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Bubbles and Experience: An Experiment with a Steady Inflow of New Traders

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We revisit the effect of traders' experience on price bubbles by introducing either one-third or two-thirds steady inflow of new traders in each of four consecutive experimental asset markets. We find that bubbles are still reduced in the treatments with a steady inflow of new traders, but at a slower pace compared to the baseline treatment in which new traders are only introduced in the last market. Our analysis of individual trading behavior shows that the slower abatement of bubbles in the inflow treatments can be attributed mainly to the inexperienced traders who make more mistakes than experienced traders.

JEL Classification: C91, D83, G12

1. Introduction

The phenomenon of asset price bubbles is important because of its possibly catastrophic consequences to the economy and society. Our study focuses on the role of new traders in the formation of price bubbles, which has very important empirical relevance. The inflow of new traders is a salient feature of an asset market when a new financial product is introduced into the market or when there is a big shock to the market environment. Furthermore, a new environment, together with an inflow of new traders, can create large differences in price expectations and thus is more likely to generate price bubbles. Many historic bubbles, such as the South Sea bubble, the Dot-Com bubble, and the recently burst housing bubble in the United States, arose from a seemingly new market environment or a market with dramatic financial innovation. Last but not least, new traders might play a big role in emerging financial markets that are becoming an essential component of the global economy.

Starting with Smith, Suchanek, and Williams (1988, SSW henceforth), experimental asset markets have been widely used to study asset price bubbles, with the advantage over real financial markets of allowing researchers to measure the fundamental values (FV, hereafter) of the assets and thus price bubbles. Numerous studies have demonstrated that bubbles and large price deviations exist in a variety of experimental settings.[1] SSW and follow-up studies also consistently find that in a *stationary* market environment, *common group experience* with an identical set of traders causes asset prices to converge toward the intrinsic FV by the third market with the identical market structure. This finding is robust even with a mix of experienced and inexperienced traders. Dufwenberg, Lindqvist, and Moore (2005, DLM henceforth) report an experiment in which the same

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[1] See Noussair and Tucker (2013) and Palan (2013) for recent literature reviews.

group of traders participated in the first three markets and a portion of these traders, either 1/3 or 2/3 of them, were replaced by new inexperienced traders in the fourth market. They find that bubbles do not return in the fourth market.

The effect of experience and learning on price bubbles, however, appears very different in empirical studies on real-world financial markets. Xiong and Yu (2011) find no evidence of investor learning in reducing asset bubbles, using data from the Chinese warrants market. They split their data sample, which spans over three years, into two halves that have investors with different levels of learning, and find that the differences between these two subsamples in warrants prices, turnover, volatility, and the magnitude of the violation of the fundamental upper bound are insignificant. Other studies show that inexperienced investors play an important role in the formation of price bubbles. Greenwood and Nagel (2009) find that, using age as a proxy for experience, around the peak of the technology stock bubble, mutual funds run by younger managers are more heavily invested in technology stocks than funds run by their older colleagues, and young managers exhibit trend-chasing behavior in their investments.

In this study, we revisit the relationship between experience and bubbles by investigating a market environment which allows experienced traders to learn while trading with a steady inflow of new traders. In previous experimental studies, the same set of traders interact with each other over time; the experienced traders gain common group experience (Hussam, Porter, and Smith 2008). This kind of stable market environment and trader composition may make learning much easier than a market environment which changes over time like a real market.[2] Therefore, incorporating the inflow of new traders into the experimental design might be crucial in reconciling the different findings from lab and field studies on price bubbles. The inflow of new traders in real asset markets not only changes the composition of groups of traders in terms of their experience levels, but also may affect experienced traders' expectations and behavior, and thus lead to a different market outcome.

In particular, we adopt an experimental design that involves both experienced and inexperienced traders in each market. All sessions consist of four consecutive markets, each with 10 periods. As opposed to previous experimental studies, the experienced traders in our study have gained their experience through interaction with a succession of new traders.[3] Our experimental design involves three treatments. The baseline treatment is the same as the design in DLM except that we use a call market rather than the double auction mechanism. The same group of six traders participate in the first three markets. At the beginning of the last (fourth) market, two new inexperienced traders replace two experienced traders and participate in the market with the other four experienced ones. In our inflow treatments, denoted IF1/3 and IF2/3, we replace either 1/3 or 2/3 of the traders with new traders after each market, while keeping a fixed group of experienced traders.

We find that the steady inflow of new traders can sustain bubbles/mispricing to a certain extent in a market where two-thirds of the traders are inexperienced. By the third market, bubbles are not significantly reduced in the IF2/3 treatment. However, by the fourth market, bubbles are significantly reduced in the both IF1/3 and IF2/3 treatments. When comparing the bubble

[2] For instance, Hussam, Porter, and Smith (2008) show that bubbles can be rekindled when experienced subjects face a large increase in liquidity and dividend uncertainty that greatly shock the environment.

[3] A recent article by Deck, Porter, and Smith (2014) investigates the impact of investor flow on price bubbles in an overlapping-generations environment. In their design, the entry and exit of generations cause a change in liquidity, and correspondingly, the market generates an M shaped double-bubble price path. In our experiment, the initial endowment of money and assets is the same at the beginning of each market, so liquidity does not change with the entry and exit of new traders. Thus, the pattern of price bubbles we found is purely due to the particular composition of experienced and inexperienced traders induced by the inflow of new traders.

reduction between treatments directly, we find that the reduction in the IF2/3 treatment is marginally larger than that in the baseline treatment. In contrast, the baseline treatment yields similar results as those found in DLM; bubbles are significantly abated by the third market and adding new traders in the fourth market does not cause price bubbles to return.

In order to understand the underlying forces behind the aggregate findings, we conduct a detailed analysis on individual trading behavior and ask the following questions: First, do inexperienced traders make more mistakes than experienced traders? Second, if this is the case, do experienced traders change their behavior in correspondence with the inflow of new traders, anticipating that new traders will make more mistakes? The analysis shows that experienced traders make fewer mistakes than inexperienced traders, where mistakes are defined as orders with sell prices substantially below FVs. However, we do not find convincing evidence that experienced traders take advantage of inexperienced traders to a greater extent in the inflow treatments than in the baseline treatment. Hence, we conclude that the slower reduction of price bubbles in the inflow treatments is more likely a result of the new traders's mistakes.

Our article is most close to that of Akiyama, Hanaki, and Ishikawa (2014). Both articles study how experienced traders respond to the inflow of new traders in experimental asset markets. Akiyama, Hanaki, and Ishikawa (2014) have one experienced human subject (EH) interact with five inexperienced human subjects (1EH5H) in order to investigate how EHs change their beliefs and trading strategies when faced with strategic uncertainty caused by the inflow of inexperienced subjects. The experienced subjects (EHs) were recruited from earlier sessions in which they gained experience in three identical markets with either five robots who always play as fundamentalists or five human subjects. However, in our experimental design, the experienced traders gain experience along with the inflow of new traders, so the learning of experienced traders may also be affected by the inflow of new traders. Akiyama, Hanaki, and Ishikawa (2014) find that the majority of the EHs did not change their trading behavior and instead acted as price stabilizers with the inflow of inexperienced subjects, which is a similar conclusion to what we found in the individual analysis.

Another closely related article is Cheung, Hedegaard, and Palan (2014), which experimentally manipulated agents' information regarding the rationality of other traders, specifically, the information on whether all other traders in the market have been trained to understand the declining FV process. They find a distinct and statistically significant effect of public knowledge over and above that of training alone. Their paper therefore reaffirms the role strategic uncertainty plays in the formation of bubbles in the asset market experiments introduced by Smith, Suchanek, and Williams (1988).

The article is organized as follows. Section 2 presents the experimental design and the hypotheses. Section 3 documents the aggregate analysis of price bubbles and the statistical tests on the hypotheses. Section 4 reports the findings on individual trading behavior and examines the possible explanations for the aggregate findings in section 3. Section 5 concludes the article.

2. Experimental Design and Hypotheses

Experimental Design

The parameters in our experimental asset markets follow DLM. An asset's life span is 10 periods. In each period, it pays a dividend of 0 or 20 francs (the experimental currency) with equal probability. Trade takes place in each period, before dividends are determined. The dividend process determines the asset's FV which equals the expected dividend in each period, 10 francs, times the number of dividend draws remaining.

A session consisted of four consecutive markets, each with 10 periods. Each market comprised six traders who could both buy and sell assets. Each of the six participants possessed an initial endowment of cash and units of the asset at the beginning of period 1 in each of the four markets. Before a market opened, half of the traders each started with a cash endowment of 200 francs and six assets, while each of the other traders started with 600 francs and two assets, so that the two endowment profiles give the same expected payoff. At the beginning of the experiment, the experiment participants were provided with a table describing the expected value of the asset's dividend stream at the beginning of each period. An individual's initial cash balance and asset inventory at the beginning of period 1 were same in each market. At the end of period 10, the total earnings for that market were calculated after the dividend for period 10 was paid. The inventory and balances held at the end of one market disappeared. However, within each market, individual inventories of asset and cash balances carried over from one period to the next. The exchange rate was 100 francs to 1 Canadian dollar.

We had three treatments: two inflow treatments (denoted as IF1/3 and IF2/3) and a baseline treatment (denoted as BL). In the IF1/3 treatment, 12 subjects were recruited in each session and participated in the training period together. After the training period, the eight subjects with computer IDs from 5 to 12 were asked to go to the waiting room and would only participate in one of the four markets, while the other four subjects whose computer ID was from 1 to 4 were selected to participate in all four of the markets. At the beginning of each market, two of the eight subjects in the waiting room were randomly selected to enter the market. They were replaced by another two inexperienced traders when a new market began. When those eight subjects were in the waiting room, they were not allowed to communicate among each other and were asked to complete as many cross-word puzzles and Sudoku puzzles as possible. They did not earn anything by doing the puzzles, so that we controlled for the initial income of the inexperienced traders when they entered the market. But the inexperienced traders were given an additional fixed payment of 15 dollars for their waiting time. The IF2/3 treatment is similar to the IF1/3 treatment, except that 18 subjects were recruited, subjects 1 and 2 participated in all the four markets and the other 16 subjects participated in only one of the four markets. The design of the baseline treatment is the same as the one-third treatment in DLM. There were eight subjects in each session. In the fourth market, two experienced subjects who had participated in the first three markets were replaced by two new inexperienced subjects. In all three treatments, when a new market opened, the initial endowments were set the same for the same computer, so the total liquidity remained the same at the beginning of each market even with the entry and exit of traders.

In a departure from DLM, we used a call market [as in, for example, Van Boening, Williams, and LaMaster (1993), Haruvy, Lahav, and Noussair (2007)] instead of a double auction market, in order to test whether the result of DLM is robust to the choice of market mechanism. The market was implemented using the software z-Tree (Fischbacher 2007).[4] In a call market, all bids and asks for a period are submitted simultaneously, aggregated into market demand and supply curves, and the market is cleared at a uniform price for all transactions of that period.[5] In each period, each participant had an opportunity to submit one buy order and one sell order to the market. An individual's submitted buy order consisted of only one price and a maximum quantity the individual was willing to purchase at that price. Similarly, his sell order consisted

[4] The program was modified from the one used by Haruvy, Lahav, and Noussair (2007), which is posted on the AEA website.

[5] See Sunder (1995) for a more detailed discussion of the advantages and disadvantages of call market versus continuous double auction design.

of only one price and a maximum quantity the individual offered to sell at that price. Individuals did not observe the orders of any other agents for the period when submitting their own orders. After all of the participants had submitted their decisions, the computer calculated the market price as the lowest equilibrium price in the intersection of the market demand and supply curves constructed from the individual buy and sell orders. Participants who submitted buy orders at prices above the market price made purchases, and those who submitted sell orders at prices below the market price made sales. Any ties for last accepted buy or sell order were broken randomly. Participants were not permitted to sell short or to borrow funds.

The information provided to each individual at the end of each period consisted of the market price, the dividend, the number of units of the asset he acquired and sold, his current inventory of the asset, the cash he received from sales and spent on purchases, his current cash balance, and the cumulative earnings for the session. For inexperienced subjects, the cumulative earnings for the session were the total earnings from the market that they participated in. Before subjects submitted their buy and sell orders, the computer screen displayed the price history of markets the subject participated in. For experienced subjects, prices from all previous periods in all markets were displayed. For inexperienced subjects, only prices from all previous periods in the market they participated in were displayed.

The experiment took place in the Bell economics experimental lab at CIRANO in Montreal. We conducted five sessions for the baseline treatment and 10 sessions for each of the IF1/3 and IF2/3 treatments. In total, 340 subjects participated in the experiment. Most subjects were undergraduate students from universities in the Montreal area. No subjects had prior experience in similar experiments and all subjects participated in only one session. All sessions lasted approximately 2.5 hours, including the first 45 minutes during which the experimenter read the instructions and trained the participants to use the market software. At the end of the experiment, participants were privately paid, in cash, the amount of their final cash holdings from all markets they had participated in, in addition to a $5 show-up fee. In order to control for the income effect, all inexperienced traders were paid the same additional payment of $15 as compensation.

Hypotheses

Previous studies indicate that bubbles are significantly reduced by the third market, so we first investigate whether it is true for both baseline and inflow treatments. Our first (second) null hypothesis is that the measures (M) of price bubbles in the first and the third (fourth) market are not significantly different, while the alternative hypothesis states that the measures in the third (fourth) market are significantly smaller than those in the first market.

H1: $M^1 = M^3$;
Alternative H1: $M^1 > M^3$.
H2: $M^1 = M^4$;
Alternative H2: $M^1 > M^4$.

We expect that price bubbles are less substantially abated across the markets in the inflow treatments compared to the baseline treatment. A steady inflow of new traders makes the trader composition of each market similar to the first market, in which all traders are inexperienced. Meanwhile, the inflow of new traders may make the learning process of the experienced traders noisier and reduce the effect of experience on the reduction of bubbles. As a result, we expect that the inflow treatments will be in favor of the null H1 and H2, but the baseline treatment will be in favor of the alternative H1 and H2, following the findings in Dufwenberg, Lindqvist, and Moore (2005).

Our third hypothesis compares the magnitude of the bubbles in markets 3 and 4. In the baseline treatment, following DLM, we expect that bubbles will be eliminated by the third market and will not reappear in the fourth market when two experienced traders are replaced by new traders. In the inflow treatments, we expect that bubbles are not significantly reduced over the markets, so there is no significant difference between the bubble measures in market 3 and market 4. Therefore, we expect the null H3 will be supported in all treatments. In the baseline treatment, since new traders are only introduced in the fourth market, the alternative H3 is that bubbles are larger in the fourth market than in the third market. In the inflow treatments, as new traders are introduced in each market and the experienced traders gain more experience in the fourth market, the alternative H3 is that bubbles are larger in the third market than in the fourth market.

H3: $M^3 = M^4$;
Alternative H3: $M^3 < M^4$ in the baseline treatment and $M^3 > M^4$ in the inflow treatments.

We propose two hypotheses to compare the bubble measures across treatments. Hypothesis four states that the magnitude of bubbles is smaller in the baseline treatment than in the inflow treatments in markets 2, 3, and 4 based on the conjecture that the bubble reduction is larger in the baseline treatment than in the inflow treatments.

H4: $M^k_{\text{Baseline}} = M^k_{\text{IF1/3}} = M^k_{\text{IF2/3}}$, for $k = 2, 3, 4$;
Alternative H4: $M^k_{\text{Baseline}} < M^k_{\text{IF1/3}} < M^k_{\text{IF2/3}}$, for $k = 2, 3, 4$.

Cross-treatment comparisons warrant caution, however, as subjects' expectations may vary with the trader composition in different treatments. In order to test the treatment effect directly, we propose a test of the bubble reduction from market 1 to market 3 (4) across treatments (the difference in difference test). Define $\text{Diff}^{1-3} = M^1 - M^3$ ($\text{Diff}^{1-4} = M^1 - M^4$) as the differences in bubble measures between market 1 and market 3 (4). Our conjecture is that the differences are larger in the baseline treatment than in the inflow treatments, and are larger in the IF1/3 treatment than in the IF2/3 treatment.

H5: $\text{Diff}^{1-3}_{\text{Baseline}} = \text{Diff}^{1-3}_{\text{IF1/3}} = \text{Diff}^{1-3}_{\text{IF2/3}}$;
Alternative H5: $\text{Diff}^{1-3}_{\text{Baseline}} > \text{Diff}^{1-3}_{\text{IF1/3}} > \text{Diff}^{1-3}_{\text{IF2/3}}$.
H6: $\text{Diff}^{1-4}_{\text{Baseline}} = \text{Diff}^{1-4}_{\text{IF1/3}} = \text{Diff}^{1-4}_{\text{IF2/3}}$;
Alternative H6: $\text{Diff}^{1-4}_{\text{Baseline}} > \text{Diff}^{1-4}_{\text{IF1/3}} > \text{Diff}^{1-4}_{\text{IF2/3}}$.

As the hypotheses discussed above provide a justified prior on the direction of changes in bubble measures, we use one-tailed statistical tests in this article as in Dufwenberg, Lindqvist, and Moore (2005).

3. Price Bubbles

Summary Statistics

Figure 1 describes the average prices along with the FV of the asset in each period, respectively for each treatment.[6] On average, the price pattern in the first market is similar across the

[6] In Figures B1–B3 in Appendix B, we also show the transaction price in each period of each market in each session, along with the FV, respectively for each treatment.

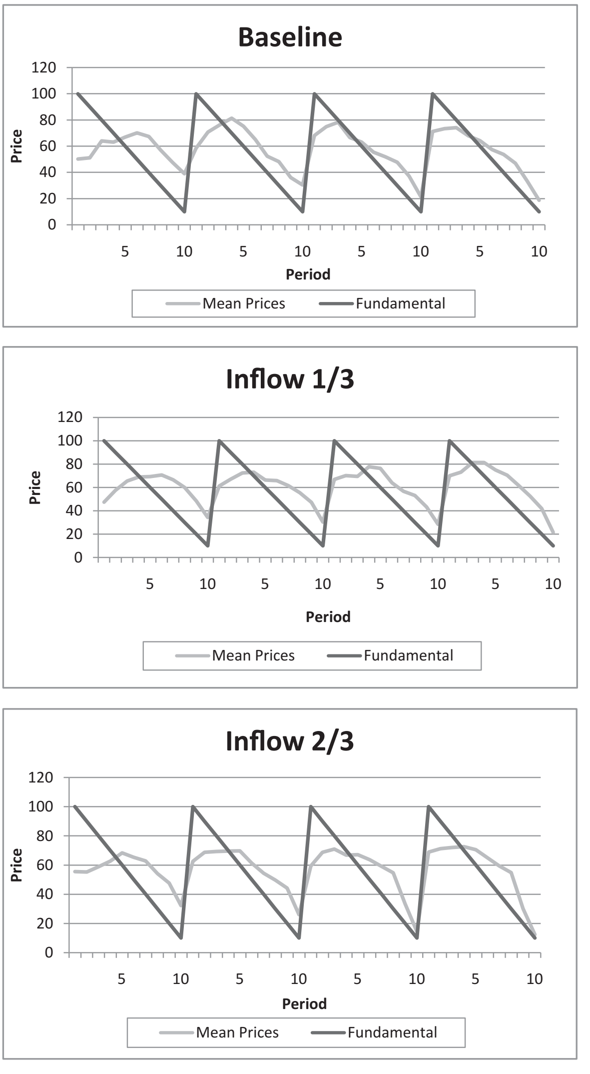

Figure 1. Mean Prices and FVs in Each Treatment.

three treatments. In the last two markets, however, the bubble-and-crash phenomenon is more salient in the inflow treatments than in the baseline treatment.

Following the literature, namely King et al. (1993), Van Boening, Williams, and LaMaster (1993), Porter and Smith (1995), Noussair and Tucker (2006), and Dufwenberg, Lindqvist, and Moore (2005), we calculate the bubble measures as defined in Table 1. *Normalized Absolute Price Deviation (NabsPD)* and *Normalized Average Price Deviation (NavgPD)* measure the extent of mispricing, when quantity is and is not taken into account. *Price Amplitude (PA)*[7] measures the magnitude of overall price change, normalized by the FV in the first period. *Share Turnover (ST)* is a normalized measure of the amount of trading activity over the entire market. *Relative Absolute Deviation (RAD)* and *Relative Deviation (RD)*, which are independent of the total number of

[7] In Haruvy, Lahav, and Noussair (2007), the Price Amplitude is defined as $\max_t\{(p_t - f_t)/f_t\} - \min_t\{(p_t - f_t)/f_t\}$. Using their definition (denoted as Price Amplitude 2 in Tables B1–B3 in Appendix B) does not change our statistical results.

Table 1. Bubble Measure Definitions

Measure	Definition
Normalized absolute price deviation	$\text{NabsPD}=(\Sigma_t\lvert p_t-f_t\rvert q_t)/(100^{*}TSU)$
Normalized average price deviation	$\text{NavgPD}=(\Sigma_t\lvert p_t-f_t\rvert)/(100^{*}TSU)$
Price amplitude	$\text{PA}=\max_t\{(p_t-f_t)/f_1\}-\min_t\{(p_t-f_t)/f_1\}$
Share turnover	$\text{ST}=\Sigma_t q_t/TSU$
Relative absolute deviation	$\text{RAD}=\frac{1}{T}\Sigma_t\lvert p_t-f_t\rvert/\lvert\bar{f}\rvert$
Relative deviation	$\text{RD}=\frac{1}{T}\Sigma_t(p_t-f_t)/\lvert\bar{f}\rvert$

Note: T = total number of trading periods; p_t = transaction price in period t; f_t=FV in period t; $\bar{f}$ = average FV over the life of the asset; q_t = number of transactions in period t; TSU=total number of shares outstanding.

periods and the FV, were recently developed by Stckl, Huber and Kirchler (2010). Similar to *NabsPD* and *NavgPD*, *RAD* measures the overall extent of mispricing without regard to sign. While, *RD* measures the extent of overvaluation and the direction of price deviation by allowing undervaluation and overvaluation to cancel each other out.

Table 2 presents the mean and standard deviation of the bubble measures in each of the four markets, respectively for each treatment.[8] As it evidenced in Figure 1, the measures exhibit mispricing behavior. However, the overall magnitude of overvaluation is small, as shown by the low value of *RD*.[9] Except *RD* in the IF1/3 treatment, all bubble measures on average decrease from market 1 to market 3 or 4 in every treatment.[10]

Statistical Tests on Bubble Reduction

In order to assess whether there is a significant bubble reduction between market 1 and market 3 or market 4, we conducted Wilcoxon matched pair signed rank tests, resulting in the p-values in Table 3 (one-tailed, 5 obs. for the baseline treatment, 10 obs. for each inflow treatment). The results from our baseline treatment resemble those in DLM.[11] All the tests except the one using the *RD* reject the null hypothesis that $M^1=M^3$ and $M^1=M^4$ at the 5% significance level. These results provide strong evidence that, when traders gain common group experience, asset bubbles are reduced substantially by the third market. Comparing the bubble measures in market three and four, we find that introducing new traders in the fourth market does not cause the bubble phenomenon to return.

Finding 1 *In the baseline treatment, bubbles are significantly abated by the third market; introducing new traders in the fourth market does not cause bubbles to return.*

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8 Tables B1–B3 in Appendix B present detailed measures for each market in each session.

9 The market price in our call market is the lowest price in the range of volume-maximizing prices, which is likely to lead to lower bubble magnitude and might account for the relatively low (and frequently negative) value for *RD*. We thank an anonymous referee for pointing this out.

10 Most of the average measures in Table 2 are largest in the IF1/3 treatment. We find that it is mostly driven by session IF1/3-1. Such a pattern disappears if session IF1/3-1 is removed.

11 In an analysis not reported in the article, we compare the results from our baseline treatment with those from the treatment with 1/3 inexperienced traders in DLM, using the Robust Rank Order test. We find that whether market institution is a double auction or a call market does not affect bubble measures based on pure price deviation (the *NavgPD* and the *PA*). However, the bubble measures incorporating trading volume (the *ST* and the *NabsPD*) are significantly larger in a double auction than those in a call market (p=0.01 for the *ST* and p = 0.1 for the *NabsPD*, one-tailed Robust Rank Order tests for markets 1–4).

Table 2. Summary Statistics of Bubble Measures (Averaged over Sessions in a Treatment) *(Between-Session Standard Deviation shown in Parentheses)*

	Market 1			Market 2		
Measure	BL	IF1/3	IF2/3	BL	IF1/3	IF2/3
NabsPD	0.407	0.442	0.407	0.343	0.247	0.307
	(0.190)	(0.308)	(0.292)	(0.207)	(0.137)	(0.121)
NavgPD	0.114	0.117	0.111	0.096	0.090	0.076
	(0.029)	(0.060)	(0.053)	(0.026)	(0.039)	(0.020)
PA	0.928	0.932	0.844	0.814	0.733	0.667
	(0.198)	(0.309)	(0.358)	(0.224)	(0.235)	(0.124)
ST	1.467	1.346	1.379	1.142	0.983	1.417
	(0.495)	(0.464)	(0.412)	(0.478)	(0.326)	(0.442)
RAD	0.498	0.511	0.485	0.420	0.395	0.332
	(0.127)	(0.262)	(0.231)	(0.112)	(0.170)	(0.089)
RD	0.049	0.070	0.023	0.081	0.092	0.046
	(0.247)	(0.332)	(0.332)	(0.281)	(0.265)	(0.106)
	Market 3			Market 4		
	BL	IF1/3	IF2/3	BL	IF1/3	IF2/3
NabsPD	0.202	0.239	0.264	0.205	0.238	0.239
	(0.125)	(0.152)	(0.146)	(0.122)	(0.292)	(0.083)
NavgPD	0.075	0.089	0.074	0.061	0.085	0.074
	(0.016)	(0.064)	(0.026)	(0.020)	(0.085)	(0.022)
PA	0.700	0.738	0.683	0.494	0.670	0.622
	(0.099)	(0.415)	(0.199)	(0.208)	(0.550)	(0.230)
ST	1.083	1.138	1.229	1.067	0.908	1.254
	(0.320)	(0.349)	(0.335)	(0.395)	(0.282)	(0.256)
RAD	0.327	0.386	0.323	0.267	0.373	0.324
	(0.069)	(0.277)	(0.113)	(0.088)	(0.370)	(0.096)
RD	0.028	0.102	0.015	0.021	0.139	0.048
	(0.171)	(0.281)	(0.152)	(0.187)	(0.384)	(0.239)

For the inflow treatments, bubbles are significantly reduced in the IF1/3 treatment but not in the IF2/3 treatment by the third market. However, by the fourth market, bubbles are significantly reduced in the both IF1/3 and IF2/3 treatments. In particular, comparing the bubble measures between market 1 and market 3, four out of six measures in the IF1/3 treatment, the *NabsPD*, *NavgPD, PA*, and *RAD*, are reduced at 5% significance level. However, only *NavgPD* (at 10% significance level) and *RAD* (at 5% significance level) are significantly different between market 1 and market 3 in the IF2/3 treatment. When comparing the bubble measures between market 1 and market 4, we find five (four) out of six measures are significantly reduced in the IF1/3 (IF2/3) treatment at least at 5% significance level. This evidence suggest that, although the inflow of new inexperienced traders can reduce the magnitude of bubble reduction as well as slowing down the price convergence, the hypothesis that bubbles will be sustained with the existence of the inflow of new inexperienced traders is not supported.[12] We summarize the findings for the bubble comparison across markets as follows.

[12] Given the different patterns in the IF1/3 and the IF2/3 treatments, treatments with more markets will help to identify any robust price pattern with the existence of new traders. However, practically it becomes difficult to run sessions with more than four markets since subjects, especially the inexperienced ones, may be unwilling to participate in a session longer than 3 hours. In addition, since we pay a fixed extra payment of $15 to inexperienced traders, they may not be willing to wait if not selected to participate in early markets.

Table 3. *p*-value of Wilcoxon Matched-Pair Signed Rank Tests on Bubble Measures

	$M^1 = M^3$			$M^1 = M^4$			$M^3 = M^4$		
Measure	BL	IF1/3	IF2/3	BL	IF1/3	IF2/3	BL	IF1/3	IF2/3
NabsPD	0.022	0.024	0.142	0.022	0.003	0.029	0.446	0.223	0.439
NavgPD	0.022	0.014	0.051	0.022	0.030	0.033	0.960	0.166	0.601
PA	0.022	0.018	0.238	0.022	0.030	0.046	0.978	0.166	0.222
ST	0.040	0.142	0.142	0.022	0.005	0.142	0.500	0.154	0.601
RAD	0.022	0.014	0.046	0.022	0.030	0.033	0.960	0.166	0.639
RD	0.446	0.746	0.712	0.446	0.899	0.746	0.607	0.746	0.712

Finding 2 *By the third market, bubbles are significantly reduced in the IF1/3 treatment but not in the IF2/3 treatment. However, by the fourth market, bubbles are significantly reduced in the both IF1/3 and IF2/3 treatments.*

We now move to a comparison across treatments. We first conducted the Mann–Whitney tests for all the measures between any two treatments for market two, three, and four. We find no significant differences across treatments for most of the tests (one-tailed tests, 15 obs. for tests between BL and IF1/3 (IF2/3) and 20 obs. for tests between IF1/3 and IF2/3). The exceptions are that *ST* in market 2 and 4 (1% significance level) and *NabsPD* (5% significance level) in market 4 are smaller in the IF1/3 treatment than those in the IF2/3 treatment. Therefore, there is no systematic evidence on H4 that the bubble magnitude is monotonically increasing when the treatment changes from the baseline treatment to the inflow treatments or from the IF1/3 treatment to the IF2/3 treatment.[13]

Finally, we conducted the one-tailed Mann–Whitney tests (15 obs. for tests between BL and IF1/3 (IF2/3), 20 obs. for tests between IF1/3 and IF2/3) on the difference in the bubble reduction, Diff^{1-3} and Diff^{1-4}, across treatments. We find only a marginally significant difference between the baseline treatment and the IF2/3 treatment, as shown in Table 4.

Finding 3 *There is no significant difference in most of the bubble measures across treatments in a given market. The bubble reduction from market 1 to market 3 or 4 is marginally significantly larger in the baseline treatment than that in the IF2/3 treatment.*

In summary, our aggregate results find that the bubbles/mispricing are significantly reduced in all three treatments, although the reduction is less significant and takes longer in the IF2/3 treatment than in the baseline and the IF1/3 treatment. The treatment effect on the bubble reduction is only marginally significant between the baseline and the IF2/3 treatment.

4. Individual Trading Behavior

In this section, we investigate the possible explanations behind the aggregate findings of slower bubble reduction with the inflow of new traders by analyzing the trading orders and earnings of both experienced and inexperienced traders. One explanation is related to learning and mistakes. New traders are likely to make more mistakes than experienced traders, which could slow down the bubble reduction across markets in the inflow treatments, especially when there is a larger proportion of new traders. The other explanation is that experienced traders behave differently in the inflow treatments than in the baseline treatment. For instance, they may strategically take advantage of new traders as

[13] We do not find any significant results on the other direction, that is, the bubble measure for a given market is larger in the baseline treatment than in either inflow treatment, or it is larger in the IF1/3 treatment than in the IF2/3 treatment.

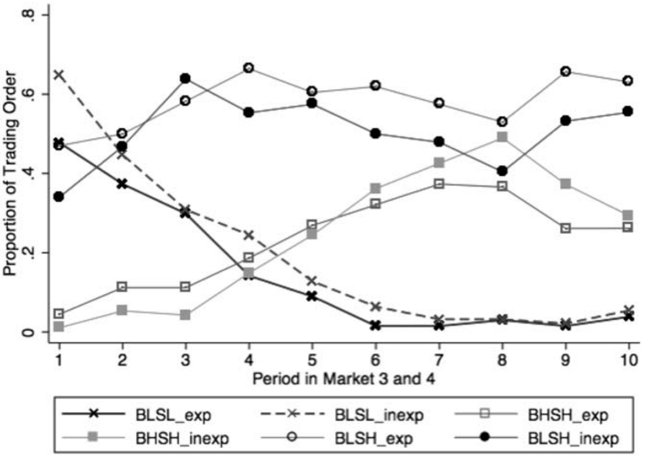

Figure 2. Trading Behavior of Experienced and Inexperienced Traders in Markets 3 and 4.

they know new traders have no experience and less information on the price history in previous asset markets, or it becomes more difficult for experienced traders to learn in the noisier environment with the inflow of new traders. We examine both explanations in the following subsections.

Individual Trading Orders

We classify individuals' trading orders in each period into the following four categories based on the deviations of the buy and sell order prices from the FVs of the asset.[14]

- Buy low sell low (BLSL): the buy and sell order prices are both lower than the FV;
- Buy high sell high (BHSH): the buy and sell order prices are both higher than the FV;
- Buy low sell high (BLSH): the buy order price is lower than (or equal to) the FV and the sell price is higher than (or equal to) the FV;
- No buy no sell (NBNS): the number of shares to buy and the number of shares to sell are both zero.[15]

The BLSL orders, especially those with a large sell-price deviation, indicate "irrational" behavior or "mistakes," as selling with a price much lower than the FV results in a significant loss in expected earnings.[16] The BHSH orders might reflect either "speculative" behavior if a trader buys at a high price to sell at an even higher price in later periods or "mistakes" if a trader is not aiming for a resale at a higher price later. The BLSL (BHSH) orders are necessary for the existence of a market equilibrium price lower (higher) than the FV. Therefore, these orders are important for us to understand under-pricing or price bubbles. The BLSH orders signal "rational" behavior,

[14] The call market regulates that the buy order price must be less than the sell order price by the same trader. Otherwise, the trader can simply buy the asset from himself. So we focus on the sell order price in BLSL orders and the buy order price in BHSH orders.

[15] For orders with zero shares to buy, we treat them as buy at zero and categorize them into BLSL or BLSH according to the sell order price. For orders with zero shares to sell, we treat them as sell at infinity and categorize them into BLSH or BHSH according to the buy order price.

[16] As pointed out by an anonymous referee, the reduction in BLSL orders over time could also be attributed to risk-averse traders, who sell their risky assets early on and then drop out of the trading process. We find nine such cases among all markets and all traders.

Table 4. *p*-value of Mann–Whitney Tests on Diff^{1-3} and Diff^{1-4} of Bubble Measures

	BL vs. IF1/3		BL vs. IF2/3		IF1/3 vs. IF2/3	
Measure	Diff^{1-3}	Diff^{1-4}	Diff^{1-3}	Diff^{1-4}	Diff^{1-3}	Diff^{1-4}
NabsPD	0.643	0.403	0.056	0.135	0.145	0.121
NavgPD	0.110	0.089	0.071	0.135	0.381	0.236
PA	0.356	0.197	0.110	0.071	0.136	0.273
ST	0.403	0.549	0.110	0.071	0.312	0.048
RAD	0.135	0.089	0.071	0.135	0.381	0.248
RD	0.270	0.135	0.196	0.196	0.339	0.530

since that is what a trader should do in order to make profits from trading. Finally, the NBNS orders (i.e., no trading activity) indicates either that the trader expects the price to equal exactly his own valuation or that the trader is not willing to participate in the market.

Figure 2 shows the proportions of the BLSL, BHSH, and BLSH orders across the 10 periods in markets 3 and 4 from all sessions, for experienced and inexperienced traders respectively.[17] As shown in Figure 2, the proportion of BLSL orders decreases steadily to nearly zero by the middle of the market, while the proportion of BLSH orders increases continuously from the beginning to period three and stays high over the remaining periods. The trends of BLSL and BLSH orders suggest that traders are making more "rational" orders over periods in a market. The proportion of BHSH orders increases steadily from near zero in period one to its highest level by period eight and then declines slightly, which indicates that mistakes or speculative behavior first increases and then decreases toward the end of a market. Among different treatments, these patterns of the three trading orders within a market are similar.

Compared with inexperienced traders, experienced traders on average submit a higher proportion of BLSH orders and a lower proportion of BHSH orders from period 4 to period 10. Moreover, experienced traders submit a lower proportion of BLSL orders especially in the first period of a market. These aggregate patterns suggest that experienced traders in general make better decisions on placing trading orders.

Do Experienced Traders Make Fewer Mistakes?

In this subsection, we study traders' "mistakes" by analyzing the BLSL and BHSH orders in which the sell prices are below the FV and the buy prices are above the FV with at least 30% deviations, respectively. Table 5 summarizes the proportions of mistake orders for both experienced and inexperienced traders in each treatment. On average, experienced traders make fewer mistakes (both BLSL and BHSH orders) than inexperienced traders, except the BLSL orders in the Baseline treatment.[18] The proportion of BLSL and BHSH orders submit by experienced traders are

[17] We only used the data from markets 3 and 4 in order to identify any difference between the experienced and inexperienced traders. In markets 1 and 2, the BLSL and the BHSH orders are slightly higher than those in markets 3 and 4 given the corresponding period, and the difference between the experienced and inexperienced traders is smaller, compared to the difference in markets 3 and 4. The proportion of NBNS orders is close to zero in general, so it is not included in the graph.

[18] This is probably due to the small set of inexperienced traders associated with the design of the baseline treatment, 10 subjects (baseline) vs. 80 (IF1/3) vs. 160 (IF2/3). In the one-tailed Mann-Whitney test on the BLSL individual measure defined in the next subsection, we find the BLSL measure for the inexperienced traders in the baseline treatment is marginally significantly smaller than that for the inexperienced traders in the inflow treatments ($p = 0.9$ for baseline vs. IF2/3 and $p = 0.11$ for baseline vs. IF1/3.).

Table 5. Proportion of BLSL and BHSH Orders with At Least 30% Deviation

	Baseline		IF1/3		IF2/3	
	Exp.	Inexp.	Exp.	Inexp.	Exp.	Inexp.
BLSL average (market 2–4)	0.10	0.08	0.06	0.12	0.06	0.11
BLSL reduction (market 1–4)	0.07		0.06	0.00	0.15	0.00
BHSH average (market 2–4)	0.14	0.22	0.17	0.22	0.10	0.18
BHSH reduction (market 1–4)	0.14		0.06	−0.01	0.09	0.01

reduced significantly (varying between 6 and 15%) from market 1 to market 4 in all three treatments. On contrast, the proportion of mistake orders submitted by inexperienced traders changes very little from market 1 to market 4.

To evaluate the statistical difference of mistake reduction at individual level between experienced and inexperienced traders, we estimate the following Probit model:

$$P(\text{mistake}_{i,m,p}=1)=G(\alpha_i+\beta_e\text{exp}_i+\sum_{t=0}^{2}\beta^t_{\text{treat}}\text{treat}^t_i \\ +\sum_{t=0}^{2}\beta^t_e(\text{exp}_i\cdot\text{treat}^t_i)+\sum_{k=2}^{4}\gamma^k\text{market}^k_m+\delta\cdot\text{period}), \tag{1}$$

where G is the standard normal cumulative distribution function. The dependent variable, $\text{mistake}_{i,m,p}$, is an indicator variable that is equal to 1 if a trader i's order in period p of market m is a "mistake" and zero otherwise. Trader's type, exp_i, is equal to 1 if trader i is assigned as an experienced trader and 0 otherwise. We include treatment dummies (treat^t_i, $t = 0, 1, 2$ denotes baseline, IF1/3, and IF2/3 treatment respectively), market dummies (market^k_m, $k = 2, 3, 4$), and period p, in order to control for the impact of treatment effect, market repetition, the declining FVs over periods. To examine the effect of experience in different treatments, we incorporate the interaction items between experience and treatment dummies $\sum_{t=0}^{2}\beta^t_e(\text{exp}_i\cdot\text{treat}^t_i)$.

Table 6 shows the estimation results of the random effect Probit model, using the data from markets 2 to 4, in which we expect to observe the effect of traders' experience, if any. We find that experience reduces mistakes significantly for the both BLSL and BHSH orders, as shown in the second row of Column 2 and 3 in Table 6. The effect of experience on the probability of mistakes is significantly negative for all three treatments except on the probability of the BLSL orders in the baseline. Furthermore, the treatment variable is not significant if the regression already includes the interaction dummies of experience*treatment. Consistent with the patterns in Figure 2, the probability of the BLSL orders decreases with the trading period within a market while the probability of the BHSH orders is positively correlated to the trading period. Finally, in market 4 there is a significant decrease in the probability of the BHSH orders.

The robustness of our analysis is demonstrated by changing the bound of deviations that are used to define the BLSL and BHSH orders to 10, 50, and 60% of deviations from the FVs in Tables B6 and B7 in Appendix B.[19] The qualitative conclusions are essentially the same in terms of the effect of experience on mistakes, but we observe several interesting patterns when the bound of deviations increases. First, the overall effect of experience on the reduction of mistakes becomes larger as the bound of deviations gets larger. The estimated effect of experience changes from

[19] More robustness analysis using 0, 5, 20, 40, and 70% of deviations are available upon request, but are not included in the paper due to the limited space. Including the results with these additional deviations shows the same patterns.

Table 6. Random Effect Probit Estimation of the Likelihood of Mistakes

	BLSL (30% deviation)	BHSH (30% deviation)	BLSL (30% deviation)	BHSH (30% deviation)
experienced	−0.482***	−0.458***		
	(0.132)	(0.106)		
exp*Baseline			0.120	−0.509**
			(0.370)	(0.216)
exp*IF1/3			−0.649***	−0.479***
			(0.166)	(0.0883)
exp*IF2/3			−0.441**	−0.425**
			(0.203)	(0.209)
IF1/3	−0.221	−0.275	0.387	−0.307
	(0.314)	(0.188)	(0.362)	(0.323)
IF2/3	−0.257	−0.426**	0.251	−0.486
	(0.322)	(0.179)	(0.369)	(0.341)
market3	0.00141	−0.139	0.00094	−0.140
	(0.103)	(0.0995)	(0.103)	(0.0993)
market4	−0.0502	−0.312**	−0.0236	−0.316**
	(0.123)	(0.133)	(0.121)	(0.134)
period	−0.338***	0.259***	−0.339***	0.259***
	(0.039)	(0.0295)	(0.039)	(0.0295)
constant	0.176	−2.243***	−0.349	−2.197***
	(0.355)	(0.248)	(0.397)	(0.344)
No. of Obs.	4,494	4,494	4,494	4,494

Note: 1. Robust standard errors at the session level are reported in parentheses, calculated by the Gallamm package in Stata 13.

2. ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level.

3. The data are from market 2 to 4 where there is a real difference in traders' experience.

−0.262 and −0.686 for the BLSL orders and changes from −0.413 to −0.575 for the BHSH orders as the bound of deviations changes from 10 to 50 percent. This suggests that experience not only reduces the likelihood of mistake orders but also the extent of mistakes. Second, the reduction of the likelihood of the BHSH orders in market 4 gets larger and more significant as the bound increases. Finally, we find that, as the bound of deviations gets larger, the decrease in the likelihood of the BLSL orders with period becomes smaller and the increase of the likelihood of the BHSH orders with period becomes larger. This is probably due to the decreasing FVs over periods, with which the orders with larger percentages of deviations occur more frequently in later periods.

The main findings from this subsection are summarized as follows.

Finding 4 *In both inflow treatments, experienced traders are less likely to submit the BLSL and BHSH orders than inexperienced traders. The effect of experience on reducing the likelihood of mistakes is larger on mistake orders with larger deviations from FVs.*

Do Experienced Traders in the Inflow Treatments More Strongly Take Advantage of Inexperienced Traders?

The analysis above shows that inexperienced traders make more BLSL orders and BHSH orders than experienced traders. However, it remains a question whether the slower reduction in the IF2/3 treatment is purely due to the different composition of experienced and inexperienced traders, or it is due to a confound effect with behavior change of experienced traders responding to the inflow of inexperience traders. In order to examine whether experienced traders change their behavior across markets and treatments, we create the following measures for each trader in each market:

$$\text{BLSL} = \sum_t I_t(f_t - p_t^S)/f_t,\ \text{where } I_t = 1 \text{ if } p_t^B < p_t^S < f_t;$$

$$\text{BHSH} = \sum_t I_t(p_t^B - f_t)/f_t,\ \text{where } I_t = 1 \text{ if } p_t^S > p_t^B > f_t;$$

$$\text{BLSH} = \frac{1}{2}\sum_t I_t(p_t^S - p_t^B)/f_t,\ \text{where } I_t = 1 \text{ if } p_t^B < f_t < p_t^S,$$

in which p_t^B and p_t^S are the buy and sell order prices submitted by an experienced trader in period t, and I_t is an index function. These measures represent the summation of the normalized deviations from the FV over all periods within a market for each type of trading orders.

Table 7 reports the p-value of Wilcoxon matched-pair signed rank tests (one-sided) on the individual measures for experienced traders. Consistent with Table 5, we find that the BLSL and BHSH measures are significantly reduced from market 1 to market 3 and 4, in all three treatments. The BLSH measure, however, shows a different pattern. It is significantly increased in the baseline treatment but does not change significantly in the inflow treatments from market 1 to market 3 or 4. Notice that when the experienced traders in the baseline treatment are facing the inflow of inexperienced traders in the fourth market, where experienced traders' behaviors are most likely to change, the BLSL and BHSH measures are further reduced, but the BLSH measure does not change significantly. This evidence, consistent with what Akiyama, Hanaki, and Ishikawa (2014) find, suggests a continuous learning effect of experienced traders in reducing mistakes, but does not support De Long et al.'s (1990) preditction that experienced traders strategically take advantage of nave inexperienced traders.

We further calculated the difference between market 1 and 3 (Diff^{1-3}) and between market 1 and 4 (Diff^{1-4}) for each of these measures and conducted the Mann-Whitney tests between each of these treatment pairs. As shown in Table B4 in the Appendix B, we do not find that any of these measures of experienced traders is significantly different across treatments. Therefore, this evidence does not support the hypothesis that experienced traders in the inflow treatments take advantage of inexperienced traders to a greater extent than experienced traders in the baseline treatment. We summarize this part of the analysis into the following finding.

Finding 5 *The magnitude of the BLSL and BHSH measures of experienced traders is significantly reduced across markets in all three treatments. The magnitude of the BLSH measure of experienced traders is increased across markets in the baseline treatment but not in the inflow treatments. The difference of these measures between market 1 and market 3 (4) is not significantly different across treatments.*

Table 8 shows the average earnings of experienced and inexperienced traders in the third and fourth market for each treatment and the results for one-tailed unpaired Welch t tests using the

Table 7. p-value of Wilcoxon Matched-Pair Signed Rank Tests on Individual Measures of Experienced Traders

	$M^1 = M^3$			$M^1 = M^4$			$M^3 = M^4$		
Individual Measure	BL	IF1/3	IF2/3	BL	IF1/3	IF2/3	BL	IF1/3	IF2/3
BLSL	0.000	0.003	0.000	0.001	0.001	0.000	0.053	0.239	0.122
BHSH	0.000	0.012	0.020	0.000	0.000	0.002	0.042	0.004	0.117
BLSH	0.060	0.418	0.124	0.090	0.452	0.411	0.700	0.760	0.898
No. of obs.	30	40	20	20	40	20	20	40	20

Notes: One-sided test Alternative hypotheses: $M^1 > M^3$, $M^1 > M^4$ and $M^3 > M^4$ for BLSL measure and BHSH measure. $M^1 < M^3$, $M^1 < M^4$ and $M^3 < M^4$ for BLSH measure.

Table 8. Average Earnings in the Third and Fourth Market

	Market 3			Market 4		
Treatment	Exp.	Inexp.	*p*-value	Exp.	Inexp.	*p*-value
BL	\$8.00	N/A	N/A	\$8.75	\$7.46	0.06
	(2.03)	N/A	N/A	(2.77)	(1.69)	(30)
IF1/3	\$9.49	\$7.17	0.00	\$8.65	\$7.41	0.01
	(2.49)	(2.01)	(60)	(2.18)	(1.59)	(60)
IF2/3	\$8.14	\$7.20	0.09	\$9.18	\$8.12	0.09
	(2.58)	(2.23)	(60)	(3.15)	(2.16)	(60)

Note: One-sided Welch t test; standard deviation and number of observations in parentheses

individual-level data. In all three treatments, the earnings of experienced traders are significantly larger than those of inexperienced traders. The difference in earnings is consistent with the previous finding that inexperienced traders are more likely to make mistake orders.

Finding 6 *In the third and fourth market, the earnings made by experienced traders are significantly larger than those by inexperienced traders in all three treatments.*

5. Conclusion

The experimental literature on price bubbles has the robust finding that experience can eliminate bubbles in a stationary environment and this effect can dominate the impact of inexperienced traders in a setting with even a small fraction of experienced traders. In this article, we examine the price pattern in consecutive identical experimental markets when new inexperienced traders are introduced steadily to the market. We find that the magnitude of bubbles is significantly reduced even when each market consists of two-thirds new traders, although the inflow of inexperienced traders may slow down the convergence of the price to the intrinsic FV. In our analysis of individual trading orders, we find that experienced traders made much fewer mistakes than inexperienced traders. On the other hand, little evidence supports the hypothesis that experienced traders in the inflow treatments anticipate more mistakes by inexperienced traders and take advantage of that, when compared to experienced traders in the baseline treatment. Our finding is consistent with Akiyama, Hanaki, and Ishikawa (2014), who find experienced subjects act as price stabilizers, instead of destabilizers, when faced with an inflow of inexperienced subjects.

The importance of new traders and their interactions with experienced traders echo empirical findings in Greenwood and Nagel (2009) and Seru, Stoffman, and Shumway (2010), among others. The inflow of new traders can, in concert with confusion and heterogeneous beliefs, sustain bubbles to some extent, as suggested by other studies (Hong and Stein 1999; Bloomfield, O'Hara, and Saar 2009; Palfrey and Wang 2012; Kirchler, Huber, and Stckl 2012). This article also complements the empirical studies on the new-trader effect on bubbles by Xiong and Yu (2011). In a similar vein, Gong, Pan, and Shi (2015) use field data from a real financial market and find that the entry of new investors helps sustain price bubbles.

Further studies could investigate the role of the inflow of new traders in the formation of price bubbles by incorporating other factors that are essential elements in asset pricing, such as expectations and heterogeneity of investors. For example, Sutter, Huber, and Kirchler (2012) introduce asymmetric information into the market and find that it reduces price bubbles. In essence, the differences in information possessed by different traders creates a different composition of investors. It might be interesting to show what role asymmetric information would play in a market with a steady inflow of new traders.

Appendix A: Instructions for Experiment (Inflow1/3 treatment)

1. General Instructions

This is an experiment in the economics of market decision making. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money, which will be paid to you in cash at the end of the experiment. The experiment will consist of several sequences of 10 trading periods in which you will have the opportunity to buy and sell in a market. The currency used in the market is francs. All trading will be in terms of francs. The cash payment to you at the end of the experiment will be in dollars. The conversion rate is 100 francs to 1 dollar.

2. How to Use the Computerized Market

In each period, you will see a computer screen like the one shown below. You can use the interface to buy and sell *Shares.* At the top of your computer screen, in top left corner, you can see the Money and Shares you have available.

At the beginning of each trading period, if you wish to purchase shares you can send in a *buy order*. Your buy order indicates the number of shares you would like to buy and the highest price that you are willing to pay. Similarly, if you wish to sell shares, you can send in a *sell order*. Your sell order indicates the number of shares you are offering to sell and the lowest price that you are willing to accept. The price at which you offer to buy must be less than the price at which you offer to sell. The price you specify in your order is a per-unit price, at which you are offering to buy or sell *each* share.

The computer program will organize the buy and sell orders and uses them to determine the *trading price* at which units are bought and sold. All transactions in a given period will occur at the same trading price. Generally, the number of shares with sell order prices at or below this clearing price is equal to the number of shares with buy order prices at or above this clearing price. The people who submit buy orders at prices above the trading price make purchases, and those who submit sell orders at prices below the trading price make sales.

Example of how the market works: Suppose there are four traders in the market and:

- Trader 1 submits an offer to buy at 60.
- Trader 2 submits an offer to buy at 20.
- Trader 3 submits an offer to sell at 10.
- Trader 4 submits an offer to sell at 40.

At any price above 40, there are more units offered for sale than for purchase. At any price below 20 there are more units offered for purchase than for sale. At any price between 21 and 39 there is an equal number of units offered for purchase and for sale. The trading price is the lowest price at which there is an equal number of units offered for

Table A1. Average Holding Value Per Share

Current Period	Average Holding Value Per Share
1	100
2	90
3	80
4	70
5	60
6	50
7	40
8	30
9	20
10	10

purchase and for sale. In this example that price is 21. Trader 1 makes a purchase from trader 3 at a price of 21.

3. Specific Instructions for This Experiment

The experiment will consist of four independent sequences of 10 trading periods. In each sequence, there are six traders in the market. Before the start of the first sequence, four of you, whose computer number is between 1 and 4, will be selected to participate in all the four sequences. The other eight individuals will only participate in one of the four sequences. If your computer number is between 5 and 12, you will be asked to go to the waiting room after the training period and will be randomly selected to participate in one of the four sequences. You will not be doing anything connected with this experiment when you stay in the waiting room.

At the beginning of the sequence, half of the six traders will have an endowment of 6 shares and 200 francs and the other half will be endowed with two shares and 600 francs.

In each period of a sequence, there will be a market open, operating under the rules described above, in which you are permitted to buy and sell shares. Shares have a life of 10 periods. Your shares carry over from one trading period to the next. For example, if you have five shares at the end of period 1, you will have five shares at the beginning of period 2.

You receive dividends for each share in your inventory at the end of each of the 10 trading periods. At the end of each trading period, including period 10, each share you hold will pay you a dividend of 0, or 20, each with equal chance. This means that the average dividend for each share in each period is 10. The dividend is added to your money balance automatically after each period. After the dividend is paid at the end of period 10, the market ends and there are no further earnings possible from shares in the current market.

A new 10-period market will then begin, in which you can trade shares of a new asset for 10 periods. If you are selected to participate in all the four sequences, the amount of shares and money that you have at the beginning of the new market will be the same as at the beginning of the first 10-period market. There will be four 10-period markets making up the experiment.

4. Average Holding Value Table

You can use the *average holding value* Table A1 to help you make decisions. It tells you how much, on average, each share will pay you in dividends if you hold it from now until the end of the 10-period market.

The first column indicates the current period. The second column gives the average earnings from each unit that you keep in your inventory for the remainder of the 10-period market. It is calculated by multiplying the average dividend in each period, 10, by the number of periods remaining, including the current period.

5. Price History

In each period, when you send in a buy order and/or a sell order, you can observe your previous trading prices. If you are selected to participate in all the four sequences, you will observe all the previous trading prices formed in each period of each sequence. If you are selected to participate in one of the four sequences, you will observe all the previous trading prices formed in each period of the sequence that you participate in.

6. Your Earnings

Your earnings for a 10-period market will equal the total amount of cash that you have at the end of period 10, after the last dividend has been paid. It is calculated in the following way:

The money you have at the beginning of period 1
+ the dividends you receive
+ the money received from sales of shares
− the money spent on purchases of shares.

If you are selected to participate in all the four sequences, your earnings for the entire experiment will equal the total earnings from all the four sequences of the 10-period markets that make up the experiment, plus $5 show-up fee.

If you are selected to participate in only one of the four sequences, your earnings for the entire experiment will equal the total earnings from the sequence that you have participated in, plus $15 fixed payment, plus $5 show-up fee.

Appendix B: Additional Figures and Tables

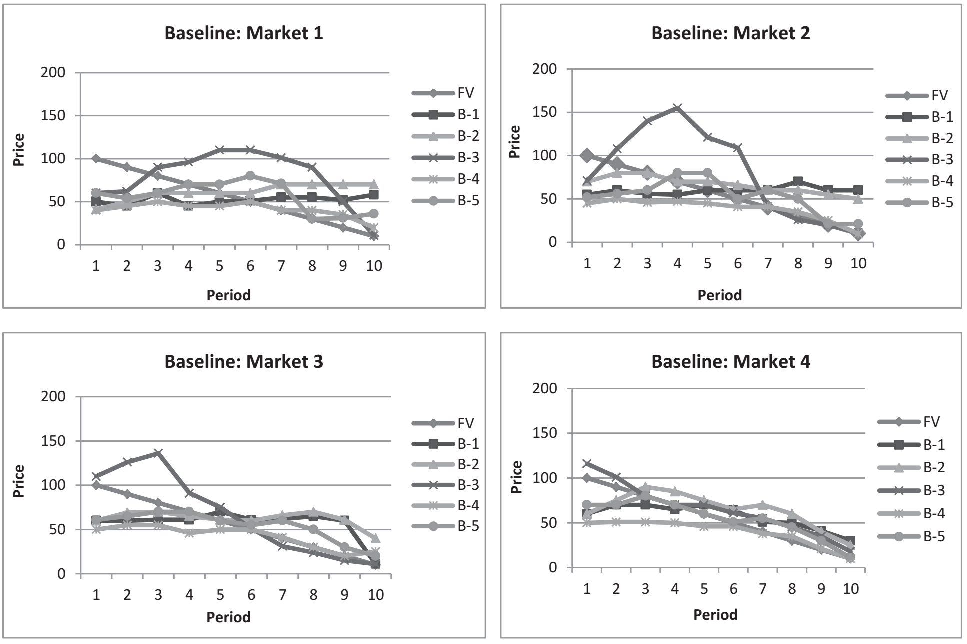

Figure B1. Transaction Price in Each Period, All Markets and Sessions in Baseline Treatment.

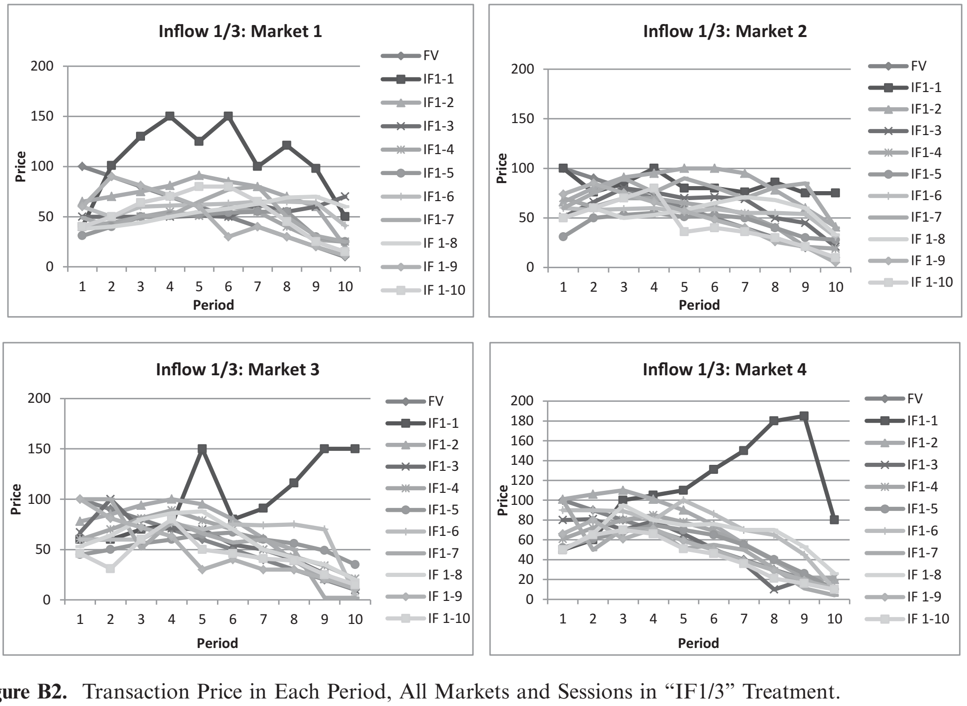

Figure B2. Transaction Price in Each Period, All Markets and Sessions in "IF1/3" Treatment.

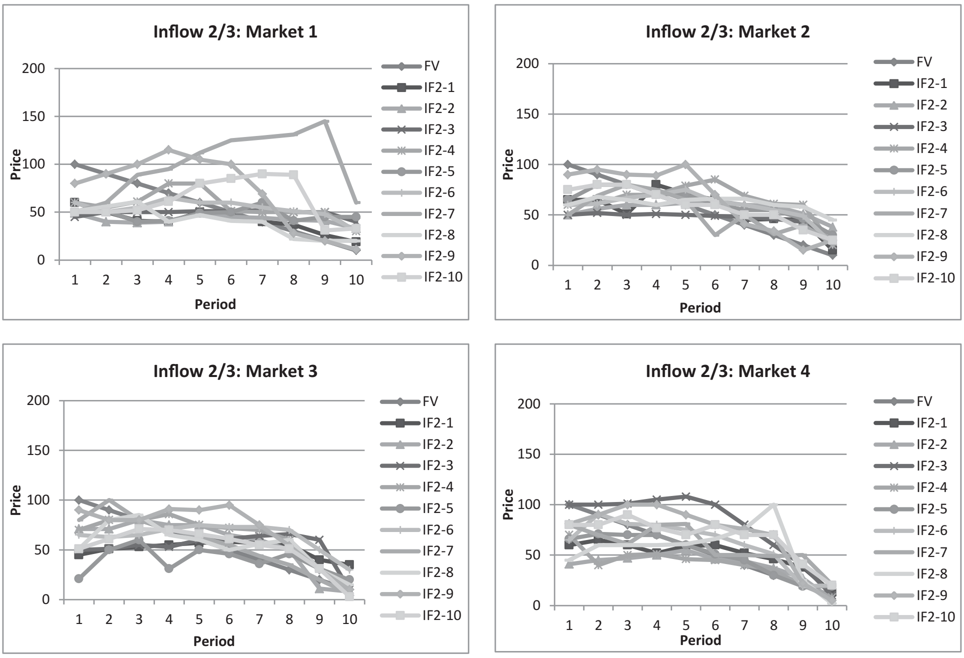

Figure B3. Transaction Price in Each Period, All Markets and Sessions in “IF2/3” Treatment.

Table B1. Various Measures, By Market and Session, in Baseline Treatment

	Session				
Market	BL1	BL2	BL3	BL4	BL5
Normalized absolute price deviation					
1	0.591	0.621	0.315	0.319	0.188
2	0.663	0.365	0.283	0.313	0.090
3	0.270	0.312	0.050	0.295	0.083
4	0.220	0.371	0.081	0.260	0.091
Normalized average price deviation					
1	0.113	0.133	0.153	0.088	0.085
2	0.114	0.080	0.133	0.078	0.077
3	0.090	0.093	0.067	0.067	0.058
4	0.071	0.085	0.042	0.068	0.038
Price amplitude					
1	0.980	1.190	1.010	0.750	0.710
2	0.950	0.700	1.140	0.600	0.680
3	0.800	0.810	0.650	0.650	0.590
4	0.610	0.700	0.160	0.550	0.450
Price amplitude-2					
1	5.300	6.590	2.400	1.600	3.000
2	5.450	4.300	1.504	0.800	1.580
3	2.400	3.400	0.950	2.000	1.390
4	2.400	1.900	0.800	0.667	0.800
Share turnover					
1	1.917	2.000	0.833	1.417	1.167
2	1.708	1.500	0.583	1.167	0.750
3	1.208	1.250	0.708	1.458	0.792
4	1.208	1.667	0.625	0.875	0.958

Table B1. (*Continued*)

	Session				
Market	BL1	BL2	BL3	BL4	BL5
Relative absolute deviation					
1	0.493	0.580	0.665	0.382	0.371
2	0.498	0.347	0.578	0.340	0.335
3	0.395	0.407	0.291	0.291	0.253
4	0.311	0.373	0.184	0.298	0.167
Relative deviation					
1	−0.053	0.111	0.418	−0.255	0.022
2	0.084	0.202	0.458	−0.300	−0.036
3	0.038	0.131	0.218	−0.233	−0.016
4	0.038	0.173	0.184	−0.276	−0.015

Table B2. Various Measures, By Market and Session, in IF1/3 Treatments

	Session									
Market	IF1_1	IF1_2	IF1_3	IF1_4	IF1_5	IF1_6	IF1_7	IF1_8	IF1_9	IF1_10
Normalized absolute price deviation										
1	1.206	0.351	0.473	0.605	0.168	0.231	0.436	0.512	0.145	0.291
2	0.391	0.351	0.226	0.083	0.393	0.283	0.362	0.271	0.053	0.058
3	0.568	0.244	0.067	0.242	0.358	0.335	0.118	0.137	0.093	0.226
4	1.048	0.150	0.102	0.197	0.109	0.155	0.127	0.292	0.054	0.145
Normalized average price deviation										
1	0.265	0.111	0.123	0.090	0.102	0.108	0.111	0.143	0.026	0.090
2	0.130	0.143	0.081	0.050	0.088	0.088	0.128	0.115	0.023	0.058
3	0.255	0.072	0.040	0.070	0.105	0.110	0.053	0.077	0.032	0.074
4	0.317	0.071	0.037	0.061	0.063	0.081	0.038	0.108	0.029	0.050
Price amplitude										
1	1.600	0.750	1.100	0.750	0.940	0.840	0.910	1.120	0.410	0.900
2	0.790	0.890	0.780	0.440	0.870	0.740	1.050	0.900	0.270	0.600
3	1.800	0.570	0.430	0.600	0.840	0.900	0.490	0.750	0.310	0.690
4	2.150	0.300	0.290	0.580	0.630	0.500	0.500	0.900	0.350	0.500
Price amplitude-2										
1	4.600	2.350	6.500	2.100	2.190	3.544	2.056	5.620	0.500	1.225
2	6.656	3.440	1.740	1.222	2.490	2.500	3.650	2.800	0.550	0.643
3	14.400	0.820	0.663	1.500	3.050	3.000	1.567	1.470	0.600	1.156
4	8.750	0.990	1.129	1.590	0.855	1.350	0.850	2.150	0.440	0.500
Share turnover										
1	1.833	1.375	1.333	2.167	0.667	0.792	1.333	1.333	0.958	1.667
2	1.208	0.833	1.000	0.792	1.625	1.208	1.000	0.875	0.917	0.375
3	1.042	1.500	0.583	1.125	1.375	1.667	0.875	0.833	0.917	1.458
4	1.250	0.792	0.708	1.500	0.750	0.792	0.833	1.083	0.792	0.583
Relative absolute deviation										
1	1.155	0.485	0.538	0.395	0.445	0.471	0.485	0.624	0.115	0.393
2	0.565	0.625	0.355	0.218	0.384	0.384	0.560	0.502	0.100	0.253
3	1.113	0.313	0.173	0.304	0.456	0.482	0.229	0.335	0.138	0.322
4	1.384	0.309	0.162	0.267	0.273	0.355	0.164	0.471	0.125	0.216
Relative deviation										
1	0.936	0.267	−0.004	−0.187	−0.195	0.075	−0.056	−0.005	−0.104	−0.029
2	0.515	0.465	0.089	−0.033	−0.198	−0.005	0.360	0.033	−0.096	−0.213
3	0.822	0.215	0.016	0.085	−0.013	0.136	0.029	0.069	−0.131	−0.213
4	1.093	0.309	−0.104	0.060	−0.051	0.318	−0.102	0.202	−0.118	−0.216

Table B3. Various Measures, By Market and Session, in Inflow 2/3 Treatment

	Session									
Market	IF2_1	IF2_2	IF2_3	IF2_4	IF2_5	IF2_6	IF2_7	IF2_8	IF2_9	IF2_10
Normalized absolute price deviation										
1	0.173	0.425	0.405	0.298	0.325	0.338	1.210	0.358	0.284	0.252
2	0.180	0.336	0.360	0.478	0.310	0.240	0.274	0.440	0.378	0.075
3	0.231	0.250	0.556	0.198	0.410	0.371	0.050	0.126	0.223	0.225
4	0.313	0.249	0.199	0.222	0.088	0.253	0.228	0.377	0.307	0.154
Normalized average price deviation										
1	0.078	0.103	0.103	0.085	0.108	0.085	0.252	0.072	0.088	0.135
2	0.073	0.099	0.085	0.101	0.064	0.081	0.060	0.099	0.054	0.044
3	0.098	0.056	0.101	0.070	0.097	0.100	0.022	0.054	0.077	0.066
4	0.068	0.078	0.106	0.065	0.033	0.056	0.067	0.105	0.088	0.078
Price amplitude										
1	0.490	0.740	0.850	0.700	0.850	0.680	1.750	0.590	0.700	1.090
2	0.600	0.810	0.730	0.800	0.610	0.690	0.700	0.780	0.500	0.450
3	0.800	0.490	0.900	0.600	0.950	0.750	0.300	0.790	0.550	0.700
4	0.580	0.660	0.500	0.550	0.430	0.560	0.500	1.250	0.590	0.600
Price amplitude-2										
1	1.388	2.856	3.550	2.400	4.000	2.544	6.750	1.490	1.200	2.800
2	1.613	3.300	1.650	2.400	2.350	1.850	1.600	3.900	1.750	1.750
3	3.050	1.117	2.500	1.300	1.790	2.350	0.567	1.490	1.011	1.400
4	1.300	0.940	1.000	0.722	1.240	1.350	1.738	3.133	1.833	1.533
Turnover										
1	0.917	1.500	1.667	1.292	1.250	1.625	2.125	1.333	1.458	0.625
2	1.000	1.125	1.375	1.583	1.375	1.125	1.458	1.500	2.542	1.083
3	0.958	1.583	1.875	1.000	1.167	1.417	0.917	0.833	1.125	1.417
4	1.625	0.958	1.292	1.375	1.125	1.542	1.250	1.083	1.458	0.833
Relative absolute deviation										
1	0.338	0.451	0.449	0.373	0.473	0.373	1.100	0.313	0.385	0.591
2	0.320	0.433	0.373	0.442	0.278	0.355	0.260	0.431	0.235	0.191
3	0.425	0.244	0.440	0.304	0.424	0.435	0.095	0.236	0.336	0.287
4	0.296	0.342	0.462	0.282	0.144	0.244	0.291	0.456	0.385	0.342
Relative deviation										
1	−0.258	−0.233	−0.111	0.031	−0.142	−0.027	0.809	−0.276	0.305	0.129
2	−0.004	0.018	−0.165	0.155	0.115	0.056	−0.071	0.115	0.180	0.064
3	−0.080	0.029	−0.036	0.147	−0.289	0.155	0.007	0.004	0.264	−0.055
4	−0.082	−0.276	0.462	−0.264	−0.089	0.113	0.076	0.009	0.298	0.233

Table B4. *p*-value of Mann-Whitney Tests on Diff^{1-3} and Diff^{1-4} of Individual Measures of Experienced Traders

	BL vs. IF1/3		BL vs. IF2/3		IF1/3 vs. IF2/3	
Measure	Diff^{1-3}	Diff^{1-4}	Diff^{1-3}	Diff^{1-4}	Diff^{1-3}	$Diff^{1-4}$
BLSL	0.910	0.958	0.662	0.495	0.223	0.223
BHSH	0.243	0.559	0.380	0.272	0.622	0.250
BLSH	0.334	0.569	0.753	0.882	0.856	0.837
No. of Obs.	30 vs. 40	20 vs. 40	30 vs. 20	20 vs. 20	40 vs. 20	40 vs. 20

Notes: one-sided test Alternative hypotheses: $\mathrm{Diff}^{1-3}_{\mathrm{Baseline}} > \mathrm{Diff}^{1-3}_{\mathrm{IF1/3}} > \mathrm{Diff}^{1-3}_{\mathrm{IF2/3}}$ and $\mathrm{Diff}^{1-4}_{\mathrm{Baseline}} > \mathrm{Diff}^{1-4}_{\mathrm{IF1/3}} > \mathrm{Diff}^{1-4}_{\mathrm{IF2/3}}$ for the BLSL and BHSH measures; $\mathrm{Diff}^{1-3}_{\mathrm{Baseline}} < \mathrm{Diff}^{1-3}_{\mathrm{IF1/3}} < \mathrm{Diff}^{1-3}_{\mathrm{IF2/3}}$ and $\mathrm{Diff}^{1-4}_{\mathrm{Baseline}} < \mathrm{Diff}^{1-4}_{\mathrm{IF1/3}} < \mathrm{Diff}^{1-4}_{\mathrm{IF2/3}}$ for the BLSH measure.

Table B5. Summary Statistics of Bubble Measures (Averaged over Sessions in a Treatment, Session IF1-1 Excluded) *(Between-session standard deviation shown in parentheses)*

	Market 1			Market 2		
Measure	BL	IF1/3	IF2/3	BL	IF1/3	IF2/3
NabsPD	0.407	0.357	0.407	0.343	0.231	0.307
	(0.190)	(0.160)	(0.292)	(0.207)	(0.134)	(0.121)
NavgPD	0.114	0.101	0.111	0.096	0.086	0.076
	(0.029)	(0.032)	(0.053)	(0.026)	(0.038)	(0.020)
PA	0.928	0.858	0.844	0.814	0.727	0.667
	(0.198)	(0.213)	(0.358)	(0.224)	(0.248)	(0.124)
ST	1.467	1.292	1.379	1.142	0.958	1.417
	(0.495)	(0.457)	(0.412)	(0.478)	(0.336)	(0.442)
RAD	0.498	0.439	0.485	0.420	0.376	0.332
	(0.127)	(0.141)	(0.231)	(0.112)	(0.169)	(0.089)
RD	0.049	−0.026	0.023	0.081	0.045	0.046
	(0.247)	(0.141)	(0.332)	(0.281)	(0.232)	(0.106)
	Market 3			Market 4		
	BL	IF1/3	IF2/3	BL	IF1/3	IF2/3
NabsPD	0.202	0.202	0.264	0.205	0.148	0.239
	(0.125)	(0.104)	(0.146)	(0.122)	(0.067)	(0.083)
NavgPD	0.075	0.070	0.074	0.061	0.060	0.074
	(0.016)	(0.026)	(0.026)	(0.020)	(0.025)	(0.022)
PA	0.700	0.620	0.683	0.494	0.506	0.622
	(0.099)	(0.194)	(0.199)	(0.208)	(0.190)	(0.230)
ST	1.083	1.148	1.229	1.067	0.870	1.254
	(0.320)	(0.369)	(0.335)	(0.395)	(0.270)	(0.256)
RAD	0.327	0.306	0.323	0.267	0.260	0.324
	(0.069)	(0.115)	(0.113)	(0.088)	(0.109)	(0.096)
RD	0.028	0.022	0.015	0.021	0.033	0.048
	(0.171)	(0.130)	(0.152)	(0.187)	(0.199)	(0.239)

Table B6. Robustness Check for BLSL Orders

	10% dev.	10% dev.	50% dev.	50% dev.	60% dev.	60% dev.
Experienced	−0.262*		−0.686***		−0.800***	
	(0.144)		(0.125)		(0.128)	
exp*Baseline		0.218		−0.380		−0.820***
		(0.416)		(0.289)		(0.283)
exp*IF1/3		−0.315		−0.867***		−0.862***
		(0.200)		(0.154)		(0.193)
exp*IF2/3		−0.343*		−0.516**		−0.712***
		(0.191)		(0.207)		(0.213)
IF1/3	−0.081	0.342	0.140	0.439	0.172	0.180
	(0.341)	(0.296)	(0.410)	(0.473)	(0.424)	(0.372)
IF2/3	−0.120	0.289	0.053	0.246	0.151	0.124
	(0.363)	(0.293)	(0.426)	(0.486)	(0.413)	(0.383)
Market 3	−0.045	−0.046	0.184	0.186	0.195	0.196
	(0.090)	(0.090)	(0.136)	(0.136)	(0.195)	(0.195)
Market 4	−0.219**	−0.203**	0.193	0.212	0.105	0.104
	(0.090)	(0.090)	(0.138)	(0.139)	(0.183)	(0.184)
Period	−0.346***	−0.347***	−0.224***	−0.224***	−0.161***	−0.161***
	(0.034)	(0.034)	(0.031)	(0.032)	(0.031)	(0.031)

Table B6. (*Continued*)

	10% dev.	10% dev.	50% dev.	50% dev.	60% dev.	60% dev.
Constant	0.543	0.144	−1.071**	−1.299**	−1.706***	−1.692***
	(0.373)	(0.303)	(0.491)	(0.539)	(0.522)	(0.477)
No. of Obs.	4,494	4,494	4,494	4,494	4,494	4,494

Note: 1. Robust standard errors at the session level are reported in parentheses, calculated by the Gallamm package in Stata 13.
2. ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level.
3. The data are from market 2 to 4 where there is a real difference in traders' experience.

Table B7. Robustness Check for BHSH Orders

	10% dev.	10% dev.	50% dev.	50% dev.	60% dev.	60% dev.
experienced	−0.413***		−0.575***		−0.603***	
	(0.105)		(0.117)		(0.130)	
exp*Baseline		−0.480*		−0.573**		−0.572**
		(0.264)		(0.278)		(0.288)
exp*IF1/3		−0.357***		−0.527***		−0.568***
		(0.125)		(0.123)		(0.135)
exp*IF2/3		−0.446**		−0.677		−0.687
		(0.179)		(0.533)		(0.593)
IF1/3	−0.304	−0.403	−0.293	−0.315	−0.332	−0.319
	(0.206)	(0.305)	(0.267)	(0.449)	(0.275)	(0.440)
IF2/3	−0.452***	−0.499	−0.457*	−0.437	−0.483*	−0.443
	(0.163)	(0.314)	(0.273)	(0.447)	(0.264)	(0.440)
Market 3	−0.031	−0.031	−0.162	−0.162	−0.153	−0.153
	(0.073)	(0.074)	(0.117)	(0.117)	(0.110)	(0.111)
Market 4	−0.204*	−0.207*	−0.392***	−0.390***	−0.392***	−0.389***
	(0.105)	(0.108)	(0.143)	(0.147)	(0.142)	(0.145)
period	0.189***	0.190***	0.316***	0.316***	0.320***	0.320***
	(0.026)	(0.026)	(0.036)	(0.036)	(0.037)	(0.037)
constant	−1.487***	−1.425***	−2.956***	−2.955***	−2.954***	−2.978***
	(0.234)	(0.393)	(0.347)	(0.531)	(0.351)	(0.534)
No. of Obs.	4,494	4,494	4,494	4,494	4,494	4,494

Note: 1. Robust standard errors at the session level are reported in parentheses, calculated by the Gallamm package in Stata 13.
2. ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level.
3. The data are from market 2 to 4 where there is a real difference in traders' experience.

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