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The Effects of Subject Pool and Design Experience on Rationality in Experimental Asset Markets

Lucy F. Ackert and Bryan K. Church

Empirical evidence suggests that prices do not always reflect fundamental values and individual behavior is often inconsistent with rational expectations theory. We report the results of fourteen experimental asset markets designed to examine whether the interactive effect of subject pool and design experience (i.e., previous experience in a market under identical conditions) tempers price bubbles and improves forecasting ability. Our main findings are: 1) price run-ups are modest and dissipate quickly when traders are knowledgeable about financial markets and have participated in a previous market under identical conditions; 2) price bubbles moderate quickly when only a subset of traders are knowledgeable and experienced; 3) the heterogeneity of expectations about price changes is smaller in markets with knowledgeable and experienced traders, even if such traders only represent a subset of the market; and 4) individual forecasts of prices are not consistent with the predictions of the rational expectations model in any market, although absolute forecast errors are smaller for subjects who are knowledgeable of financial markets and for those subjects who have participated in a previous market. In sum, our findings suggest that markets populated by at least a subset of knowledgeable and experienced traders behave rationally, even though average individual behavior can be characterized as irrational.

Models of economic behavior are commonly based on the assumption that aggregate behavior is rational. Yet empirical evidence suggests that asset prices do not always reflect fundamental values. The Dutch tulipmania (Kindleberger [1989]) and observed large premia in closed-end country funds (Ahmed et al. [1997]) provide specific examples of extreme market price adjustments, which may be interpreted as mispricing.[1] Additional evidence is provided by experimental bubbles markets, which report price run-ups followed by crashes relative to fundamental value.

Experimental studies have attempted to identify factors in isolation that mitigate price bubbles, including design experience (i.e., previous experience in an experimental market under identical conditions), margin buying, futures markets, price limits, short sales, and the timing of dividend payments (Smith, Suchanek, and Williams [1988]; King et al. [1993]; Porter and Smith [1995]; Smith, van Boening, and Wellford [2001]). More recent evidence suggests that certain institutional features, in combination, can dampen price bubbles (Ackert et al. [2000]).

Researchers also have find that individuals' forecasts of market price are inconsistent with rational expectations theory. Empirical evidence suggests that forecasts are biased and serially correlated and that the formation of price expectations can be described as adaptive (Williams [1987]; Smith, Suchanek, and Williams [1988]; Peterson [1993]). Moreover, forecast accuracy does not appear to improve with experience.

This article reports the results of fourteen experimental bubbles markets designed to examine the effects of subject pool and design experience (i.e., previous market participation in the same design) on market price deviations from fundamental value and individual forecasting behavior. Subjects from different pools bring divergent knowledge sets to the experiment—specifically, what is known about the workings of financial markets. Subjects' knowledge sets may affect the rate at which they learn to transact effectively in our experimental markets (i.e., to exploit profitable trading opportunities) and develop an

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understanding of the fundamental determinants of asset value. If differences are observed across subject pools, accurate modeling of behavior may require more attention to agent-specific characteristics (Ball and Cech [1996]).

In addition to the information that subjects bring with them about financial markets, subjects acquire further knowledge by taking part in more than one market. In our study, subjects who participated in at least two markets are referred to as having design experience. Previous findings suggest that design experience leads to common expectations, reducing behavioral uncertainty.

We investigate the interactive effects of subject pool and design experience on price deviations from fundamental value and forecast accuracy. Our data suggest that price bubbles moderate quickly when traders are more knowledgeable about financial markets *and* have design experience. Furthermore, this result holds when only a subset of traders are knowledgeable and experienced. In contrast, individual forecasts, on average, are not consistent with rational expectations predictions under any conditions. Hence, the rational expectations model may provide a good description of market behavior but a poor representation of average individual behavior (see also Lei, Noussair, and Plott [2001]).

The first section provides a framework for our investigation, and the second section describes the experimental design. In the third section we summarize the procedures to familiarize the reader with our experimental setting. Section four examines deviations in prices from fundamental value and makes comparisons across markets. We also examine individual forecasting behavior and the resultant implications for the rational expectations model. Section five provides a conclusion and direction for future investigations.

Framework

Several studies have examined the occurrence of bubbles in experimental asset markets. Typically, a cohort of subjects trade certificates over a finite horizon. The certificates have a common dividend, determined at period end, based on a known, fixed probability distribution. At any point in time, fundamental value can be computed simply as the number of periods remaining times the expected dividend per period. Experimental results are quite robust.

In markets with inexperienced subjects (i.e., those without design experience), trading typically yields large bubbles in asset prices followed by crashes. This result holds even with traders who are knowledgeable about the functioning of financial markets. Smith, Suchanek, and Williams [1988] and King et al. [1993] find evidence of bubbles and crashes using professional businesspeople, including corporate executives and stock market dealers. But when subjects have design experience, price bubbles are moderated and, with enough experience, often disappear completely.

Although asset prices eventually approach behavior consistent with rationality, empirical evidence does not suggest that individual forecasts, on average, are unbiased, even for experienced subjects (Williams [1987]; Peterson [1993]). While these results may appear contradictory, economists have long recognized that agents have cognitive limitations (e.g., Simon [1955, 1959]), and that aggregate rationality does not rely on the rationality of individuals in the market (Smith [1985]; Camerer [1992]).

Moreover, agents differ in ability, and various economic models of behavior reflect such heterogeneity (e.g., Figlewski [1978]; Haltiwanger and Waldman [1985]). Market behavior may approach rationality because a subset of agents is better able to trade effectively and exploit profit-making opportunities (e.g., Foster and Viswanathan [1996]).

Agents bring different knowledge sets to the marketplace, including facts stored in memory about the workings of financial markets. Cognitive psychologists use the term declarative knowledge to describe what is known about a particular domain (e.g., Anderson [1982, 1987]). This article uses subject pool to proxy for declarative knowledge. We identify two subject groups that bring distinctly different sets of knowledge to the experiment: senior business students and freshman arts and sciences students who have declared majors outside of business and economics. The difference in educational background affects what is known about asset valuation and trading institutions. We investigate whether differences arise between markets with business and non-business students.

Agents' declarative knowledge is enriched through hands-on experience. Trading experience provides agents with procedural knowledge (e.g., Anderson [1982, 1987]), which refers to what is known about participating in financial markets. In our experiment, design experience (participation in an earlier market) gives subjects declarative knowledge about our specific trading institution as well as procedural knowledge. Subjects' store of declarative knowledge also facilitates their acquisition of procedural knowledge.

Cognitive psychologists suggest that both types of knowledge are necessary for learning. In our markets, learning enables subjects to recognize capital gain opportunities and avoid capital loss. We investigate the interactive effect of subject pool and design experience on market and individual behavior. Specifically, we examine whether deviations in price from fundamental value decline and forecast accuracy improves in markets with business students who have design experience as compared to markets with other participants. In addition, we examine whether market prices converge to fundamental value when only a subset of market traders are knowledgeable and experienced. Smith, Suchanek, and Williams [1988, p. 1135] suggest that if this subset is large enough, price bubbles will dissipate.

Design

We conduct fourteen experimental asset markets, each consisting of fifteen periods. The experimental design and parameters (to be discussed subsequently) are summarized in Table 1. Traders in Markets 1–6 are all inexperienced; none had participated in an earlier bubbles market. Half are business students (Markets 4–6), with the remaining participants coming from the pool of arts and sciences majors (Markets 1–3). The business students all had successfully completed a minimum of two courses in accounting, two in economics, two in finance, and two in statistics. In addition, all business students had taken part in a required stock market trading competition.

By comparison, the non-business students had not enrolled in any business or economics course. These six markets provide a basis for comparison with subsequent markets and allow us to test for differences between subject pools.

Traders in Markets 7–10 were all once-experienced, in that all had participated in an earlier bubbles market,[2] with Markets 7–8 (9–10) consisting of non-business (business) students. These four markets allow us to examine the interactive effect of subject pool and design experience on deviations in market price from fundamental value and individual forecasting behavior.

In Markets 11–14, we mix subjects from the two pools and vary the level of design experience. Four traders in each of Markets 11–12 (13–14) were experienced non-business (business) students. At least three of the four experienced traders were twice-experienced in our bubbles markets. The remaining traders in Markets 11–12 (13–14) were inexperienced business (non-business) students. These four markets allow us to examine whether rational market behavior can be observed when only a subset of traders has a developed base of knowledge that relates to trading in our asset markets.

Table 2 summarizes the characteristics of our subjects and documents differences across the two subject pools. The non-business students were approximately nineteen years old and in their first year of university education; the business students were on average over twenty-two and in their final year of undergraduate study. Less than 10% of the non-business students had any experience managing investments for themselves or others, while over 40% of the business students had some actual investment management experience.[3] The remaining rows of the table report on student performance in the experiment (we discuss this later).

Procedures

At the beginning of each market session, subjects received a set of instructions (included in Appendix A) that an experimenter read aloud. Each market had eight traders, with the exception of Market 12, which had

Table 1. *Experimental Design*

	Treatment					
	INB	IB	ENB	EB	ENB × IB	INB × EB
	Markets 1–3	Markets 4–6	Markets 7–8	Markets 9–10	Markets 11–12	Markets 13–14
Fraction of upper division business students	0/8	8/8	0/8	8/8	4/8 or 3/7	4/8
Fraction with design experience	0/8	0/8	8/8	8/8	4/8 or 4/7	4/8
Endowments (cash, certificates)	$19.60, 1 $14.20, 2 $8.80, 3 $3.40, 4	$19.60, 1 $14.20, 2 $8.80, 3 $3.40, 4	$19.60, 1 $15.55, 2 $7.45, 3 $3.40, 4	$19.60, 1 $15.55, 2 $7.45, 3 $3.40, 4	$19.00, 1 $14.95, 2 $6.85, 3 $2.80, 4	$19.00, 1 $14.95, 2 $6.85, 3 $2.80, 4
Dividend in cents	0, 16, 56, 120	0, 16, 56, 120	0, 12, 42, 90	0, 12, 42, 90	0, 18, 48, 106	0, 18, 48, 106
Expected value of dividend	$0.48	$0.48	$0.36	$0.36	$0.43	$0.43
Fundamental value per share at Period 1	$7.20	$7.20	$5.40	$5.40	$6.45	$6.45

Note: I denotes inexperience with the design, NB nonbusiness, E design experience, and B business. In each of Markets 11, 13, and 14, three subjects are twice experienced with our design. In Market 12, four subjects are twice experienced. All markets included eight traders with the exception of Market 12, which only included seven traders. Two traders received each endowment, except in Market 12 in which only one trader was endowed with $19.00 and one certificate. Each dividend was equally likely.

Table 2. *Subject Characteristics*

	Treatment							
					ENB × IB		INB × EB	
Characteristic	**INB**	**IB**	**ENB**	**EB**	**NB**	**B**	**NB**	**B**
Age	19.29	22.04	19.19	22.81	19	22.14	19.25	23.88
Year in University	1	4	1	4.06	1	4	1	4.25
Managed Investments	13%	63%	0%	42%	13%	14%	13%	50%
Mean Experimental Earnings	$29.69	$29.70	$28.58	$28.14	$31.45	$28.58	$26.46	$34.10
					$30.11		$30.28	
Maximum Earnings	$72.25	$49.20	$41.53	$38.96	$34.84	$37.76	$33.24	$41.50
Minimum Earnings	$7.58	$6.77	$15.39	$18.84	$28.64	$23.17	$19.43	$30.28
Standard Deviation of Earnings	$16.37	$11.12	$7.58	$4.95	$2.00	$4.41	$4.30	$3.46
					$3.54		$5.46	

seven. The average compensation for the 111 participants in our markets was $32.31, which includes trading earnings, price prediction earnings, and a $3.00 bonus if on time for the session. The markets took approximately two hours to complete. The experimental parameters are summarized in Table 1.

Prior to the commencement of trading, subjects were asked to predict the average trading price for the coming year. They were informed that they would receive $0.25 for each prediction that was within ±$0.15 of the actual average price.[4] Subjects were informed that if no transaction took place, the average price would be computed as the average of the last offers to buy and sell. Price prediction earnings were paid to subjects at the conclusion of the session and these earnings were not added to the cash on hand used to finance trading in certificates.

All markets were organized as double oral auctions. Each trader was endowed with certificates and cash at the beginning of the trading session. There were four endowment classes, with two traders receiving each endowment. The specific endowments are summarized in Table 1. Traders were free to make verbal offers to buy or sell one certificate at a designated price at any time, and all offers were publicly announced and recorded. Outstanding offers stood until accepted or replaced by a better bid or ask price. Short sales were not permitted. All market years lasted four minutes. Subjects were informed that the market would consist of fifteen years.

Uncertainty regarding the dividend remained throughout each market year until year-end when the experimenter publicly announced the dividend.[5] All subjects within a session received the same dividend for each certificate held. Subjects were aware of the four possible dividend values and that each was equally likely. After the experimenter announced the year's dividend, traders calculated their cash balance by multiplying the number of certificates held by the dividend and adding their earnings from certificate holdings to their cash on hand. Certificates and cash held at the end of a year were carried forward to the following market year.[6] Endowments were not reinitialized at any time.

At the end of the experiment, subjects were paid in cash. During this time, they completed a post-experiment questionnaire (see Appendix B). The purpose of the questionnaire was to collect general information about the subjects and how they viewed the experiment.[7]

Results

The subsection Descriptives provides descriptive findings of the market data. The subsection Subject Pool and Design Experience reports tests of the effects of subject pool and design experience on deviations in price from fundamental value. The subsection Individual Forecasting Behavior reports tests of whether individual forecasts, on average, are consistent with rationality.

Descriptives

Figures 1–14 show the mean certificate price, fundamental value, and volume of trading each period for each market. With inexperienced non-business (Markets 1–3) and business (Markets 4–6) subjects, the mean price begins far below the fundamental value and then moves substantially above it, eventually crashing. With experience, the non-business traders (Markets 7–8) continue to generate price paths exhibiting large run-ups in price followed by crashes.

FIGURE 1
Market 1: INB

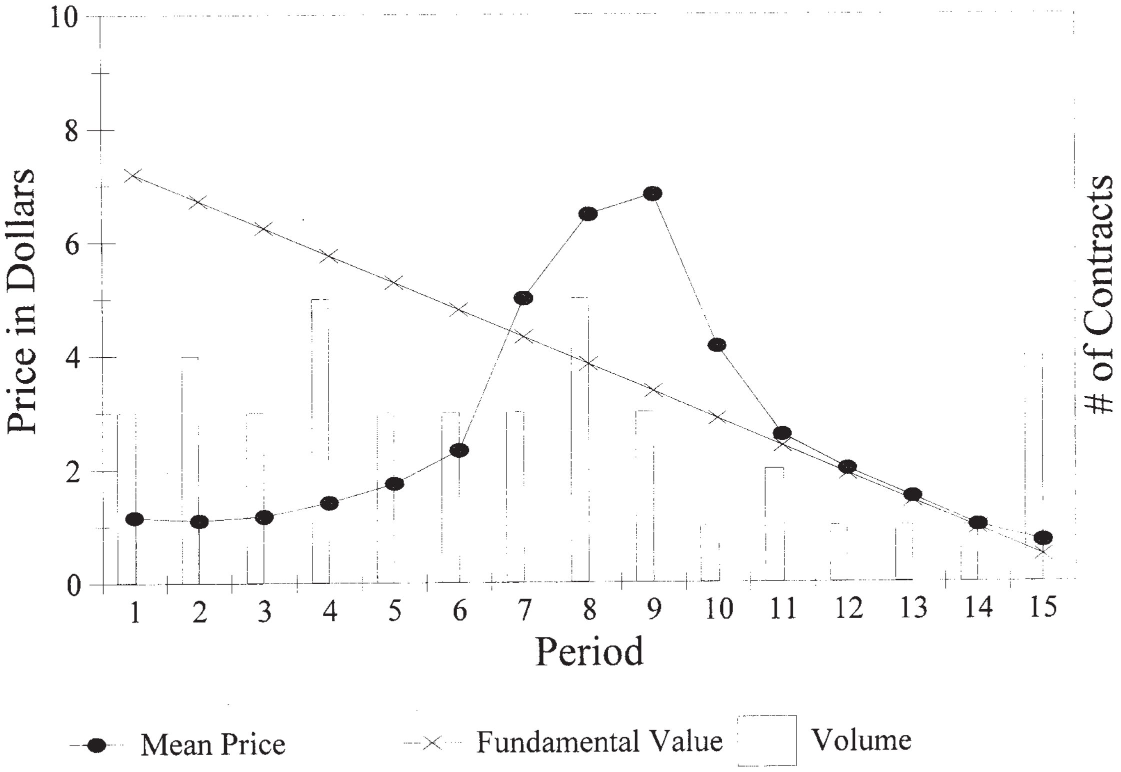


FIGURE 2
Market 2: INB

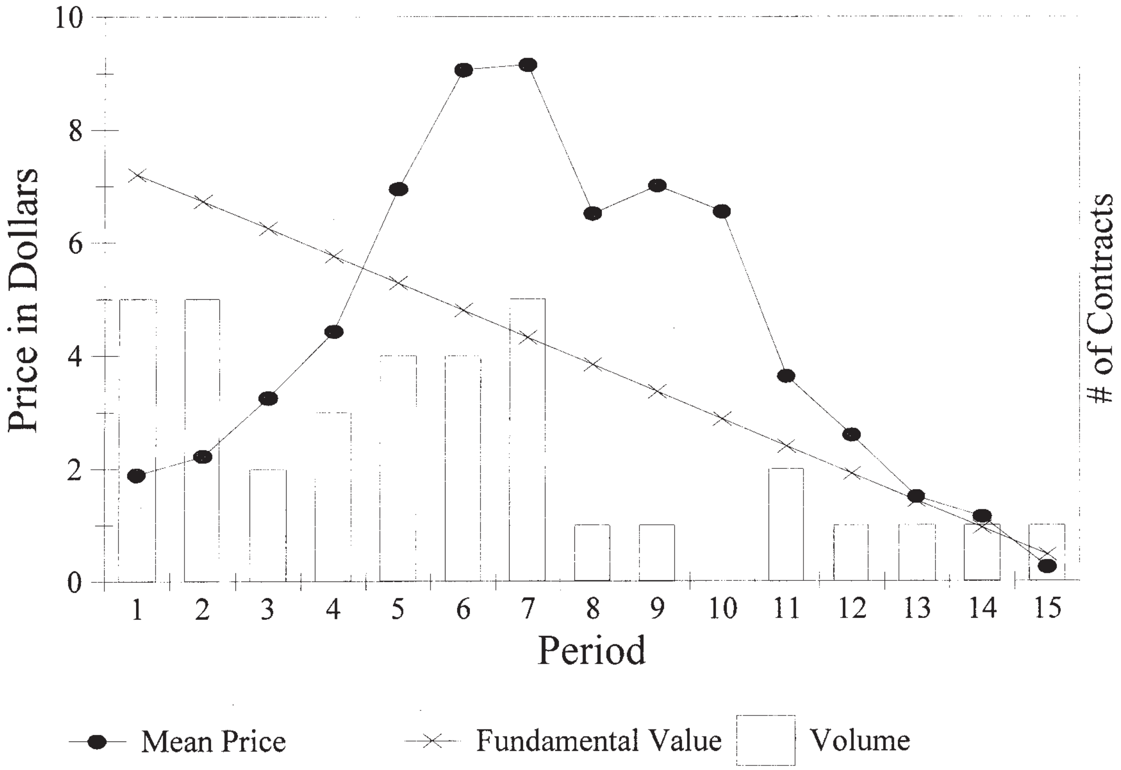


FIGURE 3
Market 3: INB

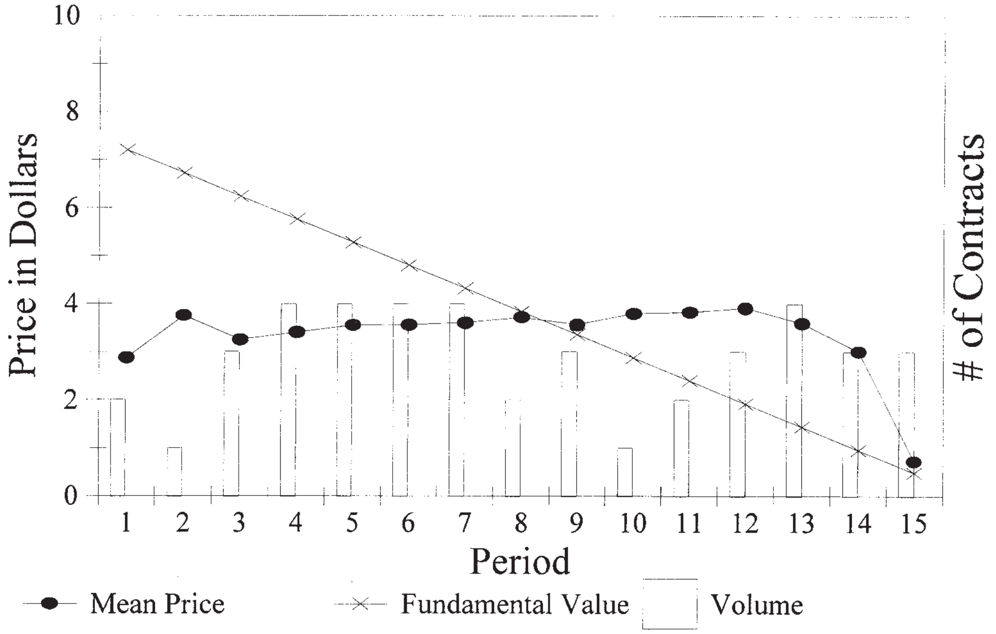


FIGURE 4
Market 4: IB

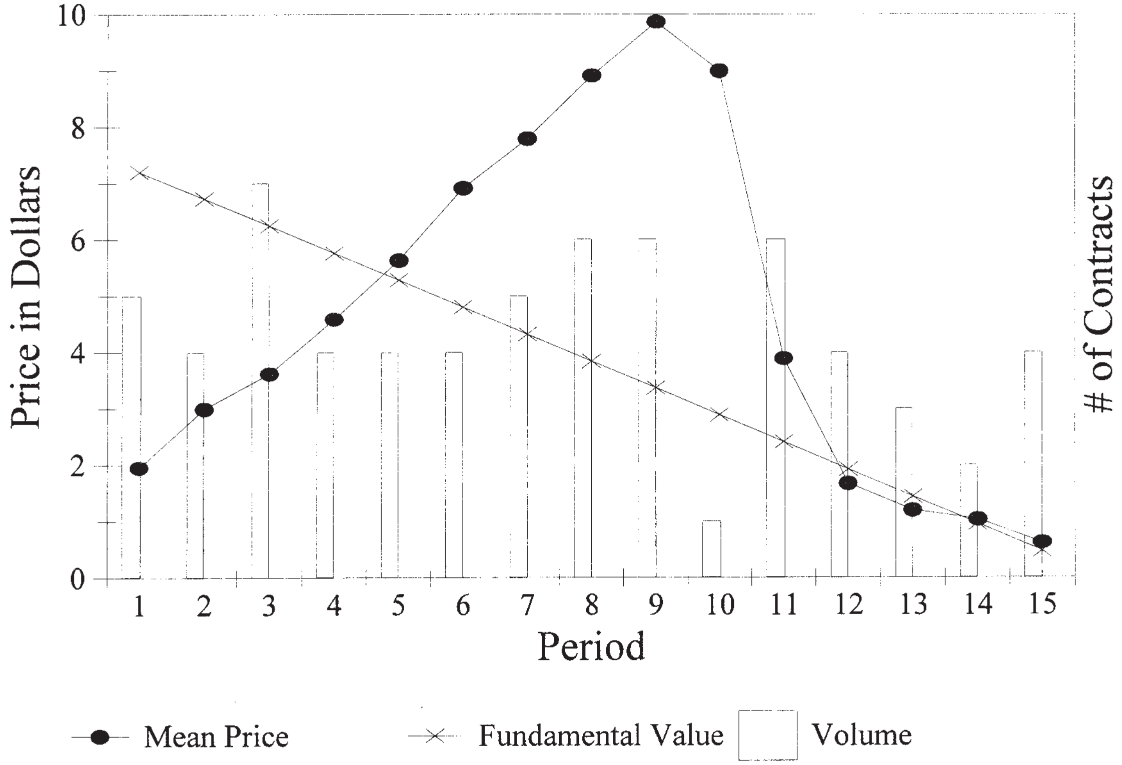


FIGURE 5
Market 5: IB

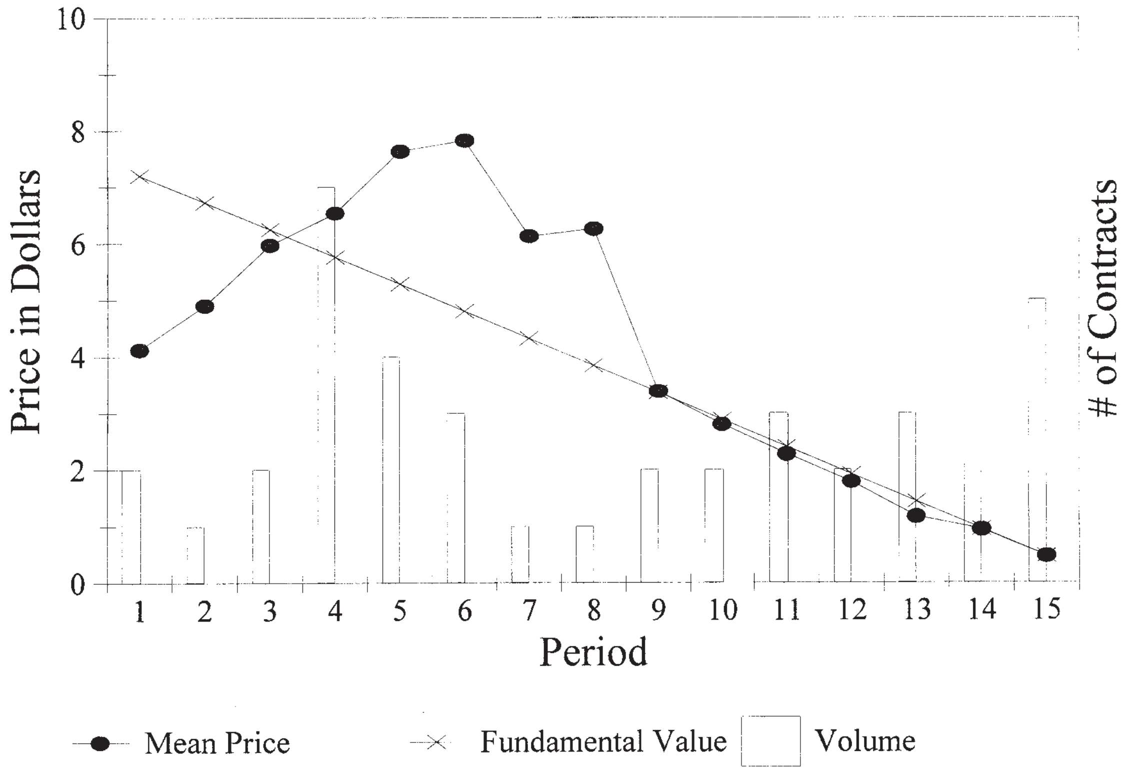


FIGURE 6
Market 6: IB

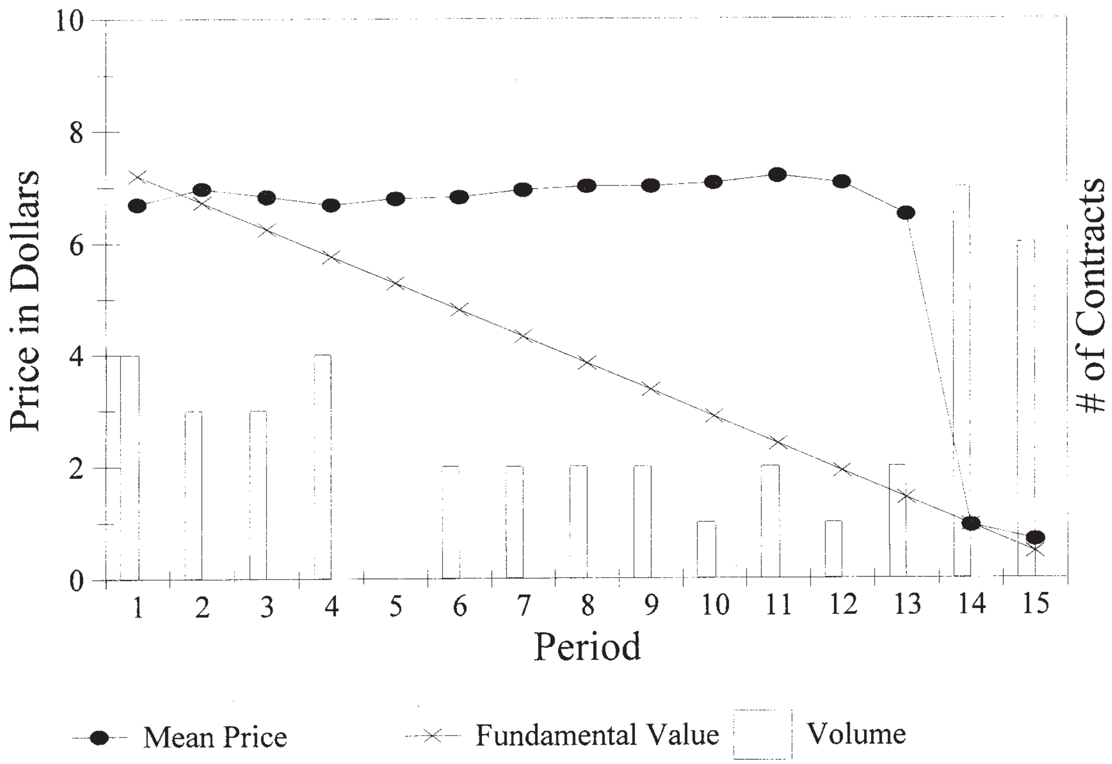


FIGURE 7
Market 7: ENB

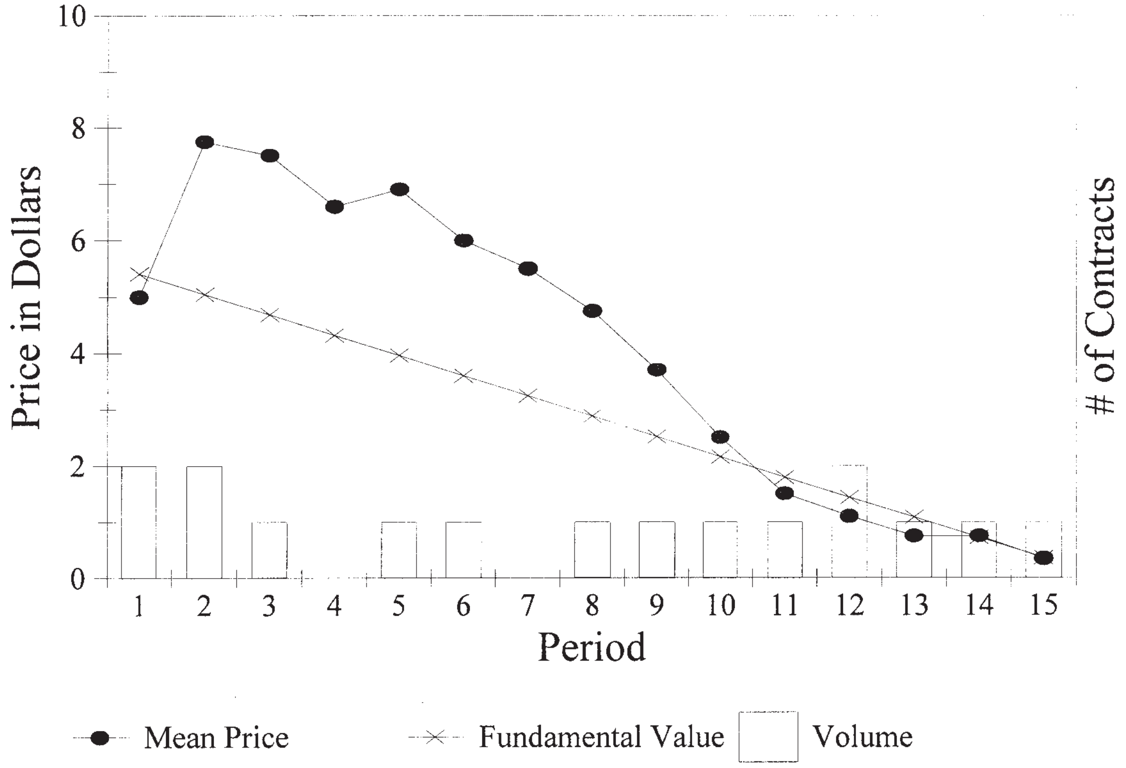


FIGURE 8
Market 8: ENB

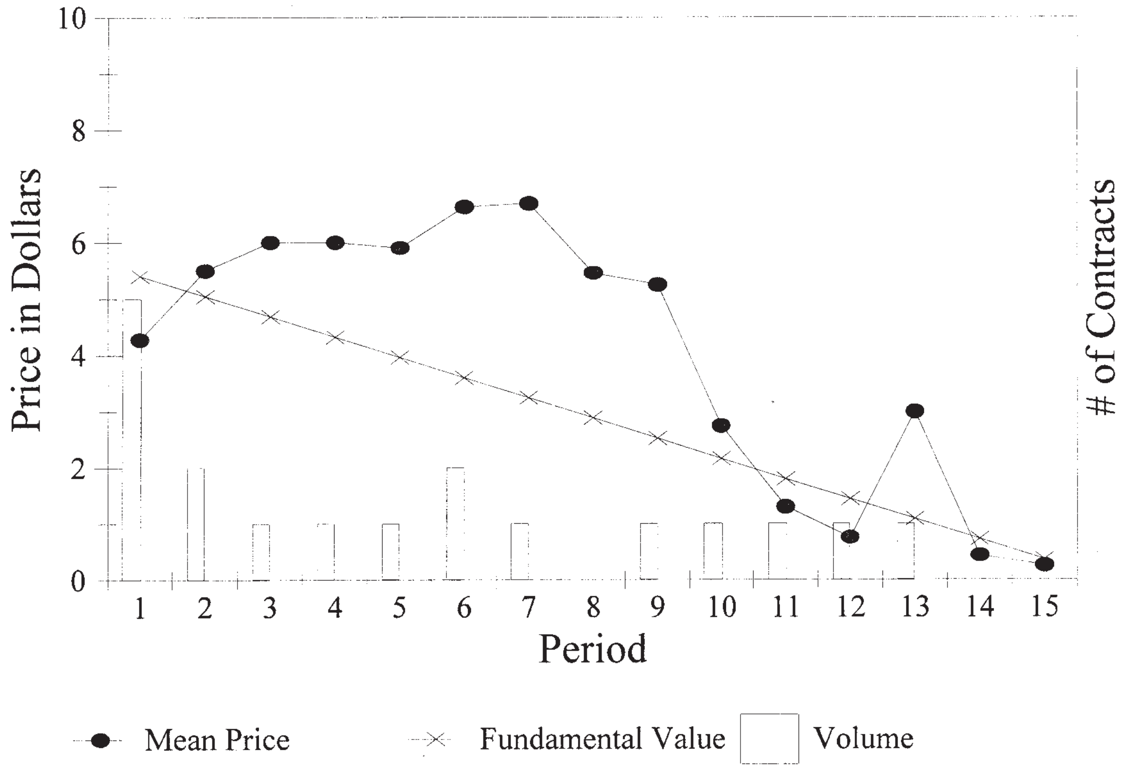


FIGURE 9
Market 9: EB

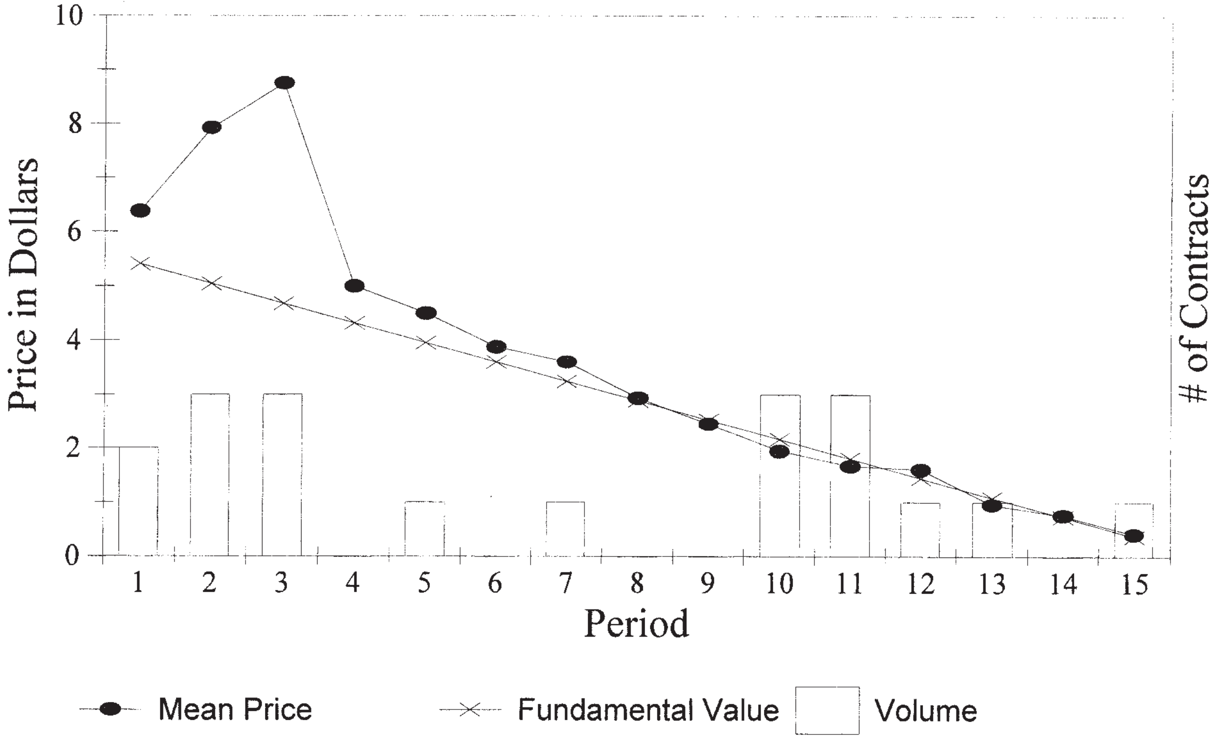


FIGURE 10
Market 10: EB

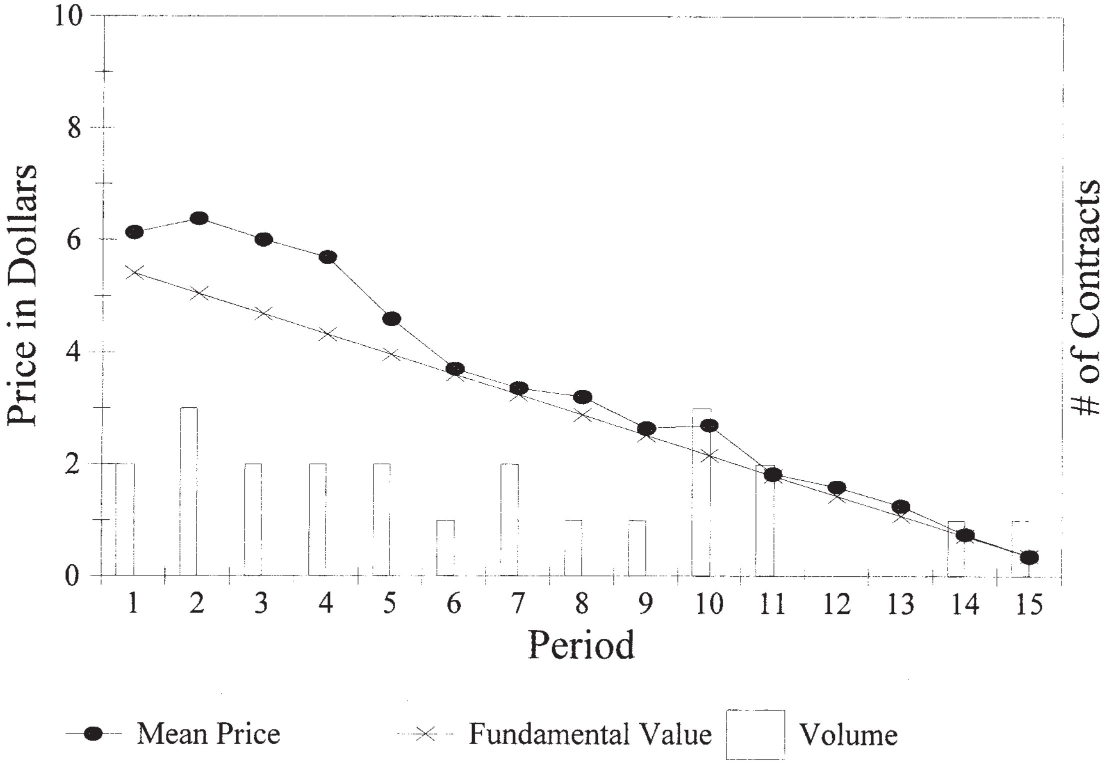


FIGURE 11
Market 11: ENB × IB

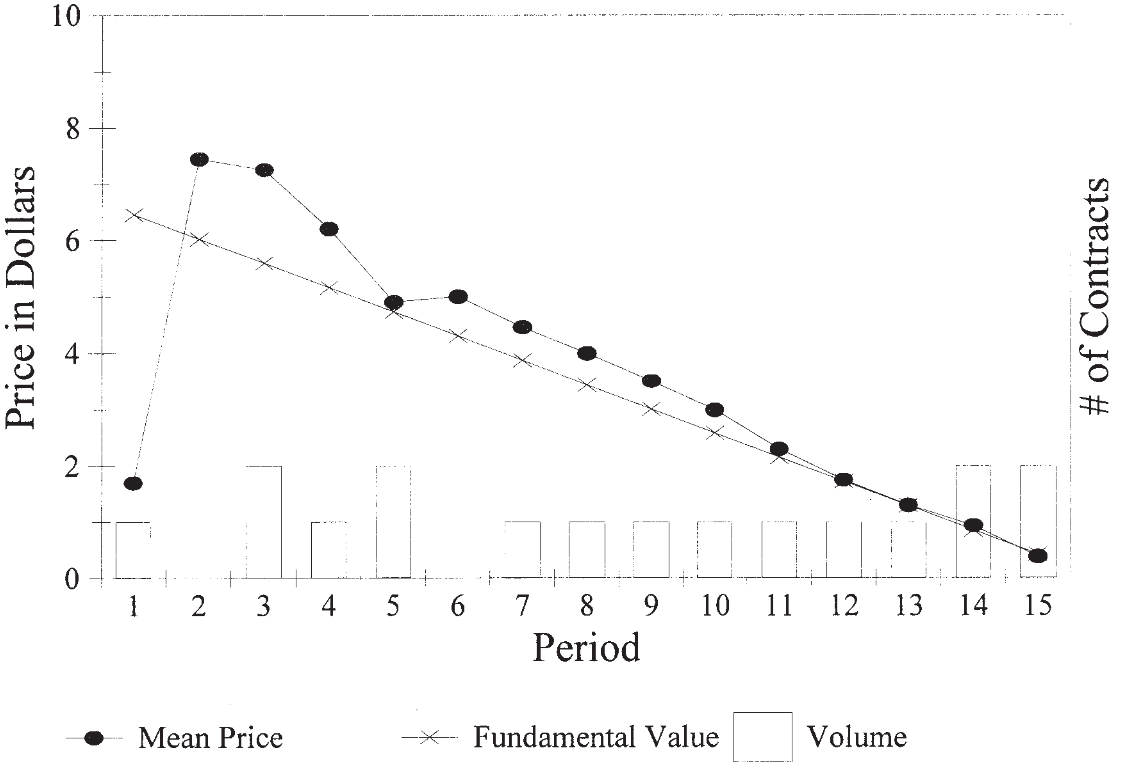


FIGURE 12
Market 12: ENB × IB

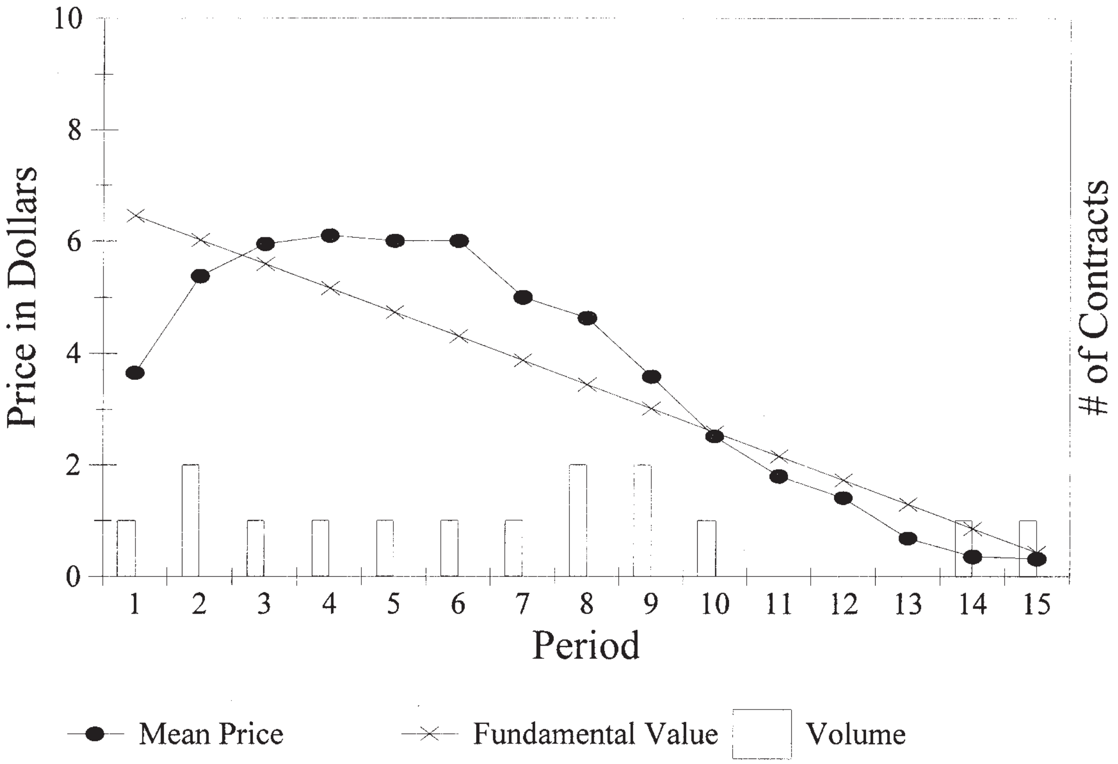


FIGURE 13
Market 13: INB × EB

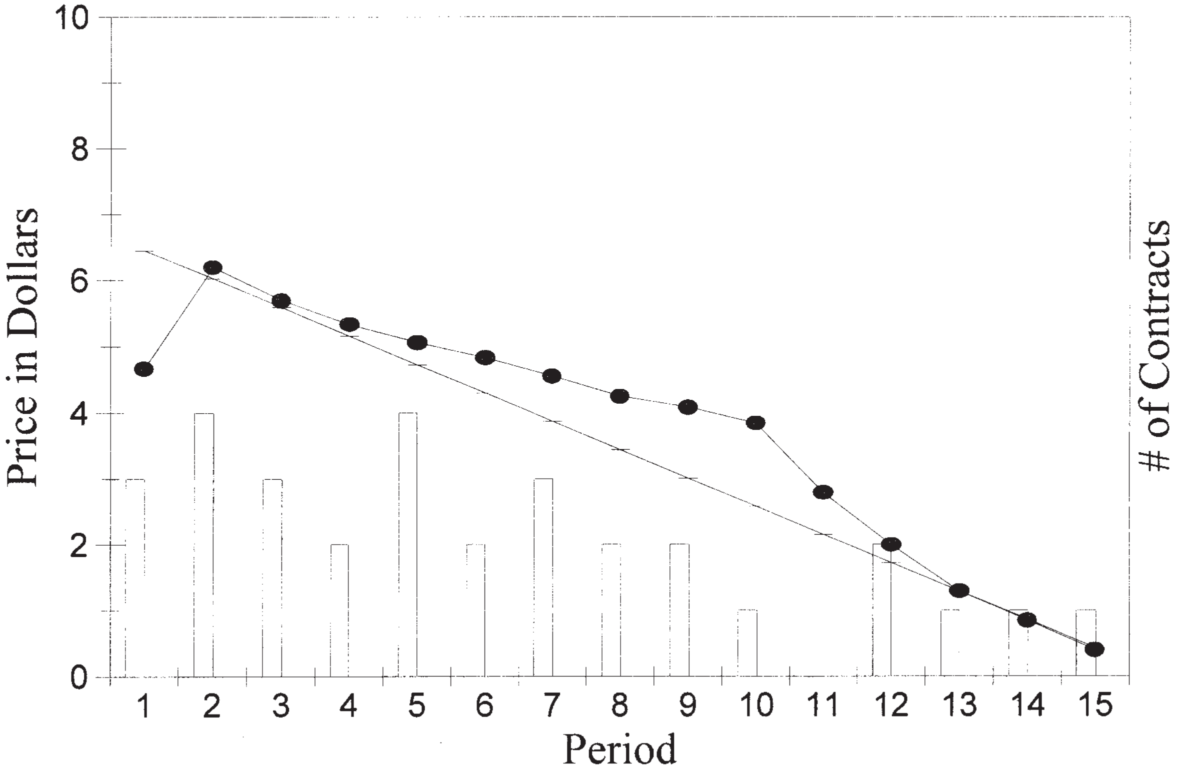
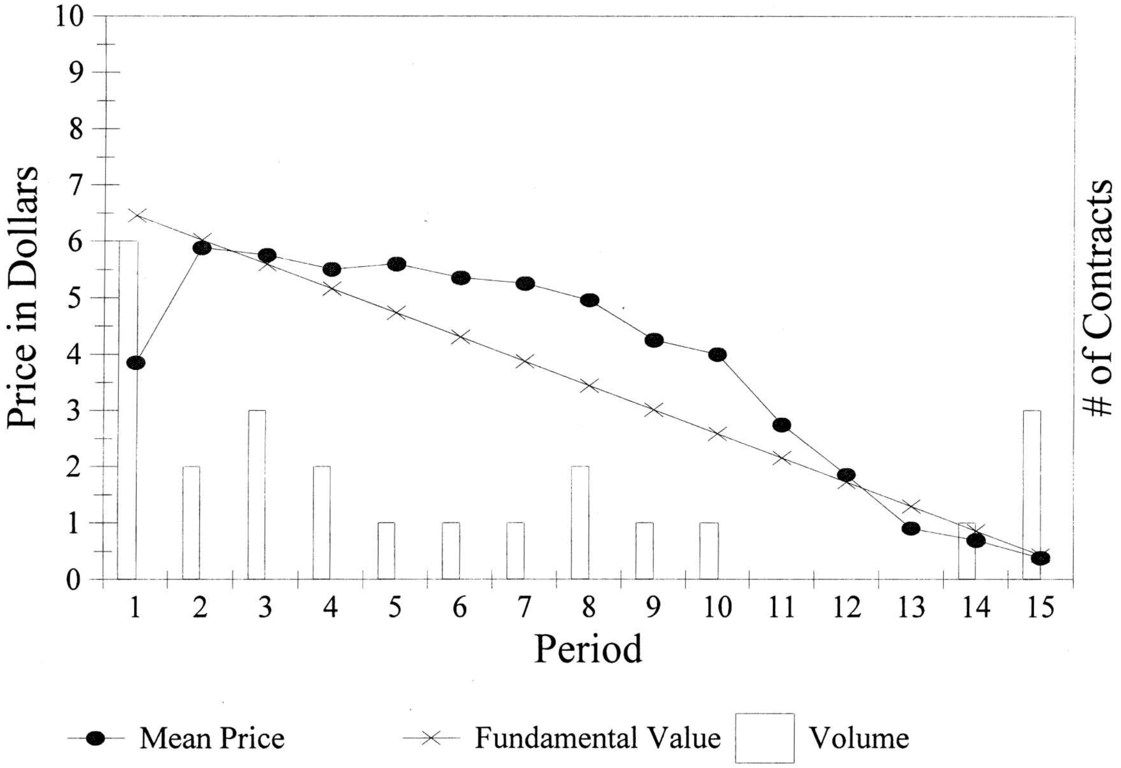


FIGURE 14
Market 14: INB × EB



A different pattern emerges for the experienced business students (Markets 9–10). Although there is some evidence of bubbles early in trading, the price paths quickly settle close to the rational expectations equilibrium value. For the mixed markets (11–14), we observe moderate deviations in price from fundamental value (i.e., smaller than the deviations observed in the inexperienced markets). The data suggest that volume decreases with design experience, even in mixed markets. Others have documented a decline in volume with experience (Smith, Suchanek, and Williams [1988]; King et al. [1993]; and Porter and Smith [1995]).

Our data also suggest that the variation in earnings between subjects decreases with experience. From the bottom portion of Table 2, the discrepancy between the maximum and minimum earnings and the standard deviation of earnings declines markedly with design experience, including mixed markets.

Table 3 reports summary statistics designed to provide empirical measures of bubbles: duration, amplitude, extreme overpricing, and price decreases. For each measure, the table reports the average value across the two or three markets in each treatment. Duration and amplitude are commonly used to measure bubbles (e.g., Porter and Smith [1995]). Duration is the number of periods in which price increases relative to fundamental value. Formally

$$\max[m: P_t - f_t < P_{t+1} - f_{t+1} < \ldots < P_{t+m} - f_{t+m}] \quad (1)$$

where P_t is the mean price and f_t is the fundamental value in the trading period t ($t = 1, \ldots, 15$). Amplitude measures the magnitude of the bubble using the peak and trough price changes relative to fundamental value and is calculated as

$$\max\left(\frac{P_t - f_t}{f_t} \text{ for } t = 1, \ldots, 15\right) - \min\left(\frac{P_t - f_t}{f_t} \text{ for } t = 1, \ldots, 15\right) \quad (2)$$

where the deviation in price from fundamental value each period is normalized by the total expected dividend value over the life of the certificate, f_1. Duration and amplitude both assume risk neutrality.

The estimates reported in Table 3 suggest duration and amplitude are reduced with design experience. When we compare inexperienced with experienced markets, the data indicate that bubbles moderate with experience, consistent with the results of earlier bubbles studies. When we compare experienced with mixed markets, the data indicate that bubbles are tempered more when all traders are experienced.

In addition to duration and amplitude, we consider two other measures of price bubbles: extreme overpricing and price decreases. These measures provide insight into bubbles and mispricing without imposing an assumption of risk neutra1ity. Extreme overpricing is the number of periods in which the average price exceeds the maximum possible price. Specifically, it is the number of market years for which

$$P_t \geq P_t^{\max} = (16 - t)d^{\max} \text{ for } t = 1, \ldots, 15 \quad (3)$$

where $d^{\max}$ is the maximum possible one-period dividend. One can hardly argue that an asset is not mispriced when extreme overpricing is greater than zero. Price decreases is the number of periods in which the average price is lower than the preceding period, defined as

$$P_t - P_{t-1} < 0. \quad (4)$$

Because our markets have a finite horizon, price should decrease each period if behavior is rational, i.e., price decreases should be 14.

From Table 3, extreme overpricing is observed only in markets with inexperienced subjects. In Markets 1–6, average price exceeds the maximum price in six out of 90 periods. These six observations are clearly inconsistent with rationality. The data also indicates that price decreases increase with experience and are greatest in markets with experienced business students (Markets 9–10 and 13–14).

Lastly, Table 3 reports the average turnover in each treatment, defined as the total volume of trade normal-

Table 3. *Summary Statistics*

Market	Treatment	Duration	Amplitude	Extreme Overpricing	Price Decreases	Turnover
1–3	INB	9	1.21	1	6.33	2.02
4–6	IB	9.33	1.07	5	6.67	2.45
7–8	ENB	5	0.67	0	9.5	0.85
9–10	EB	2.5	0.52	0	12	1.05
11–12	ENB × IB	4.5	0.86	0	11	0.8
13–14	INB × EB	8	0.56	0	12.5	1.38

Note: Duration is the number of periods in which price increases relative to fundamental value. Amplitude is a measure of the magnitude of the bubble based on the trough and peak price changes relative to fundamental value. Extreme overpricing is the number of periods in which the average price exceeds the maximum possible price. Price decreases is the number of periods in which the average price is lower than the preceding period. Turnover is the normalized volume of trade.

ized by the total shares outstanding. Consistent with earlier findings, turnover declines with experience.

Subject Pool and Design Experience

We perform analysis-of-variance (ANOVA) to formally test the effects of the treatment variables on deviations in price from fundamental value. The dependent variable is the normalized absolute deviation in price from fundamental value or $|P_t - f_t|/f_t$. The independent variables include subject pool, design experience, and an interaction term. Initially, we focus or data from Markets 1–10 because, in these markets, the treatment variables are manipulated between sessions. In addition, we exclude data from the first two periods because prices are rather erratic across these periods (see also Smith, Suchanek, and Williams 1988).[8]

The ANOVA results, reported in Panel A of Table 4, indicate that design experience and the interaction term are significant at $p < .015$. In light of the statistically significant interaction effect, we perform additional analysis. First we partition the data into two groups by subject pool and examine the simple effect of design experience on the normalized absolute deviation in price from fundamental value. We find that design experience is statistically significant for business students ($F = 9.44$, $p = .003$), but not for non-business students ($F = 0.01$, $p = .916$). An inspection of cell means, reported in Panel B of Table 4, indicates that price deviations diminish as business students gain experience.

Next we partition the data into two groups by experience and examine the simple effect of subject pool on the normalized absolute deviation in price from fundamental value. The results indicate that subject pool is statistically significant for experienced subjects ($F = 23.46$, $p = .000$), but not for inexperienced subjects ($F = 0.37$, $p = .543$). An inspection of cell means indicates that price deviations are smaller in markets with experienced business students than in those with experienced non-business students.

Overall, the ANOVA results suggest that price bubbles are tempered as business students gain design experience, but not non-business students.[9] Business students bring declarative knowledge to the experiment, which facilitates their acquisition of procedural knowledge. Through experience, they are able to trade more effectively and improve their understanding of the determinants of asset value. Thus, asset prices become more efficient. Non-business students, on the other hand, bring a relatively small base of knowledge to the experiment. For these subjects, hands-on trading experience initially provides for the acquisition of declarative knowledge and more repetition is necessary to acquire procedural knowledge (as compared to business students). Hence, price bubbles may not be moderated in markets with once- experienced non-business students because subjects do not have enough repetition to provide for an enriched base of knowledge about trading.

To provide further insight into price behavior in Markets 1–10, we regress the change in average price per period on lagged excess bids (i.e., bids minus asks). For each experimental treatment, we estimate

$$P_t - P_{t-1} = \alpha + \beta(B_{t-1} - O_{t-1}) + e_{t-1} \qquad (5)$$

where P_t and P_{t-1} are as defined previously, and B_{t-1} and O_{t-1} are the number of bids and offers, respectively, in period $t - 1$. Smith, Suchanek, and Williams (1988) suggest that equation (5) characterizes the period-to-period change in prices. If lagged excess bids is a reliable proxy for endogenous expectations, then $\alpha = -E(d)$ and $\beta > 0$, defined as the expected dividend per period. In other words, the period-to-period change in price is comprised of an adjustment to reflect a decline

Table 4. *The Effects of Subject Pool and Design Experience on the Normalized Absolute Price Deviations From Fundamental Value*

Panel A: ANOVA Results

Variable	*df*	Sum of Squares	*F*-statistic	*p*-value
Subject Pool	1	0.73	2.45	0.12
Design Experience	1	2.05	6.85	0.01
Interaction	1	1.87	6.25	0.014
Error	126	37.67		

Panel B: Cell Means

	Design Experience	
Subject Pool	Inexperienced (I)	Experienced (E)
Business (B)	0.64	0.14
Nonbusiness (NB)	0.54	0.53

Table 5. *Lagged Excess Bid Regression Results*

Market	Subjects	R^2	Constant	Coefficient of Lagged Excess Bids
1–3	INB	0.34	–0.568 [–0.47]	0.087*** [4.70]
4–6	IB	0.433	–0.535 [–0.32]	0.089*** [5.67]
7–8	ENB	0.314	–0.192 [0.92]	0.077*** [3.66]
9–10	EB	0.083	–0.335 [0.23]	0.047* [1.85]
11–12	ENB × IB	0.633	–0.191 [1.60]	0.100*** [6.90]
13–14	INB × EB	0.22	–0.297 [1.20]	0.036*** [2.94]

Note: The *t*-ratios shown in brackets use OLS standard errors and test the null hypotheses that the constant equals $-E(d)$ and that the slope equals 0, respectively. ***Denotes significance at the 1% level. *Denotes significance at the 10% level.

in value equal to the expected dividend per period, an adjustment proportional to changing expectations, and random variation (see Smith, van Boening, and Wellford forthcoming).

The regression results are summarized in Table 5. For each market set (Markets 1–10), we find that the estimated constant (α) is not significantly different from $-E(d)$ at any conventional level and that the estimated slope (β) is positive and significant at $p \leq .075$. Further, the coefficient of lagged excess bids is smallest (and the corresponding *p*-value is the largest) in markets with experienced business students. These results suggest that there is less endogenous heterogeneity in expectations in markets with experienced business students, which is consistent with the bubbles being smaller in these markets.

Next, we examine price behavior in the mixed markets. First, we investigate price deviations from fundamental value. We compare the mean normalized absolute price deviation in mixed markets with that in experienced markets, holding the subject pool of experienced traders constant. That is, we compare price deviations in Markets 7–8 (9–10) with those in Markets 11–12 (13–14). The central issue is whether prices are as efficient in markets with mixed traders as in markets with experienced traders. Because price bubbles were tempered in Markets 9–10, we are primarily interested in markets that include experienced business students.

The mean price deviation per treatment is reported in Table 6. When comparing markets that include experienced business students, the mean is slightly higher in the mixed markets. A parametric *t*-test indicates that the means are not statistically different ($p = .145$). With a nonparametric test the means are only marginally different ($p = .071$). In contrast, when comparing markets that include experienced non-business students, both tests indicate a highly statistically significant difference ($p < .001$), with a smaller average price deviation in the mixed markets.

A noteworthy finding is that price deviations from fundamental value do not appear to increase substantially with the presence of a subset of inexperienced traders, representing 43–50 percent of each mixed market. In fact, price deviations decrease significantly in mixed markets with experienced non-business students. This result may arise because non-business students require more repetition to acquire procedural knowledge. Recall that at least three out of four experienced subjects in the mixed markets are twice experienced. The data from both sets of mixed markets suggest that the subset of experienced traders largely determines the behavior of asset prices.

Table 6. *Comparisons of Normalized Absolute Price Deviations From Fundamental Value Between Experienced and Mixed Markets*

Market	Treatment	Mean	*t*-statistic (*p*-value)	*z*-statistic (*p*-value)
7–8	ENB	0.5334	4.250	–4.018
11–12	ENB × IB	0.1934	(0.000)	(0.000)
9–10	EB	0.1354	1.48	–1.803
13–14	INB × EB	0.2031	(0.145)	(0.071)

Note: We computed parametric *t*-tests and nonparametric Wilcoxon rank sum tests. The *p*-values are two tailed.

We also estimated the effect of excess lagged bids on price changes, equation (5), in mixed markets. The regression results, shown in Table 5, indicate that in both market sets (Markets 11–12 and 13–14), α is not significantly different from $-E(d)$ and β is positive and significant at $p < .01$. The coefficient of lagged excess bids is smaller in the markets with a subset of experienced business students than in the markets with a subset of experienced non-business students. Moreover, the regression results in the two sets of markets (9–10 and 13–14) with experienced business students are comparable as are the results in the two sets with experienced non-business students (Markets 7–8 and 11–12). The findings suggest that endogenous heterogeneity in expectations is reduced as long as markets are populated by a subset of experienced business students, which in turn tempers price bubbles.

Lastly, for the mixed markets, we compared the earnings of experienced and inexperienced subjects. In Markets 11–12, experienced non-business students earned, on average, \$2.77 more than inexperienced business students. The difference is not significant using a parametric *t*-test ($t = -1.72$, $p = .109$, two-tailed) and significant using a nonparametric Wilcoxon rank sum test ($z = -2.20$, $p = .028$, two-tailed). The difference between parametric and nonparametric results arises because the top earner in Market 12 was an inexperienced, business student. In Markets 13–14, experienced business students earned, on average, \$7.30 more than inexperienced non-business students. The difference is significant using parametric and nonparametric tests ($t = -3.84$, $p = .002$ and $z = -3.05$, $p = .002$). Hence, experienced business subjects were able to exploit profit-making opportunities at the expense of inexperienced subjects.

Individual Forecasting Behavior

We perform ANOVA to investigate whether experienced business students are superior forecasters. The dependent variable is the absolute, normalized forecast error, defined as

$$\frac{|P_t - F_{i,t}|}{|P_t|} \tag{6}$$

where P_t is the mean price in trading period t ($t = 3, \ldots, 15$)[10] and $F_{i,\,t}$ is trader i's forecast of the period t mean price. The independent variables include subject pool, design experience, and an interaction term. As before, we initially focus on data from Markets 1–10. The ANOVA results indicate that subject pool ($F = 4.34$) and design experience ($F = 5.17$) are statistically significant at $p < .04$.[11] The absolute normalized forecast error is smaller for business students ($\mu. = 0.24$) than non-business students ($\mu. = 0.31$) and smaller for experienced subjects ($\mu. = 0.23$) than inexperienced subjects ($\alpha = 0.31$).[12]

We also examine the accuracy of subjects' forecasts by testing whether price forecasts arc unbiased estimates of realized price. For each market set, we use ordinary-least-squares (OLS) to estimate the following equation:

$$P_t = \alpha + F_{i,\,t} + e_{i,\,t} \tag{7}$$

where $t = 3, \ldots, 15$ and $e_{i,\,t}$ is a mean zero random error term. In addition, for the mixed markets, we estimate (7) for the subsets of traders with and without experience.

Table 7 reports OLS standard errors below coefficient estimates. The final column reports the F-statistic for the joint test of the hypothesis that the intercept is zero and slope is one.[13] In seven out of eight cases, the null hypothesis of rationality is rejected at the 1% significance level.

Keane and Runkle (1990) argue that many tests of the properties of forecasts are flawed because they do not properly model the covariance structure of errors. First, errors may be serially correlated because of lags in data availability. This problem is not a concern to us because we use an experimental approach, which allows us to control the flow of information. Second, shocks in the aggregate economy may lead to correlation in errors across individuals. Our data suggest that subjects are not proficient in predicting crashes so that such a shock could lead to correlated errors across individuals. In order to assess the sensitivity of our results, we estimate (7) separately for each subject in our study, with and without correction for heteroskedasticity. Overall, we reject the null hypothesis of unbiasedness for approximately half of the subjects. We are unable to detect systematic differences across treatment conditions; however, our data suggest that some subjects are clearly better forecasters. Smith, Suchanek, and Williams (1988) and Peterson (1993) also report that some subjects had superior forecasting ability.

Interestingly, Smith, Suchanek, and Williams (1988) provide evidence that subjects who are better forecasters generate greater trading profit. For each treatment, we regress subjects' absolute average normalized forecast error on their trading profit. The regression results indicate that subjects with smaller absolute forecast errors earn superior trading profit (at the 5% significance level) in markets with (i) inexperienced business students (Markets 4–6), (ii) experienced business students (Markets 9–10), and (iii) experienced business students and inexperienced non-business students (Markets 13–14). Hence, we find evidence of a relationship forecasting ability and trading profit in markets with business students.

Table 7. *Test of Restrictions Implied by Rational Expectations: Regression of Mean Price on Price Forecast*

Market	Subjects	R^2	Constant	Slope	*F*-statistic
1–3	INB	0.7218	0.7637	0.7497	49.41***
			(0.122)	(0.026)	
4–6	IB	0.8081	0.2215	0.9205	8.71***
			(0.150)	(0.026)	
7–8	ENB	0.8949	0.1020	0.8932	30.48***
			(0.105)	(0.021)	
9–10	EB	0.8425	0.4526	0.7668	66.35***
			(0.092)	(0.023)	
11–12	ENB	0.8732	0.1233	0.8550	24.01***
			(0.156)	(0.035)	
	IB	0.9498	–0.0125	0.9397	16.29***
			(0.092)	(0.021)	
13–14	INB	0.9694	–0.1292	1.0176	2.58*
			(0.072)	(0.018)	
	EB	0.9034	–0.1300	0.9376	23.70***
			(0.132)	(0.030)	

Note: OLS standard errors are reported below coefficient estimates. The *F*-statistic is for a joint test of the hypothesis that the intercept is zero and slope is one. ***Denotes significance at the 1% level. *Denotes significance at the 10% level.

Next we test for serial correlation in forecast errors. If the current forecast fully incorporates information from past forecast errors, we should not be able to reject the hypothesis that $\beta = 0$ when estimating the regression

$$(F_{i,t} - P_t) = \alpha + \beta(F_{i,t-1} - P_{t-1}) + e_{i,t} \qquad (8)$$

Table 8 reports the results of this test for each market set. The results indicate that forecast errors persist and are clearly inconsistent with rational expectations across all treatments.[14]

Subsequently, we estimate (8) for each subject in our study and find some evidence that serial correlation in forecast errors diminishes with design experience. In Markets 1–6 (7 –10), we are able to reject the hypothesis that $\beta = 0$ for 16 out of 48 (1 out of 32) subjects or 33.33 percent (3.13 percent). A test of differences in proportions indicates a statistically significant difference at $p < .05$. Nothing in the data, however, suggests that subject pool affects the serial correlation in forecast errors.

Finally, we investigate whether the formation of price expectations can be modeled as adaptive. Others (e.g., Williams 1987; Peterson 1993) suggest that the

Table 8. *Test for Serial Correlation in Forecast Errors: Regression of Forecast Error on Lagged Forecast Error*

Market	Subjects	R^2	Constant	Slope	*F*-statistic
1–3	INB	0.2553	0.1396	0.5134	57.90***
			(0.066)	(0.050)	
4–6	IB	0.2083	0.1277	0.4592	45.47***
			(0.063)	(0.051)	
7–8	ENB	0.0305	0.2993	0.1551	19.79***
			(0.061)	(0.061)	
9–10	EB	0.1375	0.2063	0.3567	28.36***
			(0.064)	(0.062)	
11–12	ENB	0.181	0.3946	0.2523	25.32***
			(0.080)	(0.057)	
	IB	0.0441	0.2278	0.1168	14.29***
			(0.048)	(0.054)	
13–14	INB	0.0062	0.0638	0.0656	2.41*
			(0.032)	(0.082)	
	EB	0.1603	0.3177	0.2688	34.42***
			(0.055)	(0.061)	

Note: OLS standard errors are reported below coefficient estimates. The *F*-statistic is for a joint test of the hypothesis that the intercept and slope are zero. ***Denotes significance at the 1% level. *Denotes significance at the 10% level.

Table 9. *Tests of Adaptive Expectations: Regression of Forecast Change on Lagged Forecast Error*

Market	Treatment	R^2	Constant	Slope
1–3	INB	0.5722	0.0504 [9.30]***	0.8875 [–2.58]**
4–6	IB	0.6165	–0.1494 [6.24]***	0.9535 [–1.09]
7–8	ENB	0.5994	–0.2130 [3.50]***	0.7412 [–6.13]***
9–10	EB	0.5176	–0.3098 [1.12]	0.6594 [–7.68]***
11–12	ENB	0.7477	–0.0691 [5.08]***	0.8240 [–3.45]***
	IB	0.8319	–0.2317 [4.96]***	1.0127 [0.28]
13–14	INB	0.6711	–0.3685 [2.78]***	0.9998 [–0.03]
	EB	0.6895	–0.0985 [6.77]***	0.8165 [–3.40]***

Note: The *t*-ratios shown in brackets under the constant and slope estimates use OLS standard errors and test the null hypothesis that $\alpha = -E(d)$ and $\beta = 1$, respectively. ***Denotes significance at the 1% level. **Denotes significance at the 5% level.

learning process can be characterized as such. A forecast is updated to adapt to previous forecast error giving the following specification for the forecast generating process:

$$(F_{i,\,t} - F_{i,\,t-1}) = \alpha + \beta(P_{t-1} - F_{i,\,t-1}) + e_{i,\,t} \qquad (9)$$

Assuming risk neutrality, expectations are adaptive if $\alpha = -E(d)$ and $0 < \beta < 1$, where $E(d)$ is the expected value of the dividend. Table 9 reports OLS estimates of (9) for each market set. The *t*-ratios shown in brackets under the constant and slope estimates test the null hypothesis that $\alpha = -E(d)$ and $\beta = 1$, respectively. In most cases, these null hypotheses are rejected. In addition, we are able to reject the hypothesis that $\beta = 0$ in all eight cases at the 1% significance level. Taken as a whole, our results suggest that forecasts are adaptive, though a persistent bias is observed (i.e., $\alpha > -E(d)$).

Concluding Remarks

This paper investigates the effects of subject pool and design experience on market and individual behavior. We test whether the interactive effects of knowledge and experience temper price bubbles and improve forecasting ability. In markets with experienced business students, price run-ups are modest and dissipate quickly. Through their education, these students have developed a base of knowledge about the functioning of financial markets, which facilitates their acquisition of procedural knowledge. Non-business students, on the other hand, are less knowledgeable about financial markets and require more repetition to gain an understanding of the fundamental determinants of asset value. Different subject pools can lead to different results under identical conditions. Hence, theorists are advised to consider agent type in the development of models that characterize economic behavior.

We find that price bubbles moderate quickly when only a subset of traders is knowledgeable and experienced. The presence of a subset of knowledgeable and experienced traders appears to reduce the heterogeneity of expectations of price changes over time. Our findings also indicate that knowledgeable and experienced traders, in general, generate greater profit and appear to drive prices toward fundamental asset value. Hence, markets may operate efficiently even when novice traders make up half of the market.

The results indicate that absolute normalized forecast errors are smaller for business than non-business students and smaller for subjects with design experience than without. Overall though, individual forecasts are not consistent with the predictions of the rational expectations model. On average, forecasts are biased and serially correlated, though some individuals appeal to have superior forecasting ability. We provide some evidence that the correlation in forecast errors diminishes with design experience. Our evidence suggests, in general, that individuals are not very good forecasters.

In sum, our results suggest that efficient market outcomes may be observed with only a subset of knowledgeable and experienced traders. Moreover, market efficiency does not hinge on the ability of traders to produce rational price predictions. We can observe rational market outcomes with “irrational” market participants.

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Notes

1. For a discussion of these and other episodes of extreme price adjustments, the reader is referred to the Symposium on Bubbles in the Spring 1990 issue of the *Journal of Economic Perspectives* (vol. 4, no. 2).
2. Other studies maintain the same cohort of traders across inexperienced and experienced markets (e.g., King et al. [1993] and Smith and Porter [1995]). Researchers have suggested that replication with the same cohort of subjects may be necessary to create a market with common expectations in which price bubbles are eliminated. We do not maintain this requirement in our markets. In naturally occurring markets, the composition of the market is free to change continually.
3. At the conclusion of each experimental session, we asked subjects whether they had ever 1) traded securities for themselves or others, and 2) participated in the management of an investment portfolio.
4. It is unlikely that $0.25 is sufficient to create incentives to manipulate prices. Over Markets 1–14, average earnings from trading certificates are $28.74, while average earnings from predicting prices are $1.14.
5. We randomly determined the dividend before each set of markets was conducted (1–6, 7–10, and 11–14). The preselected sequence was used for each market in a set. Cason and Friedman (1996) discuss the benefits of using a preselected sequence.
6. At the end of each year, an experimenter circled the room to review each subject's record sheet to ensure that certificates and cash on hand (carried forward to the next period) were correct.
7. Questionnaire responses suggest that subjects found the experiment interesting and the monetary incentives motivating. Subjects were asked to respond on a seven-point scale as to how interesting they found the experiment. The scale endpoints were 1 for not very interesting and 7 for very interesting. The mean response was 5.86. Subjects also were asked about the amount of money earned in the experiment where 1 was a nominal amount and 7 was a considerable amount. The mean response was 5.26.
8. The average market price typically begins well below the fundamental value and adjusts upward quickly in the second and, sometimes, the third period (refer to Figures 1–14). The results, however are unaffected if data from all 15 periods are included in the analyses.
9. We performed nonparametric, Kruskal–Wallis tests to examine the simple effects of design experience and subject pool on normalized absolute price deviations. The results are similar to those reported in the text. In addition, we performed tests using one data point per market. These tests may alleviate concerns that arise due to the lack of independence of price data within a market. For Markets 1–10, we computed the average price deviation per market over Periods 3–15. Due to the small number of observations (n = 10), we focused on the comparison between the average normalized absolute price deviation in markets with experienced, business students (Markets 9–10) and that in other markets (1–8). Fundamentally, this significant difference is what drives the ANOVA results reported in Table 4. Using parametric and nonparametric tests, the difference is significant at $p < .05$ ($t = -2.435$ and $z = -2.089$). Hence, general inferences are unaffected using this more stringent test.
10. We exclude data from the first two periods to allow subjects to orient themselves to market behavior. The forecasting results reported in this subsection, however, are unaffected if data from all 15 periods are included in the analyses.
11. Caginalp, Porter, and Smith (2000) test for unbiasedness using six forecasters who were designated as experts. The forecasters were a subset of traders who earned the most money in previous experiments. Consistent with our results, Caginalp, Porter, and Smith find that these experienced forecasters were accurate forecasters.
12. We also perform the ANOVA using one observation per subject. For each subject we compute an average absolute forecast error collapsing the data over Periods 3–15. Inferences are unaffected. In addition, we repeat the analyses using the signed normalized forecast error as the dependent variable. With the signed forecast error, none of the independent variables are statistically significant at conventional levels.
13. Diagnostic tests, including the Breusch–Pagan–Godfrey (Breusch and Pagan 1979; Godfrey 1978) and ARCH (Engle 1982) tests, indicated significant heteroskedasticity in the regression residual. We used White's (1980) heteroskedastic-consistent covariance matrix estimation to correct for an unknown form of heteroskedasticity and inferences were unaffected.
14. We also performed the analysis using normalized forecast error and results were unaffected.

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Appendix A

The experimental instructions follow. Differences between markets are denoted in parentheses for Markets 7–10 and in brackets for Markets 11–14.

General Instructions

This experiment is concerned with the economics of market decision-making. We are going to simulate a market in which you will buy and sell certificates in a sequence of 15 market years. You also will attempt to predict the average trading price each year. Based on your trading decisions and predictive abilities, you are able to generate profits, which will be paid to you in cash at the conclusion of this experiment.

Attached to these materials you will find 15 information and record sheets; one for each market year, and a price prediction sheet. [See Figures A-1 and A-2 for samples.] Please refer to these sheets while going through the instructions.

Specific Instructions

Trading

Your trading profits come from two sources—from collecting dividends on all certificates you hold at the end of a year and from buying and selling certificates. During each market year you are free to purchase or sell as many certificates as you wish, provided you follow the rules below. For each certificate you hold at the end of a year you will receive a dividend of $1.20, $0.56, $0.16, or $0.00 ($0.90, $0.42, $0.12, or $0.00) [$1.06, $0.48, $0.18, or $0.00]. The method by which one of the four numbers is selected each year is explained later in these instructions. Compute your total dividends for a period by multiplying the dividend per certificate by the number of certificates held. Suppose, for example, that you hold five certificates at the end of year 1. If for that year your dividend is $0.56 ($0.42) [$0.48], then your total dividends in the year would be 5 × $0.56 ($0.42) [$0.48] = $2.80 ($2.10) [$2.40]. This number should be recorded on row 19 of your information and record sheet at year-end.

Sales from your certificate holdings increase your cash on hand by the amount of the sale price. Similarly, purchases reduce your cash on hand by the amount of the purchase price. Thus you can gain or lose money on the purchase and resale of certificates.

At the beginning of the first market year you are provided with holdings of certificates and cash on hand. Note that different traders may have different holdings. Your holdings are recorded on the endowment row of the information and record sheet for year 1. This is your private information. Do not reveal this information to anyone because it could affect the amount of money that you are able to earn for participating in this experiment.

You may sell your initial endowment of certificates or you may hold them. If you hold a certificate, then you receive a dividend at the end of the year. Notice therefore that for each certificate you hold, you can earn during the year at least the dividend amount. You earn this amount if you do not sell the certificate during the year. Your holdings of certificates at the end of the year are carried forward to the beginning of the next year.

You may use your initial endowment of cash on hand to purchase certificates or you may hold this amount. Purchases decrease your cash on hand by the amount of the purchase price and sales increase your cash on hand by the amount of the sales price. Dividends also increase your cash on hand. Your holdings of cash at the end of the year are carried forward to the beginning of the next year. Your cash on hand at the end of year 15 is yours to keep.

Dividends

Whether the dividend you receive from the certificates you hold is $1.20, $0.56, $0.16, or $0.00 ($0.90, $0.42, $0.12, or $0.00) [$1.06, $0.48, $0.18, or $0.00] is determined randomly. Each dividend amount has an equal chance of being paid. The amounts have been determined previously. At the end of each year, the experimenter will announce the dividend for the year.

Predicting Prices

At the beginning of each year, you will attempt to predict the average trading price for the upcoming year. You will receive $0.25 for each prediction that is within ± $0.15 of the actual price. The actual price is computed as the sum of the transactions prices for the year divided by the number of transactions. If no transactions take place during the year, the actual price is computed as the sum of the last buy and sell prices divided by two. The experimenter will announce the actual price at the end of each year.

Market Organization

The market for certificates is organized as follows. The market will be conducted in a series of 15 years. Each market year lasts four minutes.

Anyone wishing to purchase a certificate is free to raise his or her hand and make a verbal bid to buy one certificate at a specified price, and anyone with certificates to sell is free to accept or not accept the bid. Likewise, anyone wishing to sell a certificate is free to raise his or her hand and make a verbal offer to sell one certificate at a specified price. Please wait until the experimenter calls on you to make a bid or offer. When you are called on, please announce your trader number followed by your bid or offer. If you wish to accept an outstanding bid or offer, shout out accept to buy or accept to sell. In this case, you do not need to raise your hand and wait for the experimenter to call on you.

If a bid or offer is accepted, a binding contract has been closed for a single certificate, and the contracting parties will record the transaction on their Information and Record Sheets. Any ties in bids or acceptances will be resolved by random choice.

Trading and Recording Rules

(1) All transactions are for one certificate at a time. After each of your sales or purchases you must record the TRANSACTION PRICE in the appropriate column of your information and record sheet depending on the nature of the transaction. The first transaction is recorded on row 1, and succeeding transactions are recorded on subsequent rows.

(2) After each transaction you must calculate and record your new holdings of certificates and your new cash on hand. Your holdings of certificates may never go below zero. Your cash on hand may never go below zero.

(3) At the end of the year record your dividends in the last column of row 19 of your information and record sheet. Compute your cash on hand at the end of the year on row 20 by adding your dividends to your previous cash on hand.

(4) Your holdings of certificates and cash on hand at the end of a year are carried forward to the next year. Transfer your holdings of certificates and cash on hand (from line 20) at year-end to the row labeled "carry forward" on the following year's information and record sheet.

It is extremely important that you record transactions accurately and that you compute holdings of certificates and cash on hand without error. If at any time you have a question, please ask the experimenters for assistance.

Price Prediction and Recording Rules

(1) Prior to the beginning of each year, you attempt to predict the average trading price for the upcoming year. Record your prediction on the row corresponding to the upcoming year in column (3) of your price prediction sheet. The experimenters will walk around the room to ensure that your prediction is recorded before the year begins.

(2) At the end of the year, the experimenters will announce the average trading price. Record this amount on the appropriate row in column (4) of your price prediction sheet.

(3) If your prediction is within ± $0.15 of the actual price, record $0.25 on the appropriate row in column (5)

of your price prediction sheet. Otherwise, record $0.00. YOUR PRICE PREDICTION EARNINGS DO NOT AFFECT YOUR CASH ON HAND.

(4) At the conclusion of the experiment, sum up your price prediction earnings and record the total on row 16.

(5) At the bottom of the price prediction sheet, compute your total experimental earnings. This amount equals your cash on hand at the end of year 15 plus your total price prediction earnings plus your bonus for being on time (if received). This amount will be paid to you in cash.

FIGURE A-1
Information and Record Sheet: Year 1

Trader No. _____

		Transaction Price			
	Transaction Number	Sale	Purchase	Certificates on Hand	Cash on Hand
Beginning of Year Holdings	Endowment				
	1				
	2				
	3				
	4				
	5				
	6				
	7				
	8				
	9				
	10				
	11				
	12				
	13				
	14				
	15				
	16				
	17				
	18				
	19 Actual div. rate is _____	Dividends Actual Dividend Rate multiplied by # of Certificates on Hand at Year End			
	20	Total Cash on Hand			

FIGURE A-2
Price Prediction Sheet

Trader No. _____

(1)	(2)	(3)	(4)	(5)
Row	MarketYear	Predicted Price	Actual Price	Earnings ($0.25 or $0.00)
1	1			
2	2			
3	3			
4	4			
5	5			
6	6			
7	7			
8	8			
9	9			
10	10			
11	11			
12	12			
13	13			
14	14			
15	15			
16	Total Price Prediction Earnings			

TOTAL EXPERIMENTAL EARNINGS

Cash on hand at the end of year 15	
Total price prediction earnings	
Bonus for being on time ($3.00 or $0.00)	
Total Experimental Earnings	

Appendix B:
Post-Experience Questionnaire

Trader No. _____

This questionnaire is designed to collect general information. Such information may help us better understand differences found between participants in this experiment.

1. What year are you in university? ________
2. What department are you in at university (e.g., business, economics)? _____________
3. What is your sex **(check one)** male ______ female ______
4. What is your age? _______years
5. How interesting did you find this experiment? **(circle the appropriate number)**

Not Very Interesting	1- - - - - - - -2- - - - - - - -3- - - - - - - -4- - - - - - - -5- - - - - - - -6- - - - - - - -7	Very Interesting

6. Have you ever participated in a market experiment where you actively traded with other participants? **(check one)** yes ________ no ________
7. Have you ever traded securities for yourself or others? **(check one)** yes _______ no _______
8. Have you ever participated in the management of an investment portfolio? **(check one)** yes ________ no ________
9. Compared to the amount of money available to you from alternative sources, how would you characterize the amount of money earned for participating in this experiment? **(circle the appropriate number)**

Nominal Amount	1- - - - - - - -2- - - - - - - -3- - - - - - - -4- - - - - - - -5- - - - - - - -6- - - - - - - -7	Considerable Amount

10. How would you characterize your attitude toward risk while participating in the market experiment? **(circle the appropriate number)**

Very Risk Averse	1- - - - - - - -2- - - - - - - -3- - - - - - - -4- - - - - - - -5- - - - - - - -6- - - - - - - -7	Very Risk Taking

11. How would you characterize the difficulty/ease of predicting the price each year? **(circle the appropriate number)**

Extremely Difficult	1- - - - - - - -2- - - - - - - -3- - - - - - - -4- - - - - - - -5- - - - - - - -6- - - - - - - -7	Extremely Easy