Momentum and overreaction in experimental asset markets

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Abstract

Price volatility and investor overreactions are commonplace in experimental asset markets. Understanding the price dynamics in these markets is crucial for designing successful new trading institutions. We report on a series of experiments to test the predictions of a new momentum model using a dynamical systems approach. This model is then pitted against several standard models to predict prices, as well as against expert human forecasters. The comparative results suggest that each model has its advantages and regions of best performance. Overall, the best predictive methods are the momentum model and expert human forecasters. © 2000 Elsevier Science B.V. All rights reserved.

1. Introduction

Understanding the conditions that promote stable, efficient and viable asset markets has become increasingly important in recent years as: (i) a large part of the world's nations are adopting free market economies after disappointing experiences with state managed economies; (ii) countries with well established free market economies, create new asset markets, such as trading pollution permits (see Stavins (1998)) or wholesale electricity (see Smith (1995)), offer the promise of a better utilization of resources. The success of these endeavors is contingent upon the particular market reflecting a price that is close to the 'realistic' or rational value of the asset. For example, imposed after the stock market 'crash' of

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October 1987 asset markets started to impose 'circuit breakers', in which a particular price drop would trigger a trading halt for a set time period. The experiments of King et al. (1992) showed that these circuit breakers would not eliminate a crash and may actually aggravate it. This prediction was borne out when these limits were triggered in the NYSE in October 1997 and prices dropped quickly to the next limit.

The experimental study and modeling of markets can be instrumental in helping regulators of markets determine policy as it relates to the role of speculators with large amounts of capital in the stability or instability of markets. The impact of experimental economics can be enhanced by intertwining it with quantitative theories and methods, in addition to formulating qualitative explanations and predictions. We pursue this goal in this paper as we test a range of models and quantitative methods on a set of experiments.

Two phenomena that are of fundamental interest in the development of markets and regulatory policy are: (1) a boom–bust cycle that first takes prices far above the rational value into a 'bubble,' only to be followed by a rapid decline or 'crash' in prices; and (2) a prolonged undervaluation. These two circumstances share an undesirable consequence: the choking off of capital that is critical to their viability. An important aspect of asset markets that has been highlighted by experimental economics is the tendency of participants to examine not only the fundamental value of the asset but the reactions and motivations of other traders as well (see Beard and Beil (1994) for a simple experimental game, and Porter and Smith (1994) for a discussion related to experimental asset markets). A rapid decline in the absence of significant fundamental change or a persistent discount from realistic value tends to deter investment by reminding investors that their return depends on the actions of others who may not be willing to buy the asset near the fundamental value. A market that is not liquid or viable in its early stages provides fodder for market critics.

A laboratory asset market devised by Smith et al. (1988) established a number of trading periods in order to examine the time evolution of the trading prices and volume. A series of experiments that has been replicated under many different conditions (see Porter and Smith (1994)) demonstrated the boom and subsequent bust endogenous to trading in these asset markets. Similar asset markets have also been used to study the role of asymmetric information and insider trading (see Guth et al. (1997)).

The 'bubble' experiments performed in this paper utilize the same experimental protocol of Smith et al. (1988). The market involves participants who are given a distribution of cash and shares of an asset or security which will pay a dividend, with expected dividend of 24 cents, at the end of each of 15 periods. Thus, the realistic or 'fundamental' value of the asset is $3.60 at the outset of the experiment and declines stepwise by $0.24 each period until it becomes worthless after the 15th period. Classical theories of economics and finance, such as the rational expectations would predict a time evolution of the trading price that is similar to

this fundamental value with some fluctuations due to randomness of trading. In these experiments, however, one usually observes an initial trading price that is well below the realistic value of $3.60, followed by rising prices that overshoot the fundamental value in the intermediate periods, creating a characteristic 'bubble' and a dramatic 'crash' of prices near the end of the experiment.

This draws attention to the idea, expressed above, that the actions and strategies of other traders can provide the only element of uncertainty to participants. Consequently, the price action reflects a key aspect of the aggregate motivation of traders, particularly as they relate to price momentum and overreaction among traders. This idea of momentum and overreaction is captured in a differential equation model in which contains two parameters, F_1 and F_2, which characterize the extent of trend based and fundamentally based trading strategies. Given values for these parameters and the underlying fundamental value, cash and asset supply, a price path can be derived (see Caginalp and Ermentrout, 1990, 1991).[1]

The basic objectives of this paper are: (1) to better understand some of the reasons for the formation of a bubble and its magnitude; (2) to test mathematical ideas that can be used to predict the entire time evolution of an experiment before it starts; (3) to modify the differential equations (momentum and asset flow) described below so that an updated prediction can be made each period, utilizing the trading price information of the prior periods; and (4) to make a comprehensive test of the short term predictions made by the differential equations model relative to several standard prediction models (e.g. excess bids, time series forecasting [ARIMA(1,1,1)], random walk and 'expert' human forecasters).

In order to implement (2) above, we modify one set of experiments so that (only) the initial period trading is restricted to a narrow range. This allows one to make predictions about the entire experiment using the differential equations approach before the experiment begins. In addition, it facilitates a test of a key prediction made by the differential equations approach, namely, that the size of the bubble in an experiment should be an increasing function of the extent of undervaluation at the outset. Thus, by using 'collars' to restrict trading to a lower price in the first period, we should be able to obtain a larger bubble, and similarly, reduce the extent of the bubble by restricting the trading to values close to the initial fundamental value of $3.60.

The basic idea of this dynamical system, from the differential equations approach, is that a large initial undervaluation motivates traders to buy due to fundamental considerations. As this continues, the trend becomes robust, as traders continue to bid higher prices, even as the trading price crosses the fundamental value. As the asset now becomes overvalued, this causes some selling by traders who are influenced by the positive difference between price and the fundamental

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[1] Grinblatt et al. (1996) find that momentum-based investment strategies are pervasive in mutual fund trading behavior.

value. Simultaneously, as prices move higher, the fraction of cash to the total value in the system begins to diminish and the trading price becomes ripe for a break, like an overextended rubber band.

2. Part I: A test of the momentum model

This part of the paper examines the properties of the momentum model developed by Caginalp and Ermentrout (1990, 1991). We first present the basic structure of the model and then describe the experimental design based on the price path determined by the opening period price in the experiment.

2.1. The momentum model

The main feature of the momentum model, which focuses on the flow of a finite supply of assets in the form of cash or a particular financial instrument, is to derive a system of differential equations in which supply and demand exhibit dependence on price trend as well as price itself.

The laboratory experiments of Porter and Smith (1995) exhibit a very strong autocorrelation that implies a trend dependency that cannot be explained endogenously with flow supply (s) and flow demand (d) that is a function of price only. The dependence of supply and demand on the trend implies that price movements are a function of price p and price trend p':

$$\frac{d}{dt}(\log p) = F\left(\frac{d(p, p')}{s(p, p')}\right) \tag{2.1}$$

where F is a smooth increasing function that satisfies $F(1)=0$.

The total demand for a stock is given by the amount of funds in cash multiplied by the rate, k (normalized so that it assumes values between 0 and 1), that investors place orders to purchase stock. With a similar description for the total supply of stock, one has,

$$D = k(1 - B) \quad S = (1 - k)B \tag{2.2}$$

where B is the fraction of asset value held in stock.

An analysis of asset flow on the conservation of total capital implies:

$$\frac{dB}{dt} = k(1 - B) - (1 - k)B + B(1 - B)\frac{1}{p}\frac{dp}{dt} \tag{2.3}$$

This equation states that the fraction of assets in stocks changes in accordance with stock purchases, stock sales and stock appreciation respectively.

The price equation then has the form:

$$\frac{d}{dt} \log(p) = \log\left(\frac{k(1-B)}{(1-k)B}\right) \qquad (2.4)$$

The notation $p_a(t)$ is used for the equilibrium point on the $p'=0$ plane of the supply–demand curve so that $p_a(t)$ is the intrinsic value of the asset. If k depended only on the fundamental value of $p_a(t)$, then one would have a generalization of price adjustment theory only in terms of the finiteness of assets and delay in taking action.

The rate k is specified through ζ, defined as investor sentiment, or preference for stock over cash. In particular, ζ is the sum of ζ_1 and ζ_2 where the former involves the trend and the latter the valuation. In each case the basic motivation is summed with a weighting factor that declines as elapsed time increases. This leads to the equations:

$$k(\zeta) = \frac{1}{2}\left[1 + \tanh \zeta\right] \qquad (2.5)$$

$$\frac{d\zeta_1}{dt} = F_1 \frac{d}{dt} \log p, \quad \frac{d\zeta_2}{dt} = F_2 \frac{p_a(t) - p(t)}{p_a(t)} \qquad (2.6)$$

These equations are coupled with the equations for price, $p(t)$, and the fraction of assets in stock $B(t)$. These equations can be solved numerically for any particular function for $p_a(t)$. For example, suppose that $p_a(t)$ is a constant function and that price for the stock is initially 'undervalued', i.e., $p(0) < p_a$. The undervaluation means that price increases rapidly at first, since $\zeta_2 > 0$. By the time price exceeds p_a, there is a strong up-trend established and ζ_1 is sufficiently positive so that $p(t)$ becomes even more overvalued. At a certain point buying is offset by selling against the premium over fundamental value and the price turns. The trend based effect then pushes the price lower as it crosses p_a and turns once again, precipitated by buying due to undervaluation. The price then oscillates across the p_a value like a coiled spring, with diminishing amplitudes.

2.2. The experimental design

In order to test the momentum model and understand its ability to 'predict' asset prices, a set of experiments were designed that allow for a prediction before the experiments were actually conducted. Each subject was recruited to participate in an experiment that would last approximately two hours. Subjects were recruited from undergraduate economics classes at the University of Arizona. Each subject started the experiment endowed with a certain number of shares of an asset and cash. The asset would pay a dividend at the end of each of 15 trading periods. The dividend was random and had equally likely payments of either $0.00, $0.08, $0.28 and $0.60 per share. Thus, the asset has an average dividend pay-out of $0.24 per period. If the asset were held for all fifteen periods of the experiment a

trader could expect to earn \$3.60 in dividends (15 trading periods times \$0.24). If a trader bought a share in period 2 and held it for the rest of the trading periods he could expect to accumulate \$3.36 in dividends. Hence, the asset declines, on average, by \$0.24 per period until period 15 after which it has no useful life and expires worthless. All subjects were made aware of this information in three ways. First, in the instructions, subjects were given the dividend distribution and the average cumulative value for each period in which they held the asset. Second, after each period, the maximum, average and minimum dividend value per share was printed on each subject's computer screen. Third, before each trading period each subject was recounted the dividend distribution.

Subjects in the experiment were allowed to trade the asset each period prior to knowing that period?s dividend draw using the double auction trading mechanism.[2] Subjects were not allowed to sell short or buy on margin. The efficient market model would predict that trading prices would be at Net Asset Value. For our experiments, 9 subjects were placed in the market with initial shares and cash as described in Table 1. Notice that each trader has an expected value of \$20.25[3] if they did not trade in the experiment and just held onto their initial endowment and that any expected gains above this amount must come from other traders earnings (a zero sum game).

In order to estimate the two parameters (F_1 and F_2) of the momentum model, that determine the dynamic price path, we conducted two initial baseline experiments in which no price controls were used. These experiments were used to estimate the parameters (F_1 and F_2) in Eq. (2.6) using OLS estimates of the 15 period price data. These parameters were then used to determine the price predictions when the opening price is restricted to trade in a specified range. Table 2 lists the experiments we conducted. These set of experiments utilize a common subject pool. An initial group from the selected population was recruited and

Table 1
Trader initial endowments[4]

Traders	Initial shares	Initial cash
1, 2 and 3	4	\$ 5.85
4, 5 and 6	3	\$ 9.45
7, 8 and 9	2	\$13.05

[2] The double auction is the standard real-time continuous trading process in which traders submit bids and asks with the spread determined by a standard bid–ask improvement rule (see Williams (1980) for a complete description).

[3] Subjects also received \$5.00 for showing-up on time for the experiment so that the expected earnings are \$25.25.

[4] The use of different initial endowments is not crucial in generating price bubbles in this environment (see King et al. (1992) for results of experiments with equal initial endowments).

Table 2
Experimental design

Dividend environment	Price control range	# of Sessions	Trading system[a]	Comments
Baseline $3.60	None	2	ESLDA	Experiments used to estimate F_1 and F_2
Declining $0.24	[$2.90, $3.10]	1	ESLDA	Period 1 expected value is $3.60
Declining $0.24	[$1.40, $1.60]	2	ESLDA	Period 1 expected value is $3.60
Declining $0.24	[$2.40, $2.60]	1	ESLDA	Period 1 expected value is $3.60
Declining 0.48	[2.90, 3.10]	1	ESLDA	Values not in U.S. dollars
Declining 0.48	[4.40, 4.60]	2	ESLDA	Values not in U.S. dollars

[a] The trading system is a an electronic double auction conducted on a local area network system developed by the Economic Science Laboratory at the University of Arizona.

baseline experiments were conducted to determine the parameters (F_1 and F_2) that describe the 'sentiment' of the subject pool. Then, experiments were conducted in which the opening price was fixed by a price control. The price controls used in the experiments were always below the initial $3.60 expected value. They ranged from a price ceiling range of [$1.40, $1.60] to a ceiling range of [$2.90, $3.10]. We conducted two types of price control experiments. The first set used the standard $0.24 dividend, while the second set doubled the dividend distribution (0.48 in experiment money) and cash, but made the conversion of experiment money into US currency at one-half so that there would be no difference in real money space. While this treatment makes the ratio of cash to shares different it does not change the momentum model prediction in real money space.

3.1. Results

Two baseline experiments were conducted to determine the basic market parameters F_1 and F_2. The results of those two experiments are given in Fig. 1. $F_1 = 1.07$ for experiment 1 and 0.965 for experiment 2 for an average estimate of 1.02; $F_2 = 0.054$ for experiment 1 and 0.07 for experiment 2 for an average estimate of 0.06. With these values the momentum model can be solved to determine the equations of motion to predict prices for each of the price control experiments. These predictions are provided in Fig. 2.

In Fig. 3 we plot the ratio between the momentum model prediction and the actual mean contract price for each experiment. In particular, the value of the ratio $R_t = P_{at}/P_{mt}$ is charted where P_{at} is the actual mean contract price in period t and P_{mt} is the prediction from the momentum model for each of the opening price
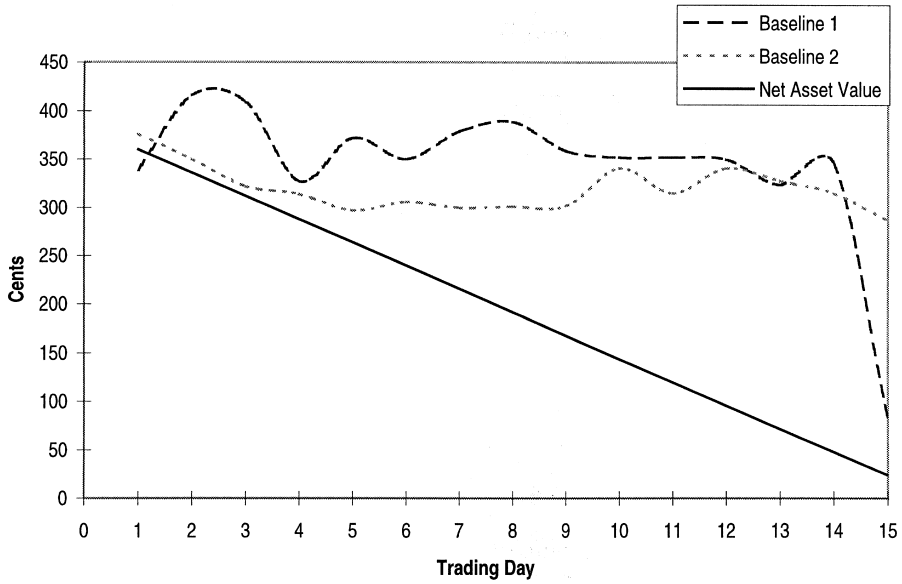
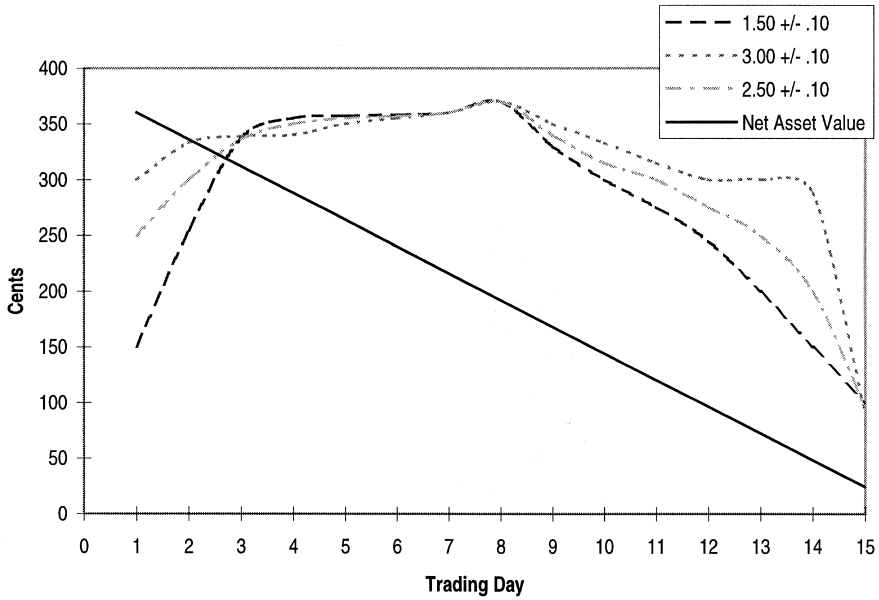Fig. 1. Baseline experiment asset prices.

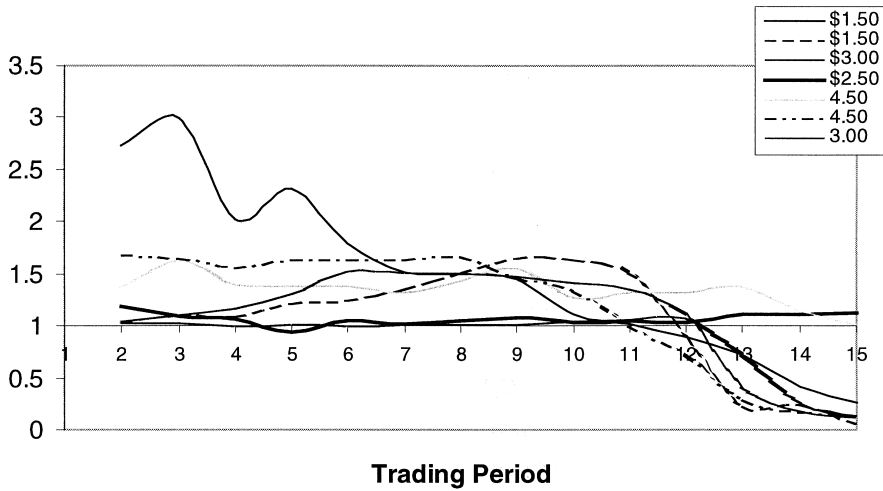

Fig. 2. Momentum model predictions.

Fig. 3. Actual prices/momentum predictions.

control treatment. Thus, if $R_t = 1$ there is a perfect match between the actual mean price and the momentum prediction for period t; if $R_t > 1$ then the momentum model prediction is less than the actual price for period t; if $R_t < 1$ then the momentum model prediction is greater than the actual price for period t.

Result 1: The momentum model under-estimates the mean contract price in the early trading periods and over-estimates the price in the later trading periods.

Support: Table 3 shows the mean value and standard deviation of the ratio used as the dependent variable in Fig. 3. In each case except for the $2.50 treatment, the mean falls for the later trading periods.

Result 2: The momentum model out-performs the rational expectations model.

Support: Table 4 shows the sum of square errors of the actual mean prices to the momentum model predictions and the predictions from the rational expectations

Table 3
Momentum model ratio statistics

Price Control Treatment		Mean ratio periods 2–8	Mean ratio periods 9–15	Std Dev. periods 2–8	Std. Dev. periods 9–15
$1.50	a	2.12	0.58	0.83	0.41
	b	1.22	0.17	0.89	0.71
$2.50		1.05	0.07	1.08	0.03
$3.00		1.02	0.01	0.76	0.40
$3.00 (0.48 dividend)		1.31	0.20	0.87	0.61
$4.50 (0.48 dividend)	a	1.41	0.11	1.29	0.17
	b	1.63	0.04	0.74	0.56

Table 4
Sum of squared forecast errors

Price control		Momentum model	Rational expectations
$1.50	a	33.28	7.49
	b	14.26	15.06
$2.50		0.65	23.48
$3.00		7.02	16.36
$3.00 (0.48 dividend)		16.82	24.96
$4.50 (0.48 dividend)	a	11.68	37.93
	b	21.02	34.26

equilibrium prediction. The sum of the momentum model deviations is 104.73 while the rational expectations value is 159.54.

Recall that in the momentum model when prices are below $P_a(t)$ there is a tendency for buy orders to increase due to the expected return. As prices approach fundamental value, the momentum is higher due to increasing prices. Thus, if we consider positive price differences from one trading period to the next, the momentum model would predict that the sum of these differences would be greatest when the initial undervaluation is greatest. The following regression was estimated:

$$\text{Sum}_i = \alpha + \beta(P_a^i(0) - P^i(1)) + \varepsilon \tag{2.7}$$

where i indexes the experiment. The prediction is that $\beta > 0$.

Result 3: A larger initial undervaluation produces a larger positive price movement.

Support: The regression in (2.7) yields the following estimates (the standard error and p-value are listed under the estimate):

$$\text{Sum} = 0.9 + 0.9 \quad \text{(undervaluation)} \quad (\text{s.e.} = 0.61)$$

In general, we find that while the momentum model has good qualitative properties, however, it misses the turning points and under-shoots prices in the later periods of the experiments. It is not surprising that the momentum model did not consistently predict the price path within 5%. This is because the momentum model predicts 15 periods in advance and is independent of the characteristics of the group that is trading. It is clear that some updating based on current and past trading activity would provide a more responsive model.

3.2. An updated momentum model

Instead of using only the baseline experiments to determine F_1 and F_2 when we begin the jth experiment, we use the previous $j - 1$ experiments to obtain optimal values of F_1 and F_2 for each of the experiments and average these values to get new estimates of F_1 and F_2. We then use the idiosyncratic behavior from prices

observed in the jth experiment to compute ζ_1 and ζ_2 values. Specifically, instead of using the ζ_i values from the differential equation, we use the actual prices in the experiment up to $k-1$ to compute the ζ_i values. At time k we treat the observed $P(k-1)$ and $B(k-1)$ values as initial conditions and estimate the values for ζ_i using the first $k-1$ price data. The F_i are not altered during the experiment but we only predict two periods in advance and then update the ζ_i from the price information.

4. Part II: A battle royal of price prediction models

In addition to the absolute prediction power of a model an important measure of its predictive abilities is how it performs relative to other models that also predict price. In this part of the paper we test the performance of the updated momentum model described above relative to other models that could be used to organize the data from the asset market experiments.

4.1. Experimental design

Subjects were recruited from undergraduate economics classes at the University of Arizona. No price controls were used in these experiments and the parameters were identical to the baseline market environment described in Part I. For each experiment, price predictions were calculated for one-period and two-period ahead forecasts using models that had access to the common information about the asset structure and fundamental value along with market trading information such as trading prices and contract prices. In addition, for these experiments we used the Sealed Offer-Bid (SOB)[5] auction to determine price. This pricing mechanism is a call market that takes submitted bids and asks and finds a single price to clear the market. Thus, unlike the continuous double auction there is only one price per trading period in which all trades are executed. This eliminates the need to explain to rely on average price predictions and does not allow outliers to influence the price. This mechanism has been used in this asset market structure without any significant change in the asset price path over the trading periods (see LaMaster et al. (1993)). Fig. 4 shows the price path of our baseline SOB Asset Market experiments.

4.2. Price prediction models

In this section we describe the models we used to predict future period asset prices in an experiment. We then see how well each model performs relative to the

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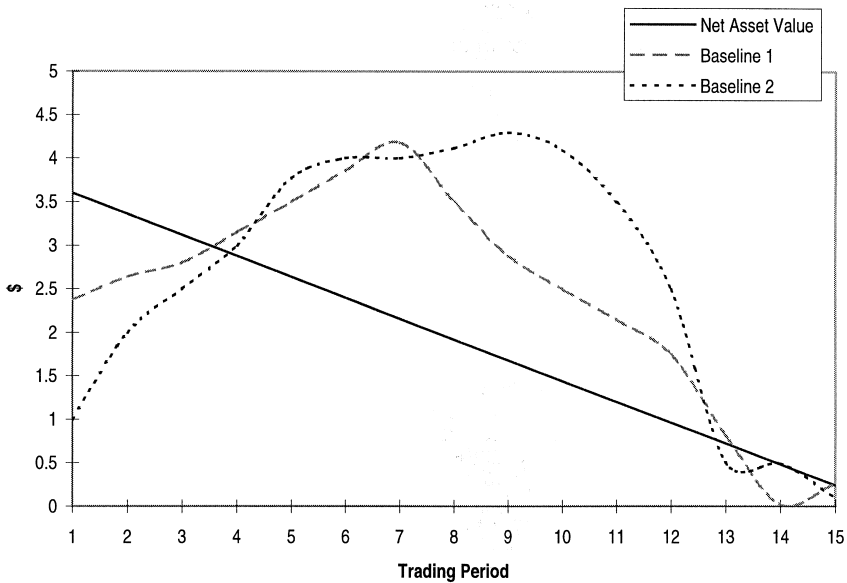[5] See Van Boening (1991) for more details on this mechanism.

Fig. 4. Baseline SOB asset prices.

momentum model described in Part I in predicting prices over a one and two-period ahead forecast.

4.2.1. Expert trader model

In three experiments, we recruited the highest earners from the previous experiments to be price forecasters in the next experiments we conducted. These subjects did not trade in the market but could see all bids, asks and contract prices as forecasters. These professional forecasters would submit forecasts each period of their prediction of the asset price for the next two periods. These subjects were paid for each of their forecasts as follows.

Let C_t be the price forecast, F_t the fundamental value and P_t the actual mean contract price in period t. Then the reward for the period t forecast is:

$$\text{Maximum} \quad \{\$2.00 \quad \begin{matrix} 0 \quad \text{or} \\ (1 - (|P_t - C_t|)/(0.15[F_t])) \end{matrix} \}$$

so that as long as the forecast error is within 15% of the period's fundamental price the forecaster receives a relative proportion of a $2.00 reward. Since a

forecaster will make 30 total forecasts, the maximum reward they could receive if they perfectly forecasted price would be$60.00.[6]

4.2.2. ARIMA (1,1,1) and (0,1,0)

A standard method for modeling time series data uses the Box–Jenkins methods to estimate the equation:

$$w_t = \alpha_1 w_{t-1} + \alpha_2 w_{t-2} + \cdots + \alpha_0 + \varepsilon_t - \beta_1 \varepsilon_{t-1} - \beta_2 \varepsilon_{t-2} - \cdots - \beta_q \varepsilon_{t-q}$$

where $w_t = \Delta^d y_t$ is the original data y_t difference d times. In this way, the data at time t, is predicted from data of prior times. Here the error at time t is denoted by ϵ_t, while the coefficients α and β are estimated by least squares. Two particular ARIMA models are of interest to us. The ARIMA (0,1,0) is the *random walk* model that is simply:

$$y_t = y_{t-1} + \varepsilon_t$$

That is, the next trading period price has expected value that equals that of the current period.

The second model is the ARIMA (1,1,1) which is described by:

$$y_t - y_{t-1} = \alpha_1 \{y_{t-1} - y_{t-2}\} + \varepsilon_t - \beta_1 \varepsilon_{t-1}$$

Thus, with $\alpha_1 = 1$ this model would predict that the change in price from this period to the next will be the same as that from the last period to the current period. A coefficient of $\alpha_1 = 0.5$ would be halfway between the random walk ($\alpha_1 = 0$ and $\beta_1 = 0$) and pure momentum ($\alpha_1 = 1$). The parameters β are not as important for our purpose since we are not considering the extent of price fluctuations in the market. With 15 data points it is not possible to evaluate the best value for α_1, so we use both $\alpha_1 = 0$ and $\alpha_1 = 0.5$. The $\alpha_1 = 0.5$ emerged as the optimal value in an ARIMA analysis for a ratio of similar closed-end funds (see Caginalp and Constintine (1995)).

These ARIMA models, namely (0,1,0) and (1,1,1), are chosen for two reasons. First, in order to understand the relative significance of the most recent price *change* (momentum) versus the significance of the most recent price (random walk) one needs to compare (1,1,1) with (0,1,0). Secondly, the (1,1,1) model was chosen objectively (i.e. Box–Jenkins criteria) as the most suitable model of the closed-end fund data in which valuation had been extracted. This model had also

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[6] Instructions and data for these experiments can be found at http://www.econ.ku.dk/cie/ijio/exptsup.htm

been successful in explaining some experimental data (see Porter and Smith (1994)).

4.2.3. Excess bids model

This model is only a one-period ahead price forecast using a Walrasian type adjustment process based on bids versus asks submitted in the market. Specifically, a least squares regression is updated across all previous experiments that estimates the parameters α and β in the following equation:

$$P_t - P_{t-1} = \alpha + \beta(b_{t-1} - o_{t-1}) + \varepsilon_{t-1}$$

where b is the number of bids submitted in the period and o is the number of offers submitted. Given the excess bids from the past period we can estimate the price change and thus forecast the next period price. In particular, the forecasted price in period $t+1$ is given by:

$$P_{t+1} = P_t + \hat{\alpha} + \hat{\beta}(b_t - o_t)$$

5. Results

For each prediction regime, we examine its performance relative to the momentum model predictions based on the relative Absolute Forecast Errors.

5.1. Professional forecasters vs. momentum prediction

Result 4: The Momentum Model and Human forecasters price predictions have similar forecasting efficiencies.

Support: The momentum model had a lower absolute forecast error in out of three of the experiments and the cumulative forecast errors are within 10% of each other (see Table 6).

If forecasters price estimates are unbiased, then when estimating a stationary time series:

$$w_t = \alpha_1 w_{t-1} + \alpha_2 w_{t-2} + \cdots + \alpha_0 + \varepsilon_t - \beta_1 \varepsilon_{t-1} - \beta_2 \varepsilon_{t-2} - \cdots - \beta_q \varepsilon_{t-q}$$

it should be that there is a linear relationship through the origin of the difference between the forecast surprise (actual price(t) – one period forecast price(t)) and the updated two-period forecast (one period forecast $p(t + 1)$ two period forecast made at $(t-1)$ of price($t+1$)), see Harvey (1994).

Result 5: Forecasters update price predictions based on a forecast surprise.

Support: Table 5 shows the forecast revisions of subjects based on the 'surprise' in the current period forecast and actual price. In the regressions only one subject had a significant intercept and the surprise coefficient is significant and positive for each forecaster.

Table 5
Forecast revision regressions[a]

Forecaster	Intercept	Surprise coefficient	R^2
Subject 1	-0.046 $t=0.820$ $p=0.43$	0.768 $t=5.395$ $p=0.00$	0.71
Subject 2	0.012 $t=0.364$ $p=0.34$	0.750 $t=8.915$ $p=0.00$	0.87
Subject 3	-0.056 $t=2.383$ $p=0.04$	0.838 $t=23.75$ $p=0.00$	0.98
Subject 4	0.202 $t=1.875$ $p=0.09$	0.587 $t=4.235$ $p=0.00$	0.60
Subject 5	0.156 $t=0.804$ $p=0.44$	0.515 $t=2.728$ $p=0.02$	0.38
Subject 6	0.074 $t=1.047$ $p=0.32$	0.853 $t=14.71$ $p=0.00$	0.95

[a] We estimated the following regressions for each subject forecaster: $(F_t^{t-1} - F_t^{t-2}) = \alpha + \beta(F_{t-1}^{t-2} - P_{t-1})$ where F_t^{t-1} denotes the forecast made at time $t-1$ of the price in period t and P_t is the actual price in time t.

5.2. Excess bids model and ARIMA vs. momentum predictions

Result 6: The Excess Bids Model outperforms the Momentum Model in 1-period ahead predictions.
Support: The excess bids model has lower absolute errors than the momentum model in two out of three experiments and has an overall absolute forecast error that is almost half that of the momentum model.

5.3. Random walk vs. momentum prediction

One of the most common models of time series prediction in asset markets is the Random Walk. This model predicts the current period price as precisely the price observed last period.
Result 7: The random walk and Momentum Model have equivalent prediction efficiencies for one-period ahead forecasts, but the Momentum Model is superior for 2-period ahead forecasting
Support: See Table 6.

Table 6
Absolute forecast errors relative to the momentum prediction

Prediction regime	Experiment 1		Experiment 2		Experiment 3		Total	
	1-Period	2-Period	1-Period	2-Period	1-Period	2-Period	1-Period	2-Period
Human	-0.54	-0.75	0.29	0.36	0.03	0.39	17.19	31.25
Excess bids	-1.20	NA	0.20	NA	-1.56	NA	-0.89	NA
Random walk	-0.70	-0.63	0.49	0.59	0.15	0.52	-0.04	0.25
ARIMA (1,1,1)	11.73	15.57	2.77	4.07	8.26	8.89	22.76	28.53

5.4. ARIMA(1,1,1) vs. momentum prediction

Result 8: The ARIMA(1,1,1) forecasts are slightly more efficient than the Momentum Model for one-period ahead forecasts, while the Momentum Model is slightly more efficient for 2-period ahead forecasting.

Support: See Table 6

6. Conclusion

A series of experiments provide a test for a spectrum of theoretical models of asset pricing that are derived from very different perspectives. A key prediction of the momentum model, that a larger initial undervaluation produces a larger positive price movement, is supported by the experiments. The predictions of the momentum model are also more accurate than those of rational expectations.

A new feature of the experiments is the use of price controls on the initial period. This means that one can use the momentum model to make predictions of the entire experiment before the experiment begins. In addition the momentum model was used in a new way to make predictions period by period on an updated basis, utilizing the price evolution up to that point. The use of the additional information improves the predictive power of the method and facilitates comparison with other methods that can be used for short term prediction. The latter include random walk, ARIMA methods and excess bids models. An additional forecasting method involved the use of human forecasters who were chosen on the basis of trading performance in previous experiments. The accuracy of the predictions of the momentum model was comparable to that of the human forecasters. Both were better in forecasting for one period ahead than two periods.

In terms of one period ahead predictions, the momentum model and random walk had approximately the same level of accuracy, while the ARIMA(1,1,1) had a slight edge and excess bids fared somewhat better. For the two period ahead forecasts, the momentum model had the superior forecasts. Note that excess bids predictions are limited to one period ahead. Finally, the momentum model appears to be the only one that indicates a downturn in prices in advance.

The comparative predictions suggest that each model has its advantages and regions of best performance. For example, the momentum model is best at the beginning and end of the experiments, while it is least accurate in the middle periods. The experiments suggest the development of a composite model that would merge the best features of each. For example, if the information used in the excess bid model and the ARIMA model could be incorporated into the momentum model, then one could presumably construct a better model for the one-period ahead forecast.

As indicated in the introduction, the methodology used in terms of the experiments and the theory is quite general and can be applied to other market

situations that are of interest to industrial organization. The momentum model has the capability to make a forecast for the entire experiment, such as an asset experiment with a different evolution of fundamental value. This means that many of the potential problems that may confront a market, e.g. an exogenous shock, can be tested using methods similar to those above.

Acknowledgements

Further reading

Caginalp, G., Balenovich, D., 1994. Market oscillations induced by the competition between value-based and trend-based investment strategies, Applied Mathematical Finance.

Caginalp, G., Porter, D., Smith, V.L., 1998. Initial cash/asset ratio and asset prices: An experimental study. Proc. Nat. Acad. Sci. 95, 756–761.

Lee, C., Scheilfer, A., Thaler, D., 1991. Investor sentiment and the closed-end fund puzzle. Journal of Finance 48, 75–109.

Peterson, S., 1993. Forecasting dynamics and convergence to market fundamentals: evidence from experimental asset markets. Journal of Economic Behavior and Organization 22, 3.

Smith, V., Williams, A., 1992. Experimental Market Economics, Scientific American.

References

Beard, T., Beil, R., 1994. Do people rely on the self? interested maximization of others? an experimental test. Management Science 40, 252–262.

Caginalp, G., Constintine, G., 1995. Statistical inference and modeling of momentum in stock prices, Applied Mathematical Finance.

Caginalp, G., Ermentrout, G., 1990. A kinetic thermodynamic approach to the psychology of fluctuations in financial markets, Applied Mathematics Letters, Vol. 4.

Caginalp, G., Ermentrout, G., 1991. Numerical studies of differential equations related to theoretical financial markets, Applied Mathematics Letters Vol. 4.

Grinblatt, M., Titman, S., Wermers, R., 1996. Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behavior. American Economic Review 85, 5.

Guth, W., Krahnen, J., Rieck, C., 1997. Financial markets with asymmetric information: a pilot study focusing on insider advantages. Journal of Economic Psychology 18, 235–258.

Harvey, A., 1994. Time Series Models, MIT Press.

King, R., Smith, V.L., Williams, A., Van Boening, M., 1992. The robustness of bubbles and crashes in experimental stock markets. In: Prigogine, I., Day, R.H., Chen, P. (Eds.), Nonlinear Dynamics and Evolutionary Economics, Oxford University Press, Oxford, UK.

LaMaster, S., Van Boening, M., Williams, A., 1993. Price bubbles and crashes in experimental call markets. Economic Letters 41.

Porter, D., Smith, V.L., 1994. Stock market bubbles in the laboratory. Applied Mathematical Finance 1.

Porter, D., Smith, V.L., 1995. Futures markets and dividend uncertainty in experimental asset markets. Journal of Business 68, 4.

Smith, V., 1995. Regulatory Reform in the Electric Power Industry, Economic Science Laboratory Working Paper, University of Arizona.

Smith, V., Suchanek, G., Williams, A., 1988. Bubbles, crashes, and endogenous expectations in experimental asset markets, Econometrica, Vol. 56.

Stavins, R., 1998. Market-Based Environmental Policies, Resources for the Future, Discussion Paper 98-26.

Van Boening, M., 1991. Call Versus Continuous Auctions: An Experimental Study of Market Organization. Dissertation, University of Arizona.

Williams, A., 1980. Computerized double-auction markets: some initial experimental results. Journal of Business 53.