AN ARTIFICIAL STOCK MARKET

Martin Sewell
The Cambridge Centre for Climate Change Mitigation Research (4CMR), Department of Land Economy, University of Cambridge, 16-21 Silver Street, Cambridge, CB3 9EP, United Kingdom

Keywords: Artificial stock market, Technical analysis, Fundamental analysis, Behavioural finance, Multiagent systems.

Abstract: To set the scene, fundamental analysis, technical analysis, behavioural finance and multiagent systems are introduced and discussed. The work utilizes behavioural finance; the evolved heuristics and biases exhibited by fundamental analysts and technical analysts, inducing underreaction and overreaction, are used to build an agent-based artificial stock market. Results showed that whether a fundamental analyst, or a technical analyst, it pays to be in a small majority of about 60 per cent, whilst being in a small minority is the least profitable position to be in. As the number of technical analysts increases, the standard deviation of returns decreases, whilst the skewness increases. Whilst kurtosis of market returns peaks with around 40 per cent technical analysts, and rapidly declines as the number of technical analysts exceeds 90 per cent. The autocorrelation of returns is close to zero with 100 per cent fundamental analysts, and approaches one as the proportion of technical analysts approaches 100 per cent. The artificial stock market replicates mean returns, the standard deviation of returns, the absolute returns correlation and the squared returns correlation of a real stock market, but failed to accurately replicate the skewness, kurtosis and autocorrelation of returns.

1 INTRODUCTION

1.1 Objectives

The focus of this paper is modelling. The aim is to build an agent-based artificial stock market and explore the effect of the ratio of fundamental analysts to technical analysts, and whether and when the resultant time series displays the statistical properties exhibited by a real market.

1.2 Background

1.2.1 Fundamental Analysis

Fundamental analysis is a method of forecasting markets through the analysis of relevant news.

1.2.2 Technical Analysis

The second class of 'actors' employed in the model are technical analysts. Technical analysts rely on the assumption that markets discount everything *except information generated by market action*, ergo, all you need is data generated by market action. Let us formally define technical analysis. If P is price, D is data generated by the process of trading, and t is time, then *technical analysis* is the art of inferring $E(P_{t|t>0}|D_{t|t<0})$.

A taxonomy of the various methods of technical analysis applied by practitioners is provided by the syllabus of the Society of Technical Analyst's Diploma.[1] However, the technician's number one rule is that they follow the trend. Quoting a best-selling practitioner's book on technical analysis (Murphy, 1999, p. 49), 'The concept of *trend* is absolutely essential to the technical approach to market analysis. All of the tools used by the chartist—support and resistance levels, price patterns, moving averages, trendlines, etc.—have the sole purpose of helping to measure the trend of the market for the purpose of participating in the trend. We often hear such familiar expressions as "always trade in the direction of the trend," never buck the trend," or "the trend is your friend."'

1.2.3 Behavioural Finance

The algorithms employed by the artificial stock market are based on the behaviour of real market participants, rather than the actions of the rational but hy-

[1] http://www.sta-uk.org/sta_diploma.html

Sewell M..
AN ARTIFICIAL STOCK MARKET.
DOI: 10.5220/0003687002930300
In *Proceedings of the 4th International Conference on Agents and Artificial Intelligence* (ICAART-2012), pages 293-300
ISBN: 978-989-8425-96-6

pothetical *Homo economicus*. *Behavioural finance* is the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets. Behavioural finance is of interest because it helps explain *why* and *how* markets might be inefficient.

Consider some common heuristics and biases. *Availability* (Tversky and Kahneman, 1973) is a cognitive heuristic in which a decision maker relies upon knowledge that is readily available rather than examine other alternatives or procedures. *Representativeness* (Tversky and Kahneman, 1974) leads people to predict future events by looking for familiar patterns and taking a short history of data and assuming that future patterns will resemble past ones. The *status quo bias* (Samuelson and Zeckhauser, 1988) is a cognitive bias for the status quo; in other words, people tend to be biased towards doing nothing or maintaining their current or previous decision. The status quo bias can lead to another cognitive heuristic, known as *anchoring* (Tversky and Kahneman, 1974), which describes the common human tendency to make decisions based on an initial 'anchor'. We prefer relative thinking to absolute thinking. Other observed consistent but irrational behaviour includes *overconfidence*, *optimism* and *herding*.

1.2.4 Multiagent Systems

A *multiagent system* is a system in which several interacting, *autonomous*, intelligent agents pursue some set of goals or perform some set of tasks.

The artificial stock market in this paper employs a multiagent system. Two good books on multiagent system are (Weiss, 1999) and (Wooldridge, 2002). In a classic paper, (Arthur et al., 1997) proposed a theory of asset pricing based on heterogeneous agents who continually adapt their expectations to the market that these expectations aggregatively create, thus creating an artificial stock market. (LeBaron, 2006) surveys research on agent-based models used in finance. (Railsback, 2001) addresses the problem of getting 'results'—general principles and conclusions—from multiagent systems and recommends a pattern-oriented approach.

1.3 Criticisms of Multiagent Systems

Agent-based modelling can stand accused of being poor science. To do science, one needs ways to test hypotheses and reach general conclusions. Some of the problems with multiagent systems:

- Too many free parameters.
- In common with all empirical research, one can always find evidence to support what one seeks to prove. Too many possible explanations of the results leads to the opportunity for story telling.
- No general theoretical way to know whether a given simulation configuration is the only way to get from some set of initial conditions to a result or one of a family of hundreds or millions of ways to get to a result.
- Model validation can be complicated.
- Difficult to verify that the models are consistent enough to be useful.

Daniel Kahneman shared the Nobel Prize in Economics in 2002 with Vernon Smith. Economists once thought of their science as inherently non-experimental, but Smith pioneered laboratory experimental economics, and spearheaded 'wind tunnel tests', where trials of new markets could be tried out in the lab before being implemented in the real world, giving policy makers a better understanding of how a new market is likely to work in practice. Going one step further, from the laboratory to the computer, on balance I consider agent-based modelling to be an effective way of studying behavioural finance, because empirical results derived from the laboratory can be aggregated and modelled flexibly and at low cost.

2 HEURISTICS AND BIASES

From my work on the evolutionary foundations of heuristics and biases (Sewell, 2011b), I identified the following heuristics and biases in the modern day investor.

- Overconfidence is likely to lead investors to trade too much, generally preferring actively managed funds. Excess overconfidence among males in particular explains the popularity of trading among men.
- Optimism naturally creates a 'bullish' tendency and can create asymmetry in the behaviour of markets.
- Availability could, for example, cause us to purchase shares in a company simply because it comes to mind more readily.
- Herding can lead investors to focus only on a subset of securities, whilst neglecting other securities with near identical exogenous characteristics.
- Representativeness leads analysts to believe that trends we observe are likely to continue. Representativeness causes trend following by technical analysts and overreaction among fundamental an-

alysts.

- Anchoring is likely to cause fundamental analysts to underreact, for example to earnings announcements.

Overconfidence leads to excess trading and helps create a liquid market in the first place, optimism likely increases market participation in general, whilst availability and herding will generally only effect a subset of stocks so their impact would be diluted when aggregated across stocks in general. So I only implement the final two points above, which are the most relevant regarding market impact. In summary, following (Barberis et al., 1998) we expect *underreaction* to news but an *overreaction* to a series of good or bad news from fundamental analysts, and trend following from technical analysts. We do not have sufficient news data to test this hypothesis directly, but would expect it to generate kurtosis and nonlinearities in market data, which are indeed found in real markets (Sewell, 2011a).

3 MARKET PARTICIPANTS

The objective is to model a stock market using a multiagent system. The main criteria is to be as realistic as possible; that is, the problem domain is mapped onto the model. The only other criteria is to keep the model as simple as possible (which is often at odds with the quest for realism). In practice, traders are essentially divided into two groups, fundamental analysts (who tend to be longer term) and technical analysts (who tend to be shorter term); the distribution of agents in our model shall mirror this dichotomy ((Lux, 1995; Hong and Stein, 1999) took a similar approach). Reviewing the existing literature, at one extreme, some artificial markets employ agents with zero intelligence (Gode and Sunder, 1993; Farmer et al., 2005). Whilst in some implementations agents are able to swap between technical analysis and fundamental analysis depending on their profits (they have the ability to learn) (Lux, 1998; Lux and Marchesi, 1999; Lux and Marchesi, 2000). I reject the application of zero intelligence agents, as in practice most traders have a reasonably consistent strategy (which may or may not work). I also reject the idea of agents swapping between technical analysis and fundamental analysis, because in practice technical analysts and fundamental analysts tend to be somewhat antagonistic towards each other[2]. Finally, I reject the notion of agents learning. Due to a combination of overconfidence, a limited exposure to markets (at most one working life) and noise, real traders do not learn how to predict markets[3](even if they did, as new traders replaced the old, they would not improve 'on average'); this stasis is trivially mirrored. Indeed, (Martinez-Jaramillo, 2007; Martinez-Jaramillo and Tsang, 2009) developed an artificial financial market and investigated the effects on the market when the agents learn, and, on average, their model without learning replicated the stylized facts most accurately (though not by much). In my model the technical analysts simply follow the technician's number one rule: they follow the trend, so the model fails to replicate some of the more complex strategies that chartists follow. The artificial market operates such that each time step represents one trading day, and the stock price may be interpreted as a daily closing price.

Below is a taxonomy of five groups of market participants.

Fundamental Analysts

- ***Poor:*** Trade randomly—fundamental analysts lacking sufficient skills or experience to analyse a company will make mistakes at random.
- ***Real:*** Consistent, correlated and irrational—*Homo sapiens* employed as fundamental analysts will be susceptible to behavioural biases and make systematic errors.
- ***Good:*** Rational—Skilled fundamental analysts (*Homo economicus*) with the ability to accurately analyse a company, and thus evaluate the value of its stock.

Technical Analysts[4]

- ***Poor:*** Trade randomly—those employed as technical analysts but lacking the ability or experience to follow the rules of technical analysis.
- ***Good:*** Consistent, correlated and irrational—experienced technical analysts able to trade in accordance with the rules of technical analysis.

Assuming that all five types of market participant exist (they do), with imperfect arbitrage opportunities

[2]There are two forms of analysis and the practitioners of each tend to be somewhat antagonistic. Fundamental analysts have referred to Technical analysts as indulging in voodoo and shamanism and a technician once described the former's efforts as "fundamentally a waste of time"' (Society of Technical Analysts, 1999, p. 2).

[3]Indeed, there is a negative relationship between the tenure of a hedge fund manager and hedge fund returns (Boyson, 2003).

[4]Technical analysis *is* a behavioural bias (representativeness), here a 'good' technical analyst is one who accurately and consistently trades according to the rules of technical analysis.

and no 100 per cent rational traders, the resultant effect on the market is the aggregate effect of real fundamental analysts trading against good technical analysts. A multiagent system with technical and fundamental agents is used to model price action. This work employs a bottom-up approach and has been developed from first principles.

4 ARTIFICIAL STOCK MARKET

4.1 Fundamental Analysis

News, by definition, is unpredictable (otherwise it would have been reported yesterday), so let us assume that the cumulative impact of relevant news on a stock follows a geometric random walk. Fundamental analysts calculate the intrinsic value of a stock by the analysis of relevant news. Let the exogenous variable V_t be the perceived fundamental value at time t, where $\log V$ follows a random walk. Note that V is not directly observable, but changes in the variable are observable in the form of news, and the model assumes that V may be calculated. If V increases, this corresponds to good news, if it decreases, this corresponds to bad news. The fundamental analysts trade on the basis of this perceived fundamental value alone (they do not consider historical prices). At each time step, if the price of a stock is below (above) the perceived fundamental value of the stock, fundamental analysts will take a long (short) position in proportion to the logarithm of the perceived fundamental value over the price. In other words, the fundamental analysts trade in such a way that they always move the price towards the fundamental value. Formally,

$$\log \frac{V_t}{V_{t-1}} > 0 \text{ represents good news, and}$$
$$\log \frac{V_t}{V_{t-1}} < 0 \text{ represents bad news.}$$

Let n_{f} be the proportion of the total number of trades made by fundamental analysts and P_t the price at time t. The idea is to model an underreaction to news, but an overreaction to a series of good or bad news. Therefore, the fundamental agents overreact to three or more successive good (or bad) news items, are neutral towards exactly two successive good (or bad) news items and underreact otherwise. In a market populated entirely by fundamental analysts, the log return of the price between time t and time $t+1$ would be F_t. The values for the reaction variable, r, below, are chosen with reference to (Theobald and Yallup, 2004)'s direct measures of the degrees of overreaction and underreactions in financial markets, but the figures used here are subject to significant uncertainty.

$$F_t = r \log \frac{V_t}{P_t} \tag{1}$$

where

$$r = \begin{cases} 1.1 & \text{if } V_t > V_{t-1} > V_{t-2} > V_{t-3} \text{ or} \\ & V_t < V_{t-1} < V_{t-2} < V_{t-3}\text{; else} \\ 1 & \text{if } V_t > V_{t-1} > V_{t-2} \text{ or } V_t < V_{t-1} < V_{t-2}\text{;} \\ & \text{else} \\ 0.9. & \end{cases} \tag{2}$$

4.2 Technical Analysis

The technical analysts follow the trend, i.e. display momentum; they consider the historical price of a stock, and nothing else. At each time step, they exhibit persistence by trading in such a way that the price is biased towards continuing in the same direction as the recent past.

Let n_{t} be the proportion of trades made by technical analysts. The technical analysts' trend-following strategy looks back three days and weights the price changes by recency. In this model if the market were populated entirely by technical analysts, the log return of the price between time t and time $t+1$ would be T_t.

$$T_t = c^3 \log \frac{P_{t-2}}{P_{t-3}} + c^2 \log \frac{P_{t-1}}{P_{t-2}} + c \log \frac{P_t}{P_{t-1}}, \tag{3}$$

where the coefficients c^3, c^2 and c form an increasing geometric sequence so that more recent price changes have a greater impact on T, and sum to one. Solving $c^3 + c^2 + c = 1$, which has one real root, gives us $c = 0.544$.

4.3 Stock Price Returns

Changes in price are determined by the following equation:

$$\log \frac{P_{t+1}}{P_t} = n_{\mathrm{f}} F_t + n_{\mathrm{t}} T_t. \tag{4}$$

By way of example, if $P_t > V_t$, the fundamental analyst believes that the stock is overvalued. Those who hold the stock may sell it, those who don't may either do nothing or short the stock. Or the fundamental analyst may publish a recommendation that the stock is a sell. The point is that on aggregate the actions of the fundamental analysts will put pressure on the stock price to fall. If, however, the technical analysts put even greater selling pressure on the stock, the fundamental analysts will become net buyers.

Table 1: Statistics of daily stock log returns (Taylor, 2005).

	Coca Cola	General Electric	General Motors	Glaxo	Marks & Spencer	Shell	Mean	Standard deviation
Mean	0.001167	0.000742	0.000558	0.001473	0.000725	0.000763	0.000905	0.000344
Standard deviation	0.0169	0.0151	0.0176	0.0179	0.0166	0.0130	0.0162	0.0018
Skewness	0.08	0.03	0.13	0.33	0.03	0.23	0.14	0.12
Kurtosis	5.68	5.43	4.56	6.93	4.40	5.18	5.36	0.91
Returns autocorrelation	-0.035	-0.023	-0.003	0.08	0.034	0.045	0.016	0.044
Absolute returns autocorrelation	0.329	0.224	0.204	0.247	0.155	0.196	0.226	0.059
Squared returns autocorrelation	0.545	0.303	0.398	0.414	0.288	0.293	0.374	0.100

(Taylor, 2005) includes various statistics on stocks, repeated in Table 1. In order to determine the mean and standard deviation of the Gaussian random variable $\log \frac{V_t}{V_{t-1}}$, first, a realistic ratio of 50% fundamental trades and 50% technical trades ($n_{\mathrm{f}} = 0.5$ and $n_{\mathrm{t}} = 0.5$) was chosen. Then the mean and standard deviation space was discretised, an exhaustive enumeration of return sequences generated, one for each discrete parameter setting pair, and the pair for which the mean and standard deviation of the simulated stock returns most closely matched those of the empirical data in Table 1 was chosen. This resulted in a mean of 0.0013 and a standard deviation of 0.023 for the Gaussian random variable $\log \frac{V_t}{V_{t-1}}$. The model was run over 50,000 days twenty times, and averages of various statistics calculated.

5 RESULTS

Recall that P_t is the price of a stock at time t, and V_t is the perceived fundamental value of the stock at time t. Note that (Shiller, 1981) calculated that stock market volatility is five to thirteen times too high to be attributed to new information, so we should not expect the standard deviation of P log returns to equal the standard deviation of V log returns (although perhaps surprisingly, in this model, the latter is slightly greater). Table 2 (p. 6) lists various statistics of the returns generated by the model as the proportion of technical analysts to fundamental analysts varies. Figure 1 shows the mean return per analyst, as the proportion technical analysts/fundamental analysts varies. Figure 2 shows the mean, standard deviation and skewness of market log returns as the proportion technical analysts/fundamental analysts varies. Figure 3 shows the kurtosis of market log returns as the proportion technical analysts/fundamental analysts varies. Figure 4 (page 6) shows the autocorrelations of returns, absolute returns and squared returns as the proportion technical analysts/fundamental analysts varies. Table 3 (p. 6) shows that with a realistic proportion of technical and fundamental trades, the artificial stock market replicates mean returns, the standard deviation of returns, the absolute returns correlation and the squared returns correlation of a real stock market. However, the artificial stock market failed to accurately replicate the skewness, kurtosis and autocorrelation of returns.

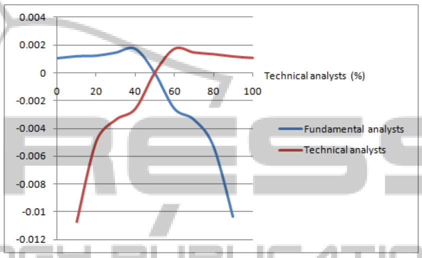

Figure 1: Mean log return (P&L) per analyst.

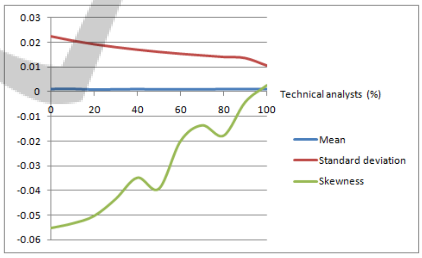

Figure 2: Statistics of price log returns.

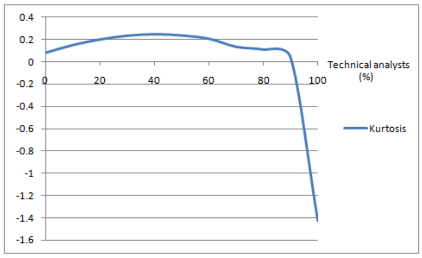

Figure 3: Kurtosis of price log returns.

6 DISCUSSION

The results show that whether a fundamental analyst, or a technical analyst, it pays to be in the majority, ideally of about 60 per cent, whilst being in a small minority is the least profitable position to be

Table 2: Statistics generated by the artificial stock market.

Fundamental analysts (%)	100	90	80	70	60	50	40	30	20	10	0
Technical analysts (%)	0	10	20	30	40	50	60	70	80	90	100
Mean fundamental analyst return	0.0011	0.0012	0.0012	0.0015	0.0017	0.0000	-0.0026	-0.0033	-0.0053	-0.0103	
Mean technical analyst return		-0.0107	-0.0049	-0.0034	-0.0026	0.0000	0.0017	0.0014	0.0013	0.0011	0.0010
Mean return	0.0011	0.0011	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0011	0.0010	0.0010
Returns standard deviation	0.0226	0.0208	0.0194	0.0182	0.0172	0.0163	0.0155	0.0149	0.0143	0.0138	0.0108
Returns skewness	-0.0552	-0.0533	-0.0503	-0.0434	-0.0348	-0.0393	-0.0201	-0.0136	-0.0178	-0.0043	0.0025
Returns kurtosis	0.0822	0.1512	0.2010	0.2350	0.2476	0.2371	0.2073	0.1348	0.1100	0.0394	-1.4268
Returns autocorrelation	0.0658	0.2038	0.3338	0.4566	0.5690	0.6710	0.7627	0.8423	0.9088	0.9617	1.0000
Absolute returns autocorrelation	0.0093	0.0364	0.0931	0.1750	0.2803	0.4045	0.5403	0.6730	0.7984	0.9083	1.0000
Squared returns autocorrelation	0.0088	0.0401	0.1029	0.1899	0.3021	0.4259	0.5650	0.6974	0.8226	0.9244	1.0000

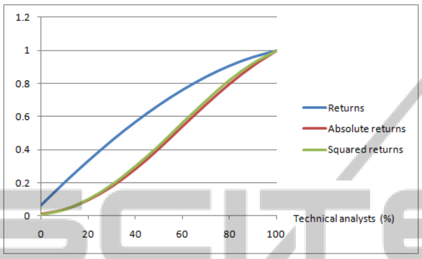

Figure 4: Autocorrelations of price log returns.

Table 3: Range of proportions of technical analysts in the artificial stock market that replicate stylized facts.

Statistic	Proportion of technical analysts
Mean return	0–100%
Returns standard deviation	40–70%
Returns skewness	none
Returns kurtosis	none
Returns autocorrelation	none
Absolute returns autocorrelation	30–40%
Squared returns autocorrelation	40–50%

in. Mean stock returns are low and positive regardless of the relative proportions of analysts, this is consistent with a real market. As the number of technical analysts increases, the standard deviation of returns decreases, whilst remaining realistic, whilst the skewness increases. The model exhibited slight negative skewness, whilst real markets exhibit significant positive skewness. The kurtosis of returns peaks at around 0.25 with around 40 per cent technical analysts, and rapidly declines as the number of technical analysts exceeds 90 per cent. In contrast, the kurtosis of daily stock returns in real markets is around 5. The autocorrelation of returns is close to zero with 100 per cent fundamental analysts, and approaches one as the proportion of technical analysts approaches 100 per cent. Unsurprisingly, the trend-following technical analysts created positive autocorrelations in returns in the model, but autocorrelations of returns are close to zero in real markets. The autocorrelation of absolute and squared returns is realistic only around the region of 30%–50% technical analysts. How has the model fared in light of the criticisms of multiagent systems that were highlighted in Section 1.3 (p. 2)? The main concern, that one can vary any free parameter until one obtains the result that one desires, i.e. high kurtosis, was mitigated by keeping the number of varying parameters to a minimum, by using realistic assumptions. (Martinez-Jaramillo, 2007; Martinez-Jaramillo and Tsang, 2009) investigated the different conditions under which the statistical properties of an artificial stock market resemble those of a real financial market. Their approach replicated the stylized facts of a financial market far more accurately than my own; this was possible by including and adjusting a much larger number of parameters.

7 CONCLUSIONS

Those heuristics and biases which contribute to behavioural finance were identified, and used to build a theoretical model of market action which simulates the aggregates of many interacting agents. The artificial market exposed the effect of varying the proportion of technical analysts to fundamental analysts. It pays to be among the majority, whether a fundamental analyst, or a technical analyst. The artificial stock market replicates mean returns, the standard deviation of returns, the absolute returns correlation and the squared returns correlation of a real stock market, but failed to accurately replicate the skewness, kurtosis and autocorrelation of returns. This implies that the model has failed to capture some of the dynamics underlying the process of price formation.

ACKNOWLEDGEMENTS

Thanks to David Barber, Edward Tsang and the anonymous reviewers for various suggestions.

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