greater than the minimum selling price, i.e., $a_t^i \geq b_t^i$. Once all of the traders in the market have submitted their orders, the price that clears the market is calculated,[10] 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.[11]

The entire experiment was computerized using z-Tree (Fischbacher, 2007). Each session lasted for about one and a half hours, including a post-experiment questionnaire. We also administered the CRT as a part of the post-experiment questionnaire, with no monetary incentive for correct answers. On average, subjects earned 3000 yen ($\approx$ 22 euros at the average exchange rate prevailing during the period of the experiment), including a 1000-yen participation fee. See the Appendix for an English translation of the instructions.

[8]Of course, a trader can choose not to submit any orders by specifying zero as the quantities to buy and sell. We imposed a 60-second, non-binding time limit for submitting orders. When the time limit is reached, the subjects are instructed via a flashing message in the upper right corner of their screen to submit their orders as soon as possible.

[9]Thus, the budget constraint implies (i) $d_t^i \times b_t^i \leq$ cash holding at the beginning of the period t, and (ii) $s_t^i \leq$ units of asset on hand at the beginning of the period t.

[10]Following the previous experiments (Haruvy et al., 2007; Akiyama et al., 2014, 2015), when there are several such prices, the lowest one is chosen as the market clearing price. This is important to ensure that the price does not rise in the absence of transactions at the market clearing price.

[11]Any 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.

Table 1: Summary of treatments

Treatment	No. of subjects	No. of markets
Unknown composition, 6H	48	8
Unknown composition, 6L	48	8
Unknown composition, 3H3L	48	8
Known composition, 6H	72	12
Known composition, 6L	72	12
Known composition, 3H3L	72	12

3 Results

The experiment was conducted at Waseda University in Tokyo, Japan between November 2014 and July 2016. A total of 360 subjects participated; 144 subjects in unknown composition treatments, of which 96 participated in 6H/6L sessions and 48 participated in 3H3L sessions, and 216 subjects in known composition treatments, of which 144 participated in 6H/6L sessions and 72 participated in 3H3L sessions. Subjects were recruited from the main university campus via emails and flyers. These subjects had never participated in a similar experiment before, and each subject only participated in one session. Therefore, we had eight markets for the unknown composition treatment and 12 markets for the known composition treatment, each market comprising six subjects. Table 1 summarizes the treatments and the number of subjects participating in each treatment.

Figure 1 shows the empirical cumulative distributions of the scores from the RPM test (RPM scores) for the participants in the unknown composition (left) and known composition (right) treatments. In each panel, three types of markets are shown separately: 6H (thick, solid red line), 6L (thick, dashed blue line), and 3H3L (thin black line). By construction, the empirical cumulative distribution of the RPM scores is in the order 6L, 3H3L, and 6H from left (lowest) to right (highest). The distribution of RPM scores between unknown and known composition treatments are not statistically significantly different for each of the market types (p-values are 0.123 for 6H markets, 0.592 for 6L markets, and 0.22 for 3H3L markets according to a two-sample permutation test (PT), two-tailed).

The results from the previous studies mentioned in the Introduction suggest a negative relationship between the average level of cognitive ability among traders and mispricing in markets. If the diversity (or heterogeneity) of cognitive ability among traders does not have

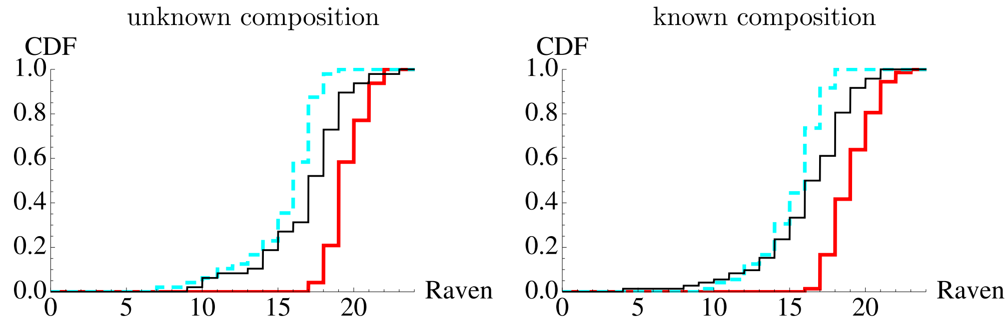


Figure 1: Distribution of scores from the RPM test in 6H (thick, solid black line), 6L (thick, dashed gray line), and 3H3L (thin black line) markets in the unknown composition treatment (left) and the known composition treatment (right). For the unknown composition treatment, there are 48 subjects in each of the 6H, 6L, and 3H3L groups. For the known composition treatment, there are 72 subjects in each of the 6H, 6L, and 3H3L groups. The highest score obtainable is 24.

a strong effect on the magnitude of mispricing, then we would expect larger mispricing in 6L markets than in 3H3L markets and in 3H3L markets than in 6H markets. Conversely, if the diversity has a significant effect, we should observe a larger mispricing in the 3H3L markets than in the two homogeneous markets.

3.1 Prices

Figure 2 shows the observed price dynamics from the unknown (top) and known (bottom) composition treatments. The three types of markets, 6H (left), 3H3L (center), and 6L (right), are shown separately. The results for the three types of markets look very similar, regardless of whether the compositions of cognitive types within a market are ex ante known or not. In both the unknown and known composition treatments, while prices follow FV very closely in most of the 6H and 6L markets, they deviate substantially from FV in the 3H3L markets.

To systematically analyze the magnitude of mispricing in various markets, we employ the relative absolute deviation (RAD) proposed by Stöckl et al. (2010). For each market m, the RAD is defined as

$$RAD^m = \frac{1}{20} \sum_{p=1}^{20} \frac{|P_p^m - FV_p|}{|\overline{FV}|}, \tag{1}$$

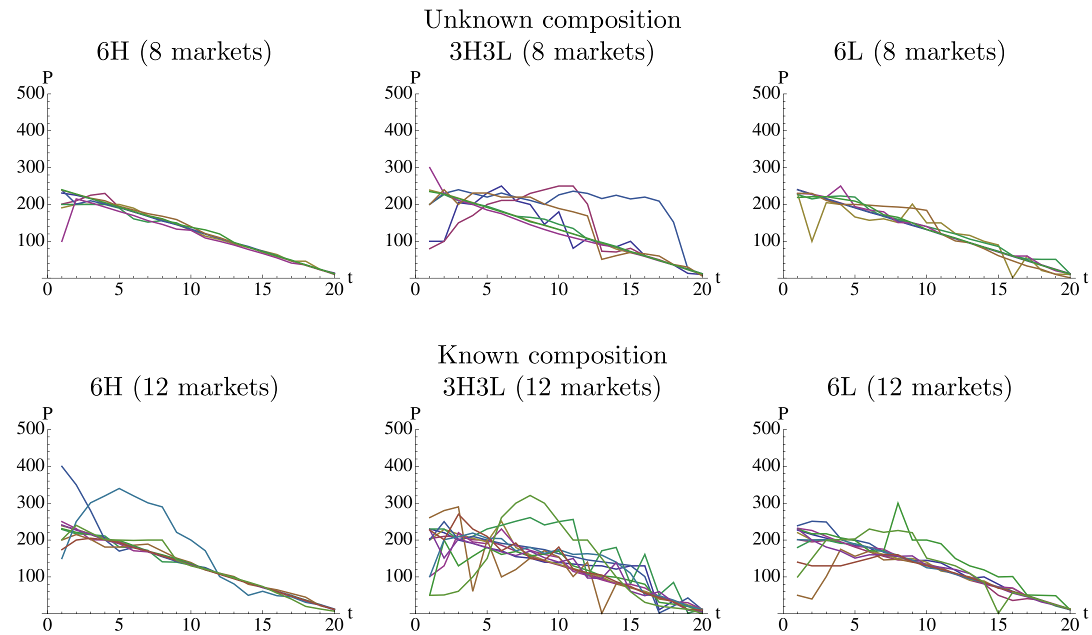


Figure 2: Realized price dynamics in unknown (top) and known (bottom) composition treatments for three market types: 6H (left), 3H3L (center), and 6L (right).

where P_p^m is the realized price in period p in market m, FV_p is the FV of the asset in period p, and $|\overline{FV}| = |\frac{1}{20}\sum_{p=1}^{20} FV_p|$. We supplement the analysis by computing the positive and negative deviations separately. That is, we define, relative positive deviation (RPD) and relative negative deviation (RND) as follows:[12]

$$RPD^m = \frac{1}{20}\sum_{p=1}^{20}\frac{\max(P_p^m - FV_p, 0)}{|\overline{FV}|} \tag{2}$$

$$RND^m = \frac{1}{20}\sum_{p=1}^{20}\frac{\max(FV_p - P_p^m, 0)}{|\overline{FV}|}. \tag{3}$$

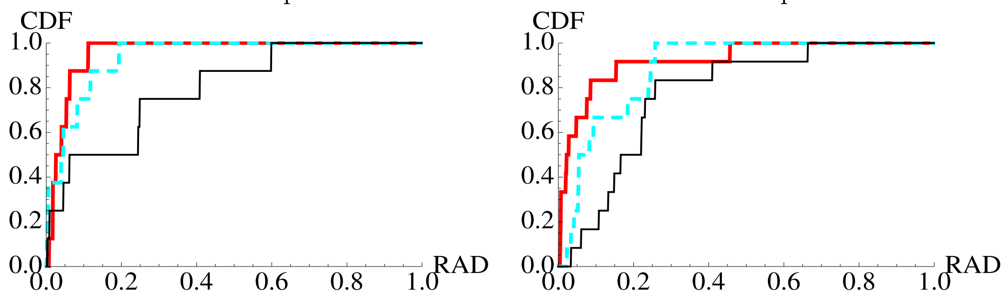
Figure 3 shows the empirical cumulative distribution function (CDF) of the RAD (top), RPD (middle), and RND (bottom) observed in unknown (left) and known (right) composition treatments.[13] In each panel, the outcomes from three types of markets are shown: 6H (thick, solid red line), 6L (thick, dashed blue line), and 3H3L (thin black line).

As could be expected from the price dynamics shown in Figure 2, the distribution of the

[12]RPD and RND are defined based on the positive and negative deviations often used in the literature. We call them relative deviations because we normalize them by $20|\overline{FV}|$ to ease the comparison with RAD.
[13]See Appendix A for the values of these measures for each market.

Relative Absolute Deviation (RAD)

unknown composition | known composition

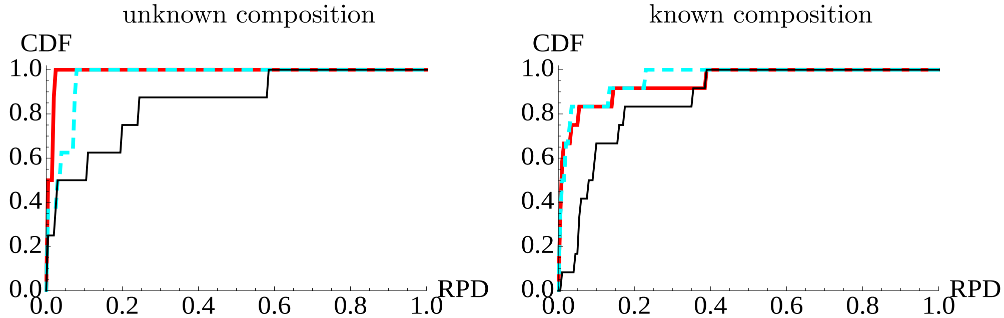


	6L	3H3L
6H	0.504	0.055
6L		0.098

	6L	3H3L
6H	0.440	0.021
6L		0.057

Relative Positive Deviation (RPD)

unknown composition | known composition

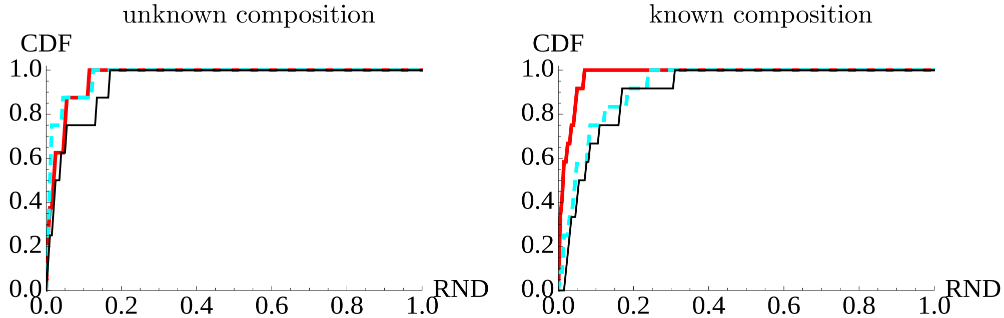


	6L	3H3L
6H	0.064	0.025
6L		0.117

	6L	3H3L
6H	0.716	0.140
6L		0.033

Relative Negative Deviation (RND)

unknown composition | known composition



	6L	3H3L
6H	0.699	0.373
6L		0.248

	6L	3H3L
6H	0.015	0.002
6L		0.595

Figure 3: Empirical cumulative distribution of RAD (top), RPD (middle), and RND (bottom) in unknown (left) and known (right) composition treatments. In each panel, the outcomes from three types of markets are shown: 6H (thick, solid red line), 6L (thick, dashed blue line), and 3H3L (thin black line). The table below each panel reports the p-values from pair-wise comparisons based on two-sample PTs, two-sided.

RAD from the 3H3L markets lies to the right of those from the 6H and 6L markets in both unknown and known composition treatments. The pair-wise comparisons show that the RAD in the 3H3L markets is significantly greater than those in the 6H and 6L markets (p-values are 0.055 for 6H vs 3H3L markets and 0.098 for 6L vs 3H3L markets in the unknown composition treatment, and 0.021 for 6H vs 3H3L markets and 0.057 for 6L vs 3H3L markets in the known composition treatment, according to two-sample PTs, two-tailed). The RAD does not differ significantly between the two homogeneous markets, 6H and 6L (p-values are 0.504 and 0.440 for the unknown and known composition treatments, respectively, according to two-sample PTs, two-tailed).

Similar results are obtained for the RPD, but not for the RND. The RPD from the 3H3L markets lies to the right of those from the 6H and 6L markets in both the known and unknown composition treatments, although the RPDs are no longer statistically significantly different between the 3H3L and 6L markets in the unknown composition treatment or between the 3H3L and 6H markets in the known composition treatment at the 10% level. The distributions of the RNDs observed in the three types of markets in the unknown composition treatment are almost aligned. For the known composition treatment, the RND in the 6H markets is significantly smaller than that in both the 6L and 3H3L markets. The distributions of the RNDs in the latter two markets are aligned. This suggests that the significantly larger mispricing in the 3H3L markets compared with that in the 6H and 6L markets is mainly the result of positive deviations.

Is there a significant effect of ex ante common information about the composition of cognitive types within markets on the degree of mispricing? Contrary to our expectations, we did not find such an effect. For each market type, the RADs and RPDs are not significantly different for the two information treatments (p-values are 0.629 for 6H, 0.175 for 6L, and 0.846 for 3H3L markets, two-sample PT, two-tailed for RAD. For RPD, they are 0.258, 0.947, and 0.788, for 6H, 6L, and 3H3L markets, respectively). The RND for the 6L markets is significantly different at the 10% level (p=0.093, PT) for the two information treatments, but not for the 6H and 3H3L markets (p=0.457 and p=0.318, respectively). Therefore, informing the subjects about the composition of the market in terms of the cognitive type (H or L) of other participants does not have a significant effect on the degree of mispricing.

The small mispricing in the 6L markets might seem surprising in light of the existing literature that has demonstrated systematically larger mispricing for markets that consist of subjects with low cognitive ability. However, it should be noted that our experiment is much simpler than other studies in that there is no uncertainty regarding the amount of the dividend payment. Furthermore, the cognitive ability of subjects in our 6L markets is still high in relation to the overall pool of experimental subjects. One of the authors has administered a shorter version of the advanced RPM test (16 questions to be answered in 10 minutes) in various experimental laboratories and found that, unsurprisingly, the distributions of the scores vary greatly across laboratories. The distribution of scores obtained by our subjects recruited at Waseda University is the highest among all subject pools for which data are available. Thus, the low level of mispricing in the 6L markets is, in addition to our simple structure regarding dividend payments, likely due to our particular subject pool.

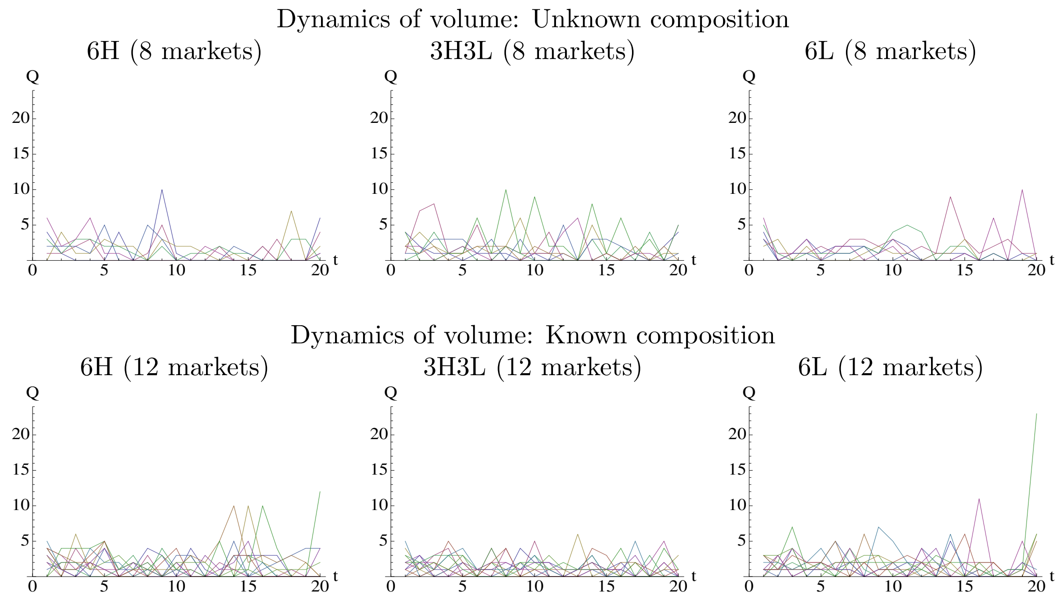
However, the larger mispricing observed in the 3H3L markets compared with the two homogeneous markets (6H and 6L) is very surprising in light of the above remark about the pool of subjects we are dealing with, as well as our simple dividend payment process. Below, we provide further analyses with the aim of better understanding this result.

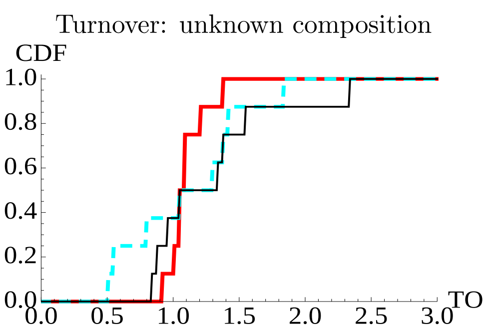
3.2 Trading volumes and volume-adjusted mispricing

The top two panels in Figure 4 show the observed dynamics of trading volume from the unknown (top) and known (middle) composition treatments. The three types of markets, 6H (left), 3H3L (center), and 6L (right), are shown separately for each treatment. While the trading volumes seem to be higher in the 3H3L markets than in the 6H and 6L markets for the unknown composition treatment, the opposite seems to be the case for the known composition treatment. We also note that in many markets, there are periods with zero transactions.[14]

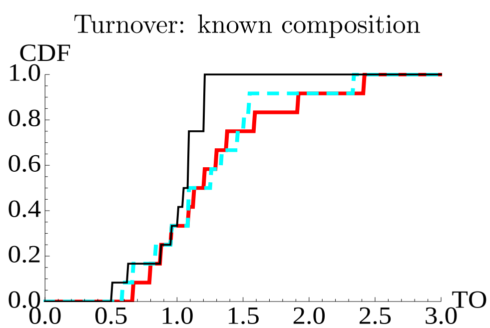
The bottom panel in Figure 4 shows the empirical cumulative distribution of turnover, $\sum_p Q_p^m/24$, where Q_p^m is the realized trade volume in period p of market m. It can be seen that there is no statistically significant difference across the three types of markets in the two information treatments, except for the 6H and 3H3L markets in the known composition treatment. Furthermore, except for the 3H3L markets, there are no statistically significant

[14] Our price determination procedure returns a price even in the absence of transactions.



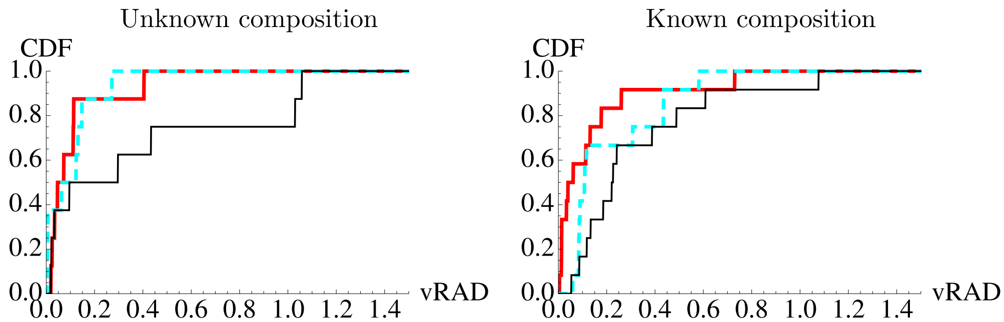


	6L	3H3L
6H	0.994	0.369
6L		0.464



	6L	3H3L
6H	0.779	0.088
6L		0.152

Figure 4: Top: realized trade volume dynamics in unknown (top) and known (bottom) composition treatments. Three types of markets are shown: 6H (left), 3H3L (center), and 6L (right). Bottom: empirical cumulative distribution of turnover in unknown (left) and known (right) composition treatments. In each panel, three market types are shown: 6H (thick, solid red line), 6L (thick, dashed blue line), and 3H3L (thin black line). The table below each panel reports the p-values from pair-wise comparisons based on two-sample PTs, two-sided.



Unknown composition:

	6L	3H3L
6H	0.871	0.147
6L		0.109

Known composition:

	6L	3H3L
6H	0.357	0.080
6L		0.290

Figure 5: Distribution of $vRAD$ in unknown (left) and known (right) composition treatments. In each panel, three market types are shown: 6H (thick, solid red line), 6L (thick, dashed blue line), and 3H3L (thin black line). The table below each panel reports the p-values from pair-wise comparisons based on two-sample PTs, two-sided.

differences in turnover between the two information treatments (p-values are 0.367, 0.592, and 0.095 for the 6H, 6L, and 3H3L markets, respectively).

It is possible that the significantly larger mispricing we observed in the heterogeneous markets (3H3L) compared with the homogeneous markets (6H and 6L) is the result of mispricing that only occurred when the trading volume was zero or very low. If this is the case, the straight measure of mispricing, RAD, that we have considered above overrepresents the degree of mispricing. To address this potential problem, we define the volume-adjusted RAD for market m, $vRAD^m$, as follows:

$$vRAD^m = \frac{1}{20} \sum_{p=1}^{20} Q_p^m \left(\frac{|P_p^m - FV_p|}{|\overline{FV}|} \right). \tag{4}$$

Figure 5 shows the empirical cumulative distributions of $vRAD$ in unknown (left) and known (right) composition treatments. In each panel, three market types are shown: 6H (thick, solid red line), 6L (thick, dashed blue line), and 3H3L (thin black line). However, these distributions are ordered in a similar manner to those of RAD shown in Figure 3 above. For the unknown composition treatment, the distributions of $vRAD$ for the two homogeneous markets are almost aligned, while that for the 3H3L markets lies to the right of them. For the known composition treatment, the distribution of $vRAD$ for the 6H markets lies to the left of that for the 6L markets, which in turn lies to the left of that for the 3H3L markets. As in the case with RAD, there is no statistically significant difference in $vRAD$ between the two information treatments in each market type (p-values are 0.833 for 6H, 0.116 for 6L, and 0.728 for 3H3L markets based on two-sample PTs, two-tailed).

However, unlike the case of RADs, $vRAD$s are no longer statistically significantly different between the heterogeneous markets and the homogeneous markets, except between 3H3L and 6H markets with known composition (p-values are 0.080 for 6H vs 3H3L markets, 0.290 for 6L vs 3H3L markets, and 0.357 for 6H vs 6L markets for the known composition treatment, and 0.147 for 6H vs 3H3L markets, 0.109 for 6L vs 3H3L markets, and 0.871 for 6H vs 6L markets for the unknown composition treatment based on two-sample PTs, two-tailed). This suggests that the mispricing in periods with zero or a low number of transactions does indeed explain a part of the larger mispricing in the heterogeneous market compared with the homogeneous market, but that is not the whole story.

Note, however, that if we pool the known and unknown composition treatments (because there is no statistically significant difference between the two treatments in any of the three types of markets), the $vRAD$s for the 3H3L markets are significantly greater than those for the 6H and 6L markets (p-values are 0.014 for 6H vs 3H3L markets, 0.043 for 6L vs 3H3L markets, and 0.445 for 6H vs 6L markets).

3.3 Gender composition

In our analyses above, we have not controlled for the possible effects of gender composition on mispricing. Eckel and Füllbrunn (2015) found that experimental asset markets with a larger proportion of female subjects experienced smaller mispricing. Cueva and Rustichini (2015) compared all-female, all-male, and mixed-gender markets and found that the mixed-gender markets resulted in smaller mispricing than the other two types of markets. In this subsection, we report the results of linear regression analyses investigating the relationship between the cognitive ability of market participants and the degree of mispricing while controlling for gender composition. Because we found no significant differences between known and unknown composition treatments, we pooled the data from these two treatments for the following analyses.

The dependent variables are the four mispricing measures we considered above: RAD, RPD, RND, and $vRAD$. The independent variables are the mean and standard deviation

Table 2: Descriptive statistics

Variable	No. Obs	Mean	Std. Dev.	Min	Max
RAD	60	0.124	0.145	0.002	0.664
RPD	60	0.071	0.115	0	0.583
RND	60	0.052	0.063	0	0.309
vRAD	60	0.208	0.257	0.003	1.077
mCRT	60	2.019	0.483	0.667	3
sdCRT	60	0.975	0.293	0	1.506
mRPM	60	16.967	1.857	14	20.333
sdRPM	60	2.157	0.982	0.632	5.404
gender	60	4.167	1.107	2	6
gender^2	60	18.567	9.101	4	36

of the CRT scores of subjects in the market (mCRT and sdCRT), the mean and standard deviation of the RPM scores of subjects in the market (mRPM and sdRPM), and the number of male subjects (out of 6) in the market and its square (gender and gender^2). We have included the squared term of the gender composition to capture the nonlinear effect of the gender composition reported by Cueva and Rustichini (2015). Table 2 summarizes the descriptive statistics for these variables.

We consider both CRT and RPM scores because these two tests capture different aspects of the subjects' abilities. It should be noted, however, that the CRT and RPM scores are positively correlated in our data (the correlation coefficients are 0.40 for the mean and 0.15 for the standard deviation). Therefore, we also report the results of regressions that have either CRT or RPM scores, but not both. However, because the results of the estimation using either CRT or RPM scores are similar to those of the estimation including both CRT and RPM scores, we only comment on the results of the estimation that includes both scores.

Table 3 shows the results. Let us look at the results for RAD, the main mispricing measure we consider. The mean CRT score, but not its standard deviation, is negatively and significantly correlated with the RAD. This is consistent with previous findings (such as those of Breaban and Noussair, 2015). Conversely, the standard deviation of the RPM score, but not its mean, is positively and significantly correlated with the RAD, as reported above. We also find that the larger the number of male subjects in the market, the higher the RAD becomes, as in Eckel and Füllbrunn (2015). Furthermore, as we can see from the negative and significant coefficient of gender^2, the marginal effect of additional male subjects on the RAD decreases with the number of male subjects in the market. The magnitudes

Table 3: Results of linear regression

	Dependent variables											
	RAD			RPD			RND			vRAD		
mCRT	-0.111***		-0.103**	-0.053		-0.037	-0.058***		-0.065***	-0.191**		-0.173**
	(0.042)		(0.041)	(0.033)		(0.033)	(0.019)		(0.018)	(0.077)		(0.074)
sdCRT	0.042		0.032	0.095*		0.078	-0.053*		-0.046	0.045		0.027
	(0.066)		(0.067)	(0.053)		(0.055)	(0.029)		(0.029)	(0.122)		(0.121)
mRPM	0.020	0.004		0.024**	0.012		-0.004	-0.008		0.030	0.005	
	(0.013)	(0.012)		(0.010)	(0.010)		(0.006)	(0.006)		(0.023)	(0.023)	
sdRPM	0.049**	0.044*		0.043**	0.039**		0.006	0.005		0.062	0.538	
	(0.022)	(0.023)		(0.017)	(0.018)		(0.010)	(0.010)		(0.040)	(0.042)	
gender	0.210*	0.19	0.170	0.196**	0.187**	0.154*	0.012	0.003	0.016	0.409**	0.379*	0.355*
	(0.108)	(0.116)	(0.109)	(0.087)	(0.092)	(0.090)	(0.048)	(0.052)	(0.047)	(0.200)	(0.211)	(0.198)
$gender^2$	-0.027**	-0.026*	-0.022*	-0.025**	-0.024**	-0.020*	-0.002	-0.001	-0.003	-0.050**	-0.048*	-0.044*
	(0.013)	(0.014)	(-0.013)	(0.011)	(0.011)	(0.011)	(0.006)	(0.006)	(0.006)	(0.024)	(0.026)	(0.024)
Const	-0.499	-0.361	0.003	-0.773**	-0.554*	-0.207	0.271*	0.190	0.209*	-0.867	-0.682	-0.130
	(0.361)	(0.360)	(0.243)	(0.290)	(0.287)	(0.199)	(0.160)	(0.161)	(0.106)	(0.668)	(0.657)	(0.441)
R^2	0.273	0.136	0.203	0.256	0.135	0.157	0.252	0.107	0.217	0.211	0.093	0.172
N. Obs.	60	60	60	60	60	60	60	60	60	60	60	60

[i] Standard errors are in parentheses.
[ii] Gender: number of male subjects (out of 6) in the market.
[iii] ***, **, and * signify statistical significance at the 1%, 5%, and 10% level, respectively.

of the estimated coefficient of gender and its squared term show that there is an inverse-U-shaped relationship between the number of male subjects in the market and the extent of mispricing, as in Cueva and Rustichini (2015).

The results are similar for the RPD, the differences from the results in relation to the RAD being that the mean CRT score loses its statistical significance, while the mean RPM scores and the standard deviation of CRT scores become statistically significant. The standard deviation of RPM scores remains positively significantly correlated with the RPD.[15] Thus, even after controlling for the potential effects of gender composition, the heterogeneity in cognitive ability among market participants increases the mispricing, especially the positive deviation in prices from FV.

The results are quite different for the RND. For the RND, either the mean or the standard deviation of the RPM scores is statistically significant. Further, the gender composition (both the term and its square) is not statistically significant. However, the mean CRT score is significantly negative in this regression.

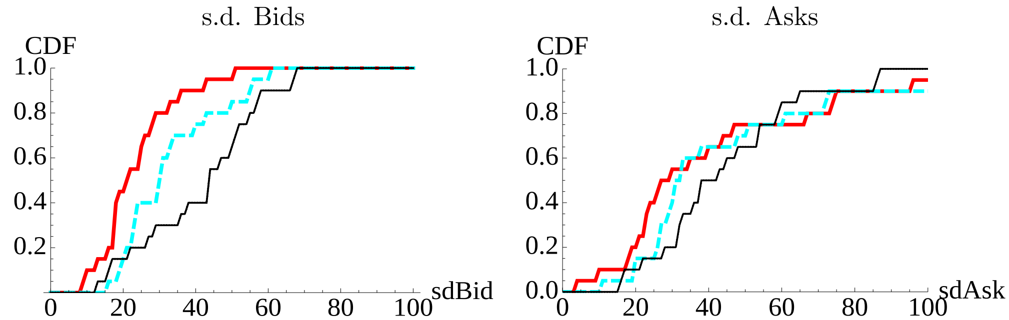
Finally, for the ($vRAD$), while the mean CRT score remains statistically significantly negative, both the mean and standard deviation of the RPM scores become statistically insignificant once the gender composition is controlled for. The gender composition effect remains statistically significant, with the same sign as in the case of the RAD.

3.4 Heterogeneity in trading behavior and mispricing

Why does heterogeneity in cognitive ability increase mispricing? We hypothesize that heterogeneity in cognitive ability results in heterogeneity in trading behavior, which results in larger price variations and mispricing.

To capture the heterogeneity in trading behavior among market participants, we compute the standard deviation of bids and asks submitted by market participants for each period in each market, and take the average across 20 periods. Figure 6 shows the empirical cumulative distributions of the within-market standard deviations of bids (left) and asks (right). It can be seen from the left panel that within-market bid heterogeneity is largest in the 3H3L markets and smallest in the 6H markets. As the table below the left panel shows,

[15]It is also interesting to note the significant positive coefficient of mRPM. However, we do not have a very clear interpretation of this result.



	6L	3H3L
6H	0.020	< 0.001
6L		0.078

	6L	3H3L
6H	0.863	0.875
6L		0.976

Figure 6: Distribution of within-market standard deviations of bids (left) and asks (right). In each panel, three market types are shown: 6H (thick, solid red line), 6L (thick, dashed blue line), and 3H3L (thin black line). The table below each panel reports the p-values from pair-wise comparisons based on two-sample PTs, two-sided.

these are statistically significantly different (p-values are 0.02 for 6H vs 6L markets, less than 0.001 for 6H vs 3H3L markets, and 0.078 for 6L vs 3H3L markets, based on two-sample PTs, two-tailed). However, the right panel shows that within-market ask heterogeneity is similar across the three market types. Indeed, the table below the panel shows that they are not statistically significantly different (p-values are 0.863 for 6H vs 6L markets, 0.875 for 6H vs 3H3L markets, and 0.976 for 6L vs 3H3L markets, based on two-sample PTs, two-tailed).

Table 4 shows the results of linear regressions that take mispricing measures as dependent variables and the average within-market heterogeneity of bids (sdBids) and asks (sdAsks) as independent variables. Except for the RND, the within-market heterogeneity of bids is positively and statistically significantly correlated with the mispricing measures. However, the heterogeneity of asks is not statistically significantly correlated with any of the mispricing measures we consider.

These results support our hypothesis. That is, heterogeneity in cognitive ability among market participants results in heterogeneity in trading behavior, in particular the bids they submit, which in turn results in larger mispricing.

Table 4: Heterogeneity in orders and mispricing

	Dependent variables			
	RAD	RPD	RND	vRAD
sdBids	0.0056***	0.0047***	0.0009	0.008***
	(0.0011)	(0.0008)	(0.0005)	(0.002)
sdAsks	-0.0003	-0.0002	-0.0001	-0.0003
	(0.0004)	(0.0003)	(0.0002)	(0.0008)
Const	-0.046	-0.074**	0.028	-0.052
	(0.038)	(0.029)	(0.020)	(0.071)
R^2	0.330	0.374	0.04	0.239
N. Obs.	60	60	60	60

[i] Standard errors are in parentheses.
[ii] ***, **, and * signify statistical significance at the 1%, 5%, and 10% level, respectively.

3.5 Profits and cognitive ability

Finally, we examine the relationship between cognitive ability and profit (at the end of period 20), controlling for gender. Table 5 shows the results of the linear regressions. The dependent variable is the individual trader's profit at the end of period 20 in all of the regressions. We consider the three market types, 3H3L, 6H, and 6L, separately. For each market type, we pool the data from two information treatments (known and unknown compositions) and report the results of three regressions: one including both RPM and CRT scores, and two others that consider RPM and CRT scores separately. We consider these three specifications because although the RPM and CRT capture different aspects of cognitive skills, RPM and CRT scores tend to be positively correlated in our sample (the correlation coefficient is 0.345 at the individual level).

The results for the 3H3L and 6L markets show that considered separately, both RPM and CRT scores are significantly positively related to profit. This is in line with previous findings, such as those of Corgnet et al. (2015) and Cueva and Rustichini (2015). The male dummy is not statistically significantly correlated with profit in the 3H3L markets, but it is significantly positively correlated with profit in the 6L markets. However, in the 6H markets, neither cognitive ability nor gender is significantly correlated with profit.

Table 5: Total profit and cognitive ability

	3H3L			6H			6L		
RPM	19.34	23.38*		2.66	7.66		18.50**	25.01**	
	(12.53)	(12.12)		(12.61)	(15.82)		(8.90)	(8.83)	
CRT	34.71		53.77**	32.57		33.59	46.68		58.09*
	(20.64)		(22.84)	(31.99)		(34.11)	(31.31)		(30.12)
Male	8.12	31.57	4.94	81.30	89.73	80.95	131.22	130.80**	130.78**
	(61.67)	(59.81)	(59.55)	(48.11)	(50.83)	(48.13)	(61.84)	(62.48)	(60.82)
Const	1614.50	1595.10	1899.43	1912.51	1886.15	1961.52	1629.89	1621.00	1891.05
	(195.65)	(195.87)	(44.65)	(297.94)	(326.89)	(99.14)	(125.23)	(126.40)	(69.35)
R^2	0.06	0.05	0.03	0.02	0.01	0.02	0.06	0.05	0.05
N. Obs.	120	120	120	120	120	120	120	120	120

[i] Robust standard errors corrected for group clustering effects are in parentheses.
[ii] Male: = 1 if male, and = 0 if female.
[iii] ***, **, and * signify statistical significance at the 1%, 5%, and 10% level, respectively.

4 Summary and conclusion

How does the average cognitive ability among market participants, as well as their diversity, influence mispricing in an experimental market? We investigated this question by first measuring an aspect of the cognitive ability of our subjects using the RPM test, and then constructing markets by grouping subjects based on their relative test scores. We defined those subjects whose scores were above and below the median score as H type and L type, respectively. We then considered three kinds of markets: those in which all six traders were H type (6H), those in which all six traders were L type (6L), and those in which H and L types were equally mixed (3H3L).

To investigate whether knowledge of the heterogeneity of cognitive ability among market participants can have an additional effect on mispricing, we considered two information treatments: the known composition treatment and the unknown composition treatment. In both treatments, we informed our subjects of their own type (H or L). In the known composition treatment, we also informed them of the types of the other five traders in their market. Thus, for example, those in the 6H markets were informed that they were H type and the other five traders in the same market were also H type. In the unknown composition treatment, this information was not provided.

Contrary to what one may infer from the results of earlier experimental studies that found a negative relationship between the average cognitive ability of subjects in a market and the degree of mispricing, the degree of mispricing observed in the 3H3L markets was significantly larger than that observed in the 6H and 6L markets in both the known and unknown composition treatments. Thus, it is not only the average cognitive ability of traders in the market but also the diversity in cognitive ability that matters when it comes to the degree of mispricing. However, contrary to our expectations, we did not find any significant additional effect of heterogeneity being ex ante known on the degree of mispricing.

We hypothesized that the reason for the larger mispricing in the 3H3L markets compared with that in the 6H and 6L markets was the positive correlation between heterogeneity in cognitive ability among market participants and heterogeneity in their trading behavior, and that this heterogeneity in trading behavior generated larger mispricing. Our analysis supports this hypothesis. The within-market heterogeneity of submitted bids was significantly larger in the 3H3L markets than in the 6H or 6L markets, and this heterogeneity was significantly positively correlated with mispricing measures. We believe that a more in-depth analysis of heterogeneity in trading behavior dynamics can be a fruitful area for future research. However, it may be useful to conduct experiments for this purpose under continuous double auction conditions to enable more observations to be gathered about the dynamics of trading behavior.

Recently, several researchers have investigated the effects of other types of heterogeneity on mispricing in a similar experimental setup. Levine et al. (2014) report that knowledge of ethnic diversity among market participants reduces the degree of mispricing. Their interpretation of the data is that participants do not think critically about others' decisions in ethnically homogeneous markets, and thus tend to ride "bubbles" compared with participants in ethnically diverse markets.

Eckel and Füllbrunn (2015) and Cueva and Rustichini (2015) study the effect of gender composition on mispricing and disagree somewhat in their findings. While Eckel and Füllbrunn (2015) find that all-male markets generate higher levels of mispricing than all-female markets and the mispricing observed in mixed-gender markets falls between the two, Cueva and Rustichini (2015) find that mispricing in mixed-gender markets is larger than that in both all-male and all-female markets. Our regression result is in line with that of Cueva and Rustichini (2015), in that while an increasing proportion of male participants in a market increases the degree of mispricing, its marginal effect is negative, which results in an inverted-U-shaped relationship between the proportion of male participants in the market and the degree of mispricing.

Hefti et al. (2016) consider the effect of heterogeneity in relation to two distinct capabilities: analytical capability (cognitive skills) and mentalizing capability (the theory of the mind). They find that, consistent with their hypotheses, to be successful in asset-market experiments, one has to have both high analytical capabilities and high mentalizing capabilities because one's success depends on understanding not only market fundamentals (which requires analytical capability) but also the price dynamics resulting from the behavior of other participants (which requires mentalizing capability). It will be very interesting to undertake future research constructing various types of markets by grouping subjects based on heterogeneity in various dimensions such as gender, ethnic identity, analytical capability, and mentalizing capability to investigate how heterogeneities in these various dimensions interact among themselves and determine aggregate market outcomes.

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Table 6: Definitions of the measures of mispricing

Relative absolute deviation (RAD)	$\frac{1}{20}\sum_{p=1}^{20}\frac{\lvert P_p - FV_p\rvert}{\lvert\overline{FV}\rvert}$
Relative deviation (RD)	$\frac{1}{20}\sum_{p=1}^{20}\frac{P_p - FV_p}{\lvert\overline{FV}\rvert}$
Relative Positive Deviation (RPD)	$\frac{1}{20}\sum_{p=1}^{20}\frac{\max(P_p - FV_p, 0)}{\lvert\overline{FV}\rvert}$
Relative Negative Deviation (RND)	$\frac{1}{20}\sum_{p=1}^{20}\frac{\max(FV_p - P_p, 0)}{\lvert\overline{FV}\rvert}$
Boom Duration	the greatest number of consecutive periods that prices are above fundamental values
Bust Duration	the greatest number of consecutive periods that prices are below fundamental values
Turnover	$\sum_{p=1}^{20} Q_p/24$

A Various measures of mispricing

Here we present the values of various measures of mispricing for each market. In addition to RAD, RD, RPD, RND, and turnover, we also report boom and bust durations. Table 6 summarizes the definitions of these measures. Table 7 reports the results for the 36 markets under the known composition treatment and Table 8 reports the results for the 24 markets under the unknown composition treatment.

Table 7: Known composition treatment

Composition	group	RAD	RD	RPD	RND	Boom Duration	Bust Duration	Turnover
6H	1	0.007	0.006	0.006	0.000	12	1	1.292
6H	2	0.004	0.002	0.003	0.001	3	2	0.667
6H	3	0.006	-0.001	0.002	0.004	3	4	1.375
6H	4	0.028	-0.014	0.007	0.021	2	3	0.958
6H	5	0.153	0.130	0.142	0.012	3	3	1.583
6H	6	0.019	-0.008	0.006	0.014	2	4	0.792
6H	7	0.076	-0.010	0.033	0.043	5	5	1.917
6H	8	0.022	0.004	0.013	0.009	7	4	2.417
6H	9	0.456	0.317	0.387	0.070	10	7	0.875
6H	10	0.006	-0.001	0.003	0.004	5	2	1.208
6H	11	0.048	-0.043	0.002	0.045	3	5	1.125
6H	12	0.086	0.016	0.051	0.035	5	2	1.083
average		0.076	0.033	0.055	0.021	5	4	1.274
s.d.		0.128	0.098	0.112	0.022	3.191	1.679	0.500
6L	1	0.053	-0.002	0.026	0.027	3	7	0.958
6L	2	0.083	-0.080	0.002	0.081	1	8	0.833
6L	3	0.055	-0.025	0.015	0.040	3	5	1.083
6L	4	0.053	-0.045	0.004	0.049	4	5	0.583
6L	5	0.034	0.027	0.030	0.004	3	6	1.083
6L	6	0.022	-0.006	0.008	0.014	3	5	1.542
6L	7	0.245	-0.233	0.006	0.239	3	9	1.333
6L	8	0.239	0.215	0.227	0.012	13	2	2.333
6L	9	0.041	-0.039	0.001	0.040	2	5	1.500
6L	10	0.094	-0.059	0.017	0.076	3	7	0.667
6L	11	0.185	-0.176	0.004	0.180	4	7	1.250
6L	12	0.257	0.011	0.134	0.123	10	4	1.458
average		0.113	-0.034	0.040	0.074	4	6	1.219
s.d.		0.091	0.109	0.069	0.073	3.499	1.899	0.473
3H3L	1	0.149	0.045	0.097	0.052	7	9	1.000
3H3L	2	0.034	-0.022	0.006	0.028	3	7	1.042
3H3L	3	0.060	0.024	0.042	0.018	10	2	0.875
3H3L	4	0.410	0.366	0.388	0.022	8	2	1.208
3H3L	5	0.220	0.128	0.174	0.046	13	3	0.500
3H3L	6	0.165	-0.047	0.059	0.106	5	6	0.958
3H3L	7	0.257	-0.068	0.094	0.163	4	7	0.625
3H3L	8	0.221	-0.112	0.055	0.167	10	6	1.208
3H3L	9	0.231	0.084	0.157	0.073	12	3	1.208
3H3L	10	0.133	-0.032	0.050	0.083	4	7	1.083
3H3L	11	0.108	0.043	0.075	0.032	8	2	1.083
3H3L	12	0.664	0.046	0.355	0.309	9	5	1.083
average		0.221	0.038	0.129	0.092	7.750	4.917	0.990
s.d.		0.171	0.124	0.123	0.085	3.251	2.429	0.226

Table 8: Unknown composition treatment

Composition	group	RAD	RD	Positive Deviation	Negative Deviation	Boom Duration	Bust Duration	Turnover
6H	1	0.007	-0.004	0.002	0.006	2	2	1.083
6H	2	0.040	-0.008	0.016	0.024	3	2	0.917
6H	3	0.062	-0.028	0.017	0.045	5	5	1.375
6H	4	0.054	-0.046	0.004	0.050	4	7	1.208
6H	5	0.018	-0.014	0.002	0.016	2	4	1.000
6H	6	0.112	-0.112	0.000	0.112	0	17	1.042
6H	7	0.026	0.022	0.024	0.002	10	2	1.083
6H	8	0.017	0.017	0.017	0.000	10	0	1.042
average		0.042	-0.022	0.010	0.032	4.500	4.875	1.094
s.d.		0.034	0.043	0.009	0.037	3.703	5.357	0.140
6L	1	0.006	-0.006	0.000	0.006	0	11	1.042
6L	2	0.002	0.002	0.002	0.000	2	0	1.833
6L	3	0.194	-0.048	0.073	0.121	7	8	0.792
6L	4	0.083	0.061	0.072	0.011	12	2	1.292
6L	5	0.004	-0.002	0.001	0.003	2	5	0.500
6L	6	0.046	0.030	0.038	0.008	5	2	1.417
6L	7	0.117	0.033	0.075	0.042	6	2	1.375
6L	8	0.039	0.015	0.027	0.012	7	2	0.542
average		0.061	0.011	0.036	0.025	5.125	4.000	1.099
s.d.		0.067	0.032	0.034	0.041	3.796	3.742	0.466
3H3L	1	0.244	-0.025	0.110	0.135	6	4	0.833
3H3L	2	0.408	0.072	0.240	0.168	8	4	1.542
3H3L	3	0.009	-0.003	0.003	0.006	6	3	1.333
3H3L	4	0.046	0.004	0.025	0.021	4	4	1.042
3H3L	5	0.598	0.567	0.583	0.016	18	1	1.375
3H3L	6	0.062	-0.012	0.025	0.037	2	11	0.958
3H3L	7	0.248	0.144	0.196	0.052	9	4	0.875
3H3L	8	0.003	-0.003	0.000	0.003	0	1	2.333
average		0.202	0.093	0.148	0.055	6.625	4.000	1.286
s.d.		0.215	0.200	0.198	0.063	5.476	3.117	0.495

Appendix B

This Appendix contains English translation of the script used for the instruction videos. We have distributed handouts based on the instruction videos that are shown to our subjects as well. The handouts as well as the original instructions in Japanese are available from the authors upon request. Please note that This is the common instruction of our experiments of 6H, 6L and 3H3L. For the known-composition treatments, we announced the red-colored and blue-colored sentences highlighted with [6H/6L] or [3H3L] for 6H/6L and 3H3L, respectively in addition to the black-colored sentences. For the unknown-composition treatments, we announced only the black-colored sentences.

Instructions for Today's Experiment

Let's start today's experiment. We will explain it in the handout in front of you.

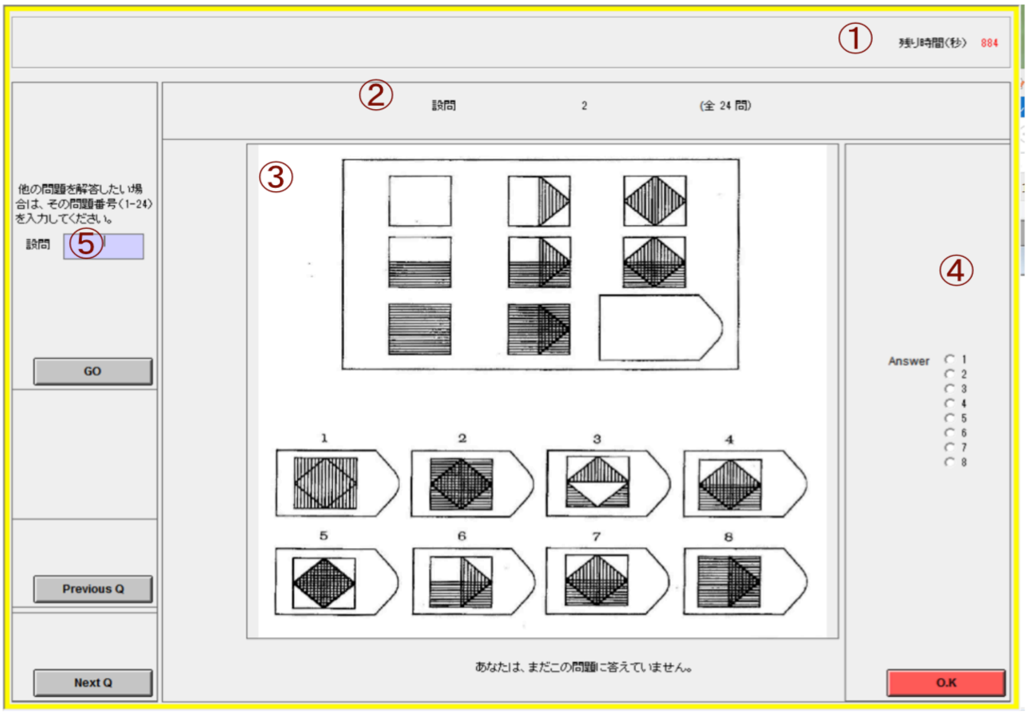
Please turn to the next page.

First, you will be asked to take a quiz. After this quiz, the instructions for today's game will be explained to you. There will be a practice period for the game so that you may familiarize yourself with the computer interface before the real experiment. Finally, we will ask you to respond to a questionnaire and take quizzes. Your earnings will be paid in cash at the conclusion.

Your earnings will consist of a common participation fee of 500 yen, and the result of the game. The questionnaire and quizzes will not impact your earnings. You will have a short bathroom break before the game begins.

We will now explain the first quiz. This quiz consists of 24 questions to be answered within a 15 minute timeframe. For each question, you will view a set of pictures at the top of the screen that are ordered according to a certain pattern. One picture is missing. Your task will be to guess the underlying pattern, and then select the best suited replacement for the missing picture from among the options shown at the bottom of the screen.

(The source of the picture used is Mullainathan and Shafir (2013, p.48). This sentence was not shown to our subjects.**)**



Please turn to the next page.

When the quiz begins, the following information will appear on the screen:

(1) This notes the time remaining. You have 900 seconds to answer as many of the 24 questions as possible.

(2) This indicates the question number.

(3) This is the display of the question.

(4) This is where you will select your option from the corresponding choices found in the bottom part of the picture in (3).

(5) You may request another question to an answer by entering that question number here. We will explain this in detail in the following instructions.

Once you have determined the answer to a question, please select from the options shown on the right side of the screen and click OK; the screen for the next question will appear. If you would like to answer another question that is different from the one shown in the screen, please enter the question number on the top left side of the screen and click GO. The screen for the question selected will appear. You can return to the previous question by clicking the [Previous Q] button, or proceed to the next question by clicking the [Next Q] button. If you would like to skip the present question, please click the [Next Q] button without selecting any options. If you answer the same question more than once, the computer will only record your last answer.

Please begin the quiz when the first question appears on the screen.

Instructions for the Stock Trading Experiment

[Today's experiment]

Today you will participate in a stock trading game 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 are divided into the top 12 scorers and the bottom 12 scorers of 24 people from the previous quiz. Before starting the game, you will know which your rank is, the top or the bottom.

The 24 people in the room are divided into four groups, each of which consists of six people:

[6H/6L] Two of the four groups consist of the top scorers, and the other two groups consist of the bottom scorers.

[3H3L] Each of four groups consists of three people in the top and three people in the bottom.

You play the stock trading game with other five people in the group you belong to.

[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 two ways of making a profit:

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

Please turn to the next page.

[Earning a profit margin]

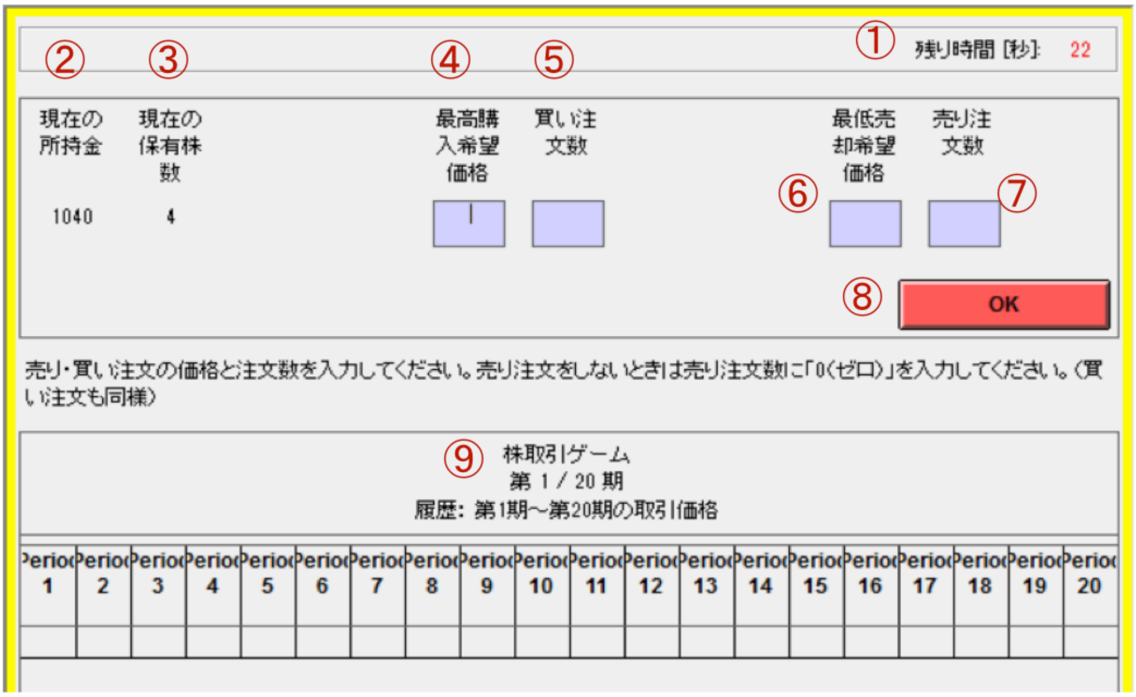
You will be given four stocks + 1040 Marks at the beginning of the game. To earn a profit margin by trading, you need to buy stocks at a lower price and sell these at a higher price. For example, suppose you buy a stock for 100 Marks, and then the price of the stock increases to 120 Marks. If you sell the stock, you will earn 120 (selling price) - 100 (purchase price) = <u>20 Marks profit</u>. 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 (selling price) - 100 (purchase price) = <u>20 Marks loss</u>. 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.



(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.

- <u>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.</u>
- <u>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.</u>

- 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:

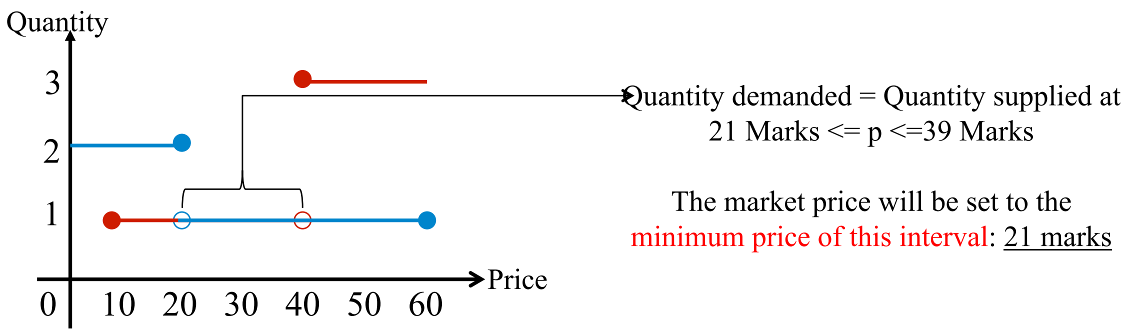
—Trader 1: One sell order, which can be executed at 10 Marks or higher

—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

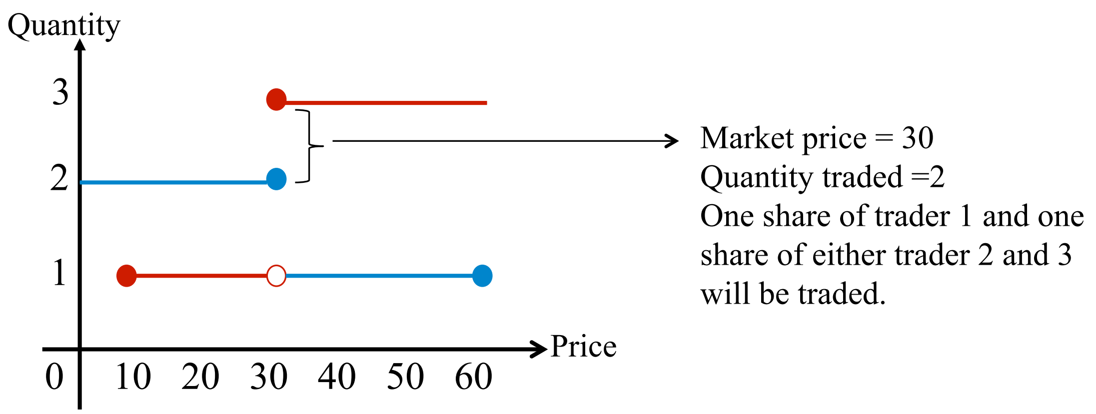
− Trader 2: One sell order, which can be executed at 30 Marks or higher

− 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.

(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.

(6) 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.

(7) By clicking this "Continue" button, you move to the next period.

Please turn to the next page.

[Earning returns from dividends]

In the game, there are twenty 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 Marks × (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 18 periods left. A dividend of 12 Marks per stock will be offered 18 times. Thus, the *Next Value* is 12×18=216 Marks.

After period 20, a dividend is also paid according to your stock holdings. Your cash balance after payment of the dividend for period 20 is the final amount you will earn in the game.

Turn to the next page to see a table of the *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.

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 (2) earning returns from dividends. At the end of the experiment, 1 Mark will be converted into 1 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.

[The instruction ends here]

Before stating the game, we will announce the following:

Let's start the game.

- There are six people in a market.
- All the people of the group are in this room. Each group consists of:
  [6H/6L] only the top scorers or only the bottom scorers from the previous quiz.
  [3H3L] three people in the top scorers and three people in the bottom scorers.
- Your rank, the top or the bottom, from the previous quiz is noted on the first screen.
- You will be given four stocks + 1040 Marks at the beginning of the game.
- After 20 periods, "You have completed the game" will appear on the screen. When this appears, please click the continue button and wait for instructions.

Below we provide two examples of the screens used in *known composition* treatment informing subjects regarding their relative rank based on the score of the quiz (top half or bottom half) and the composition of group they belong to in the asset market experiment. The first one is for 6L and the second on is for 3H3L.

This screen is shown to subjects in 6L. It states: “Your score in the earlier quiz places you among bottom scorers. Your group consists of six bottom scorers. Please press OK to confirm.”

This screen is shown to H subjects in 3H3L. It states: “Your score in the earlier quiz places you among top scorers. Your group consists of 3 top scorers and 3 bottom scorers. Please press OK to confirm.”

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