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# An experimental analysis of the IPO pricing mechanism: The case of Book-building

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## Abstract

This study conducts the first laboratory experiment using a direct mechanism to investigate the efficiency of the Book-building (BB) method in Initial Public Offering (IPO) pricing. Contrary to the global empirical regularity of IPO underpricing, our experiment frequently observes overpricing relative to the fundamental value. This phenomenon is caused by overstated offers and particularly pronounced when investors are unsophisticated, suggesting that overpricing arises from insufficient compensation on information elicitation, belief-action mismatches, and sentimental behavior as explained by investor active participant bias.

Our findings offer two main contributions. First, we demonstrate that, in the absence of ex ante screening and ex post adjustments, the theoretical model of the BB method results in severe IPO overpricing, necessitating the setting of filing range and issuer's strategic underpricing adjustment. Second, investor sentiment can be seen as the cause of price increases in both IPOs and first-day closing prices, the extent is determined by the proportion of unsophisticated investors.

These results highlight the effect of behavioral distortions in IPO pricing and point to the importance of institutional sophistication and investor screening in improving the efficiency and transparency of BB method.

*Keywords:* IPO, Book-building, Underpricing, Active Participation Hypothesis

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## 1. Introduction

This study revisits the pricing dynamics of the Book-building (BB) method in Initial Public Offerings (IPOs) using a controlled laboratory experiment based on the theoretical model of Biais and Faugeron-Crouzet [4] (B&F). The results suggest that investor-driven IPOs in the experimental setting are overpriced relative to the stock value.

IPOs play a pivotal role in financial markets by enabling private firms to raise capital and transition to public ownership. Among the various pricing mechanisms used in IPOs, the BB method has emerged as the dominant approach in both developed and emerging markets. In Japan, where IPOs have a history of more than 140 years, the BB method officially replaced the auction method in 1997 and has since become the standard for pricing new issues (Ikeda [12], Ikeda and Kaneko [13]).

The BB method solicits indicative offers from potential investors within a pre-determined price filing range, allowing issuers or underwriters to assess demand and directionally allocate shares. This interactive process is designed to improve price discovery and mitigate adverse selection by leveraging investor information (Sherman [22], Jagannathan and Sherman [14], Bonini and Voloshyna [5]). However, it is also susceptible to strategic misreporting and informational frictions. Theoretical and empirical research has long debated the implications of such features, with a central concern being IPO underpricing, the tendency to increase from the offering price to the first-day closing price.

The issue of underpricing has long been recognized on a global scale and its causes have been debated from the perspective of a variety of hypotheses. Ljungqvist [16] concludes that the reasons for IPO underpricing fall into four broad categories: asymmetric information theory, institutional reasons, control considerations and behavioral hypotheses. They also pointed out that Benveniste and Spindt [3]’s Information Revelation Hypothesis under the asymmetric information method is the most established with much empirical evidence. The behavioral hypothesis was also considered important because it argues that irrational investors bid up the IPO price. In the context of asymmetric information or behavioral hypotheses, the starting point is investors’ beliefs regarding others in an incomplete information situation and their subsequent reactions, which can be further investigated using an experimental approach.

Our experiment was set up to provide more evidence that contributes to the above hypotheses. The theoretical model of B&F captures key elements of the BB process, including belief elicitation, information asymmetries, and the endogenous price formation process. Importantly, the framework allows us to observe both the actions and beliefs of investors in a controlled environment. Surprisingly, however, we do not observe the usual underpricing. Instead, our results reveal a consistent pattern of overpricing, particularly in settings where participants have less in-depth understanding.

At first glance, this finding may seem to deviate from real-world IPOs, potentially challenging the external validity of the experimental design. However, we argue that this divergence is precisely where the experiment gains significance. Un-

like field data, where institutional features often obscure causal mechanisms, the experimental setting isolates investor behavior under the BB mechanism and highlights how sentiment and belief-action mismatches can severely undermine pricing efficiency. Thus, the observed overpricing is not a flaw, but a feature exposes the underlying vulnerabilities in the BB method.

Specifically, our findings show that subjects who receive low-value signals frequently submit optimistic (and deceptive) reports, attempting to gain allocations even when it leads to expected losses. This behavior is partly explained by the Active Participation Hypothesis (APH) proposed by Lei et al. [15], which posits that investors prefer to take action, even irrationally, over passivity. In our context, this behavior resembles “reporting good news” to avoid being excluded from allocations, regardless of the actual information.

We also observe that such behavior is significantly mitigated in groups with higher level of understanding, analogous to sophisticated institutional investors in real markets. These participants are more likely to report truthfully and achieve more precise pricing and allocation results. Thus, the experiment not only exposes the behavioral distortions that can arise under the BB method, but also demonstrates the reliability of IPO pricing under the BB method critically depends on who participates. When populated by sophisticated investors, the mechanism aligns more closely with theoretical expectations; when not, it is susceptible to sentiment-driven mispricing.

Our results also offer a fresh perspective on the empirical observation of underpricing in real-world IPOs. We suggest that the shift from IPO overpricing compared to the stock value in primary markets to underpricing compared to the first-day closing price in secondary markets may jointly explain the price dynamics, consistent with the arguments of Ljungqvist et al. [17] and Aggarwal et al. [1]. They noted that institutional investors are the primary participants in IPOs, and in the secondary market, the influx of sentiment retail investors can drive the stock price up on the first trading day compared to the IPO price, and there is a positive relationship between institutional allocation of IPOs and returns on the first-day of the secondary market.

The remainder of the paper is structured as follows. Section 2 reviews existing theoretical, empirical, and experimental studies in the area and states the objectives of our study. Section 3 discusses the mechanism presented by B&F which provides the theoretical model for our analysis, followed by the experimental design corresponding to this theory and the presence of its Nash equilibria. We then present the experimental details. Section 4 provides the experimental results and details some implications in the real world. The final section summarizes the study and discusses some future research prospects.

## 2. Literature Review

Most previous studies on IPO pricing methods are theoretical or empirical analyses. However, the focal point of this study is to combine investor behavior with their belief which cannot be observed in the real world, and to explore IPO pricing

inefficiencies due to investor behavior in a theory-backed and controlled environment, thus contributing to the establishment of pricing accuracy and information elicitation.

In theoretical and empirical studies of IPO pricing methods, the underpricing phenomenon has consistently been the main topic. Existing studies from the 1970s to the 2000s on IPO underpricing are summarized in the literature survey by Ljungqvist [16]. As discussed there, the main underpricing hypotheses are the Information Revelation Hypothesis, Winner’s Curse Hypothesis (together concluded as asymmetric information theory) and Sentiment Hypothesis (also known as behavioral hypothesis).

To start, the Information Revelation Hypothesis first noted by Benveniste and Spindt [3] and later by Ljungqvist and Wilhelm [18] and Stoughton and Zechner [23] argues that issuers prefer regular/institutional investors that can gather more information about stock value, whereas retail investors without much information tend to free-ride, and they can only produce benefits if they are controlled by limited participation and there is greater institutional demand (Neupane and Poshakwale [20]). In this model, issuers request honest reports of investor demand and allocate underpriced shares to those investors that continue to engage in investment behavior, thus rewarding them for their information disclosure.

By contrast, according to the Winner’s Curse Hypothesis proposed by Rock [21], well-informed investors can steer clear of offers from low-quality firms, a strategic move that uninformed investors given their informational disadvantage. Thus, uninformed retail investors tend to refrain from purchasing IPO shares because they anticipate losses from adverse selection, particularly in IPOs characterized by high uncertainty. To encourage uninformed investors to participate in IPOs and help reach the fundraising target, issuers must lower the offering price, and this results in underpricing.

Finally, behavioral finance explanations such as the Sentiment Hypothesis (Ljungqvist et al. [17]) assume the presence of irrational investors. Given investor sentiment, some optimistic investors may overvalue the stock, causing the initial market price to rise. Therefore, the issuer must set the IPO price lower than the initial market price to benefit those rational investors who continue to hold the shares. However, while this hypothesis assumes positive sentiment, the existing theory remains silent about precisely why sentiment in IPOs is more often positive.

Despite the secondary market stage in our experimental design, which omits the first-day price in the procedure, our design primarily sheds light on information elicitation of informed investors, as discussed primarily in asymmetric information theory. To design a feasible experiment for the implementation of the BB method, we draw on Biais and Faugeron-Crouzet [4]. B&F analyzed and compared various IPO pricing methods, including BB, fixed price, and auction methods. According to their analysis, the fixed price method leads to inefficient pricing and the winner’s curse. Dutch auctions also encourage implicit collusion among investors and lead to inefficiency. They contend that the BB method and the *Mise en Vente* (or sale offering) can lead to optimal information exposure and price discovery and further

empirically demonstrate the similarity between the two.<sup>1</sup>

As in B&F, many studies also focus on comparing performance between different IPO methods. However, it has been difficult to establish a definitive preference between the two most common methods, namely the BB and auction methods. Consequently, why many issuers opt for the BB method despite underpricing remains unresolved. This motivated us to identify information disclosure behavior, and it is crucial to employ an experimental approach to represent the theoretical BB model and to perform further comparisons with the auction method.

Against this background, the BB method is always considered superior in reducing risk. Because the BB method allows issuers to control the number and type of investors, issuers have allocation power and award more shares to investors that provide additional information in their offers (Cornelli and Goldreich [9], Jagannathan and Sherman [14]). Thus, Bubna and Prabhala [6], Chen et al. [7], and Chen et al. [8] all suggest that the BB method can achieve a higher pre-market price discovery level, concluding that the characteristics of the BB method can reduce unexpected underpricing. However, Ikeda and Kaneko [13] state that the BB method with filing range restrictions and issuer manipulation lacks a more specific explanation of the reasons behind the determination. From another perspective, Tatumi [24] noted that while institutional investors provide information to select stocks, it is necessary to establish what is known as “signaling” by issuers to show their ability and transparency in IPO procedures. This described information elicitation procedure can be represented by the B&F model using experiments.

Existing experimental analyzes such as Almeida and Leal [2] compare the BB method, the Dutch auction, and the competitive IPO, and determined that the BB method has the potential to establish a more favorable IPO price for investors, although at the expense of the issuer. The study also highlighted that the BB method improves price stability and reduces the deviation of the IPO price from the fundamental value of the stock. According to the experimental results in Bonini and Voloshyna [5], while the BB method fulfills long-term objectives such as price stability, improves information collection by financial analysts and enhances the signaling effect of the issuer, it grants the issuer excessive discretion. In contrast, the auction method avoids conflicts of interest while facilitating necessary investor “learning” and allowing intermediaries to construct accurate “valuations.” By contrast, Füllbrunn et al. [11] also compared the BB method with the auction method, as all are based on auction settings. According to their results, underpricing was always observed regardless of the IPO method, and the observations remained unchanged even when the experiment was repeated and the subjects were considered more empirical.

Among experimental studies, Zhang [25] is most like our work. They conducted experiments based on the B&F model to compare the auction and fixed price methods and concluded that the former yields higher prices and greater revenue to the

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<sup>1</sup>Mise en Vente is an IPO method similar to the bidding method commonly used in France. However, as with the BB method, there is no explicit algorithm to map demand to price.

issuers. Instead, we conduct an experiment specifically designed for the BB method of the B&F model. We highlight the similarities and differences between their research and ours in the experimental section of this paper.

So far, previous experimental research on the BB method has mainly been utilized to assess the discrepancy between the IPO price and the first-day closing price, with little emphasis placed on the disclosure of information during the IPO stage. Furthermore, although numerous auction models have been utilized for comparison, there is no BB model that formally encloses its strict forward pricing and allocation structure without using auction properties. Hence, the objective of this study is to evaluate the performance of the BB method using the direct mechanism proposed by B&F.

Our contribution is to establish the first formal framework for testing the BB method in a controlled setting. Unlike previous theoretical or empirical studies, the experiment directly measures information disclosure behavior, allowing for a more precise evaluation of investor strategies. Furthermore, by quantifying the gap between investor beliefs and actions, it reveals that investors tend to overestimate others' honesty and profitability of purchasing. In addition, the study incorporates the Active Participation Hypothesis (APH) to elucidate why investors, even when receiving negative signals, may still engage in aggressive bidding, leading to systematic price deviations, which demonstrates investor positive sentiment.

Note that we did not compare the IPO price with the secondary market first-day closing price given the absence of a secondary market stage in our experiments. In fact, our main objective is to evaluate the efficiency of the BB method proposed by B&F and to learn whether investors have the correct beliefs and react rationally against others. As a result, our focus will be on comparing the IPO price with the fundamental value of the stock. Henceforth, to be accurate in the context of this study, the terms “underpricing” and “overpricing” will specifically refer to the comparison between the IPO price and the stock value.

In the following, we present our theoretical model based on the direct mechanism discussed and a detailed explanation of the experimental model, as well as the specifics of the experiments conducted.

### 3. Experiment

#### 3.1. Experimental model

##### 3.1.1. Experimental model setup

We now outline the direct mechanism introduced by B&F to represent the BB method. In their theory, the IPO involves the trading of a total of  $S$  shares. The issuer encounters two types of investors:  $N$  strategic informed investors and a group of small uninformed investors. Informed investors receive a private information signal regarding the value of the IPO firm and have the ability to acquire all of the IPO shares independently. In contrast, uninformed investors lack any information and are unable to collectively purchase all IPO shares. The maximum number of shares they can collectively buy is limited to  $S(1 - k)$ , where  $k \in (0, 1]$ . All investors

are assumed to be rational and risk-neutral, and the value of the shares represents a common value. This implies that the stock value is uniformly determined by the distribution of private information, remaining the same for all investors.

Each informed investor receives a private signal  $s_i (i = 1, \dots, N)$ . These signals follow a binomial distribution such that they are Good ( $(g)$  below) with probability  $\pi$  and Bad ( $(b)$  below) with probability  $1 - \pi$ , which collectively show whether the stock has a high or low value. The distribution is independent. The stock value  $v$  depends only on the number  $n$  of  $(g)$  signals,  $v_n = \lambda n$  ( $\lambda$  is a constant). These settings are common knowledge among investors. After each informed investor  $i$  obtains a private signal  $(g)$  or  $(b)$ , the conditional expected value of the stock can be calculated using the number of other informed investors; the investor with a signal of  $(g)$  becomes a high-expected value investor and the investor with a signal of  $(b)$  becomes a low-expected value investor. Based on the expected value, an informed investor sends a report based on the value of the stock  $m_i \in \{g, b\}$ .

This mechanism complies with the following conditions. First, the IPO price  $p$  is uniform for all investors and is determined by the function  $p(\hat{n})$ , where  $\hat{n}$  represents the total number of  $m_i = g$ . Second, the allocation rule is symmetric for all investors. In the case of an informed investor  $i$ , the allocation of shares  $q$  is contingent on their own report  $m_i$  and the number of  $(g)$  reports  $l_i$  provided by other informed investors excluding themselves:  $q_i(m_i; l_i)$ .

The following experimental setting is provided in the following to correspond to the original model, taking into account the informed investor's inducement compatibility and participation constraints to achieve mechanism optimization.<sup>2</sup> The specific values of each parameter used in the experiment are provided in Table 1.

Compared to the theoretical setting of B&F, the experimental model for player symmetry and experimental simplicity omits uninformed investors, as they do not possess a strategy to influence the allocation and pricing of shares in this mechanism. That is, considering the case of  $k = 1$ , the setting is  $S(1 - k) = 0$ .

Furthermore, we set  $\lambda = 100$ , and add a constant 100 to the value of the stock.<sup>3</sup> With this setting, the value of the stock  $v$  is 100 times the number of  $(g)$  signals in the society plus 100. In this process, the five informed investors receive private signals about the value of the stock. They then assess the value of the stock based on that signal and submit their reports accordingly. The allocation and pricing of the shares are determined by the outcomes of these reports.

- If all informed investors report  $(b)$ , the IPO price is  $p_0 = v_0 = 100$ . All 40 shares will be allocated equally among five investors:  $q_i(b; 0) = 8$ .
- If the number of investors that report  $(g)$  is  $n = \{1, 2, 3, 4\}$ , investors that report  $(b)$  will have no allocation of shares:  $q_i(b; l_i) = q_i(b; \hat{n}) = 0$ .

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<sup>2</sup>Proof that the mechanism is optimal can be found in the Appendix of the original paper.

<sup>3</sup>Using the original theoretical model settings, the value would be 0 if all five investors receive a  $(b)$  signal, but this may cause problems in conducting the experiment and affect decision-making, so we add a constant of 100. By adding the constant 100, the value of the stock is 100 even if there is no  $(g)$  signal in the society. In the later part of stock pricing, we also add 100 correspondingly.



Table 1: Model Settings

	Original Theoretical Model	Experimental Model
Investor Type	Informed Investor & Uninformed Investor	Informed Investor Only
Purchasing Power of Informed Investor $k$	$k \in (0, 1]$	$k = 1$
Number of IPO Shares	$S$	40
Number of Investors	$N$	5
Private Information $s_i$	$\{g, b\}$	$\{g, b\}$
Probability of Receiving ( $g$ )	$\pi$	$\frac{1}{2}$
Report $m_i$	$\{g, b\}$	$\{g, b\}$
Value of Shares $v$	$v_n = \lambda n$	$v_n = 100n + 100$
Price of Shares $p$	$p(\hat{n}) = v_{\hat{n}}, \forall \hat{n} < N;$ $p(\hat{n}) = v_N - k(\frac{1-\pi}{\pi})^{N-1}(v_1 - v_0), \hat{n} = N.$	$p(\hat{n}) = 100\hat{n} + 100, \forall \hat{n} < 5;$ $p(5) = 500.$
Allocation $q$	$q_i(b; 0) = \frac{Sk}{N};$ $q(b; l_i) = 0, (l_i \neq 0);$ $q(g; l_i) = \frac{Sk}{l_i+1} = \frac{40}{\hat{n}}.$	$q(b, 0) = 8;$ $q(b; l_i) = 0, (l_i \neq 0);$ $q(g; l_i) = \frac{Sk}{l_i+1} = \frac{40}{\hat{n}}.$
Investor Profit	$(v - p) \times q$	$(v - p) \times q$

The investors that report ( $g$ ) will be equally allocated shares:  $q_i(g; l_i) = \frac{40}{l_i+1} = \frac{40}{\hat{n}}.$

- The rules for pricing are as follows:

$$p(\hat{n}) = 100\hat{n} + 100, \forall \hat{n} < 5;$$

$$p(5) = 500.$$

This scenario highlights an structural underpricing setting in a situation where all society members receive ( $g$ ) signals. As noted by B&F, the pricing rule that meets the incentive compatible condition is not uniquely determined. However, there must be a space of potential benefits to compensate informed investors for truthful reporting.

Our experiment is based on this direct mechanism, where the investor's strategy is only to provide a report based on the signal and to ensure that the shares are fully subscribed.<sup>4</sup>

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<sup>4</sup>We can also compare our experimental model with Zhang [25]. Although B&F provided the same environment including the value function, the most significant difference from Zhang is that we tested the BB method, which is chosen by more countries and firms, and not the auction or fixed price methods. In their experiment, investors must bid on both price and quantity, and both institutional and retail investors bid simultaneously, allowing for insufficient subscription.

### 3.1.2. Equilibria of the experimental model

To evaluate the performance of the experimental model, we derive the Nash equilibria for the case of the five investors presented in Section 3.1.1. In a game-theoretic analysis, the experimental model can be regarded as an incomplete information game with five symmetric players. The strategy of each player is to report  $(g)$  or  $(b)$  after receiving the signal  $(g)$  or  $(b)$ . Furthermore, we derive the expected price of the stock in the obtained Nash equilibria and the expected profit of the investor and the issuer.

For simplicity, we limit our discussion to symmetric equilibria in this study.

According to B&F, as the mechanism satisfies Bayesian incentive compatibility, the optimal response is for players to report honestly regardless of the signal received. Thus, the first Nash equilibrium is obvious.

**Equilibrium 1.** *Reporting  $(b)$  when the  $(b)$  signal is received and reporting  $(g)$  when a  $(g)$  signal is received becomes the Bayesian Nash equilibrium and is expressed as follows:*

$$\text{If } s_i = b, \text{ then } m_i = b;$$

$$\text{If } s_i = g, \text{ then } m_i = g.$$

According to the mechanism setup, players who receive a  $(b)$  signal have no incentive to purchase shares and always report  $(b)$ . Specifically, if players who received a signal of  $(g)$  always report type  $(g)$ , a player who received a signal of type  $(b)$  will never benefit from reporting type  $(g)$ . Therefore, there is no other equilibrium in situations where the player that received a  $(g)$  signal always reports honestly. Thus, in the following discussion, we will only consider symmetric equilibria in situations where the player that received a  $(b)$  signal always reports honestly.

Suppose that all players with a  $(g)$  signal report  $(g)$  or  $(b)$  with a mixed strategy  $\alpha = (\alpha_i, 1 - \alpha_i)$ ,  $0 \leq \alpha_i \leq 1$ . Calculations are performed such that the expected profits that the two strategies produce are equal. As a result, the mixed strategy of the players with a  $(g)$  signal is  $(\alpha_i, 1 - \alpha_i) = (0.88, 0.12)$ .<sup>5</sup>

**Equilibrium 2.** *Reporting  $(b)$  if a  $(b)$  signal is received; reporting  $(g)$  with a probability of 0.88 and  $(b)$  with a probability of 0.12 if a  $(g)$  signal is received. This is expressed as follows:*

$$\text{If } s_i = b, \text{ then } m_i = b;$$

$$\text{If } s_i = g, \text{ then } m_i = (\alpha_i, 1 - \alpha_i) = (0.88, 0.12).$$

In addition to the above two equilibria, there could be multiple Nash equilibria in the five-person game presented in this paper, including other symmetric mixed-strategies. However, the objective of the mechanism is to have investors report

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<sup>5</sup>See Appendix A for details of the derivation process; calculation results rounded to two decimal places.

honestly and elicit information, meaning that we should minimize the distribution to investors who reported ( $b$ ) and incorporate an underpricing setup to increase the gain of investors who received ( $g$ ). We expect the result to more coincide with the Bayesian Nash equilibrium in which all players report honestly or the symmetric mixed strategy equilibrium in which only deceptive reports of people with ( $g$ ) signal are considered.

The following Table 2 summarizes the expected equilibrium price, the issuer’s expected revenue, and the investors’ expected profit in the above equilibria.<sup>6</sup> In this game, the monetary unit is a “point.” In simple terms, when following a mixed strategy, the expected profit of investors is higher than that in the honest reporting case. Thus, the overall profit of investors (investor surplus) in the society will increase and the issuer’s revenue (issuer surplus) will be relatively lower.<sup>7</sup>

Table 2: IPO Price, Issuer’s Revenue, and Investor’s Profit in the Equilibria (in points)

	Eq. 1 (Honest Report)	Eq. 2 (Mixed Strategy)
Equilibrium Price	347	319
Issuer’s Revenue	13875	12750
Profit of Investor with ( $b$ ) Signal	0	23
Profit of Investor with ( $g$ ) Signal	25	401

In Section 4, we test the efficiency of the experimental model in the laboratory experiment considering the prices and other measures mentioned as theoretical criteria.

### 3.2. Experimental Method

The experimental program was designed and run with z-Tree (Fischbacher [10]) software with the experiment consisting of two treatments, BN and BP. One session is held for each treatment. The following is the general experimental flow.

In both treatments, the flow consists of completing the participation consent form to the experiment, an explanation of the introduction to the experiment, a comprehension test, treatment, the experiment questionnaire, and payment. Given that there was no practice period, all the results are used in the analysis. The points for each period are independent and do not carry over into the next period. The points earned in a random period are drawn by the computer at the end of the treatment and converted into a ratio of 10 points = 1 Japanese yen and paid together with a show-up fee of 1,500 yen. The experimental questionnaire includes CRT

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<sup>6</sup>Although the issuer is not a player in the game, issuer revenue is an important measure of the model’s performance because our model aims to maximize issuer’s revenue. As we do not consider the issuer’s direct costs of issuance, we simply calculate expected revenue as  $40p$ .

<sup>7</sup>See Appendix A for the calculation process.

questions. The experiments for the BB method were conducted on July 26, 2022, in two treatments at the Economical Laboratory of Waseda University. The language used is Japanese, with a total of 60 people participating, 30 subjects in each session. All subjects are Waseda University undergraduate or graduate students with half being male and a quarter being economics or commerce majors. As participation in both sessions was not allowed, we observed the results of the experiment for 60 subjects. The duration of the experiment was approximately 70 minutes for both sessions and the average payment for the BN session was 1,467 yen, while the average payment for the BP session was 1,501 yen.

Table 3: HR-SG

No. of Good reports other than yours	0	1	2	3	4
Prob. of occurrence	$\frac{1}{16}$	$\frac{4}{16}$	$\frac{6}{16}$	$\frac{4}{16}$	$\frac{1}{16}$
You report Good	0	0	0	0	800
You report Bad	800	0	0	0	0

Table 4: HR-SB

No. of Good reports other than yours	0	1	2	3	4
Prob. of occurrence	$\frac{1}{16}$	$\frac{4}{16}$	$\frac{6}{16}$	$\frac{4}{16}$	$\frac{1}{16}$
You report Good	-4000	-2000	-1333	-1000	0
You report Bad	0	0	0	0	0

Table 5: BHR-SG

No. of Good reports other than yours	0	1	2	3	4
Prob. of occurrence	$\frac{81}{256}$	$\frac{108}{256}$	$\frac{54}{256}$	$\frac{12}{256}$	$\frac{1}{256}$
You report Good	5333	2000	889	333	800
You report Bad	1867	0	0	0	0

Table 6: BHR-SB

No. of Good reports other than yours	0	1	2	3	4
Prob. of occurrence	$\frac{81}{256}$	$\frac{108}{256}$	$\frac{54}{256}$	$\frac{12}{256}$	$\frac{1}{256}$
You report Good	1333	0	-444	-667	0
You report Bad	1067	0	0	0	0

Table 7: RR-SG

No. of Good reports other than yours	0	1	2	3	4
Prob. of occurrence	$\frac{1}{16}$	$\frac{4}{16}$	$\frac{6}{16}$	$\frac{4}{16}$	$\frac{1}{16}$
You report Good	8000	2000	0	-1000	-800
You report Bad	2400	0	0	0	0

Table 8: RR-SB

No. of Good reports other than yours	0	1	2	3	4
Prob. of occurrence	$\frac{1}{16}$	$\frac{4}{16}$	$\frac{6}{16}$	$\frac{4}{16}$	$\frac{1}{16}$
You report Good	4000	0	-1333	-2000	-1600
You report Bad	1000	0	0	0	0

The major distinction between these two treatments is that the Example Profit Tables are exclusively provided in the experimental instruction of Treatment BP. The Example Profit Tables below describe three cases of one investor's expected profit with the possible information distribution when the four other subjects in the same group are assumed to take a particular strategy. The three cases are as follows: (1) all other investors always report honestly regardless of their private signal (HR);

(2) other investors report honestly if they received a ( $b$ ) signal and report ( $g$ ) or ( $b$ ) with probability  $1/2$  if they received a ( $g$ ) signal (BHR); (3) other investors always report ( $g$ ) or ( $b$ ) with probability  $1/2$  regardless of their private signal (RR). In each case, two profit tables were presented, one for “if your signal is Good (SG)” and the other for “if your signal is Bad (SB).” Details are available in Table 3 to Table 8. In the experiment, subjects’ profits are recorded in units of “points” (the points shown in the Example Profit Tables are rounded to one decimal place).

One reason for incorporating the Example Profit Tables is that subjects can more intuitively compare the possible consequences of their actions given the strategies of others. Although it is possible to understand the game using only the experimental instructions, we expect that the subjects of Treatment BP will have a better understanding of the game by presenting the Example Profit Tables, given the lengthy experimental description and the complexity of the game structure. The three cases used in the Example Profit Tables are a set of strategies chosen from a neutral perspective. The instruction was written in a manner intended to provide no bias toward truth-telling. The Example Profit Tables are constructed in the same manner, but with more visible losses.

In each treatment, the game described in Section 3.1.1 is played 10 times. Thus, each treatment consists of 10 periods, with each period representing one independent IPO process (pricing and allocation procedures); the 30 subjects in one session were divided into six groups of five persons each, and the group members were not changed during the 10 periods. The subjects did not know who was else within their group. All subjects played the same role: that of informed investors considering purchasing newly issued shares and being able to purchase the whole share.

What follows is an explanation of the treatment (common to BN and BP).

The experiment was described to the subjects as a stock allocation game, which coincides with the experimental model in Section 3.1.1. The 30 subjects in a given treatment were numbered in sequence and divided into six groups in the following format: subjects 1 to 5 formed group 1, subjects 6 to 10 formed group 2, etc. The 50 signals given to one group in a given treatment ( $5 \text{ persons} \times 10 \text{ periods}$ ) follow the binomial distribution of  $p = 1/2$ , generated in advance and at random by the computer; There is no difference in the distribution of a ( $g$ ) or ( $b$ ) signal among the groups.<sup>8</sup> That is, for one group, the number of ( $g$ ) signals  $n = 0, 1, 2, 3, 4, 5$  in a period appeared 1, 1, 3, 3, 1, 1 times. The assignment of signals is shown in Table 9. Subjects were not informed of these settings in advance.

Each subject could observe a ( $g$ ) or ( $b$ ) signal about the stock value at the beginning of each period. The report prediction stage then began, and the subjects were asked to enter their predictions about other people’s reports. Specifically, the two questions were “Possibility of people who received a good signal reporting good (%)” and “Possibility of people who received a bad signal reporting bad (%)” Subjects could enter their predictions as a number between 0 and 100, in increments

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<sup>8</sup>For example, subject No. 1 always received the same signals as subjects No. 6, No. 11, No. 16, No. 21, and No. 26. These six subjects are called PlType1 subjects, as well as PlType2-PlType5.

of 0.1. The decision-making time was 30 seconds. This question has no correct or incorrect answer and was not incentivized by earning points. There are two reasons for incorporating this question. First, it allows us to analyze the consistency between subjects' predictions and their actual behavior. Second, as explained in the following settings, the only incentivized decision-making action (action related to earning points) in this experiment was to decide to report either ( $g$ ) or ( $b$ ). Thus, the questions were intentionally designed to be sufficiently complex to keep the participants active and focused during the repetition of the 10 periods.

Table 9: Private Information

Period	PIType1	PIType2	PIType3	PIType4	PIType5	Number of ( $g$ ) Signals in Each Period
1	( $b$ )	( $g$ )	( $b$ )	( $g$ )	( $g$ )	3
2	( $b$ )	( $g$ )	( $g$ )	( $b$ )	( $b$ )	2
3	( $g$ )	( $b$ )	( $b$ )	( $b$ )	( $b$ )	1
4	( $g$ )	( $g$ )	( $b$ )	( $g$ )	( $b$ )	3
5	( $b$ )	( $b$ )	( $b$ )	( $b$ )	( $b$ )	0
6	( $g$ )	( $b$ )	( $g$ )	( $b$ )	( $b$ )	2
7	( $g$ )	( $g$ )	( $g$ )	( $g$ )	( $g$ )	5
8	( $g$ )	( $g$ )	( $g$ )	( $b$ )	( $g$ )	4
9	( $g$ )	( $g$ )	( $b$ )	( $b$ )	( $b$ )	2
10	( $g$ )	( $g$ )	( $g$ )	( $b$ )	( $b$ )	3
Number of ( $g$ ) Signals throughout 10 periods	7	7	5	3	3	25

After entering the predictions of the five members of one group, the report selection stage begins. The same signal as in the prediction stage of the report can be observed, and the subjects were asked to select a report of “Good” or “Bad.” The decision-making process consists of clicking a button on the selected report. The reports of the group of five determine the price and allocation of the stock, which could be viewed on the results screen. The information on the result screen was as follows: your private information, your report, the number of people who received Good private information, the number of people who received Bad private information, the number of people who reported Good, the number of people who reported Bad, the value of the stock, the price of the stock, the number of shares you were allocated, and your profit. After all subjects reviewed these results, the next period began.

In Section 4, we conduct an analysis of the experimental data and evaluate the performance of the mechanism and investor behavior in the BB method. Based on the results, we compared our findings with previous studies to identify inconsistencies. Moreover, we derive insights that can contribute to the improvement of current policy.

## 4. Data and Results

This section presents the results of the experiment. Across two treatments with 60 participants and 600 observations, we uncover three key experimental findings.

First, we frequently observe significant IPO overpricing compared to stock value, particularly when the fundamental value is low. This overpricing is largely driven by investors who receive low-value signals but report receptively, contributing to inflated prices.

Second, regression analyses reveal a systematic belief-action mismatch, especially in the BN treatment. Subjects receiving low-value signals (denoted as  $(b)$ ) often make deceptive reports in an attempt to secure shares, even when they result in losses. This behavior is explained by a tendency to mirror strategies onto others, a reluctance to update strategies despite past losses, and the influence of sentiment-driven participation, a phenomenon consistent with the Active Participation Hypothesis (APH).

Third, deceptive reporting under a  $(b)$  signal leads to substantial welfare losses for investors, especially under BN treatment, while issuer surplus increases. At the group level, profit decreases significantly when more participants engage in deceptive  $(b)$ -to- $(g)$  reporting. In treatments where the level of understanding is higher (BP), both price accuracy and allocation efficiency improve.

Together, these findings indicate that while the BB method can perform well under ideal conditions with sophisticated participants, the presence of sentiment investors or IPOs with extremely low value can severely undermine its pricing efficiency.

### 4.1. Analysis of prices

In this section, we analyze the results observed in a two-treatment experiment, consisting of 600 pairs of data collected over 10 periods with a total of 60 subjects.

Regarding the realized prices of IPOs, contrary to the expectations of the theoretical equilibria, we observe minimal underpricing and, instead, a significant amount of overpricing, especially for low-value IPOs. We compared the realized IPO prices with the stock value of 10 periods in 12 groups (Treatment BN and Treatment BP), as expressed in the following Figure 1 and Figure 2. Together with the average price of each period (each identical IPO) compared to the stock value in Figure 3. For all figures, the horizontal axis is for periods corresponding to the IPOs. The histogram represents the value or price of the stock. The bar graph represents the stock value, and the line graphs represent the realized stock prices.

Figure 1: Price Formation of BN in Relation to Stock Value

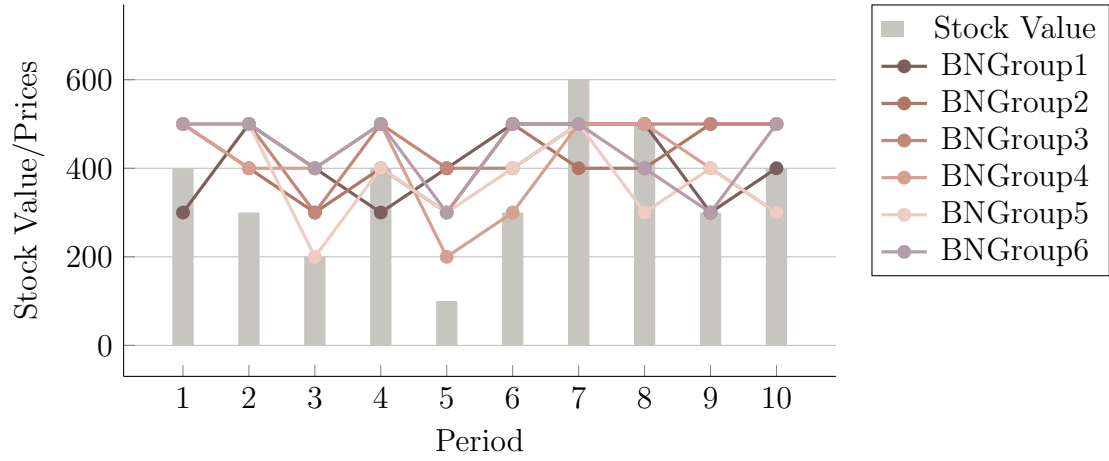


Figure 2: Price Formation of BP in Relation to Stock Value

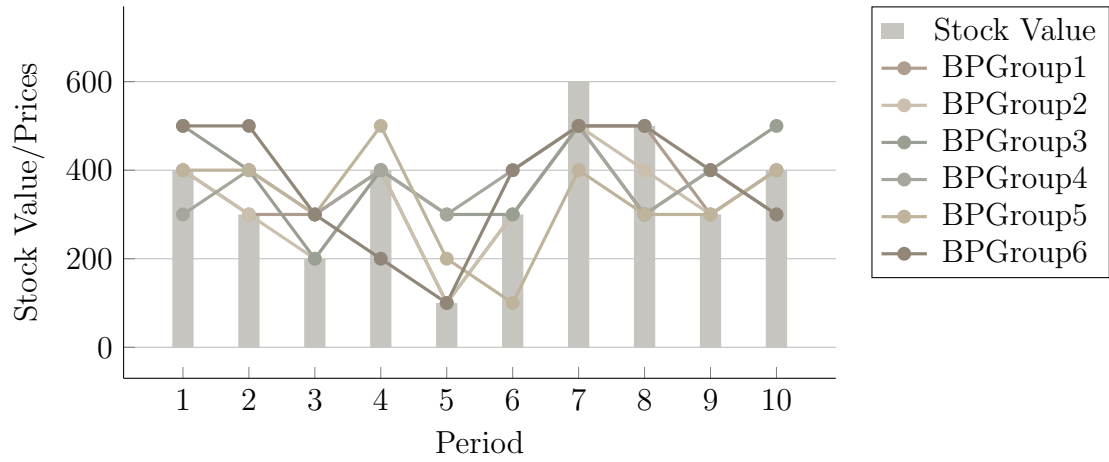
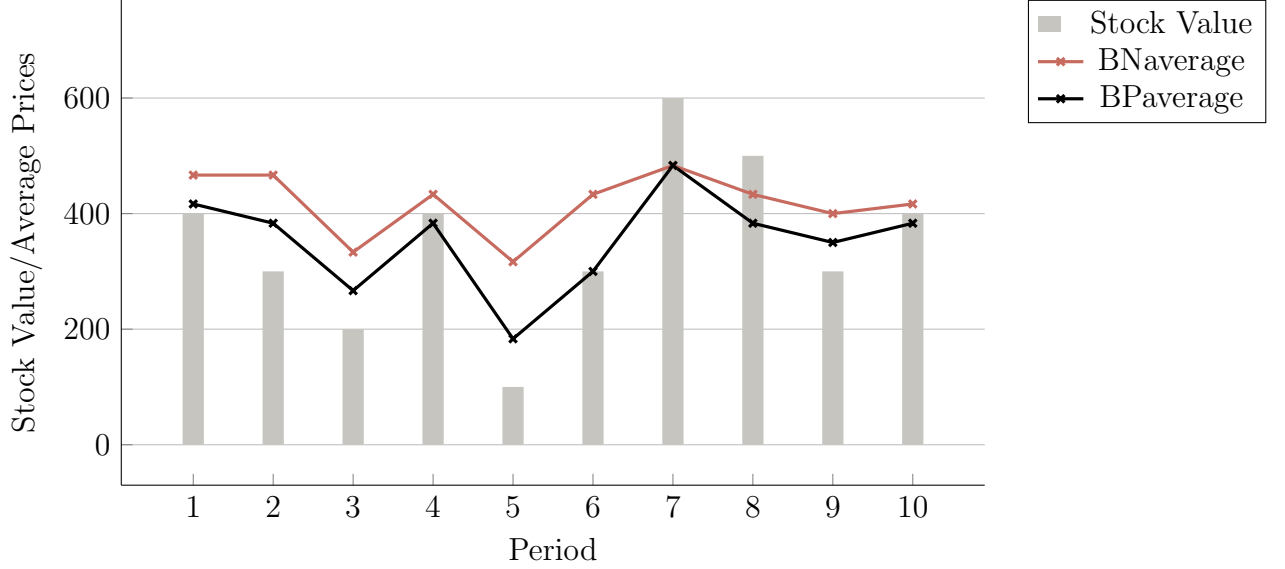




Figure 3: Average Prices Comparison in Relation to Stock Value



Compared between Figures 1 and 2, we can easily have the intuition that the circular marks (which represent the realized prices) on the line graph of Figure 2 correspond more to the histogram. A clearer comparison can be observed in Figure 3, which shows that for eight out of ten periods, the average price of BP is closer to the stock value (with period 7 equivalent to BP and period 8 lower than BP). Another observation is that, for all ten periods, the average prices of BP are lower than or equivalent to those of BN, indicating that there are more frequent cases of overpricing in BN, especially when the stock value is lower.

To examine whether underpricing occurred statistically in each period, we performed a Wilcoxon signed rank test. Based on the results of this one-sided test, when the number of ( $g$ ) signals is 0, 1, or 2, the IPO prices in the experiment were higher than the theoretical value of the stock. The corresponding p-values were 0.002, 0.002, and 0.000, rejecting the null hypothesis of no difference in outcomes and indicating significant results at the level 1%. In other words, the results indicate overpricing. However, when the number of ( $g$ ) signals is 3, no significant differences were observed between the realized price and the value of the stock. Furthermore, when the number of ( $g$ ) signals is 4 or 5, the IPO prices in the experiment were lower than the theoretical value of the stock. The corresponding p-values were 0.008 and 0.000, indicating significant results at the 1% level, suggesting the occurrence of underpricing. At this stage, it was observed that when the number of ( $g$ ) signals is less, the overpricing occurs more.

On the other hand, as Ljungqvist et al. [17] and numerous studies discussed, IPOs can be considered overpriced in the secondary market when viewed over a longer time frame. As the stock value determined in the model is the fundamentals of

the stock, from the perspective of the Efficient Market Hypothesis, it can be regarded as the convergence point of the price on the secondary market. Consequently, the overpricing observed in our experiments supports the previous literature even with the absence of the secondary market stage.

**Result 1.** *Using the BB method, IPO prices are often overpriced compared to the fundamental value. Underpricing occurs only when the stock value is high.*

In the following analysis, we focus on the reasons for this phenomenon.

#### 4.2. Analysis of subjects' behavior

Next, we analyze the behavior of the subjects. The experimental approach enables the integration of investor actions with their underlying beliefs. As revealed by the Nash equilibria of the experimental model, it is considered rational for subjects to choose honest reporting when receiving a (*b*) signal. In addition, subjects with a (*g*) signal can increase their profits by adopting a mixed strategy. It is possible to not only determine whether the subjects report in accordance with the equilibrium but also to identify whether the subjects behave consistently to their beliefs.

As a result of the experiment, the reports of the 30 subjects along with their beliefs about the others are recorded in the 10 periods of BN and BP. Two tables B.16 and B.17 that include specific information on subjects' reporting behavior as a result of their private signal are attached in Appendix B.

In addition to the intuitive results in Tables B.16 and B.17, we have the collective results as in Table 10.

Table 10: Percentage of Truthful Reporting in Equilibria, Predictions, and Reports

Behavior/Belief/Eq. \ Private Information	Good	Bad
BN Reports	87%	53%
BN Predictions	72%	53%
BP Reports	83%	80%
BP Predictions	77%	70%
Outcome of Eq. 1	100%	100%
Outcome of Eq. 2	88%	100%

In the case of (*g*) signals, there is a strong tendency to report honestly in both sessions. In the case of (*b*) signals, a significant number of subjects reported (*g*), which can be considered the cause of the observed overpricing mentioned above. Given the relatively better performance of the BP in price disclosure and the high

percentage of honest reporting observed in the cases of signal ( $b$ ), it can be concluded that the BP is a more accurate representation of the underlying principles in the theoretical model. The increased occurrence of deceptive reporting in BN especially suggests that it is influenced by only the difference in the experimental instructions, the absence of Example Profit Tables in the experimental instruction as shown in Section 3.2, Tables 3 to Table 8.

We employ a regression analysis to examine the deceptive reporting in conjunction with belief. This analysis is of primary concern, as information elicitation can only be analyzed in conjunction with investor beliefs by using an experimental approach, and it provides a more comprehensive representation of performance than posterior pricing accuracy. The experimental observation provides a unique perspective to examine specific behaviors and further combine the empirical results.

In order to analyze the impact of investor belief, investor private information, treatment effect, and investor’s cognitive level, on the behavior of deceptive reporting, an individual-level panel dataset of 600 observations was employed. This data set was analyzed using a random effect approach and the coefficients were estimated using ordinary least squares (OLS) with conventional standard errors.

The dependent variable, “Lie,” is set so that it takes a value of 1 when subjects engage in deceptive reporting regardless of their private signal and 0 when they report honestly. The independent variables include the following seven factors: a dummy variable for private information, “InfoB” (InfoB = 1 for a ( $b$ ) signal and InfoB = 0 for a ( $g$ ) signal); prediction entered during the report prediction stage, “pdB” and “pdG” (the inputted values ranging from 0 to 100 are divided by 100 to convert them into probabilities ranging from 0 to 1); the interaction term between private information and predictions (InfoB  $\times$  pdB, InfoB  $\times$  pdG); a dummy variable for Cognitive Reflection Test (CRT) score evaluation (CRT = 1 when the subject answers correctly to at least two out of three questions; CRT = 0 otherwise); and a treatment dummy variable for BN (BN = 1 when the treatment is BN; BN = 0 for BP). The results of the regression analysis are given in Table 11.

Ideally, we would first estimate a fixed-effects model and then determine whether a random or a fixed effects model is more appropriate. However, in this case, the key dummy variable BN, also the cognitive level variable CRT, do not vary over time for each subject, thereby making the fixed-effects model unsuitable. Moffatt [19] explores the legitimacy of this approach in economics experiments.

The InfoB coefficient indicates that, keeping all else constant, the probability of making a deceptive report when receiving a ( $b$ ) signal is higher than when receiving a ( $g$ ) signal. This result is significant at the level 1%.

Examining the coefficients of predictions, pdB and pdG, reveals the following insights. If subjects have a higher predicted probability that others will report honestly ( $b$ ), their likelihood of making deceptive reports increases (significant at the 10% level). Alternatively, if subjects have a higher predicted probability that others will report honestly ( $g$ ), their likelihood of making honest reports increases (significant at the 1% level). This finding suggests that people’s perceptions of the honesty of others are associated with their own reporting behavior, regardless of

their private information.

Table 11: Lies

(Notes) The table reports the result of the OLS regression with the individual-level random effect. Dependent variable is Lie, a dummy indicating deceptive reporting.  $*p < 0.1$ ,  $**p < 0.05$ ,  $***p < 0.01$  for the two-sided t-test of the null hypothesis that each coefficient equals zero.

Lie	Coef.	Stan. Err.
InfoB	0.436***	0.130
pdB	0.181*	0.094
pdG	-0.366***	0.117
InfoB×pdB	-0.654***	0.124
InfoB×pdG	0.174	0.146
CRT	-0.059	0.043
BN	0.080*	0.042
constant	0.327***	0.110
N	600	
$R^2$ (within)	0.0939	
$R^2$ (between)	0.3478	
$R^2$ (overall)	0.1395	

To be more precise, reporting of ( $g$ ) with a ( $b$ ) signal can be regarded as the pursuit of potential benefits, given the possibility of ( $g$ ) reporting ( $b$ ). An explanation is that subjects who receive a ( $b$ ) signal are expected to have a higher possibility of not receiving stock when they report ( $b$ ), resulting in a profit of zero. Despite the risk of incurring losses, they may choose to make deceptive reports to obtain stock. In the context of the Information Revelation Hypothesis, a limited number of retail investors can benefit from this “hiding the good information strategy.” In other words, when there are more ( $g$ ) receivers performing the behavioral strategy of reporting ( $b$ ), the probability that the specific ( $b$ ) signal receiver reports ( $g$ ) and benefits increases, especially under the condition that the other ( $b$ ) signal receivers stay reporting honestly.

It is consistent with that, in instances where the ( $b$ ) receivers hold the belief that the ( $g$ ) receivers’ probability of reporting ( $g$ ) is low, there is a greater probability that the ( $b$ ) receivers will also lower their probability of reporting honestly. However, opportunistic behavior is not generally beneficial, since the probability of honest ( $g$ ) reporting is not low enough and the probability of honest ( $b$ ) reporting is comparably low.

The interaction term, InfoB×pdB, indicates that when subjects receive a ( $b$ ) signal, if they have a higher predicted probability of others honestly reporting ( $b$ ), their own likelihood of making honest reports increases (significant at the 1% level), suggesting that their strategies are consistent with their underlying beliefs in this case, showing their prudence to some level. Furthermore, the coefficient for BN is positive and aligns with the descriptive statistical analysis. This suggests that subjects in BN treatment are more likely to make deceptive reports (significant at the level 10%).

Additionally, we examine the consistency between actions and beliefs. By aggregating the individual behavioral strategies of the subjects in each treatment, it is possible to correspond the percentages of honesty or deceptive reporting to their “mixed strategy” on average. Recall Table 10, in BN, the overall “mixed strategy” indicates that subjects report honestly at a rate of 87% when receiving a ( $g$ ) signal and at a rate of 53% when receiving a ( $b$ ) signal. Regarding beliefs about others’ strategies, subjects expect others to report honestly at a rate of 72% when receiving a ( $g$ ) signal and at a rate of 53% when receiving a ( $b$ ) signal. In BP, the overall “Mixed Strategy” indicates that subjects report honestly at a rate of 83% when receiving a ( $g$ ) signal and at a rate of 80% when receiving a ( $b$ ) signal. Regarding beliefs about others’ strategies, subjects expect others to report honestly at a rate of 77% when receiving a ( $g$ ) signal and at a rate of 70% when receiving a ( $b$ ) signal.

These findings are consistent with the results of the regression analysis, suggesting that investors’ actions exhibit a trend similar to their beliefs. However, even if beliefs are accurate, it is disadvantageous when ( $b$ ) signal receivers make deceptive reports considering that others also do so.

In the context of BN treatment, where the prediction of others who report honestly after receiving a ( $b$ ) signal is low, the rational response to this belief for an individual is to report ( $b$ ) regardless of the signal. The overall “mixed strategy” employed in this scenario does not facilitate this behavior. Therefore, it can be inferred that while subjects can predict the behavior of others to a certain extent, they are unable to respond optimally, indicating a severe level of belief-action mismatch. The belief-action mismatch indicates a non-optimal response to the belief, in our case, it refers to mirroring the belief of others as their own action. The data indicates a tendency among individuals to underestimate the frequency of honest reports of ( $g$ ) signals and overestimate their likelihood of successfully engaging in deceptive reporting ( $g$ ). In contrast, subjects in BP treatment, presumed to understand the situation to a better extent, also predicted that others would adopt a more rational strategy and exhibit more consistent behavior. Although we cannot conclude the absence of belief-action mismatch in BP treatment, its tendency to more equilibrium-like belief yields improved outcomes.

Furthermore, subjects do not change their strategies when losses occur due to deceptive reporting. Regardless of the signal, the number of transitions from deceptive reporting to honest reporting or from honest reporting to deceptive reporting was found to be 3.33 transitions per subject in BN treatment and 2.5 transitions per subject in BP treatment. Furthermore, when subjects experienced losses due to deceptive reporting of a ( $b$ ) signal, the proportion of subjects who changed their strategies after receiving the next ( $b$ ) signal was 31 out of 59 times in BN and 14 of 23 times in BP, reflecting that a change in strategy could be random but not strategic. The occurrence of losses in the previous strategy cannot be seen to have improved beliefs or more consistent behavior in response to those losses.

Therefore, we hypothesize that subjects tend to mirror their own strategy on their belief of others and are unable to adjust their responses to others, even in experienced failure cases. However, subjects in treatment for BP appear to have

superior strategies from the beginning, although they may also exhibit belief-action mismatch.

It is considered that the mismatch between belief and action cannot explain why the BN treatment has a more overactive belief and corresponding behavior of the (b) signal receivers. The hypothesis on this type of positive investor sentiment can be further explored using the APH proposed by Lei et al. [15]. The APH illustrated that there is a considerable amount of trading activity that causes bubbles, in markets where speculation is possible, because there is no other activity available to participants in the experiment. In their Two-Market Treatment, when subjects are trained and examined by the protocol of the experiment and participation such as buying and selling is the only activity available, in the market in which speculation is permitted, subjects prefer engaging in activities rather than doing nothing even it would be unprofitable. In our experiment, the experimental surveys revealed that the participants found the experiment instructions lengthy and the comprehension questions complex. Participants were influenced by the learning cost associated with the experiment, leading them to potentially pursue the acquisition of shares at the risk of not receiving anything through honest reporting in their actual decision-making. Although there is no speculation due to the primary market setting, (b) investors have the opportunity to make a profit only if they can purchase shares. That is why (b) investors want transfers to take place, otherwise they will receive nothing and never benefit.

We identify the periods in which subjects made their first lie, specifically the periods in which they received a (b) signal and lied for the first time. In the BN treatment, of the 28 subjects (with only two subjects not participating in any deceptive reporting throughout the 10 periods), 24 subjects made their first lie within the initial three periods, of which 23 subjects made deceptive reports when receiving a (b) signal. In BP treatment, among 22 subjects (with eight subjects not performing any deceptive reporting during the 10 periods), 11 subjects concentrated on their first lie within the initial three periods, of which 10 subjects made deceptive reports after receiving a (b) signal. In conjunction with the regression analysis mentioned above, it is hypothesized that some reporters of deception are motivated by getting involved and gaining allocation. However, the gap between BN and BP treatments indicates that subjects in BN treatment with less understanding tend to exhibit more APH behavior. Taking into account the similarities between the two treatments, the length of the experimental protocol does not become the only cause of APH as in the previous study. We combine the APH with the understanding level and consider it can be improved by investor screening in the BB method.

**Result 2.** *Investors have similar belief and action trends, indicating that others recognize the presence of sentiment investors. The excessive participation phenomenon is explained by the belief-action mismatch and the APH.*

#### 4.3. Analysis of subjects' payoffs

We also conduct an analysis of subject payoff. The payoff is determined by the difference between the stock price and its value, as well as the number of acquired

shares, making it highly influenced by the actions of others. Theoretically, in the two equilibria, subjects who receive a (*b*) signal would always report (*b*), preventing overpricing and avoiding losses. However, as revealed in the previous analysis, a significant number of subjects engaged in deceptive reporting after receiving a (*b*) signal. As a result, out of 600 data pairs, there were 188 instances of negative payoffs, 325 instances with zero payoffs, and only 87 instances with positive payoffs.

As shown in Table 12, the dependent variable in our analysis is the realized value of 600 payoffs, referred to as “Profit.” There are six independent variables: dummy variables for participant types, referred to as PType as defined in Table 9 (with PType1 being the reference category and coefficients observed for PType2 to PType5); a dummy variable for private information, InfoB; an interaction term between a (*b*) signal and deceptive reporting, InfoB  $\times$  Lie (takes a value of 1 if a (*b*) signal is received and a deceptive report occurs, 0 otherwise); an interaction term between a (*g*) signal and deceptive reporting, InfoG  $\times$  Lie (takes a value of 1 if a (*g*) signal is received and a deceptive report occurs, 0 otherwise); a dummy variable for CRT evaluation; and a dummy variable for the BN treatment. The analysis was carried out using a random effect model, treating the 600 observations as panel data.

Table 12: Profit by Player Type

(Notes) The table reports the result of the OLS regression with the individual-level random effect. Dependent variable is Profit. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$  for the two-sided t-test of the null hypothesis that each coefficient equals zero.

Profit	Coef.	Stan. Err.
PType2	-9.104	141.282
PType3	40.798	143.568
PType4	302.856**	147.061
PType5	296.048**	141.118
InfoB	-88.223	109.663
InfoB $\times$ Lie	-1719.590***	137.965
InfoG $\times$ Lie	57.204	177.213
CRT	33.949	96.581
BN	-281.582***	91.367
constant	34.562	139.361
N	600	
$R^2$ (within)	0.2452	
$R^2$ (between)	0.6248	
$R^2$ (overall)	0.2897	

Within the player type dummies, the coefficients for PType4 and PType5 are positive and significant at the 5% level. This means that subjects belonging to PType4 and PType5 have higher profits than those belonging to PType1. Interestingly, PType4 and PType5 received (*g*) signals only three times out of the 10 periods, which is the lowest, compared to seven times for PType1 and PType2, and five times for PType3. Theoretically, when considering pure strategy equilibrium, all five types of individuals are expected to have the same expected profits.

However, when considering the mixed-strategy equilibrium, receiving a ( $g$ ) signal leads to higher profits. Thus, it was expected that individuals that received more ( $g$ ) signals would have more chances to benefit.

One reason is that, as described above, individuals tend to exhibit more equilibrium approximate behavior when they receive a ( $g$ ) signal, often reporting it honestly. However, analysis of the behavior of participants reveals that many individuals engage in deceptive reports due to APH when they receive a ( $b$ ) signal. As a result, stock prices increase, leading to more losses for the subjects. In other words, the effect of overpricing due to ( $g$ ) reports when a ( $b$ ) signal is received outweighs the underpricing effect of a ( $g$ ) signal (due to pricing rules or mixed strategy equilibrium used). Given that the value and price of the stock are common within the group, receiving more ( $g$ ) signals increases the likelihood of incurring losses given the influence of others' actions. On the other hand, subjects who receive less ( $g$ ) signals can avoid such losses and tend to have higher profits if they remain honest. In this experiment, we cannot conclude that profits are higher when subjects receive a ( $g$ ) signal than when they do not, as predicted by the theory.

The interaction term  $\text{InfoB} \times \text{Lie}$ , which represents the cross-effect between a ( $b$ ) signal and deceptive reporting, is negative and significant at the 1% level. This implies that receiving a ( $b$ ) signal but reporting ( $g$ ) leads to a sharp decrease in profits. This observation is consistent with theoretical expectations, since the ( $g$ ) report results in an allocation of stocks that can cause losses when the price exceeds the true value. Furthermore, the coefficient for BN is negative, indicating that BN subjects have lower payoffs than BP participants, and this difference is significant at the level 1%. Analyzing subject behavior, BN subjects have a higher frequency of reporting ( $g$ ) when receiving a ( $b$ ) signal, leading to an increase in cases of overpricing and resulting in greater losses for stock buyers.

In the above analysis, we explained the payoffs in relation to the player types. Next, we consider the relationship between the profits and characteristics of each period. Each period is characterized by the number of ( $g$ ) signals (identical to the effect of the stock value), denoted  $n = 0, 1, 2, 3, 4, 5$ . In the regression analysis presented in Table 13, we recorded it as "nInfoG" and introduced a dummy variable, "5InfoG," which represents the case where all participants received a ( $g$ ) signal (5InfoG=1 for five ( $g$ ) signals, and 5InfoG=0 for other situations). This is done to examine the underpricing that is expected to occur due to the underpricing rule. Furthermore, we included the following variables: a dummy variable for private information (InfoB); a dummy variable for deceptive reporting (Lie, with Lie=1 for deceptive reporting and Lie=0 for honest reporting); the interaction term of a ( $b$ ) signal and deceptive reporting (InfoB $\times$ Lie); a CRT evaluation dummy; and a treatment dummy (BN). The analysis is carried out using panel data consisting of 600 observations and a random-effects model.

The coefficient of nInfoG indicates that as the number of ( $g$ ) signals increases within a group, the payoffs also increase. This result is significant at the level 1%. As the variable nInfoG also indicates the stock value, this result is consistent with our findings in Section 4.1. One possible reason for this is that as the number of ( $g$ )



signals increases, the probability of deceptive reporting and subsequent price inflation under a ( $b$ ) signal decreases, leading to a reduction in losses due to overpricing. Alternatively, the coefficient on the dummy variable 5InfoG is not significant, suggesting that we did not observe a significant effect of the structural underpricing designed in the theory.

Furthermore, the InfoB coefficient is positive, indicating that while other conditions remain constant, receiving a ( $b$ ) signal leads to higher payoffs than receiving a ( $g$ ) signal (significant at the 1% level). This finding is consistent with the previous analysis, where players with fewer instances of receiving ( $g$ ) signals, such as PType4 and PType5, tend to have higher payoffs. However, the coefficient on the interaction term InfoB $\times$ Lie is negative and significant at the 1% level. This implies that subjects who engage in deceptive reporting under a ( $b$ ) signal have lower payoffs than those who engage in deceptive reporting under a ( $g$ ) signal. This can be attributed to the fact that the report ( $b$ ) allows them to avoid the impact of overpricing and prevent losses, regardless of their private information. Additionally, the coefficient on BN is negative, indicating that BN participants have lower payoffs than BP participants (significant at the 1% level), aligning with the regression analysis based on player types.

Table 13: Profit by Group Type

(Notes) The table reports the result of the OLS regression with the individual-level random effect. Dependent variable is Profit.  $*p < 0.1$ ,  $**p < 0.05$ ,  $***p < 0.01$  for the two-sided t-test of the null hypothesis that each coefficient equals zero.

Profit	Coef.	Stan. Err.
nInfoG	496.667***	39.930
5InfoG	72.299	160.530
InfoB	741.410***	101.399
Lie	-119.272	150.817
InfoB $\times$ Lie	-1631.446***	190.684
CRT	19.102	81.496
BN	-281.847***	77.955
constant	-1474.231***	147.569
N	600	
$R^2$ (within)	0.3127	
$R^2$ (between)	0.5907	
$R^2$ (overall)	0.3445	

Finally, we examine the factors influencing group-level payoffs.

In Table 14, we employ regression analysis to examine the group-level payoffs (Sumprofit). Independent variables comprise the number of ( $g$ ) reports in each period (nInfoG), the number of subjects in the group that received ( $g$ ) signals but reported ( $b$ ) (nGLie), the number of subjects in the group that received ( $b$ ) signals but reported ( $g$ ) (nBLie), and the treatment dummy variable BN. A panel dataset consisting of 120 observations is used at the group level and the analysis is performed using a random-effects model.

As a result, the coefficient of nInfoG is positive and significant at the level 1%. This indicates that as the number of (*g*) signals increases, the overall profits of the group also increase. Furthermore, when more subjects in the group receive (*g*) signals but report (*b*), profits also increase, while an increase in the number of subjects receiving (*b*) signals but reporting (*g*) leads to a decrease in profits. These findings are consistent with the individual-level analyses.

As revealed by regression analysis, the main cause of lies is the deviation from the strategic choices suggested by the theoretical equilibria, specifically in the higher frequency of deceptive reporting when participants receive a (*b*) signal. Consequently, stock prices increase, leading to a decrease in investor surplus. In this environment, even if subjects receive a (*g*) signal and choose their strategies accordingly, there is the possibility of incurring losses. To avoid losses caused by deceptive (*g*) reports from group members, it is effective to report (*b*) regardless of private information, a phenomenon known as the consequence of adverse selection.

Table 14: Group Profit

(Notes) The table reports the result of the OLS regression with the group-level random effect. Dependent variable is Sumprofit, total profit of each group.  $*p < 0.1$ ,  $**p < 0.05$ ,  $***p < 0.01$  for the two-sided t-test of the null hypothesis that each coefficient equals zero.

Sumprofit	Coef.	Stan. Err.
nInfoG	534.563***	83.173
nGLie	3368.960***	168.254
nBLie	-3401.728***	139.526
BN	61.410	251.873
constant	-1228.763***	289.983
N	120	
$R^2(\text{within})$	0.9570	
$R^2(\text{between})$	0.9524	
$R^2(\text{overall})$	0.9562	

**Result 3.** *Investors are more likely to benefit when the stock value is high, while a high-expected value signal does not bring more benefits to the specific investor using the BB method because the information elicitation is deficient.*

**Result 3** can be viewed as a supplement of **Result 1**. Based on this result, we can argue that different hypotheses on the IPO underpricing problem (underpriced compared to the initial market price) do not necessarily have to be treated as entirely distinct. The winner's curse is more prevalent among investors with a lower level of understanding. However, when the winner's curse does occur, it is not only due to adverse selection caused by information asymmetry but also by the presence of sentiment investors. Based on the analyses thus far, Table 15 is used to compare the theoretical values in equilibrium, the prices, the price deviation, average investor surplus, average issuer surplus, allocation efficiency and excluded (*g*) investor in the two-session experiment for a more intuitive evaluation of the performance of the experimental model.

The realized price deviation is calculated by averaging the squared differences between each realized price and the stock value across 60 pairs of data from each treatment. Allocation efficiency is defined as the percentage of shares purchased by ( $g$ ) signal investors. The measure of the excluded ( $g$ ) signal investors shows the percentage of ( $g$ ) investors who were unable to purchase the stock.<sup>9</sup>

Table 15: Experimental Model Performance

	BN	BP
Theoretical Value	350	350
Average Realized Price	418	353
Realized Price Deviation	19500	10333
Average Investor Surplus	-2720	-120
Average Issuer Surplus	16720	14120
Allocation Efficiency	62%	75%
Excluded ( $g$ ) Investor	13%	16%

As shown in Table 15, the average realized prices exceeded the average stock value of 350 in the experiment. In particular, in periods with fewer private ( $g$ ) signals, overpricing occurs, leading to losses for investors. As a result, the average investor surplus in the experiment became negative, lower than the theoretical values. Conversely, the average issuer surplus increased with the increase in prices, exceeding the equilibrium values. The realized price deviation shows that the performance of the BN treatment deviates further from equilibrium than that of the BP treatment, resulting in a higher incidence of overpricing and loss of participants. The allocation efficiency in both cases is higher than 50%, and BP achieves better results. The percentage of excluded ( $g$ ) investors is low, and there is not much difference between the two treatments.

**Result 4.** *If all investors in the society have a thorough understanding of the IPO, the BB method can achieve a high level of price discovery & allocation efficiency, resembles the theoretical model expectation.*

Based on our experimental results, we also propose the following conjectures regarding the secondary market. Although both BP and BN treatments are designed to represent an IPO pricing process dominated by informed investors in the primary market, our current analysis reveals that investors in BN, despite having private information, lack understanding of the IPO process. This leads to a significant amount of sentiment-driven behavior.

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<sup>9</sup>The theoretical values are calculated using the distribution of private information identified in the experiment and should be expected to differ from the expected values presented in Table 2. All numbers in the table have been rounded to the nearest integer.

According to the empirical analysis of Aggarwal et al. [1], participants in the primary market are mainly sophisticated institutional investors, such as those of BP, while institutional investors in the secondary market tend to hold onto their shares on the first day, allowing a large number of retail investors to make purchases. In other words, BN presents a scenario more aligned with the Behavioral Hypothesis, suggesting the sentiment investors are inclined to push prices higher both in IPOs and on initial days. Due to the high participation of sentiment investors, the first-day price is inflated, partially confirming that IPOs are underpriced compared to the first-day closing price.

Furthermore, although the CRT questions were included in this experiment, the regression analysis did not produce significant results for the dummy variable based on the number of correct answers to the CRT questions. In the survey, many participants wrote that they were watching the behavior patterns of the group members and adjusting their strategies accordingly. Considering the pricing and allocation rules of the IPO stock, the results of the IPO heavily depend on the characteristics of the entire group and cannot be directly attributed to cognitive abilities. In other words, even a small presence of sentiment investors can lead to IPO stocks being overpriced, posing a consistent risk for rational investors seeking to purchase the stock.

## 5. Conclusion

In this study, we examined the performance of the direct mechanism representing the BB method using experimental economic methods, allowing for direct intuitive observation of investor reporting behavior combined with their beliefs. We find that investors have beliefs about others that resemble their own behavior, but cannot rationally adjust their response to the belief even if it is correct. This causes widespread deceptive reporting behavior and the subsequent overpricing problem.

We established a methodology that demonstrates that the theoretical structure can be achieved if the subjects have a thorough understanding. This methodology also illustrates the viability and representability of the B&F model. We specifically focused on the inefficient pricing issue and conducted our analysis accordingly. As a result, IPOs are commonly overpriced regarding the fundamental stock value. Hence, we provide a framework for analyzing the potential coexistence of IPO overpricing relative to fundamentals and underpricing to the secondary market.

Building upon the findings of earlier research, we elaborate on the notion that when the quality of investors cannot be regulated, there exists a risk of the winner's curse being attributed not only to adverse selection, but also to investor sentiment. Considering the discrepancy between our experimental results and the theoretical hypothesis, we propose that the three primary hypotheses (Information Revelation Hypothesis, Winner's Curse Hypothesis, and Sentiment Hypothesis) concerning IPO underpricing as ex post adjustment are not mutually exclusive but may coexist simultaneously.

Considering the characteristics of our experiments relative to reality, the positive sentiment of retail investors can be described by a constructed APH, generated both

on primary and secondary markets. The treatment with fewer explanations can also be used to explain the first-day performance of the secondary market, where many retail investors enter the market. Instead, the treatment with more explanations is believed to better represent the BB method of IPO with most institutional investors participating. Therefore, this study obtained policy implications from these results.

First, our experiments support the need to set the filing range conditions in the BB method. Although institutional investors exhibit rational behavior, there is the possibility of inappropriate pricing due to the presence of retail investors or IPOs with extremely low value. Setting price ranges ensures the avoidance of losses caused by opportunistic or sentimental behavior and provides a sense of pricing stability for institutional investors, enabling them to maintain continuous investment.

Second, our experiment shows that without investor screening and ex-post underpricing adjustment, overpricing occurs and harms the benefit of investors honestly revealing good information. Thus, expanding the opportunities for underpricing in order to compensate institutional investors, commonly known as “leaving money on the table,” is emerging as the most direct way to further secure investor profits. The need for issuer discretion in controlling share price and allocation has been partially elucidated.

The limitations of our model include the lack of representation for the secondary market. Although we have successfully represented the theoretical model by B&F, who described that the exogenously determined fundamental value equals the price settled in the secondary market considering the Efficient Market Hypothesis, we lack direct observations representing first-day activities. This leads to the following inquiries: Can we prove IPO overpricing relative to fundamentals and IPO underpricing in the secondary market coexist by experiments, and if so, what is the fundamental value’s role throughout the life of the stock? To further elaborate, how does sentiment evolve during different periods, and does it align with the theoretical suggestion of Ljungqvist et al. [17], indicating that sentiment significantly increases initial returns but decreases long-term returns?

Based on the analyses above, we can outline the prospects for our future research. First, we will design and conduct experiments using an action method while retaining the current BB method as the baseline. We aim to evaluate and compare the performance of the two IPO pricing methods from various perspectives.

Furthermore, we would like to conduct experiments that include more consistent settings, where the first stage involves the current IPO process, followed by a second stage involving decision-making in the secondary market. This would allow us to observe the formation and evolution of market prices affected by sentiment and to analyze the impact of different IPO mechanisms and their respective long-term performance.

By referring to the results of these experiments, we can provide valuable insight to improve the efficiency of current policies and contribute to overall IPO market improvements.

## Appendix A.

### *Derivation of Equilibrium 2.*

Following the assumptions in the main text, an investor that receives a  $(b)$  signal always adopts the pure strategy of honest reporting and reports a  $(b)$ . On the other hand, an investor that receives a  $(g)$  signal may adopt a mixed strategy of honest and deceptive reporting.

We consider a symmetric mixed strategy where investors that receive a  $(g)$  signal report  $(g)$  with a probability of  $\alpha$  (honest reporting) and  $(b)$  with a probability of  $(1 - \alpha)$  (deceptive reporting).

For an investor  $i^*$  that receives a  $(g)$  signal, the possible number  $n$  of  $(g)$  signals in the group is 1 to 5. Therefore, we calculate the expected profit for  $i^*$  by dividing the case  $n = 1, 2, 3, 4, 5$ . To calculate  $\alpha$ , we match the expected profit when  $i^*$  reports  $(g)$  and when she reports  $(b)$ .

As an example, we will explain the case of  $n = 5$ . The probability that  $n = 5$  is realized is  $(\frac{1}{2})^4 = \frac{1}{16}$ , given the probability that all four investors except  $i^*$  are informed a  $(g)$  signal. From the setting where the  $(b)$ -informed investor conducts an honest-reporting pure strategy and the  $(g)$ -informed investor conducts the mixed strategy, there are five possibilities of  $l_{i^*} = 0, 1, 2, 3, 4$  for the reports of four investors other than  $i^*$ . The probability of realization of each of them is  $(1 - \alpha)^4, 4\alpha(1 - \alpha)^3, 6\alpha^2(1 - \alpha)^2, 4\alpha^3(1 - \alpha), \alpha^4$ .

- Whenever  $i^*$  reports  $(g)$ , she gets an allocation of shares.
  - If  $l_{i^*} = 0$ ,
 
$$v = 600, p = 200, q_{i^*} = 40,$$
 profit becomes 16000.
  - If  $l_{i^*} = 1$ ,
 
$$v = 600, p = 300, q_{i^*} = 20,$$
 profit becomes 6000.
  - Same as in the following.
- When  $i^*$  reports  $(b)$ , there is an allocation of shares only if the other four also report  $(b)$ . Otherwise, the profit is always zero.
  - If  $l_{i^*} = 0$ ,
 
$$v = 600, p = 100, q_{i^*} = 8,$$
 profit becomes 4000.

Thus, in the  $n = 5$  case, the expected profit when  $i^*$  reports  $(g)$  and  $(b)$ , respectively, are  $16000(1 - \alpha)^4 + 24000\alpha(1 - \alpha)^3 + 16000\alpha^2(1 - \alpha)^2 + 4000\alpha^3(1 - \alpha) + 800\alpha^4$  and  $4000\alpha^4$ .

Next, perform the same calculation for cases  $n = 1, 2, 3, 4$ . Multiply the results by the probability of realization to match the expected profit of  $i^*$  reporting  $(b)$  and  $(g)$ .

The calculation yields  $\alpha = 0.88$  (rounded to two decimal places).

Similar calculations show that if players other than themselves always report honestly, the specific player with a  $(b)$  signal reporting  $(g)$  will always have the same or lower profit than that reporting  $(b)$ . Thus, it is confirmed that the optimal response is for the player with  $(b)$  signal to report  $(b)$ .

In other words, investors who receive a signal  $(g)$  can take a symmetric mixed strategy, reporting  $(g)$  with a probability of 0.88 and  $(b)$  with a probability of 0.12. This is how Equilibrium 2. is calculated.

#### *Derivation of table 2*

We derive two equilibria and obtain the price, the issuer's profit, the investor's profit on a  $(b)$  signal, and investor profit on a  $(g)$  signal in each. As the calculations in the mixed-strategy case are complex, we will illustrate the calculation of Equilibrium 2. as an example here.

- The equilibrium price is obtained by the price that can be achieved in the cases of  $n = 0, 1, 2, 3, 4, 5$  and the probability of its realization.

– If  $n = 0$ ,

$$p = 100, \quad \text{by possibility 1.}$$

– If  $n = 1$ ,

$$p = 200, \quad \text{by possibility } \alpha;$$

$$p = 100, \quad \text{by possibility } (1 - \alpha).$$

– If  $n = 2$ ,

$$p = 300, \quad \text{by possibility } \alpha^2;$$

$$p = 200, \quad \text{by possibility } 2\alpha(1 - \alpha);$$

$$p = 100, \quad \text{by possibility } (1 - \alpha)^2.$$

– Same as below.

Substituting  $\alpha$  in the derivation of Equilibrium 2. yields the equilibrium price  $p^* = 319$  (rounded to one decimal place).

- As the issuer's profit in equilibrium is the number of shares  $40 \times$  the equilibrium price  $p^*$ , here it is 12750.
- For the investor with a  $(b)$  signal, the expected profit in equilibrium is obtained by the profit that could be realized in cases  $n = 0, 1, 2, 3, 4, 5$  and the probability of each realization. There are eight shares of allocation only if the other four members of the group also report  $(b)$ .

- If  $n = 0$ ,

$$v = 100, p = 100, q = 8, \quad \text{by possibility 1.}$$

profit becomes 0.

- If  $n = 1$ ,

$$v = 200, p = 100, q = 8, \quad \text{by possibility } (1 - \alpha).$$

profit becomes  $800(1 - \alpha)$ .

- If  $n = 2$ ,

$$v = 300, p = 100, q = 8, \quad \text{by possibility } (1 - \alpha)^2.$$

profit becomes  $1600(1 - \alpha)^2$ .

- Same as in the following.

Substituting  $\alpha$ , the profit of an investor that received a  $(b)$  signal in equilibrium is 23 (rounded to the first decimal place).

- For an investor with a  $(g)$  signal, the expected profit in equilibrium is obtained by the profit that could be realized in the cases  $n = 0, 1, 2, 3, 4, 5$  and the probability of each realization. Reporting  $(g)$  would always result in an allocation of shares, and reporting  $(b)$  would result in an allocation of eight shares of stock only when the other four members of the group also report  $(b)$ .

- If  $n = 0$ , the profit becomes 0.

- If  $n = 1$ ,

$$v = 200, p = 100, q = 8, \quad \text{by possibility } (1 - \alpha).$$

profit becomes  $800(1 - \alpha)$ .

- If  $n = 2$ ,

$$v = 300, p = 100, q_b = 8, \quad \text{by possibility } (1 - \alpha)^2;$$

$$v = 300, p = 200, q_b = 40, \quad \text{by possibility } \alpha(1 - \alpha).$$

profit becomes  $1600(1 - \alpha)^2 + 4000\alpha(1 - \alpha)$ .

- Same as in the following.

Substituting  $\alpha$ , the profit of an investor that received a  $(g)$  signal in equilibrium is 401 (rounded to the first decimal place).



## Appendix B.

### *Subjects' Reports*

Table B.16: Subjects' Reports (BN)

Period \ Subject	1	2	3	4	5	6	7	8	9	10
1	(b)	(b)	(g)	(g)	(b)	(g)	(g)	(g)	(g)	(g)
2	(b)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)
3	(b)	(g)	(g)	(b)	(g)	(g)	(g)	(g)	(b)	(g)
4	(g)	(g)	(b)	(b)	(b)	(b)	(g)	(b)	(b)	(b)
5	(g)	(g)	(b)	(b)	(g)	(g)	(g)	(g)	(b)	(b)
6	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)
7	(g)	(b)	(b)	(g)	(b)	(b)	(g)	(b)	(b)	(b)
8	(b)	(g)	(b)	(b)	(b)	(g)	(b)	(g)	(g)	(g)
9	(g)	(g)	(b)	(b)	(b)	(g)	(g)	(b)	(g)	(g)
10	(g)	(b)	(g)	(g)	(g)	(g)	(b)	(g)	(g)	(g)
11	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)
12	(g)	(b)	(g)	(g)	(g)	(g)	(g)	(b)	(g)	(g)
13	(g)	(g)	(b)	(b)	(b)	(g)	(g)	(g)	(g)	(g)
14	(g)	(g)	(b)	(g)	(g)	(b)	(g)	(g)	(g)	(g)
15	(g)	(g)	(b)	(g)	(b)	(b)	(g)	(g)	(g)	(g)
16	(g)	(g)	(g)	(g)	(b)	(g)	(g)	(g)	(g)	(g)
17	(g)	(g)	(b)	(g)	(b)	(b)	(g)	(g)	(g)	(b)
18	(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)
19	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)
20	(g)	(b)	(g)	(g)	(b)	(b)	(g)	(g)	(b)	(b)
21	(g)	(g)	(b)	(b)	(g)	(g)	(g)	(g)	(g)	(g)
22	(g)	(g)	(b)	(g)	(b)	(b)	(g)	(b)	(b)	(b)
23	(g)	(g)	(b)	(b)	(g)	(g)	(g)	(g)	(b)	(g)
24	(g)	(g)	(g)	(g)	(b)	(b)	(g)	(b)	(g)	(b)
25	(g)	(g)	(b)	(g)	(b)	(g)	(g)	(b)	(g)	(b)
26	(b)	(g)	(g)	(g)	(b)	(g)	(g)	(g)	(g)	(g)
27	(g)	(g)	(b)	(g)	(b)	(b)	(g)	(b)	(b)	(b)
28	(g)	(g)	(b)	(g)	(b)	(g)	(g)	(b)	(g)	(g)
29	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(g)
30	(g)	(b)	(g)	(g)	(g)	(g)	(g)	(b)	(b)	(g)

Table B.17: Subjects' Reports (BP)

Subject \ Period	1	2	3	4	5	6	7	8	9	10
1	(b)	(b)	(g)	(g)	(b)	(b)	(b)	(g)	(g)	(g)
2	(g)	(b)	(g)	(g)	(b)	(g)	(g)	(g)	(b)	(b)
3	(b)	(g)	(b)	(b)	(b)	(g)	(g)	(g)	(b)	(g)
4	(g)	(g)	(b)	(g)	(b)	(b)	(g)	(g)	(g)	(g)
5	(g)	(b)	(b)	(b)	(b)	(b)	(g)	(g)	(b)	(b)
6	(b)	(b)	(g)	(g)	(b)	(g)	(g)	(g)	(g)	(g)
7	(g)	(g)	(g)	(g)	(b)	(b)	(g)	(b)	(b)	(b)
8	(b)	(g)	(b)	(b)	(b)	(g)	(b)	(b)	(b)	(b)
9	(g)	(g)	(b)	(g)	(b)	(b)	(g)	(g)	(g)	(g)
10	(g)	(b)	(b)	(b)	(b)	(b)	(g)	(g)	(b)	(g)
11	(b)	(b)	(g)	(g)	(b)	(g)	(g)	(g)	(g)	(g)
12	(g)	(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)
13	(g)	(g)	(b)	(g)	(b)	(g)	(g)	(b)	(b)	(g)
14	(g)	(g)	(b)	(g)	(g)	(b)	(g)	(g)	(g)	(g)
15	(g)	(g)	(b)	(b)	(g)	(b)	(g)	(b)	(g)	(g)
16	(b)	(b)	(g)	(g)	(g)	(g)	(g)	(g)	(g)	(b)
17	(g)	(g)	(b)	(g)	(g)	(g)	(g)	(b)	(g)	(b)
18	(b)	(g)	(g)	(b)	(b)	(g)	(g)	(b)	(b)	(g)
19	(g)	(g)	(b)	(g)	(b)	(b)	(g)	(g)	(g)	(g)
20	(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)
21	(b)	(g)	(g)	(g)	(b)	(b)	(g)	(g)	(g)	(b)
22	(g)	(b)	(b)	(g)	(b)	(b)	(b)	(b)	(b)	(b)
23	(b)	(g)	(b)	(b)	(b)	(b)	(b)	(b)	(b)	(g)
24	(g)	(g)	(b)	(g)	(b)	(b)	(g)	(b)	(g)	(g)
25	(g)	(b)	(g)	(g)	(g)	(b)	(g)	(g)	(b)	(g)
26	(g)	(g)	(g)	(b)	(b)	(g)	(g)	(g)	(g)	(b)
27	(g)	(g)	(b)	(g)	(b)	(b)	(g)	(b)	(b)	(b)
28	(b)	(g)	(b)	(b)	(b)	(g)	(b)	(g)	(b)	(g)
29	(g)	(g)	(b)	(b)	(b)	(b)	(g)	(g)	(g)	(b)
30	(g)	(g)	(g)	(b)	(b)	(g)	(g)	(g)	(g)	(g)

Each cell represents the report of a single subject in one period. Light gray cells indicate instances where the subject received a (g) signal but reported (b), while dark gray cells indicate instances where the subject received a (b) signal but reported (g). In other words, colored cells represent deceptive reporting, while white cells represent honest reporting.

The colored cells in the two tables intuitively show that there are a significant number of dark gray cells, indicating a lower level of information elicitation compared

to the assumption that subjects who receive a ( $b$ ) signal always report honestly.

In BN treatment, there are more dark gray cells, indicating a higher tendency of subjects to report ( $g$ ) when they receive a ( $b$ ) signal.

## Appendix C.

### Experimental Instruction

#### *About Today's Experiment*

Today's experiment will be a game about trading newly issued stocks.

Read the instructions carefully and be sure to ask questions if you do not understand them.

Even after the experiment has begun, anyone with questions can always raise their hand and call the instructor.

#### *Notes*

- Do not talk to others during the experiment.
- Do not perform any operations other than those instructed during the experiment.

#### *Stock Allocation Games*

You, the participants in the experiment, are investors considering the purchase of newly issued stock. Based on the information provided, you make a decision about the value of the new shares. Your decision determines the allocation and price of 40 new shares of stock, as well as your gain (profit from the purchase of the stock). If the value of the shares exceeds the purchase price, you will have a positive gain; if it falls below, you will have a negative gain (loss).

At the beginning of the game, participants will be randomly divided into groups of five. The other members of the group do not know who the other members are. The game will be repeated 10 times, but the members will not be changed.

At the start of each session, you will receive private information about the value of the stock that is not known to the other members. The private information will either be "Good" or "Bad", with a 1/2 probability for each. The value of a share increases with the number of members who received Good information and decreases with the number of members who received Bad information. Specifically, the value of a share is determined by

$$\text{Value of a share} = \text{Number of members who received Good information} \times 100 + 100$$

Thus, the value of a stock cannot be calculated solely from one's private information.

For example, if the private information obtained by 5 investors is 3 Good and 2 Bad, the value of the stock is:

$$3 \times 100 + 100 = 400$$

However, each individual cannot know the exact value of the stock because they do not know what information the others have obtained.

The following table shows the probabilities for different numbers of Good information received by the five members and the corresponding Stock Values:

Total number of Good information	0	1	2	3	4	5
Stock Value	100	200	300	400	500	600
Probability	1/32	5/32	10/32	10/32	5/32	1/32

Therefore, the probability that the private information obtained by you will give rise to the number of persons (0-4) who received Good information other than yourself and the corresponding share value can be calculated as follows.

If you received Good private information:

Number of Good information other than yours	0	1	2	3	4
Stock Value	200	300	400	500	600
Probability	1/16	4/16	6/16	4/16	1/16

If you received Bad private information:

Number of Good information other than yours	0	1	2	3	4
Stock Value	100	200	300	400	500
Probability	1/16	4/16	6/16	4/16	1/16

Note that the range and probability of the Stock Value depends on the private information Good or Bad you received.

The price and allocation of the shares are determined by your reports as an investor. After receiving private information, you report whether Good or Bad. You do not have to report exactly as you received; you can report Bad when you received Good private information, or Good when you received Bad private information.

Based on the number of Good reports of the five members, the Stock Price is determined as follows:

Total number of Good reports	0	1	2	3	4	5
Stock Price	100	200	300	400	500	500

After everyone reports and the price is set, the shares are allocated in the following manner.

- everyone reports Bad, shares are allocated to everyone 8 shares each.
- if at least one person reports Good, a total of 40 shares will be equally allocated only to investors who report Good.

For example, if there are three people who report Good, then 13.33 shares will be allocated to each of the three. However, you must purchase the allocated shares. If you report Good, you will be allocated shares, but you will have to buy the shares at the above price, so you may lose money. If you report Bad and all other members also report Bad, you will be allocated shares.

The gain from this game (profit from the purchase of shares) is calculated using the following formula and is earned as points:

$$\text{Gain} = \text{Number of shares allocated} \times (\text{Stock Value} - \text{Stock Price})$$

Note that your gain is determined by the personal information and reports of the others.

#### *Examples of profit calculation*

(1) Suppose that out of the five members, three have obtained Good private information and two have obtained Bad private information. Suppose further that you have obtained Good private information. Suppose also that one of the investors other than you reports Good (this is not known at the time of decision making).

- Suppose that you report Good, and since 3 people have private information of Good, Stock Value is 400. The Stock Price is 300 since there were 2 people who reported Good, including you. Since you are one of the two people who reported Good, you will receive  $40 \div 2 = 20$  shares. Therefore, your profit is

$$20 \times (400 - 300) = 2000 \text{ points.}$$

- Suppose you report Bad, and since three people have private information about Good, Stock Value is 400, as in (1.1). However, since you reported Bad, no shares were distributed. Therefore, your profit is

$$0 \times (400 - 200) = 0 \text{ points.}$$

(2) Suppose, as before, that of the five members, three have obtained Good private information and two have obtained Bad private information. But now suppose that you obtained Bad private information. Also, suppose that there were zero investors other than you who reported Good.

- Suppose that you report Good, and three people have private information about Good, so the Stock Value is 400, as in (1.1). The Stock Price is 200 since you are the only one who reported Good. Also, because you are the only one who reported Good, 40 shares are distributed. Therefore, your profit is

$$40 \times (400 - 200) = 8000 \text{ points.}$$

- Suppose you report Bad, 3 people have private information of Good, so the Stock Value is 400 as in (1.1). Zero people report Good, so the Stock Price is 100. Since everyone reported Bad, all 5 people will be allocated 8 shares. Therefore, your profit is

$$8 \times (400 - 100) = 2400 \text{ points.}$$

(3) Suppose, as before, that of the five members, three have obtained Good private information and two have obtained Bad private information. Suppose that you again obtained Bad private information. Suppose also that three investors other than you report Good.

- Suppose that you report Good, as 3 people have private information about Good, Stock Value is 400 as in (1.1). Since you are one of the four who reported Good, you will receive  $40 \div 4 = 10$  shares. Therefore, your profit is

$$10 \times (400 - 500) = -1000 \text{ points.}$$

- Suppose you report Bad. Three other people besides you report Good, so you have no allocation of shares. Therefore, your profit is 0 points.

### *Prediction Screen*

Figure C.4: Prediction Screen

At the beginning of each period, the top of the screen will indicate whether the private information you have obtained is Good or Bad.

The number of the period is shown in the upper left corner of the screen. In the upper right corner of the screen, the time remaining for decision making for the current period is shown (time limit 30 seconds). In the lower right corner of the screen is an OK button. Enter your estimate of the probability that group members other than you will report Good or Bad when they receive Good or Bad private information. Note that the unit is %, and you can enter a number between 0 and 100, in increments of 0.1.

Then press the OK button. When everyone presses the OK button, the Report Screen appears.

### *Report Screen*

The screenshot shows a web-based interface for a report screen. At the top left, there is a header bar with the text "Period" followed by "1 / 1". At the top right, there is a header bar with the text "Remaining time 28". The main content area is a large light gray rectangle. In the center of this area, there is a form with two sections. The first section is labeled "Your private information" and has a radio button next to the word "Bad". The second section is labeled "Your report" and has two radio buttons, one next to "Good" and one next to "Bad". In the bottom right corner of the main content area, there is a red button with the text "OK" in white.

Figure C.5: Report Screen

The center of the Report Screen contains your personal information. As with the Prediction Screen, the top left corner of the screen shows the period number and the top right corner of the screen shows the time remaining for decision making for the current period (30 second time limit). In the lower right corner of the screen is the OK button. Check whether the private information you have obtained is Good or Bad and then select Good or Bad report. Then press the OK button. When everyone presses the OK button, the Result Screen is displayed.

### *Result Screen*

The center of the Result Screen lists your private information, your report, the number of Good private information, the number of Bad information, the number of Good reports, the number of Bad reports, the value of the shares, the price of the shares, your allocation, and your profit.

As in the Report Screen, the Result Screen has the number of times in the upper left corner, the time remaining in the upper right corner, and the OK button in the lower right corner. When you have finished checking the results, click the OK button. Once everyone has clicked the OK button, you will move on to the next report selection screen.

We will ask everyone to repeat these rounds 10 times.

The payment for this experiment will be the amount obtained by randomly selecting one period from the 10 periods and converting the points at 10 points to 1 Japanese yen, plus the participation fee of 1,500 yen. However, units of one yen will be rounded off.



Period		1 / 1		Remaining time 27																					
<table> <tr> <td>Your private information</td> <td>Bad</td> </tr> <tr> <td>Your report</td> <td>Bad</td> </tr> <tr> <td>Number of Good informations</td> <td>0</td> </tr> <tr> <td>Number of Bad informations</td> <td>1</td> </tr> <tr> <td>Number of Good reports</td> <td>0</td> </tr> <tr> <td>Number of Bad reports</td> <td>1</td> </tr> <tr> <td>Value of the shares</td> <td>100</td> </tr> <tr> <td>Price of the shares</td> <td>100</td> </tr> <tr> <td>Your allocation</td> <td>8.00</td> </tr> <tr> <td>Your profit</td> <td>0</td> </tr> </table>						Your private information	Bad	Your report	Bad	Number of Good informations	0	Number of Bad informations	1	Number of Good reports	0	Number of Bad reports	1	Value of the shares	100	Price of the shares	100	Your allocation	8.00	Your profit	0
Your private information	Bad																								
Your report	Bad																								
Number of Good informations	0																								
Number of Bad informations	1																								
Number of Good reports	0																								
Number of Bad reports	1																								
Value of the shares	100																								
Price of the shares	100																								
Your allocation	8.00																								
Your profit	0																								
OK																									

Figure C.6: Result Screen

After completing the post-experiment questionnaire and receiving payment, today's experiment will be closed.

Above is the instructions for the experiment. If you have any questions during the experiment, please check these instructions again. We will now begin the exercises, and you can also use a calculator.

If you have any questions, please raise your hand and call the instructor.

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