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A BUBBLE Experiment

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A Bubble Experiment

Detecting currency bubbles is a difficult task especially in the noisy foreign exchange market. First-generation bubble tests are volatility tests such as West's Test and Variance-bound tests. These tests compare the volatility between the assumed fundamental currency value and the actual currency value. If the volatility of the actual currency value is significantly larger than the volatility of the assumed fundamental currency value, the test claimed that currency bubbles are being detected indirectly.

However, these indirect tests suffer from the problem of model mis-specification or omission of important variables that are known to market participants, but not to researchers. Cochrane (1991) argued that traders in the market certainly have more information than we do. The rejection of the volatility tests only suggest that currency prices move in response to changing expectations of some events that are not seen in the sample; therefore, they need not support the presence of bubbles.

Second-generation bubble tests are direct tests for the no-bubble hypothesis. If the exchange rate fundamentals are co-integrated with the exchange rate, the no-bubble hypothesis cannot be rejected. MacDonald and Taylor (1993) suggested a direct test for the speculative bubble hypothesis by examining the stationary of the currency. Charemza and Deadman (1995) used the unit root approach to test for periodical collapsing bubbles. However, these direct tests can only provide necessary, but not sufficient, evidence of bubbles because rejecting the no-bubble hypothesis is not the same as detecting a bubble.

So far, empirical results can, at most, provide a mixed conclusion regarding the presence of exchange rate bubbles. The difficulty of accepting a bubble lies in the specification of the underlying fundamental economic models. In the case of foreign exchange markets, economists are still looking for a model that can adequately describe exchange rate fundamental movements (Macdonald, 1999). Without any universally-accepted fundamental model, any bubble detected suffers from the problem of model mis-specification or regime switch processing (Flood & Garber, 1994, p. 114-119). Even economists manage to avoid the requirement of complete model specification using the cointegration method, wherein all fundamental variables still need to be correctly observed and included. In the case of high frequency data such as the daily exchange rate, it becomes impossible to identify or observe all the underlying fundamental.

The difficulty of rejecting the presence of a bubble lies in the small sample phenomenon of bubbles. No one would expect bubbles to grow forever. Researchers face a trade-off between using a sufficiently large sample size and the ability to detect short-lived bubbles (Evans, 1991). Thus, rejecting the presence of a bubble may result from the inability to detect short-lived bubbles.

Essentially, the empirical puzzles of bubble tests mentioned above such as fundamental model mis-specification, short-lived bubbles, and the presence of unobserved variables, remain unsolved (Van Norden, 1996).

Investigating currency bubble is never an easy task. In actual data, it is difficult to distinguish exactly between the fundamental currency value and the currency bubble, especially when the bubble is small-scale and self-limiting. To deal with this empirical problem, Camerer (1989) suggested that more experiments are needed, in which intrinsic values and discount rates are controlled. This paper employs an experimental method to simulate and test the dynamics of a small-scale, self-limiting currency bubble. The experimental method has the advantage of directly controlling true value of the experimental currency, thus enabling us to know the fundamental values; any other change in currency prices can be viewed as either currency bubbles or random forecasting errors.

The rest of this paper is organized as follows: Section 1 begins with a review of the distinctive characteristics and limitations of experimental methods in testing currency bubbles. Section 2 describes the purpose and design of the bubble experiment and states the market environment, institution, and behavior of the agents. Section 3 presents the experiment's results and analyzes the growth rate of the experimental bubbles, graphically and econometrically. Conclusions and implications for further study are in section 4.

1. Review of Experimental Methods

The works of Smith (1982, 1986, 1989, and 1991) established a foundation to define the methodological procedures for conducting experiments in economics. According to Smith, the framework of every laboratory experiment consists of five elements: 1) environment, 2) institution, 3) behavior, 4) privacy, and 5) parallelism. The elements of environment and institution are control variables that set up the laboratory micro-economic environment including subjects, rules, and "payoff" (reward). Behavior is the choice of agents in the specified environment and institution. Privacy requires that each participant receives only the information required to participate, so that any other influences are avoided. Control over these elements enables research economists to fulfill the objectives of the experiment; that is, to test the hypothesis of an economic theory and ensure that the results obtained are paralleled. Parallelism means that results established in the laboratory hold in other, especially non-laboratory, real-world situations where similar *ceteris paribus*, conditions hold (Smith 1982b pp. 936. Wilde, 1981, pp. 140, 143).

In studying speculative currency bubbles, the most attractive advantage of experimental methods is that a bubble experiment enables the researcher to design and specify a particular situation of interest. In this paper, the experiment aims at controlling the fundamental value of, and generating, self-limiting bubbles. However, in the design of bubble experiments, knowledge of the exact time that the experiment will end can force prices to converge to the fundamental value. Friedman (1984) suggests that knowing the time when the experiment will end enhances the informational and competitive efficiency of the observed outcome. Therefore, artificial uncertainty is imposed to ensure that bubbles exist. Smith, Suchanek, & Williams (1988) introduced stochastic dividends in their bubble experiment. Stanley (1997) extended the same experimental design, as did Smith et al. by making the timing and values of the termination uncertain. Traders in the real world know that tomorrow will not be doomsday, yet individuals in an experiment understand that an experiment will terminate by the end of the day.

To ensure that the results of the experiment are able to fulfill the parallelism condition, the reward-motivated subjects in the experiment are required to act like real traders in the foreign exchange market. As in all economic experiments, this requirement is a major limitation. The usual case is that the rewards and punishments in an experiment are not large enough to motivate individuals to act like risk aversive traders in the real world. In addition, the actions of traders in the real world are far more complex than the constraints of the experiment's rules.

Moreover, the number of subjects in an experiment is much smaller than the number of traders in the real foreign exchange market; therefore, it is relatively easy to aggregate and disseminate information in an experiment than in the real world. Clearly, these variables can be controlled by carefully designing the experiment, and the more successful the experimental design in achieving control over these variables, the less ambiguous the experimental results. However, a major limitation is that, the tighter the specifications of the laboratory situation, the less likely it is that parallelism will hold. Nikos Siakantaris, (2000) called this the "experimental economics trade-off" (p. 273).

To keep the experiment relevant, at least for the environment being studied, Bohm (2002) argued that one needs to clearly explain the choice of experimental subjects, incentive levels for the subjects, the context of the environment, and the usefulness of stationary repetitions.

2. Design of the Experiment

The purpose of the experiment is to simulate foreign exchange bubbles and test for the null hypothesis that bubbles can be small-scale and self-limiting. In the real world, professional dealers conduct 90% of daily trades; therefore, the subjects selected to do the experiment must have sufficient knowledge to make decisions similar to actual foreign exchange dealers. Professional dealers tend to be the best choice; however, it is difficult to motivate professional dealers to participate in an experimental environment with only a limited payoff amount. Perhaps the most easily accessed pool of subjects, at the lowest cost, is my students (the researcher's students).

The environment of the experiment involved twenty voluntary undergraduates from a college class on international monetary economics, playing the role of foreign exchange traders. All of them had learned about the operation of foreign exchange markets; therefore, it was assumed that they were able to act like dealers in the real foreign exchange market. To motivate the subjects to earn profit, they were told that the top five profit earners would receive 10% extra credit increment in their marks on the final examination. On the other hand, to avoid all subjects acting as "risk lovers," all subjects that make unreasonable or irrational trade would not allow to continue with the experiment and loss the chance of gaining 10% extra mark on the final examination.

Each trader randomly received an amount of experimental currency U.S. dollars and British pounds ranging from $3,000 to $30,000 at the beginning of the experiment. Traders were allowed to trade freely in each trading session with the experimental currency. There were no payments of trade commissions. Whenever a transaction was made, the traders were required to report it on the board immediately so that all participants knew about the transaction. There were three trading sessions; the first session ended after 15 minutes, the second after 14 minutes, and the last session's duration was 16 minutes. Subjects did not know when each trading session would end. After the experiment, students participated in a review session to share their trading experiences.

The experiment began at an exchange rate of $1.4 per pound. All subjects, except one, were not permitted to short sales or borrow either U.S. dollars or pounds. All pounds that had not been converted into dollars, by the end of the experiment, could only be converted at an exchange rate of $1.4 per pound. For all traders, the fundamental value of the risk-less experimental currency was $1.4 per pound and the discount rate was equal to zero. There was no reason to sell the currency below $1.4 per pound because, by the end of the experiment, each dollar was still worth $1.4 per pound. By the same reasoning, no one would buy the currency at a rate higher than $1.4 per pound. Therefore, the experiment initially created a no-bubble scenario. If all traders were trading rationally, they would trade at the fundamental value only.

To ensure that a bubble occurred, one student was assigned to act as an irrational subject buying pounds at a price above the fundamental value with unlimited resources. All other subjects knew nothing about this irrational trader, who was instructed not to reveal any information about his existence to any traders.

Another condition was that the irrational subject could only trade inactively, waiting for other traders to approach him. In the first session, the irrational subject was assigned to buy pounds at $1.5 per pound. In the second session, the irrational trading price was $1.6 per pound and, in the final sessions, the irrational price was allowed to increase to $1.7 per pound.

This experiment was carried out on May 30, 2002, the last day of the class. All subjects were issued instructions prior to beginning. I (The researcher) reviewed the instructions with the subjects and answered questions. Before the data was recorded, a ten-minute practice session was conducted so that all subjects could familiarize themselves with the rules of the experiment.

3. Results and Analysis

The main source of raw data recorded is sequences of transaction prices in each session. The following table gives a summary of the raw data.

Table 1 : Raw Data Description			
Session	One	Two	Three
Mean	1.435347	1.540143	2.110714
Median	1.430000	1.490000	1.700000
Maximum	1.500000	2.000000	5.000000
Minimum	1.400000	1.400000	1.400000
Standard Deviation	0.028237	0.162467	0.895786
Transactions	49	70	91
Transactions Per Minute	3.33333	5.071429	5.75
Percentage of Irrational Trade	12.00%	8.45%	7.61%

Table 1 shows that the transaction price became more volatile as the experiment progressed. The mean, median, maximum value, standard deviations, and transactions per minute increased over the three sessions. However, the percentage of irrational trades decreased as the experiment continued. Therefore, the relative responsibility of the irrational subject for the high volatility of the data steadily decreased.

The minimum value remained at $1.4 per pound, and the fundamental currency value was commonly known to most of the subjects; that means the subjects were rational enough to avoid trading at a price below the fundamental value. In addition, all subjects behaved in a risk aversive manner; no subject entered an “all-or-nothing” game. Each maintained a certain level of exposure at the end of each session.

The maximum value increased from \$1.5 per pound in session one to \$5 per pound in session three. Since the fundamental currency value remained at \$1.4 per pound, transaction prices that rose above the fundamental value indicated one of the following possibilities:

1. Random forecasting errors
2. Random everlasting bubbles
3. Random self-limiting bubbles

3.1 Preliminary Graphical Analysis

The analysis proceeds with a preliminary investigation of the raw data using graphical presentation.

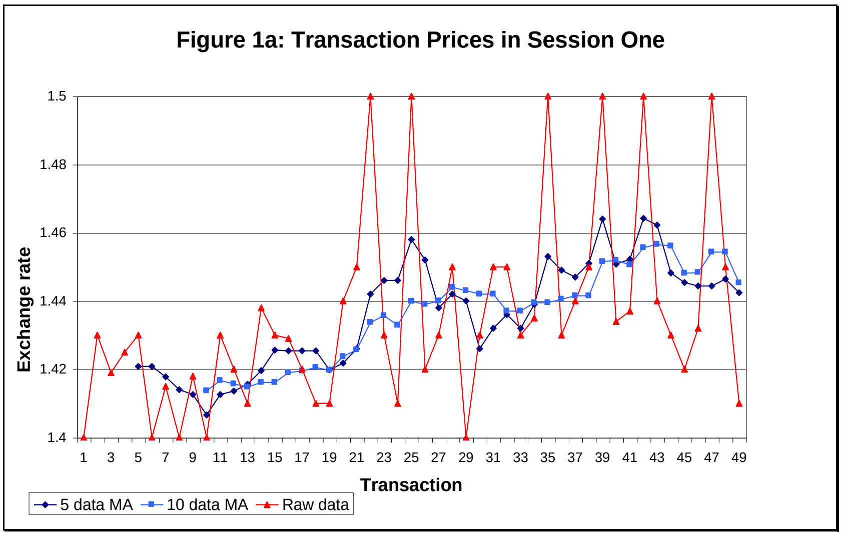
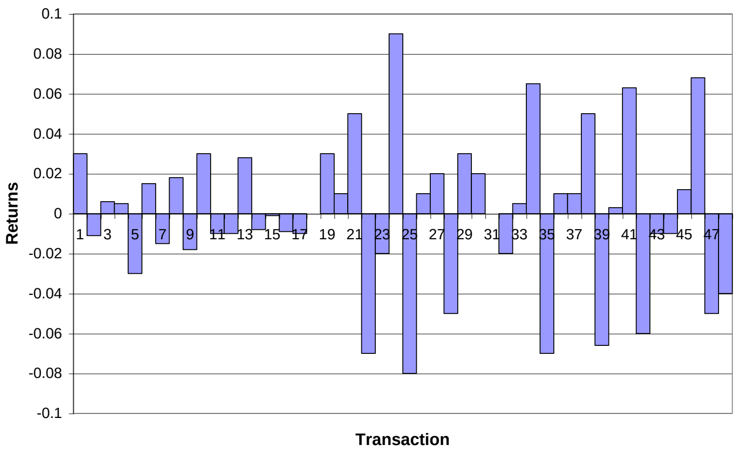


Figure 1a: Transaction Prices in Session One

Figure 1a shows that transaction prices rose rapidly even before any trader approached the irrational trader. In the review session, it was revealed that strategic traders expected to sell the experimental currency above the fundamental value before the end of the experiment. Therefore, those traders continued to trade at a price above the fundamental value. The perception of earning profit in short term trading structured the formation of short-lived bubbles. On the other hand, the fundamental traders tended to stick to the fundamental value; therefore, the transaction price periodically fell back to $1.4 per pound.

After the 21st transaction, the irrational trader initiated his first transaction. The existence of an irrational trader who was willing to buy the currency at higher prices tended to diffuse quickly and the frequency of irrational trades increased as the experiment went on. In addition, after the 29th transaction, all transaction prices remained at levels above the fundamental value; however, there was no tendency for the price level to rise quickly at an ever-accelerating rate.

Figure 1b: Returns of Transactions in Session One



The moving average (MA) curves show that both 5 and 10 data moving average transaction prices exhibited a tendency to increase during the experiment. However, the growth rate of the moving average curves fell as the curve grew above $1.44 per pound.

Since the fundamental currency value remained at $1.4 per pound, continuous and correlated transactions above the fundamental value disproved the hypothesis that the transactions resulted only from random forecasting errors. Figure 1b shows that the returns on transaction price were not increasing monotonically. A large positive return tended to associate with a large negative return and a few relatively smaller positive or negative returns. Clearly, the large returns in the data only reflected the conflict between the strategic and fundamental traders. Even if these large returns were ignored, the raw data did not exhibit the traditional everlasting bubble path: any bubble that existed can only be a self-limiting bubble.

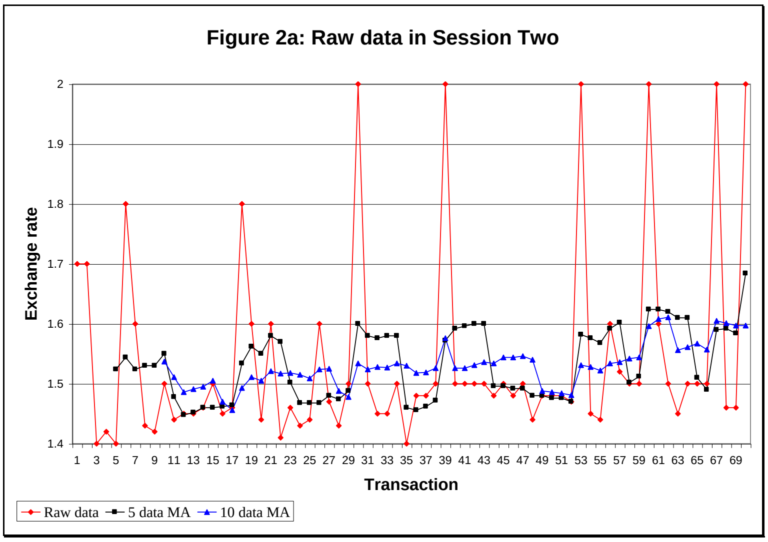
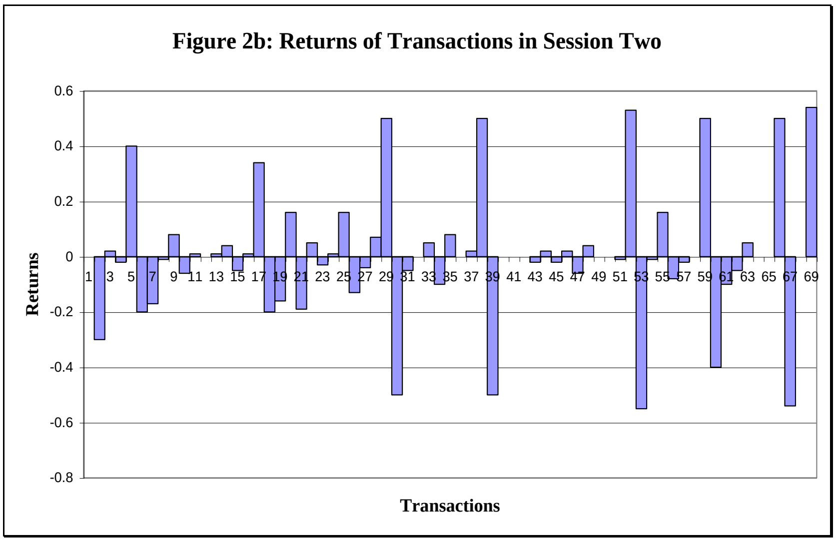
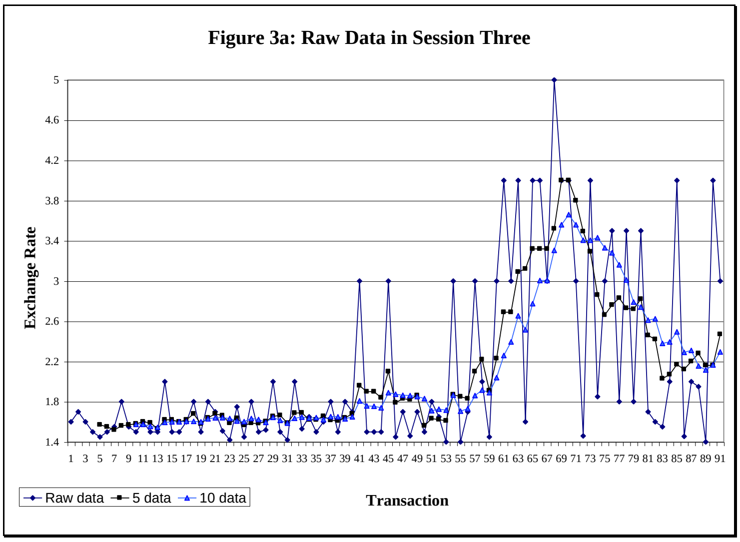


Figure 2a shows that strategic traders, after gaining experience in the first session, traded actively at a transaction price between \$1.7 per pound and \$2 per pound. In the review session, it was demonstrated that the strategic traders tended to send out a message that an accelerating bubble had been created and hoped that other fundamental traders would follow, so that the strategic traders could sell out their holdings at a price above the fundamental value. Obviously, these strategic traders could only partially convince the fundamental traders to believe in the existence of bubbles. The raw data showed that fundamental traders were smart enough to avoid following the accelerating bubble, but were not rational enough to stick to the fundamental value. Other than the transactions made by the strategic traders and the single irrational trader, all transaction prices, except one, fell between \$1.4 per pound and \$1.5 per pound, respectively. Given the chance of selling out the experimental currency to the strategic traders, the fundamental traders continued trading above the fundamental value. Both 5 data and 10 data moving average curves showed that, instead of having one single accelerating phase, bubbles repeated a birth and burst cycle.



The returns in figure 2b exhibit a similar pattern to figure 1b, a large positive return tended to associate with a large negative return. This pattern reflected the struggle between the strategic traders and the fundamental traders. The large positive returns showed that strategic traders wanted to raise the transaction price, but the large positive returns could not be sustained because fundamental traders did not follow the large positive returns. As a result, the level of transaction price fell dramatically, and produced large negative returns. Again, the transaction price tended to indicate the possibility that self-limiting bubbles occurred.



None of the traders knew the exact timing of when the experiment would end. However, in the third session, traders began to worry that the experiment would end soon. Therefore, all traders were more active in session three than in sessions one or two. Figure 3a shows that the conflicts between the strategic and fundamental traders continued to exist. The strategic traders pushed the transaction price up to $5 per pound while the fundamental traders kept trading below $1.8 per pound. The moving average curve shows that there was at least one large bubble that occurred between the 50th transaction and the 80th transaction of the experiment.

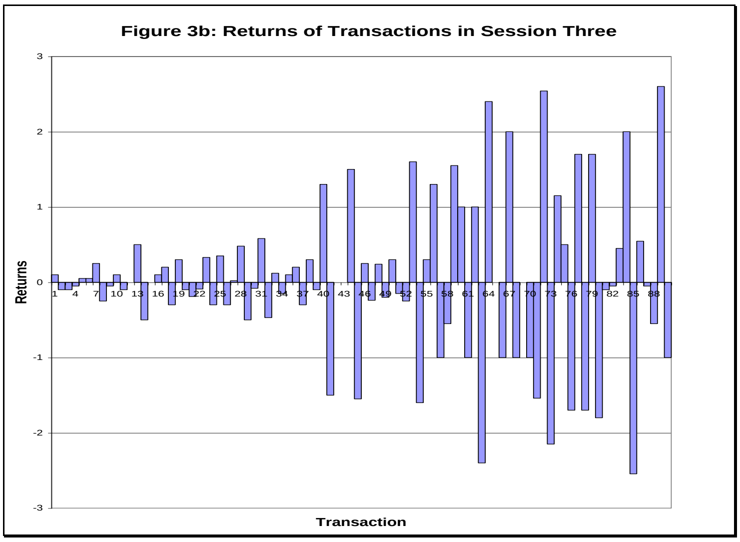


Figure 3b also shows that volatility of the returns increased after the 50th transaction. However, the growth rate of the large bubble only exhibited an accelerating phase at the beginning of the bubble. The growth rate of the large bubble remained nearly constant most of the time.

3.2 Summary of the Graphical Analysis For All Three Sessions

The graphical analysis shows that the experiment was successful in generating experimental bubbles in all three session. However, the artificial irrational trader was not the main cause of the experimental bubble. Instead, the strategic uncertainty that generated from the intention of earning speculative profit, and the misperception of the traders' ability to juggle market prices, were the main causes of the experimental bubble.

Similar to foreign exchange dealers in the real world, the experimental traders needed to gain profit within a relatively short period; this caused the experimental traders to focus on short-term speculative returns. Unlike the real foreign exchange market, the number of experimental traders was very small compared to thousands of foreign exchange dealers. There was always a temptation to act strategically because, in the small experimental market, the share of each trader was large enough to influence the market price. However, the small experimental market also made it easier to diffuse information quickly; therefore, the strategic traders failed to fool the fundamental traders. As a result, the raw data exhibited a shared conflict between the two groups of traders; the fluctuation of successful transaction prices could reach 100%.

In the real world, 100% fluctuation in high frequency spot rates seldom occurs; therefore, the experiment provides evidence against the hypothesis that fluctuations in daily spot rates result from conflict trading between the fundamental and strategic traders. Instead, with thousands of foreign exchange dealers trading with each other, the limitation of trading strategically comes from the traders' inability to influence the market price. Only very large parties such as central banks can occasionally trade strategically. Normally, most of the traders keep their transaction price close to the market price to avoid any unanticipated changes in the spot rate that results from traders' inability to process full information.

3.3 Econometric Analysis

The graphical analysis showed that the experimental bubbles were self-limiting. The growth rate of the experimental bubbles can be examined using econometric methodologies. Graphical analysis has shown that the bubbles that existed did not last forever. Statistically, the experimental data showed that data series are stationary. Augmented Dickey-Fuller (ADF) tests and Phillips-Perron (PP) tests were used to examine the unit root in the data series. Rejecting the non-stationary null hypothesis means that the experimental data series were stationary.

Table 2 Unit Root Test

Level				
Series	One	Two	Three	Critical Value at 1%
ADF Test Statistic	-4.549879	-4.836188	-2.176159	-3.5055 to -3.5745
PP Test Statistic	-6.101772	-8.028909	-6.686669	-3.5039 to -3.5713
First Difference				
Series	One	Two	Three	Critical Value at 1%
ADF Test Statistic	-10.08804	-8.328306	-7.495034	-3.5064 to -3.5778
PP Test Statistic	-14.88757	-15.52634	-24.24257	-3.5047 to -3.5745

Table 2 showed that the level of the data series for both sessions one and two managed to past the unit root test. However the ADF statistics showed that the level of the data series in session three could not reject the non-stationary null hypothesis at the 1% critical level. Graphical analysis has shown that the level of the data series in session three exhibited at least one large bubble, which was responsible for this statistical non-stationary result. The first difference of all three data series rejected the non-stationary null hypothesis. Therefore, the unit root tests supported the graphical analysis results that any bubbles that existed must have been self-limiting.

Another way to test for the existence of self-limiting bubbles was to directly investigate the growth rate of the bubble. Since the fundamental value in the experiment remained constant, any correlation between changes in transaction prices can be viewed as an experimental bubble. As a first step, the growth rate of the bubble can be estimated with the following autoregressive (AR) model using nonlinear regression techniques:

$$\Delta S_t = \beta_0 + \beta_1 \Delta S_{t-1} + residuals \qquad 1$$

where ($\beta_1 - 1$) could approximate the growth rate of the bubble and β_0 is the average return.

If the estimated growth rate of the bubble was larger than zero, the experimental bubble was growing over time. On the other hand, if the estimated growth rate of the bubble equaled zero, the bubble followed a random walk. These two results indicated that the experimental bubbles were not self-limiting. If the estimated growth rate of the bubble equaled minus one, there was no correlation between transaction prices; thus, transaction prices only fluctuated randomly.

However, the graphical analysis and the unit root test have already suggested that the experimental bubbles were self-limiting; therefore, the estimated growth rate of the bubble should be negative. If the growth rates of the bubble lie between 0 and –1 exclusively; this indicates the bubbles died out monotonically. On the other hand, if the growth rates of the bubble lie between –1 and –2, exclusively, the bubbles died out through a cyclical path. A correct specification of the residual term should enable the model to provide a significant coefficient β_1 that is smaller than one in absolute terms.

Table 3: Autoregressive Model		
Session One		
Variable	Coefficient	Std. Error
C	0.002278	0.000803
D(SER01(-1))	-0.796106	0.133216
MA(2)	-0.774499	0.133886
Session Two		
Variable	Coefficient	Std. Error
D(SER02(-1))	-0.837567	0.069109
MA(2)	-0.924699	0.037127
Session Three		
Variable	Coefficient	Std. Error
D(SER03(-1))	-0.785759	0.094400
MA(2)	-0.582025	0.121549
D(SER01) : returns of transactions in Session One D(SER02) : returns of transactions in Session Two D(SER03): returns of transactions in Session Three		

Table 3 shows that the coefficients β_1 in the three sessions were significant at the 1% significance level and were smaller than one in absolute terms. The calculated growth rates of the bubbles were 1.796, -1.838, and –1.786. All lie between –1 and –2; that means the experimental bubbles exhibited cyclical fluctuations, which eventually died out.

Instead of a first order moving average process MA(1), a second order moving average process MA(2) was found to be significant for the residuals. The MA(2) process reflected the conflict between the strategic and fundamental traders. Since the residuals of the models must be specified with the MA(2) process, the models were estimated using the backcasts procedure introduced by Box and Jenkins (1976). The initial coefficients were computed from the unconditional residual using nonlinear least squares regression. The backcasts value was computed using forward recursion. The backcasts step, forward recursion, and sum of squared residuals (SSR) minimization procedures were repeated until the estimated coefficients converged.

To identify potential problems of model mis-specification, residuals of the models in table 3 needed to undergo four diagnostic tests to check for the problem: incorrect functional form, serial correlation, ARCH effect, and out-of-sample forecasting test.

The first test is the Regression Specification Error Test (RESET) which was proposed by Ramsey (1969) and is used to test for the possibility of specification errors. RESET is a general test for omitted variables or incorrect functional form. Ramsey suggests that the powers of the predicted values of the dependent variable can be included in the augmented regression as the fitted value for comparison. The null hypothesis is that all coefficients on the powers of fitted values are all zero. If the null hypothesis cannot be rejected, then the result implies that the RESET test cannot detect any mis-specification with the powers of fitted values.

Ramsey and Alexander (1984) showed that the RESET test could detect specification errors in an equation that was known to be mis-specified, but given satisfactory values for all traditional goodness-of-fit tests. The mis-specification of the AR bubble model in equation 1 comes from the argument that a nonlinear model can describe the self-limiting bubble better. Yet, this mis-specification is less convincing if the AR bubble model can pass the RESET test.

Table 4: Ramsey RESET Test			
Session One			
F-statistic	2.515881	Probability	0.121963
Log likelihood ratio	2.712696	Probability	0.099553
Session Two			
F-statistic	0.169874	Probability	0.681826
Log likelihood ratio	0.178864	Probability	0.672351
Session Three			
F-statistic	0.043025	Probability	0.836247
Log likelihood ratio	0.045338	Probability	0.831384

Table 4 shows that the RESET test did not detect any mis-specification in sessions two and three. However, the null hypothesis of the RESET test can be rejected at the 10% significance level in session one. This implies that the RESET test detected a possibility of incorrect functional form in the transaction data of session one. Therefore, session one is reconstructed into the following nonlinear model:

$$\Delta S_t = \beta_0 + \beta_1 \Delta S_{t-1} + \beta_2 \Delta S_{t-1}^2 + residuals \qquad 2$$

where β_2 is the effect of irrationally expected profit from speculation.

Equation 2 tests the hypothesis that the dumping forces causing the experimental bubbles to become self-limiting came from irrational expected profit. The coefficient β_2 is expected to be negative and the coefficient β_1 is expected to be smaller than one in absolute terms.

Table 5: Nonlinear Model		
Session One		
Variable	Coefficient	Std. Error
C	0.005954	0.001870
D(SER01(-1))	-0.847605	0.110715
D(SER01(-1))^2	-2.814681	1.278757
MA(2)	-0.915357	0.036842

Table 5 shows that all coefficients had the right sign and were significant at the 5% significance level. The growth rate of the bubble became an endogenous variable depending on changes in the current spot rate. The following table 5.6 shows that the non-linear model passed the RESET test.

Table 6: Ramsey RESET Test for the Nonlinear Model			
Session One			
F-statistic	0.948540	Probability	0.39792

			7
Log likelihood ratio	2.188533	Probability	0.334785

The second diagnostic test used was the serial correlation Lagrange multiplier test. A test statistic for the null hypothesis that there is no autocorrelation up to the five lagging periods was used. This test involved estimating a regression of the residuals, as the dependent variables, on all the independent variables, and the specified order of lagged residuals. If the coefficients of any of the lagged residuals were significantly different from zero, the model should be reconstructed to estimate a higher order autoregressive bubble model.

Table 7: Breusch-Godfrey Serial Correlation LM Test			
Session One			
F-statistic	0.409750	Probability	0.838043
Obs*R-squared	1.995305	Probability	0.849794
Session Two			
F-statistic	0.709475	Probability	0.619061
Obs*R-squared	3.672816	Probability	0.597414
Session Three			
F-statistic	2.416277	Probability	0.044212
Obs*R-squared	10.68183	Probability	0.058066
Obs*R-squared: the number of observations times the R-square statistic			

Table 7 shows that the residuals from the model of session three rejected the null hypothesis of no serial correlation in residuals at the 10% significance level. The model for session three was reconstructed to involve the serial autocorrelation effect by estimating the following higher order autoregressive bubble models:

$$\Delta S_t = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta S_{t-i} + residuals \qquad 3$$

Table 8: AR(2) Model		
Session Three		
Variable	Coefficient	Std. Error
D(SER03(-1))	-0.992255	0.110676
D(SER03(-2))	-0.380771	0.129970
MA(2)	-0.334551	0.160292

Table 8 shows that an AR(2) model provided statistically significant coefficients which were smaller than one in absolute terms.

The third diagnostic test employed was the Ljung-Box Q-statistics for the corresponding autocorrelations and partial autocorrelations of the squared residuals up to ten lags.

$$Q = T(T+2)\sum_{j=1}^{10} \frac{t_j^2}{T-J} \qquad 4$$

where t_j is the j^{th} auto-correlation and T is the number of observations. For further discussion, see Ljung and Box (1979) or Harvey (1990, 1993). The correlograms of the squared residuals can be used to check for the autoregressive conditional heteroskedasticity (ARCH) in the residuals. If there is ARCH in the residuals, the autocorrelations and partial autocorrelations should be significantly different from zero at all lags and the Q-statistics should be significant.

Table 9: Tests for ARCH Effect						
Session	One		Two		Three	
Lags	Q-Stat	Prob	Q-Stat	Prob	Q-Stat	Prob
1	0.2920		0.3321		1.2542	
2	1.0346	0.309	0.7457	0.388	3.0760	0.079
3	1.7069	0.426	1.4004	0.496	5.4529	0.065
4	4.9529	0.175	1.7521	0.625	9.7637	0.021
5	5.6724	0.225	1.9841	0.739	9.9833	0.041
6	7.1039	0.213	2.2280	0.817	10.105	0.072
7	7.3523	0.289	4.0493	0.670	15.487	0.017
8	9.8971	0.194	4.2925	0.746	18.730	0.009
9	12.545	0.129	6.4387	0.598	19.666	0.012
10	15.430	0.080	6.8684	0.651	20.845	0.013

Table 9 shows that the residuals of models for both sessions one and two did not suffer from the problem of ARCH effect. However, the AR(2) model in session three did not disprove the null hypothesis of no ARCH effect at the 10% significance level The AR(2) model needs to be reconstructed to take into account any ARCH or GARCH effects.

$$\Delta S_t = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta S_{t-i} + \beta_v \sigma_t^2 + residuals \qquad 5$$

where $\sigma_t^2 = \sigma_o^2 + \gamma_1 \varepsilon_{t-1}^2 + \cdots + \gamma_p \varepsilon_{t-p}^2 + \phi_1 \sigma_{t-1}^2 + \cdots + \phi_q \sigma_{t-q}^2$ and β_v is a measure of the risk-return tradeoff.

Equation 4.5 describes the change in transaction prices in session three using an ARCH-in-mean (ARCH-M) model with the condition variance replacing the mean.

The ARCH-M model was used because, in the review session, most of the subjects claimed that they entered the market in session three because of the high volatility of the transaction price at that time. Therefore, the expected return on an experimental currency is related to the variance in transaction prices.

Table 10: GARCH Model			
Session Three			
	Coefficient	Std. Error	z-Statistic
GARCH	0.065535	0.014426	4.542875
D(SER03(-1))	-0.969889	0.041461	-23.39279
MA(2)	-0.956172	0.017154	-55.74208
	Variance Equation		
C	0.011765	0.013972	0.842036
ARCH(1)	0.468880	0.339589	1.380727
GARCH(1)	0.611754	0.262671	2.328970

Table 4.10 shows that, except for the constant term and the coefficient of ARCH(1) effect, all other coefficients were significant at the 5% significance level. The model for session three collapsed back to a AR(1) model and the estimated growth rate of the bubble was –1.97. This implies that the serial correlation detected by the Q-statistic came from the ARCH effect rather than the higher order AR process. In addition, Ljung-Box Q-statistics show that the model in table 10 did not suffer from the problem of ARCH or GARCH effects.

The first three diagnostic tests have filtered out three bubble models to describe the change in transaction price with the average growth rates of the bubbles being

$-1.848-2.815\Delta S_{t-1}$, -1.838, and –1.970, for sessions one, two, and three, respectively. All these models show that the experimental data contained bubbles that were self-limiting.

Session One: $\Delta S_t = 0.006 - 0.848\Delta S_{t-1} - 2.815\Delta S_{t-1}^2 + \varepsilon_t - 0.915\varepsilon_{t-1}$ 6

Session Two: $\Delta S_t = -0.838\Delta S_{t-1} + \varepsilon_t - 0.925\varepsilon_{t-1}$ 7

Session Three: $\Delta S_t = -0.970\Delta S_{t-1} + 0.065\sigma_t^2 + \varepsilon_t - 0.956\varepsilon_{t-1}$ 8

However, the growth rates of the bubbles were close to minus two. On average, the half-life of the experimental bubble was about eight transactions and about twenty transactions were required for each bubble to decrease ninety percent; hence, there were more than two experimental bubbles in every experimental session. Therefore, the experimental bubbles can be described as small-scale.

The final diagnostic test was the out-of-sample test. Since bubbles are self-fulfilling processes, past changes must be able to cause current and future changes in transaction prices. The basic definition of causality is a statement about forecasting ability; therefore, it is reasonable to place considerable weight on an out-of-sample forecasting performance to test for the existence of bubbles. To ensure that the bubble models were sufficient to describe the experimental results, the selected self-limiting bubble models had to be able to provide out-of-sample forecasting, in terms of root mean square forecasting errors (RMSE), better than the two benchmark models. Since the bubbles detected were self-limiting, the forecasting power of the bubble models was expected to decline, the longer the forecasting period was extended into the future.

The first benchmark model was the random walk model, which prescribes that any change in transaction price follows a random walk; therefore, the best forecast for any future change in the transaction price is change in the current transaction price (i.e.

$\Delta S_{t+1} = \Delta S_t$).

The second benchmark model was the fundamental model, which states that the market price remains at the fundamental value. Since the fundamental value is a controlled constant, the best forecast for any future change in transaction price should equal zero (i.e. $\Delta S_{t+1} = 0$).

Table 10: Out-Of-Sample Forecasting Test			
Session One			
Forecasting Periods	Benchmark Model One	Selected Models	
	RMSE	RMSE	Improvement
3	0.088533	0.021770	75.4103%
6	0.066733	0.022435	66.38095%
9	0.069707	0.027510	60.53481%
Session Two			
3	0.548483	0.063913	88.34731%
6	0.390512	0.051588	86.78965%
9	0.531058	0.167072	68.53978%
Session Three			
3	2.240708	0.653789	70.82221%
6	2.525102	0.920845	63.53236%

9	2.321491	0.816762	64.81735%

Tables 10 and 11 show that the selected bubble models out-performed the benchmark models in terms of RMSE. There is a tendency for the forecasting power to fall as the forecasting periods increase.

Table 11: Out-Of-Sample Forecasting Test			
Session One			
Forecasting Periods	Benchmark Model Two	Selected Model	
	RMSE	RMSE	Improvement
3	0.050251	0.021770	56.67748%
6	0.036339	0.022435	38.26192%
9	0.043020	0.027510	36.053%
Session Two			
3	0.243701	0.063913	73.77401%
6	0.173320	0.051588	70.2354%
9	0.283299	0.167072	41.02627%
Session Three			
3	1.056414	0.653789	38.11243%
6	1.529371	0.920845	39.7893%

9	1.275420	0.816762	35.96133%

Up to this stage, econometric analysis has filtered out three bubble models with either fixed coefficients or coefficients that depend on past changes in the transaction price. These coefficients describe the average growth rate of the experimental bubbles as being self-limiting.

3.1. Conclusions and Implications for Further Research

This paper has generated small-scale, self-limiting experimental bubbles. Although small-scale, they tended to exist throughout the experiment. The experiment deliberately created a fundamental certainty environment, but bubbles still occurred due to strategic uncertainty. All traders knew that a group of players was trading strategically, but did not know exactly who was doing so. All traders faced the same types of inadequate information; therefore, the traders were willing to trade at a bubble price, as long as the expected return was able to cover the risk, because there was always a chance to sell the bubble out.

In the real world, fundamental value, strategic trading, irrational behavior, and traders' ability are all uncertainties. It is obvious that bubbles that occur in the highly controlled experimental environment should also occur in the real world. If short-run, small-scale, self-limiting currency bubbles actually exist in the real world, the direction for further studies is to estimate the growth rate of bubbles in the real world.

Incomplete References

Bohm, Peter (2002) “Pitfalls in Experimental Economics” In *Experimental Economics: Financial Markets, Auctions, and Decision Making*, edited by Fredrik Andersson and Hakan Holm, pp117-126, Kluwer Academic Publishers.

Box, George E.P., and Gwilym M. Jenkins (1976). *Time Series Analysis: Forecasting and Control*. Revised Edition, Holden-Day.

Camerer, C. (1989). “Bubbles in Asset Prices.” *Journal of Economic Surveys*, 3, 3-41.

Friedman, D. (1984). “On Efficiency of Experimental Double Auction Markets,” *American Economic Review* 74, 60-72.

Hamilton, James D. (1994). *Time Series Analysis*, Princeton University Press.

Harvey, Andrew C. (1990*). The Econometric Analysis of Time Series*, 2nd edition, MIT Press.

Harvey, Andrew C. (1993). *Time Series Models*, 2nd edition, MIT Press.

Ljung G., and G. Box (1979). “On a Measure of Lack of Fit in Time Series Models,” *Biometrika*, 66, 265-270.

Siakantari, Nikos (2000). “Experimental Economics Under the Microscope.” *Cambridge Journal of Economics* 2000, 24, 267–281.

Ramsey, J.B. (1969). “Tests for Specification Errors in Classical Linear Least Squares Regression Analysis,” *Journal of the Royal Statistical Society*, Series B, 31, 350-371.

Ramsey, J.B., and A. Alexander (1984). “The Econometric Approach to Business-Cycle Analysis Reconsidered,” *Journal of Macroeconomics*, 6, 347-356.

Smith, V.L. (1982a). “Reflection On Some Experimental Market Mechanisms for Classical Environments.” In McAlister, L.ed. *Choice Models for Buyer Behavior*. Greenwich: JAL Press, 13-47.

Smith, V.L. (1982b). “Microeconomics Systems as an Experimental Science.” *American Economic Review*, December, 1982, pp. 923-955.

Smith, V.L. (1986). “Experimental Methods in the Political Economy of Exchange.” *Science*, 10th Oct. 1986, 234, pp.167-173.

Smith, V.L. (1989). “Theory, Experiment and Economics.” *Journal of Economic Perspectives*, 3, pp.151-169.

Smith, V.L. (1991). *Papers in Experimental Economics*. Cambridge: Cambridge University Press.

Smith, V.L., Suchanek, G., & Williams, A. (1988). “Bubbles, Crashes and Endogenous

Expectations in Experimental Spot Asset Markets." *Econometrica*, 56, pp.1119-51.

Stanley, T.D., (1997). "Bubbles Inertia and Experience in Experimental Assets Markets" *Journal of Socio-Economics*, 1997, Vol. 26 Issue 6, pp. 611-626.

Wilde, L. L. (1981). "On the Use of Laboratory Experiments in Economics," in Pitt, J. (ed.), *The Philosophy of Economics*, Dordrecht, Reidel.

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