Charting the Market: Fundamental and Chartist Strategies in a Participatory Stock Market Experiment

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Abstract

Agent-based finance is a novel branch of computational economics, seeking to understand the complex social system of stock markets. A prominent model of the field is the Santa Fe Institute Artificial Stock Market (SFI ASM). This paper continues a line of research that explores the effect of human traders in the early version of the SFI-ASM model. To achieve this, the methodology of participatory agent-based simulation is applied, where human subjects control a certain number of agents in a simulation.

The focus of the experiments reported here is on the effect and evolution of fundamental and chartist strategies. According to rational expectations theory, only fundamental strategies that relate price to fundamental value by using dividend information will yield success. Real-world market deviations are then ascribed to *market psychology*. This paper explores how extreme market deviations affect the strategies adopted by inexperienced traders. Furthermore, it studies what effect these adopted strategies, in turn, have on aggregate market behavior.

1. Introduction

Theorists and market traders have strikingly different views about financial markets. [1] Standard theory assumes identical investors who share their rational expectations about an asset's future price. Consequently, speculation cannot be profitable, except by luck; trading volume stays low, and market bubbles and crashes reflect rational changes in the asset's valuation. In contrast, traders do speculate in practice. Also, market deviations exist and are often ascribed to *market psychology*. There is also an interpretation of these differences at the level of practical rules. If speculation works, technical rules that are based on only price or trade volume information may be useful. According to rational expectations theory, however, only fundamental strategies that relate price to fundamental value by using dividend information will yield success.

One way to study questions related to the debate above is using the methodology of agent-based finance, a novel branch of computational economics. This methodology constructs artificial markets with computational agents, building on the methodology of agent-based modeling (ABM). One of the first and most prominent models of agent-based finance is the Santa Fe Institute's Artificial Stock Market model (SFI ASM). [1][7][8][9] In [3] and [4] we describe a participatory extension of that model, in which human traders replace some of the agents. This methodology can be seen as a bridge between the laboratory experiments performed in experimental economics and the abstract explorations carried out in agent-based modeling. [6] Alternatively, participatory simulation can also be seen as a special experimental setting, where the environment for the experiment consists of a number of artificial agents as well as the human participants.

Our experiments in [3] and [4] show that even a few agents that play a different strategy from that described in the SFI ASM model may significantly alter aggregate market performance. Furthermore, our results suggest that technical trading lends itself easily to inexperienced traders, but fundamental strategies perform better in the artificial stock market. There we conjectured that the latter may be due to the dominance of computational agents, who might have developed mostly fundamental strategies. In this paper we report on further experiments designed to investigate this hypothesis. We explore how extreme market deviations effect the strategies adopted by inexperienced traders and show that market deviations may lead participants to use technical strategies. Furthermore, we study what effect these adopted strategies, in turn, have on aggregate market behavior. We show that the chartist rules adopted by the human traders may, in fact, contribute to a rational expectations equilibrium.

The paper is organized as follows. Section 2 describes the SFI ASM model and its participatory extension. It also summarizes basic findings about the behavior of these models. Section 3 introduces artificial chartist agents and the settings of our current experiments. Section 4 presents our experimental findings. This is followed by a discussion of the results and future works in Section 5, which concludes the paper.

2. The Santa Fe Artificial Stock Market Model

The SFI ASM is a minimalist model with a risk-free financial asset (e.g., Treasury bills) available in infinite supply that pays a constant risk-free return rate per period, and with a risky stock, the fundamental share value of which is unknown to the traders. Traders are computational agents that are identical except that each trader individually forms his trading rules over time through an inductive learning process. Each trader chooses his portfolio of financial assets in each period in an attempt to maximize his wealth.

At the start of the market process, each trader has a set of rules that it evolves over time in such a way that new rules are continually being introduced. Each rule determines what the agents should do in the given market situation. The possible actions are buying or selling a stock, or doing nothing. Several versions of the SFI-ASM model exist. More modern versions are improved, among others, in their economic realism and in the use of more sophisticated trading rules. In this paper, however, we consider the early version of the model published in [9] following technical specifications from [7], [8] and [2].

The early SFI ASM model yields a stable system with two distinct behavioral regimes. [1][9] In simple cases, the simulated time series data is consistent with the rational expectations equilibrium (REE). In contrast, in more complex setups, the market does not appear to settle down to any recognizable equilibrium. While market price vaguely follows the fundamental value of the stock, upward and downward deviations exist that may be called crashes and bubbles. In this regime, simulation results appear to be in accordance with actual financial time series data. [1][9]

2.1 The Artificial Stock Market

Let $t=0, 1, 2\ldots$ identify time periods, $t=0$ corresponding to the initial state of the system. Moreover, let $A=\{a_1, a_2, \ldots, a_N\}$ be the set of agents, the positive integer N denoting the number of agents in the system. The number of stocks held by agent a in the t^{th} time period is given by $h_a^t \in \Re$, $\Re$ standing for the set of real numbers. Similarly, $m_a^t \in \Re$ denotes the amount of financial asset (money) the agent owns. Notice, that both holdings and money is represented as a *real value*, for reasons of simplicity discussed further below. The price $p^t \in \Re$ per share of the stock depends on the overall buying and selling behavior of the agents. The stock, however, may also pay a dividend $d^t \in \Re$ in money. The agents' money is assumed to be invested in a fixed-rate fund, such as a savings account, that pays an interest rate r in each period. Agents can thus make profit in three ways: due to the interest derived from their cash, due to the dividend stream, or through *speculation* on price changes of their shares. The wealth $w_a^t \in \Re$ of agent a is defined as

$$(1) \qquad w_a^t = m_a^t + p^t h_a^t .$$

At the beginning of the t^{th} period, the interest and the dividend is paid, so that

$$(2) \qquad M_a^{t+1} = r \cdot m_a^t + d^t \cdot h_a^t ,$$

for each $a \in A$ and $t \geq 0$. Then agents have the chance to change their holdings. They can sell or buy one share, subject to the availability of shares or money, respectively. The latter constraint can be relaxed by allowing the agents to borrow money subject to a certain limit. At the end of the period, bids and offers are matched and the market clears. As there must be a buyer for every seller, agents may not be able to achieve the holdings they desire.

Let $b_a^t = 1$, if agent a attempts to buy a share in the t^{th} period, and $b_a^t = 0$ otherwise. Similarly, let $o_a^t = 1$, if agent a offers to sell, and $o_a^t = 0$ otherwise. Furthermore, let B^t and O^t stand for the *totals* of bids and offers, respectively.

$$(3) \qquad B^t = \sum_{a \in A} b_a^t$$

$$(4) \qquad O^t = \sum_{a \in A} o_a^t$$

If B^t=O^t, then all bids and all offers are satisfied, giving

$$(5) \qquad h_a^t = h_a^{t-1} + b_a^t - o_a^t$$

for each $a \in A$ and for each $t>0$ (where either b_a^t or o_a^t is zero). However, if $B^t>O^t$ then all offers are fully satisfied, while only a fraction O^t/B^t of each bid is filled, giving

$$(6) \qquad h_a^t = h_a^{t-1} + \frac{O^t}{B^t} b_a^t - o_a^t .$$

Similarly, the case when $B^t<O^t$ yields

$$(7) \qquad h_a^t = h_a^{t-1} + b_a^t - \frac{B^t}{O^t} o_a^t .^*$$

The volume of trade V^t in the t^{th} period is then defined as $V^t=min(B^t, O^t)$. Notice that this *rationing* scheme may result in non-integer holdings.

To complete our description of the market, we need to define how the dividends d^t and prices p^t are set. Dividends are generated by a discrete, stochastic colored noise process,

$$(8) \qquad d^{t+1} = \max(\bar{d} + \rho(d^t - \bar{d}) + \xi^t, 5 \cdot 10^{-5}),$$

where $\bar{d} > r$ is the theoretical dividend mean (0.75), ρ is a 'speed' parameter (0.95), and ξ^t is a Gaussian noise source with mean 0 and a variance δ^2 (0.07429^2). This is the discrete version of the mean-reverting autoregressive Ohrnstein-Uhlenbeck process (see [9] and [2]), often used as a simple model of stock market time series. [2] [1] In contrast to the purely stochastic series of dividends, prices depend on the actual bids and offers. If more agents want to buy than sell, the price should go up, while it should fall if the supply exceeds the demand. This is achieved by the following formula.

$$(9) \qquad p^t = p^{t-1} \cdot \left(1 + \eta\left(B^t - O^t\right)\right)$$

The parameter η has a crucial role in determining market behavior. When it's small, the price adjusts slowly to different market conditions. On the other hand, a large η leads to large oscillations of price. In principle, it is assumed to be small enough to ensure that $\eta\left(B^t - O^t\right) << 1$.

Obviously, agents have to pay for filled bids and they cash in on satisfied offers. This yields the following formula for agent *a*'s money at the end of period *t*, which completes the specification of the market.

$$(10) \qquad m_a^t = M_a^t - \frac{V^t}{B^t} b_a^t \cdot p^t + \frac{V^t}{O^t} o_a^t \cdot p^t$$

2.2 The Trading Agents

The trading agents of the SFI ASM model try to maximize their wealth by regularly changing their portfolio. Their behavior is based on rules that specify what to do when certain market conditions are met. The general form of the rules is as follows: *(condition,*

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* The *rationing* scheme described here is far from being fully satisfactory. In fact, this is one point where more modern versions of the SFI ASM had been significantly improved. However, for the one-stock scenario discussed in this paper it works well, even despite its lack of realism.

action, strength). The third element of the triple is a real value, whose role will be discussed later. The *action* is a simple ternary choice:

(i) **bid**: $b_a^t = 1, o_a^t = 0$,

(ii) **offer**: $b_a^t = 0, o_a^t = 1$, or

(iii) **neither/hold**: $b_a^t = o_a^t = 0$ (default action).

The *condition* part of a rule is a fixed-length string of symbols drawn form the alphabet *{0, 1, *}*, e.g., 11*0*****1*0. This string is matched against a binary string (with 0's or 1's only) of the same length, representing the current state of the market. 0s and 1s in the condition string only match to the same symbols in the market string, while *'s match to any value. The symbols represent market indicators detailed on Table 1. When the corresponding statement is true, the appropriate symbol is 1 and 0 otherwise. Therefore, rules specify certain actions, based on the state of market indicators, allowing for some of them to be indifferent to the application of the given rule.

Bit	Market Indicator
1	$p^t \cdot rd^t > 1/4$
2	$p^t \cdot rd^t > 1/2$
3	$p^t \cdot rd^t > 3/4$
4	$p^t \cdot rd^t > 7/8$
5	$p^t \cdot rd^t > 1$
6	$p^t \cdot rd^t > 9/8$
7	p^t > 5-period moving average price
8	p^t > 10-period moving average price
9	p^t > 100-period moving average price
10	p^t > 500-period moving average price
11	On: 1
12	Off: 0

Table 1: Market Indicator Bits (based on [7]).

The first 6 bits of the market indicator string represent information used in fundamentalist strategies. In contrast, bits 7-10 are technical (chartist) bits. Bits 11 and 12 are zero information bits, providing a way to check whether the agents' behavior is actually dependent on market processes. The table also shows the possibility of rules whose conditions can never get matched, because they contain contradictory conditions. For this reason, agents have a meta-rule that *generalizes* rules that haven't been matched for a long period of time. Generalization is done by randomly replacing a few bits in the condition string with the * symbol. The length of the 'maximum sleeping period' for rules is 200 in our studies.

Agents have a set of 60 such rules. Each time the agent has to make a decision, it first lists those rules whose condition is met and whose strength is positive. Next it selects one of these randomly, with probability proportional to strength. The action of this *selected* rule is then executed. If there is no matched rule, the agent defaults to the **neither/hold** action. At the end of the period, the strength of each rule whose condition was met is updated, according to the following formula.

$$(11) \qquad s_{a,k}^{t+1} = (1-c)\cdot s_{a,k}^{t} + A_{a,k}\cdot c\cdot \pi^{t}$$

where $s_{a,k}^{t}$ is the strength of agent *a*'s k^{th} rule in the t^{th} time period and *c* is a small constant (0.01). $A_{a,k}$ is a numerical representation of the rule's action, so that

$$(12) \qquad A_{a,k} = \begin{cases} -1, & \text{if the action is sell} \\ +1, & \text{if the action is bid} \\ 0, & \text{otherwise} \end{cases}.$$

π^{t} is the net profit made by investing in one share of stock in the t^{th} period. Its value is given by

$$(13) \qquad \pi^{t} = p^{t} - (1+r)\,p^{t-1} + d^{t}.$$

The structure described above is a *classifier system*. [7] Its rules classify the states of the market into categories, and then provide probabilities for each possible action to be taken in each category. The agents in the SFI ASM model, however, may also improve upon their rules. This is done by the application of a *genetic algorithm* [7] [8], which is executed at random intervals. When the algorithm is run, the agent replaces 10 of its weakest rules by new ones. The new rules are copies of some of the strongest ones, selecting candidates with a probability proportional to the rule's strength. However, the copied rules are modified by mutation or crossover. Mutation randomly changes bits of the rule, with probabilities adjusted so that the average number of *'s stays constant. Crossover combines a pair of "parent" rules, getting a part of the new rule from one parent, and the rest from the other. The probability of crossover is 0.3.

Agents are initially endowed with certain money m^{init} and shares h^{init}. In our experiments, agents start with $m^{init}=200$ units of money and $h^{init}=5$ shares of stock. Agents are allowed to borrow money (to buy stocks) to the limit of their initial monetary endowment. That is, they are allowed to buy until $m_a^t \geq -m^{init}$ holds. The interest rate on this credit r^d is equal to the interest rate paid for the fixed-rate investments, i.e., $r^d=r=0.01$.

The final piece of the agents' strategy is the meta-rule that reverses the action of rules with a negative strength. The intuition behind this rule is that if a condition was particularly weak for buying, it should be good for selling, and vice versa.

2.3 The Participatory SFI ASM Model

The PSFI ASM model is a participatory extension of the above model, using the General-Purpose Participatory Architecture for the RePast agent-based simulation platform. [10] The GPPAR package is a collection of Java classes [5] that helps transforming RePast models to participatory simulations. In GPPAR, the simulation runs on a central server. Artificial agents inhabit the server, while human agents connect to the simulation via the network by running a client application on their own computer. The connections and all communication are handled by the GPPAR infrastructure.

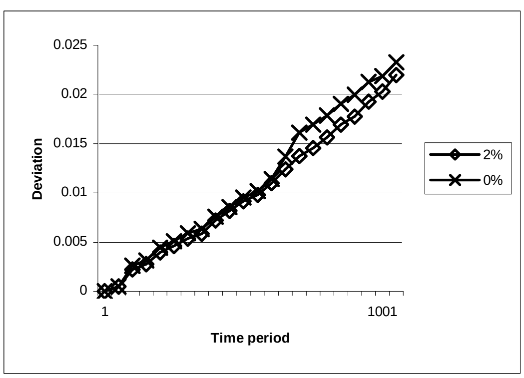
One goal when building the experimental environment for the PSFI ASM was to present the human participants with the fast-changing, on-line nature of stock markets, in which prices change by the fraction of a second. However, the SFI ASM model is organized around rounds, each agent making a decision in each round. Clearly, human agents cannot be expected to make decisions in such limited time. The GPPAR package offers several ways to deal with the extended time requirement of human participants. The simplest of which is a timing-out system, where participants are given a certain amount of time to make their move. If they fail to do so, a default action is executed. Since, giving ample time to deliberate would slow down the simulation significantly, in the PSFI ASM the time-out is low (at the order of 0.1sec), but the participants' bids and offers are regarded as continuous. That is, the last action is resubmitted in each round, until the player explicitly changes it, e.g., to 'do nothing'. Technically, this is implemented by defining the default action as the last action initiated by the user.

2.4 The Behavior of the Participatory SFI ASM Model

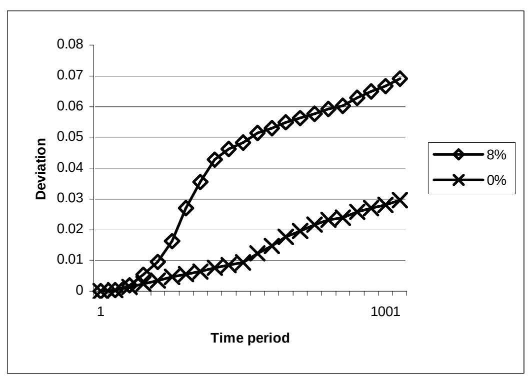
The participants of the PSFI ASM experiments were all skilled computer users, but they lacked any stock market experience. The participants used personal computers, connected through a local area network. Despite their physical proximity, participants were not allowed to discuss the game or their performance, before the end of the experiments.

The experiments were stopped without warning, at the discretion of experiment leader. The reason for this 'random' stopping rule was to avoid human strategies that could take the extra information of the experiment's length into account. In the given experiments, the system was run for about 5 minutes (1000-1500 rounds). Following the sessions, we carried out post-interviews, in order to collect information about the participants' strategy, use of market indicators, etc.

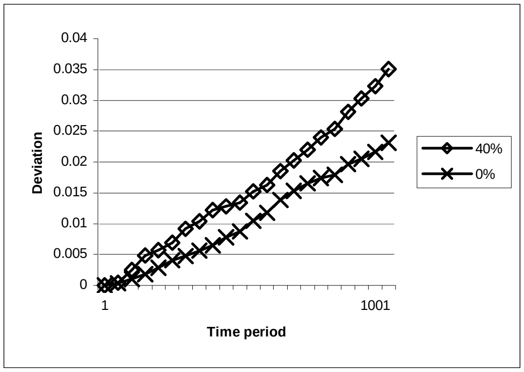
In the first set of experiments reported in [3] and [4], we found that the presence of human traders yielded higher market deviations. One measure of deviations is the cumulative difference between stock price and fundamental value.



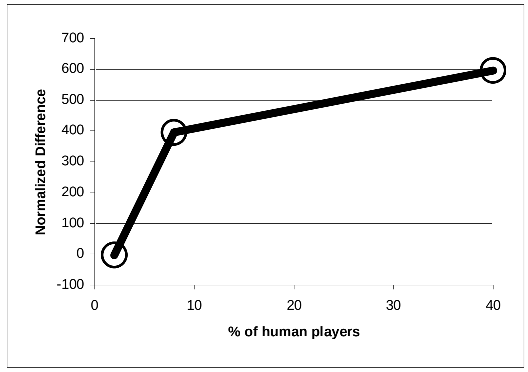
a) 2% (8 players of 400 agents)



b) 8% (8 players of 100 agents), second run



c) 40 % (8 players of 20 agents)



d) The scaling of the normalized difference as a function of the percentage of human participants.

Figure 1: Cumulative market deviations in runs with and without human players. (The deviation axis shows the values in millions.)

$$(14) \qquad D^t = \sum_{i=1}^{t} \left| p^i - \frac{d^i}{r} \right|$$

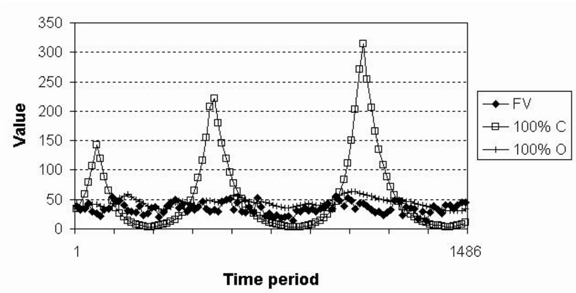
The a)-c) graphs on Figure 1 plot D^t versus time, comparing participatory experiments ($D^t_{participatory}$) to corresponding simulations with identical parameters ($D^t_{computational}$). It is clear that significant human presence increases the level of deviation. Graph d) on Figure 1 shows the *normalized difference* after 1050 steps as a function of the percentage of human participants. By normalized difference we mean the difference between $D^t_{participatory}$ and $D^t_{computational}$, divided by the number of agents. The graph suggests that the more human players, the larger the deviation is.

Another interesting finding was that, judging from their answers in the post-interviews, human players tended to start with technical (chartist) strategies, then, gradually, a few of them discovered fundamental strategies. Indeed, in experiments where a human participant accumulated the most wealth, the winner turned out to play perhaps the purest of fundamental strategies: buy if *price < fundamental value*, sell if it is the other way around.

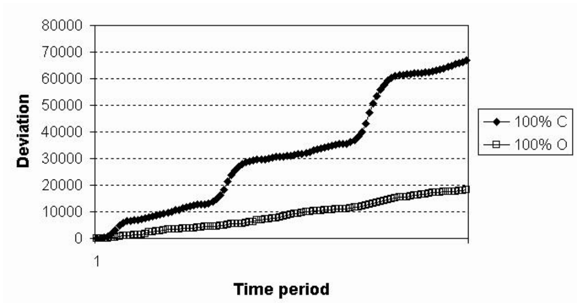
3. Experimental Settings

In this paper, we investigate the effect of chartist agents, and thus extreme market deviations, may have on the performance of human participants and the learning agents of the original SFI ASM model. In order to do so, we introduce two new types of artificial traders: chartists and fundamentalists. Chartist agents evolve rules that depend on technical market indicators only. To achieve this, the condition part of each of their rules is overwritten at the beginning of each round. Namely, bits 1 to 6 and bits 11 to 12 are set to the * symbol (see Table 1). In contrast, fundamentalist agents evolve rules that only take fundamentalist indicators into account. This is done by rewriting bits 7 to 10 in the conditions of their rules by *'s.

The presence of chartist agents generally yields more volatile markets with crashes and bubbles, and thus they increase cumulative market deviation. Figure 2 compares a population of chartist agents with one consisting original SFI ASM agents only.



a) Price and fundamental value versus time.



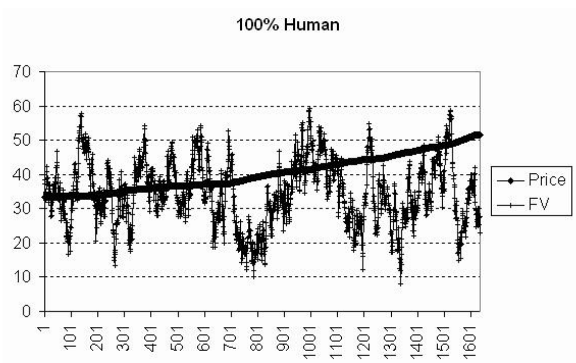
b) Cumulative deviation (D^t) versus time.

Figure 2: Comparison of markets with 100% chartist (C) and 100% original SFI ASM (O) agents, driven by the same fundamental value series (FV).

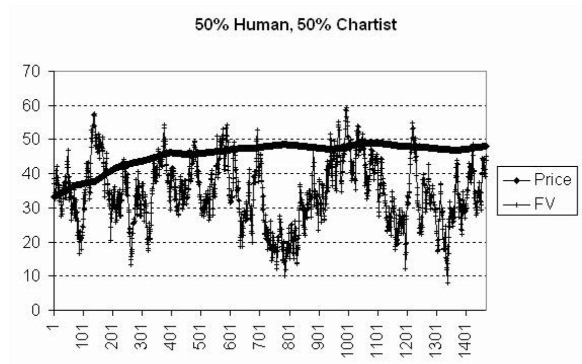
In the introductory briefing preceding the current series of experiments the different types of market indicators received a special emphasis. Since technical bits are generally easier to grasp, the focus of the discussion was on fundamental indicators. After the briefing, the participants were subjected to five different market environments.

- First, they played an introductory session among themselves without any artificial agents.
- Second, human subjects were confronted with an equal number of artificial chartist agents.
- Third, human participants consisted the 5% of the market. The remaining 95% consisted of chartist agents.
- Fourth, human participants amounted for the 5% of the market as in the previous case. However, the remaining 95% was split between chartist agents (50%) and the original learning agents (45%) of the SFI ASM model.
- Finally, human subjects were confronted with an equal number of SFI ASM agents.

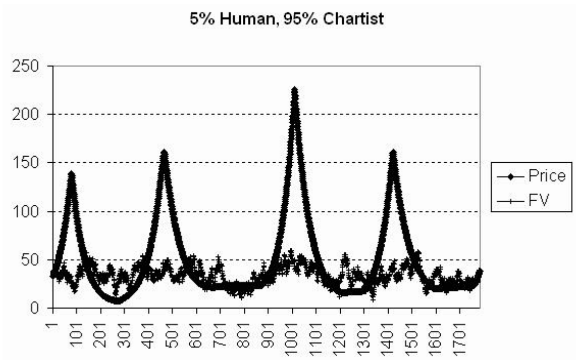
The concept behind these settings was to confront the subjects with markets of very high volatility (significant bubbles and crashes) and study how people who received a special briefing on fundamentalist indicators will react.



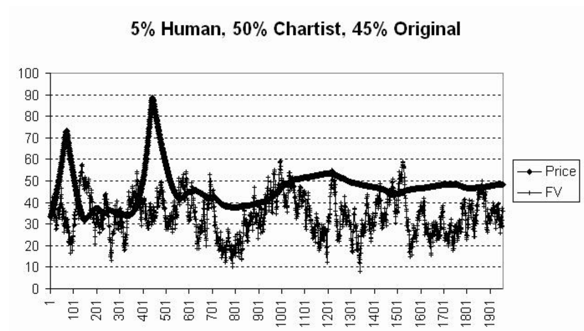
a) Setting 1



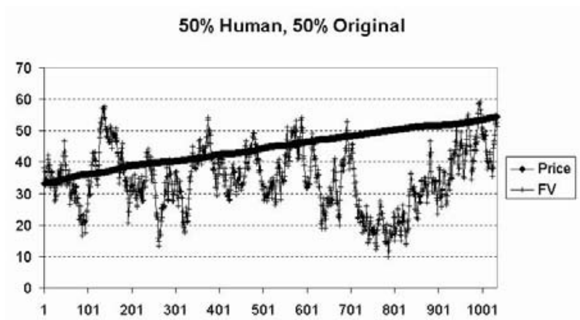
b) Setting 2



c) Setting 3



d) Setting 4



e) Setting 5

Figure 3: Market behavior in the five experimental settings.
(The charts show price and fundamental value versus simulated time.)

4. The Effect of Chartist Agents: Experimental Results

Figure 3 shows the general market behavior in the five experimental settings. In the first two experiments, the human participants represented a significant portion of the market (100% and 50%). Therefore, their trading decisions have played a crucial role in determining the aggregate behavior of the system. In particular, as the players bought up most of the stocks, the market's liquidity fell drastically. Scenario 5 shows a similar behavior.

Setting 3 and Setting 4 deserve special attention. The market behavior demonstrates the effect of technical trading in the first case, while the latter displays signs of chartist trading being modulated by the market. Whether this modulation was caused by the presence of human traders or that of the original SFI ASM agents is an intriguing question. This will be studied next.

4.1 Participant Strategies: A Shift toward Technical Trading

An analysis of the user questionnaires filled out after each experimental run shows that in response to being subjected to 'bubble-and-crash' markets, the human subjects gradually adopted chartist strategies.

In the first scenario, 80% of the users claimed to use a fundamentalist strategy, while the remaining 20% could not identify clear trading rules. The introduction of 50% chartist agents (which were equaled by the 50% human players) caused a slight shift towards chartist strategies. In particular, 40% of the participants reported taking chartist considerations into account. However, none of the subjects used a pure chartist strategy. Facing a dominating 95% of chartist agents caused human players to switch to chartist strategies, a significant part of them in mid-run (40%). Only a single participant remained faithful to the fundamentalist strategy.

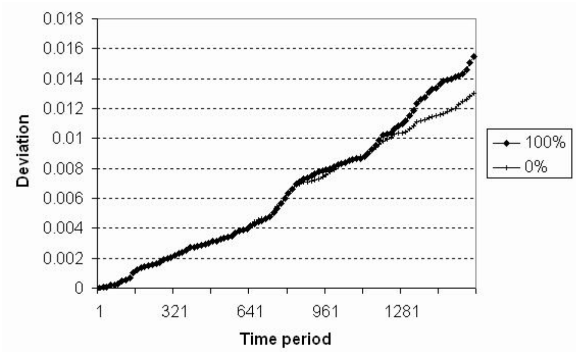
In the fourth scenario, the artificial agents remained in a dominating position on the market (95%). However, only a slight majority of them (55%) used a chartist strategy, while the rest was unbiased. As a result the market showed the typical bubbles and crashes of technical trading in the beginning, then price followed FV for a while, then a new bubble rose and burst. Finally, a longer period of close-to-REE behavior followed. During this run, the majority of the participants applied a chartist strategy, while 40% of them traded according to, at least partial, fundamentalist rules. Only a single player used a pure fundamentalist strategy.

By the time participants were subjected to the fifth market setting, they were 'conditioned' to technical trading. In this last scenario, they confronted an equal number of non-biased agents. The 50% ratio of human traders granted the participants a significant influence over the market. According to the questionnaires, by this time one player has completely given up on strategizing, while among the rest, 75% applied technical trading.

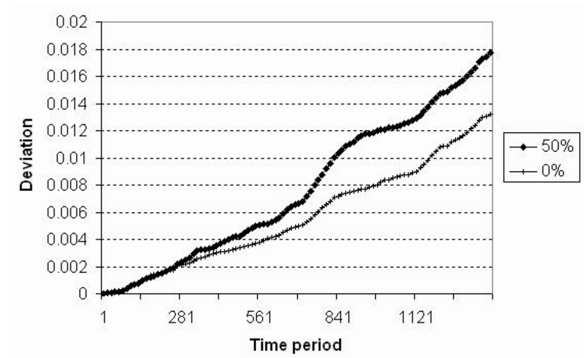
4.2 Market Behavior: A Shift toward the Rational Expectations Equilibrium?

In contrast to the changes in the reported strategies of the human participants, the changes of the market behavior in the five scenarios suggest a shift towards the rational expectations equilibrium. That is, aggregate market behavior seems to testify an increasing dominance of fundamental strategies.

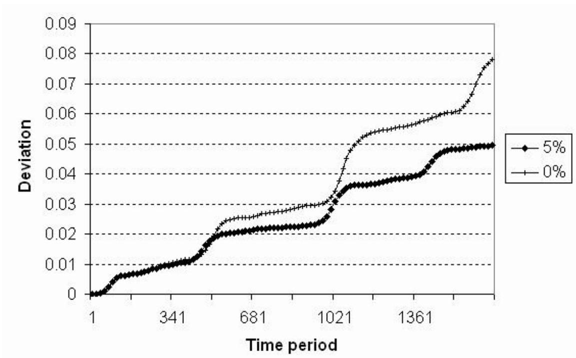
Figure 4 provides a more detailed look at the effect of human presence in terms of cumulated market deviation (D^t, shown in millions). The five charts of the figure stand for the five experimental scenarios, respectively. They each display D^t versus simulated time in two cases. The dotted series stand for the participatory runs, while the ones with the crosses represent identical experiments, except that the human players were replaced by the appropriate number of original SFI ASM learning agents. (That is, the charts compare the market behavior when a given percentage of human players are present to a case when 0% of the market is controlled by humans.)



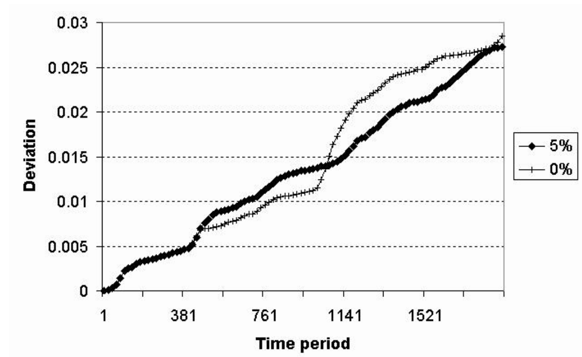
a) Setting 1



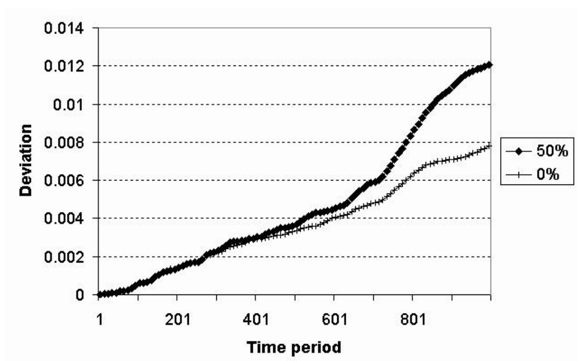
b) Setting 2



c) Setting 3



d) Setting 4



e) Setting 5

Figure 4: Comparing the effect of human presence to the effect of learning agents. The charts show cumulative deviations (D^t – shown in millions) versus time for the five experimental scenarios. The two data series on the charts stand for participatory experiments (dotted series) and for runs where human players were substituted by an appropriate number of SFI ASM agents (0% human participation), respectively.

The first chart of the figure is consistent with our findings in [3] and [4], in that inexperienced traders slightly increase market deviation. Nonetheless, the aggregate market behavior stays very similar in the compared two cases. The chart for the second scenario shows that original SFI ASM agents are better at moderating a half-population of chartist agents than human participants who reportedly applied fundamentalist strategies. In contrast, the next chart shows that, confronted with a 95% of technical traders, human participants adapted better. Let's recall that many of our subjects reported switching to a chartist strategy in mid-run in case of Setting 3. These statements are confirmed by the chart showing that starting with the second bubble, the bursts appear earlier in the participatory runs. This is probably due to the human subjects cashing in on the increased price level. Not surprisingly, the absolute winner of this scenario (i.e., the wealthiest trader in the end) was one of the human players. A similar effect is visible on the fourth chart, apart from a period in the second quarter, when participatory deviation exceeds the baseline case of the SFI ASM market. Finally, the last chart shows that, in lack of artificial chartist traders, the human subjects, who already adopted technical trading strategies, cause a pronounced increase in market deviation.

4.3 Contradictory Trends: A Detailed Analysis

Comparing Scenarios 3 and 4 we have seen that human participation appear to modulate the bubbles and crashes of chartist trading. The above analysis of reported participant strategies, however, does not support the hypothesis that a potential human bias towards fundamental trading is behind this phenomenon. In contrast, subjects reported a gradual switch towards technical trading strategies. On the other hand, the comparison of cumulative market deviations in case of participatory experiments and their baseline cases (with original SFI ASM agents) shows that it is indeed human presence that modulates extreme market behavior.

In the following we have a more detailed look at these two scenarios, also comparing human performance to that of artificial fundamentalist agents.

4.3.1 The 95% Chartist Scenario

In this series of experiments, we had 95% of the traders applying a chartist strategy and varied the remaining 5% to use chartist (C), fundamentalist (F), or the original SFI ASM learning strategy (O), and compared the resulting behaviors to the effect of 5% human traders. Figure 5 summarizes our findings. The additional 5% chartist agents seemed to cause a little difference, as this setting yielded practically the same results as the 5% SFI ASM agents. This is plausible as the key to the SFI ASM strategy is inductive learning. Surprisingly, however, a 5% of agents playing fundamentalist strategies resulted in slightly increased deviation. Finally, it is clear that the 5% of human-controlled agents significantly decrease market deviation in comparison to any of the previous cases.

The figure also shows the effect discussed in the previous section. That is, human participants did not make any difference during the first bubble, but starting from the second they terminated them 'early'. Additionally, the figure also shows evidence that not only the peaks became smaller, but, after the third bubble, the participants also made the valleys shallower. Perhaps, this is the partial reason while the fourth bubble appears much earlier in the participatory case. Another likely contributing factor is the increased number of human subjects applying technical strategies.

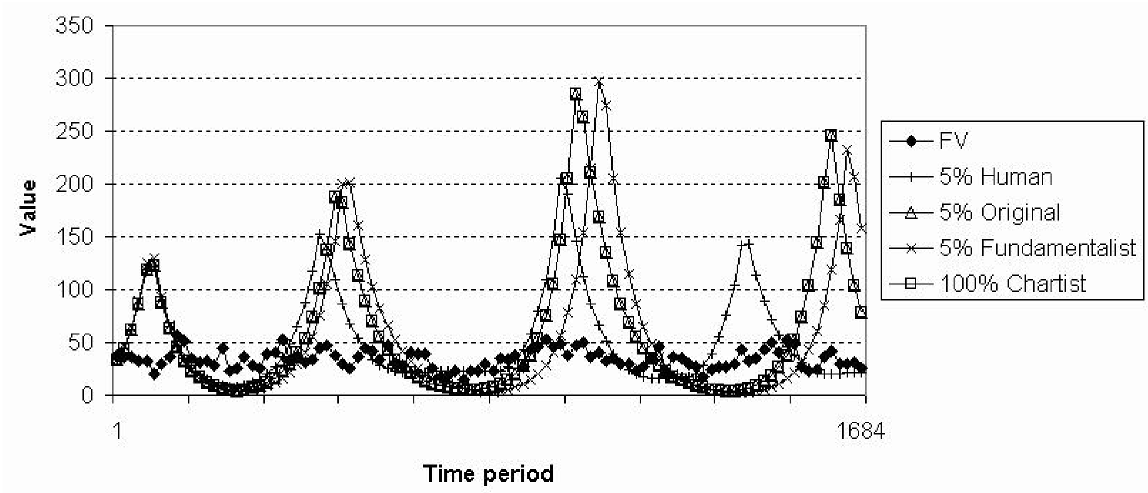


Figure 5: Comparison of different strategies and the performance of human subjects when confronting a market of 95% technical traders. The chart shows fundamental value (FV) and price (for the various cases) versus simulated time.

4.3.2 The 50% Chartist, 45% SFI-ASM Scenario

In this series of experiments we had 50% of the traders applying chartist strategies and another 45% using the original SFI ASM rules. We varied the remaining 5% to use fundamentalist (F), or the original SFI ASM learning strategy (O), and compared the resulting behaviors to the effect of 5% human traders. Figure 5 summarizes our findings.

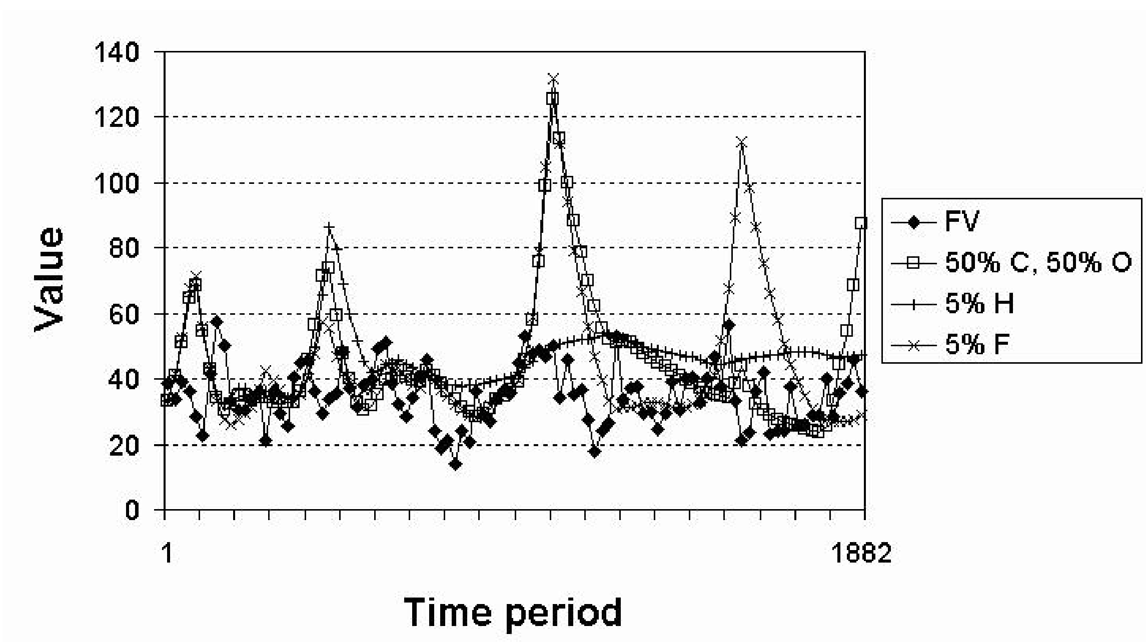


Figure 6: Comparison of different strategies and the performance of human subjects when confronting a market of 50% technical traders and 45% SFI ASM agents. The chart shows fundamental value (FV) and price (for the various cases) versus simulated time. (C stands for chartist, O for the original SFI ASM, and F for fundamentalist agents, respectively. H denotes human participants.)

An equal split between chartist and SFI ASM traders results in large market deviations, albeit in smaller ones than in the 95% chartist scenario. The replacement of 5% original learning agents with fundamentalists slightly increases the deviance, making the peak both little higher and the valleys shallower. While surprising, this behavior is consistent with that found in the previous scenario. In contrast, the presence of 5% human players, whose majority by this time followed technical trading rules, clearly decreased market deviation significantly.

From the detailed analysis above we conclude that it is indeed human presence that moderates market deviations. Moreover, our results also suggest that fundamental strategies, when applied in the given small percentages, have a counter-intuitive effect in amplifying deviations caused by technical trading. This observation resolves the apparent contradiction between the participants reported shift towards chartist strategies and the observed REE-like market behavior.

5. Discussion and Future Work

This paper continued our line of research exploring the effect of human traders in the early Santa Fe Institute Artificial Stock Market model. In particular, we were interested in how extreme market deviations affect the strategies adopted by inexperienced traders, and in what effect these adopted strategies, in turn, have on aggregate market behavior.

Our experiments showed human traders adopting technical strategies in response to highly volatile markets with drastic price bubbles. The effect of this experience also carried through to more stable markets. On the other hand, technical trading performed by humans had a moderating effect on aggregate market behavior in comparison to chartist-dominated markets with artificial traders only. This is a surprising finding, whose likely cause is in the specifics of the SFI ASM market and the design of its agents. More specifically, our current hypothesis is that the phenomenon can be, at least in part, explained by the learning rate of the artificial agents. That is, we conjecture that human traders were able to adapt to market situations more quickly than the artificial agents with a fixed adaptation rate. The same time, human participants' impatience on capitalizing on their gains (e.g., during the raising period of a bubble) may also explain why chartist participants actually caused bubbles to burst earlier. The detailed investigation of these issues is the subject of future work, including experiments with various adaptation rates for the artificial agents.

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