CHAPTER 6

AN ANALYSIS OF INVESTOR BEHAVIOR IN BSE USING AN AGENT BASED MODEL

6.1 Introduction

ASM are models of financial markets used to study and understand market dynamics. Agent based models are potentially very suitable tools to generate or test various hypotheses. The agent based ASM developed here explores the macro level aggregate market phenomena arising as a consequence of micro level individual investor behavior. Investor behavior is modeled as agents falling in three different categories, depending on their investment strategy as follows: fundamental (based on fundamental value of shares); technical (based on performance of share prices in the past) and uninformed (trading done in a random manner). The market under study is BSE. The market behavior arising as an outcome of interaction of different proportions of investors of each category is analysed. The simulated share price series obtained from the model are correlated with the movement of actual share prices by varying the proportion of these three categories of investors, with a view to suggest a probable ratio prevailing in the investor population trading in the BSE. Study of investor behavior of NYSE and NASDAQ has also been done to enable comparison among these markets.

Agent-based artificial financial markets are mathematical models, usually comprising of a number of bounded rational agents, which interact through some trading mechanism, while possibly learning and evolving [70,116]. These agent based models are built for the purpose of studying investor behavior, price discovery mechanisms, the influence of market microstructure, the reproduction of the stylized facts of real-world financial time-series etc. A similar bottom-up approach has been utilized in Agent-based Computational Economics (ACE) - the computational study of economies modeled as evolving systems of autonomous interacting agents [114]. The traditional economic models generally use either a simple distribution of returns such as the Gaussian and treat extreme events as outliers, or construct a statistical process which reproduces some of these features. The agent-based approach
considers a population of intelligent adaptive agents and let them interact in order to maximize their financial performance. It has been shown that such an approach can replicate features of real stock markets \[2,63,65,76\]. Further, Chan \[16,17\] has shown that agent-based models can incorporate complex learning behavior, asymmetric information and heterogeneous preferences. These simulations are particularly suitable to test and generate various behavioral hypotheses. The model presented here combines the theories proposed in behavioral finance and agent-based computational economics.

The model adopted addressing the behavioral aspects of investors in BSE, is inspired by the basic theoretical work of Levy, Levy, and Solomon (LLS) \[71\] and the extension work done by Lovric M. \[75\] which has been discussed in Chapter 4. However, this study is based on the actual market scenario at the BSE, as against the theoretical setting of the two papers mentioned above. The LLS is a suitable model which enables study of investor behavior. As a prelude, the LLS model has been implemented and the results have been compared before proceeding to model the behavioral pattern in an endeavour to capture the pattern prevailing in BSE. One investor type in LLS model, the Efficient Market Believer (EMB), uses a uniform distribution of past stock returns to predict future returns, which greatly impacts the market price. The behavior of a technical trader (Chartist) has been modeled based on the EMB.

### 6.2 Levy, Levy, Solomon (LLS) Model

The model proposed by Levy, Levy, Solomon (LLS)\[71\], discussed earlier in Chapter 4 is reviewed here, prior to adopting a modified version for the BSE. It is developed in the framework of expected utility maximization based on the microscopic simulation approach. In the LLS model, the market consists of two types of investors: Rational Informed Investors (RII) and Efficient MarketBelievers (EMB). There are two asset classes in the market: a risky stock that pays a dividend following a multiplicative random walk and has a finite number of outstanding shares; and a risk-less bond that pays a definite interest and has an infinite supply. All investors are supplied with the same amount of wealth in the beginning of the simulation, comprising of cash and a number of shares. The pricing mechanism
based on the temporary market equilibrium, is used to determine the price so that the total demand for the risky asset equals the total number of outstanding shares. The goal of all the investors in the LLS model is the maximization of the expected utility of the next period wealth. The risk attitude of the investors is risk aversion, and is captured by the parameter of the utility function. The investors maximize their one-period-ahead expected utility. The memory lengths of past return are used in the prediction of future returns. Although both RII and EMB investors have the same goal of expected utility maximization, their strategies are different because of the differences in information that they possess. RII investors are presumed to know the properties of the dividend process, and can estimate the fundamental price of the risky asset as a discounted stream of future dividends. The fundamental price is used in their prediction of the next period return. EMB investors, however, do not know the dividend process, and must use ex-post distribution of returns to estimate ex-ante distribution. EMB investors use a rolling window of a fixed size, and in the absence of any additional information, in the original model assume that returns come from a discrete uniform distribution. In each period investors perceive information about the new price and new dividends, which they can use to update their wealth status.

Both types of investors are rational expected utility maximizers. With EMB investors some noise is added to the optimal proportion to account for any departure from optimal behavior. LLS model is based on the temporary market equilibrium. All agents will have information about the current market price, which will allow them to update their wealth status and decide on their investment strategies. They will also receive news, such as dividends on risky assets and interest on risk-less assets. However, some agents will also have information about the determinants of the fundamental price, such as the dividend generating process. Depending on their strategies, agents will translate their price expectations or predictions into orders or demand functions, which will be cleared using a specific market mechanism, and finally a new market price will be formed.

6.3 ABM of Investor Behavior

Lovric M.[75] extended the LLS model by including behavioral issues viz overconfidence, sentiments, loss aversion etc into the character of EMB investors.
This model has been modified and adopted for this study. Experiments have been carried out for analyzing various investor behaviors in the BSE, NYSE and NASDAQ.

6.3.1. Categories of Investors

Three categories of investors are modeled, namely:

- Fundamental Investors (FI).
- Technical Investors (TI) or Chartists.
- Uninformed Investors (UI).

According to Levy et al. [71], when empirical support is taken into account, the choice of utility function would be Decreasing Absolute Risk Aversion (DARA) and Constant Relative Risk Aversion (CRRA). It has been further established that when DARA and CRRA prevail, the only possible utility function is the power function. Hence,

$$U(W) = \frac{W^{1-\alpha}}{1-\alpha}$$

(6.1)

Where

$W$: Wealth of an investor

$U(W)$: is the utility at a given wealth $W$

$\alpha$: Risk aversion factor.

$\alpha$ is greater than zero for risk averters and less than zero for risk lovers. Experimental and empirical studies have further proved that the value of the relative risk aversion parameter $\alpha$ seems to be in the range of 0.6 to 2.0 [71]. When $\alpha$ is zero, utility is sure wealth $W$ itself with which the subject is satisfied/happy. If $\alpha$ is 1 (risk averter), utility tends towards infinity i.e., a person is not prepared to take risk and same wealth $W$ gives him immense happiness.

6.3.2. Behavior of Fundamental Investors (FI)

In the LLS model, the RII invest based on dividend process of the given entity. They estimate the fundamental value as a discounted stream of future dividends, according to the Gordon [42] model. In the model proposed here, since actual stock
market values are to be introduced, the fundamental value is calculated using Graham’s model [43]:

\[ P_{t+1}^f = \frac{(\text{EPS} \times (8.5 + 2g) \times 4.4)}{Y} \]  

(6.2)

Where:

- \( P_{t+1}^f \) is the fundamental price of a stock
- \( \text{EPS} \) is Earnings Per Share
- \( g \) is the company’s growth rate
- \( Y \) is the risk free interest rate.

The fundamental investor would take a constant growth rate that the company has been maintaining in the past 10 years and these investors assume that the price will converge to the fundamental value in the next period, i.e.

\[ P_{t+1} = P_{t+1}^f \]  

(6.3)

In each period, the fundamental investor \( i \) chooses the proportion of wealth to invest in stocks and bonds so that the expected utility of wealth is maximized in the next period, given by the equation

\[ \text{EU} \left( \bar{W}_{t+1}^i \right) = \text{EU} \left( W_{t+1}^i \left( 1 - x \right) \left( 1 + r_f \right) + x \bar{R}_{t+1}^i \right) \]  

(6.4)

Where:

- \( \text{EU} \): Expected utility
- \( W_t^i \) represents wealth of investor \( i \) in period \( t \) given that the price in period \( t \) is some price \( P_h \)
- \( x \) is the proportion of wealth invested in shares
- \( r_f \) is the risk free interest rate
- \( W_{t-1}^i \) consists of the previous period wealth \( W_{t-1}^i \), interest and dividend accumulated from the last period, and capital gains or losses incurred on the difference between \( P_h \) and \( P_{t-1} \).

The returns of each year are calculated using,

\[ R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} \]  

(6.5)
Where

\( D_t \) is the dividend in the given time period,

\( P_t \) is the price at time step \( t \).

The dividend \( D_t \) in the proposed model is the entity’s quarterly dividend, whereas, in case of simulation in [71] and [75], it is a random variable with a constant growth rate. Based on the optimal proportion \( x \), which maximizes the expected utility of next period wealth, fundamental investors determine the number of stocks demanded by multiplying their wealth with this optimal proportion. The rest of their wealth is invested in the risk-less asset.

### 6.3.3 Behavior of Technical Investors (TI) or Chartists

The technical investors believe that the price accurately reflects the fundamental value. However, since they do not know the dividend process, they use *ex-post* distribution of stock returns to estimate the *ex-ante* distribution. In the original LLS model, the unbiased EMB’s assume that returns come from a discrete uniform distribution. In this model various behavioral characteristics of technical investors viz normal and overconfident are considered. Normal TI assumes that returns come from a stable normal distribution, and in each period estimate the mean \( \hat{\mu} \) and standard deviation \( \hat{\sigma} \) using the rolling window of size \( m_i \).

\[
\Pr^i(\hat{R}_{t+1} = R_{t-1}) = \frac{pdf(R_{t-1}|\hat{\mu}, \hat{\sigma})}{\sum_{k=1}^{m_i} pdf(R_{t-k}|\hat{\mu}, \hat{\sigma})} \tag{6.6}
\]

\[
pdf(x|\mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{6.7}
\]

### 6.3.4 Uninformed Investors

The behavior of uninformed investors in the market is modeled in this category. As is the case prevailing in a stock market, they invest randomly and are totally unpredictable. These investors neither have any intelligent information about the market performance nor do they consider the information embedded in the previous returns while investing. The proportion of wealth to be invested in risky assets will take a random seed with both mean and standard deviation as 0.5, chosen so as to enable variation of \( x \) in equation 6.4 in a range between 0 and 1.
6.3.5 Price mechanism

The pricing mechanism is based on the temporary market equilibrium, according to the classification by LeBaron [70]. FI and TI investors determine optimal proportion in the stock so as to maximize the expected utility of their wealth in the next period. Since expected utility is a function of the price, which is still unknown in the current period, investors therefore determine optimal proportions of wealth to invest in the risky asset $x^i_h(P_h)$, and generate respective demands for shares $N^i_h(P_h)$, for various hypothetical prices $P_h$. The equilibrium price $P_t$ is set to that hypothetical price for which the total demand of all investors in the market equals the total number of outstanding shares, according to:

$$\sum_i N^i_h(P_t) = \sum_i \frac{x^i_h(P_t)w^i_h(P_t)}{P_t} = N. \quad (6.8)$$

Where

- $N$ is the total number of shares
- $P_t$ is the share price at timestep $t$
- $x^i_h$ being the proportion of wealth invested in risky assets at hypothetical price $P_h$.

6.4 Implementation and Performance Evaluation

The flow chart of the market mechanism is given in Figure 6.1.

![Flowchart of the market mechanism](image)

The model for analysis of the stock markets has been implemented in Java. The entities used in the model and the pseudo-code are given at Appendix C. The financial data pertaining to the experiment and the simulated price series are given at Appendix D. The IT bellwether stock of Infosys has been considered for the study of BSE. The historical beta of Infosys is close to one and hence chosen as the
experimental data to depict the BSE behavior. The salient aspects in the implementation are given below:

(a) Graham’s model [43] is employed to represent the behavior of FI.
(b) The dividend for calculation of Graham’s Intrinsic Value (GIV), is taken as the actual value from the BSE Index of dividends. The dividends are added in the months of their issue, it remains 0 otherwise.
(c) All the time stamps have been considered on quarterly basis. The EPS and risk free interest rate are also taken on a quarterly basis from the BSE stock index.
(d) The fzero function is used to compute the temporary market equilibrium share price by Walrasian auction.

6.4.1 Replication of LLS Model
Initially, the LLS model with only fundamental investors present in the market was replicated, using Gordon’s model [42]. Figure 6.2 shows the obtained price series. Subsequently, replication of LLS model was done incorporating technical investors. The price series obtained is captured in Figure 6.3. These results are similar to that obtained in LLS implementation and also as obtained by Lovric [75].

![Figure 6.2: Price Variation with 100% FI](image)

Figure 6.2: Price Variation with 100% FI
6.4.2 General Characteristics of BSE Investor

For applying this model to BSE, the parameters (EPS, dividends, and share price of Infosys) are given as input to the model to obtain the simulated price. Figure 6.4 shows the graph of simulated price versus actual graph when there are only fundamental investors (FI) in the market. Figure 6.5 shows the results when technical investors (TI) are introduced into the model. It is seen that the simulated price series is similar to the BSE price series when TI are present preponderantly. The similarity between the actual market price series and simulated price series is measured in terms of correlation coefficient, which is higher in the presence of TI. With 85% TI, it was as high as 0.83, whereas it was just 0.43 with only FI present. Therefore it can be inferred that TI play a large role in the Indian market.

Figure 6.4: Price Variation with 100% FI present in BSE.
6.4.3 Overconfident Technical Investors

A new TI investor agent is introduced, incorporating the characteristics of a technical investor, with an overconfidence factor (depicting miscalibration) built into the model. Overconfident TI also estimates normal distribution from the sample, but they underestimate the variance of the distribution. The standard deviation is multiplied by a factor to model this departure in behavior:

$$\sigma = oc \cdot \tilde{\sigma}$$  \hspace{1cm} (6.9)

where $oc$ is the overconfidence coefficient, $0 < oc < 1$. Here the expected utility of wealth is given by:

$$EU(\tilde{W}_{t+1}) = \frac{(\tilde{W}_h)^{1-\alpha}}{1-\alpha}[(1-x)(1+r_f) + x\tilde{\mu}]^{(1-\alpha)}$$  \hspace{1cm} (6.10)

The probabilities are calculated and normalized using the probability density function (pdf) of the peaked normal distribution:

$$pdf(x|\mu = \tilde{\mu}, \sigma = oc \cdot \tilde{\sigma}) = \frac{1}{oc \cdot \tilde{\sigma} \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2(oc \cdot \tilde{\sigma})^2}}$$  \hspace{1cm} (6.11)

Here FI and TI in varying ratios of population were modeled with varying confidence levels and memory lengths. The quantum of uninformed investors is taken constant at 1%, and memory lengths are taken as 5 or 7 quarter periods. The behavior of the TI has been studied for different levels of confidence level swings. Actual returns from the Infosys company history have been taken as a proxy for the BSE. The price series generated for various combinations of investors, considered in random ratios (Table 6.2), can be seen in the respective graphs (Figure 6.6 to Figure 6.9).
Table 6.1: Price series generated for various combinations of investors in BSE

<table>
<thead>
<tr>
<th>FI (%)</th>
<th>TI (%)</th>
<th>UI (%)</th>
<th>OC</th>
<th>Memory Length</th>
<th>Correlation Coefficient</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>99</td>
<td>0</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>0.43</td>
<td>Figure 6.6</td>
</tr>
<tr>
<td>15</td>
<td>84</td>
<td>1</td>
<td>0.4</td>
<td>5</td>
<td>0.809</td>
<td>Figure 6.7</td>
</tr>
<tr>
<td>50</td>
<td>49</td>
<td>1</td>
<td>0.5</td>
<td>5</td>
<td>0.3998</td>
<td>Figure 6.8</td>
</tr>
<tr>
<td>17</td>
<td>82</td>
<td>1</td>
<td>0.4</td>
<td>5</td>
<td>0.789</td>
<td>Figure 6.9</td>
</tr>
</tbody>
</table>

It is seen that the simulated price series generated good correlation at particular values of investor composition, overconfidence levels and memory length values, as can be seen in the correlation coefficients at Table 6.1.

Figure 6.6: Price series – Modeling of BSE (99%FI; 0%TI; 1%UI)

Figure 6.7: Price series – Modeling of BSE (15%FI; 84%TI; 1%UI)
6.4.4 Investor Composition in BSE

The next step was an endeavor to ascertain the ratios of investors that might be populating the BSE by comparing the actual market prices with the simulated price series generated in various combinations. The highest correlation between the two series is envisaged to suggest a ratio of investor composition in the BSE. A procedure was written to arrive at the combination of parameters in the experiment which gave maximum correlation between the simulated price series and the actual BSE market price series (Table 6.2). The maximum correlation results were attained at about 0.83 and the corresponding price series is given in the graphs at Figure 6.10 and Figure 6.11. The maximum values of correlation coefficient obtained, suggest
that the ratio of various categories of investors that might prevail in the BSE is likely to be approximately:

- Fundamental investors (FI) - 10% to 16%.
- Technical investors (TI) - 83% to 89% and
- Uninformed Investors (UI) - 1%.

Results are seen to mimic the market price series for a memory length of 5 (i.e. about past one and half years) and overconfidence factor at 0.4 (marginally overconfident).

Table 6.2: Price series generated for highest correlation coefficient (BSE)

<table>
<thead>
<tr>
<th>FI (%)</th>
<th>TI (%)</th>
<th>UI (%)</th>
<th>OC</th>
<th>Memory Length</th>
<th>Correlation Coefficient</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>83</td>
<td>1</td>
<td>0.4</td>
<td>5</td>
<td>0.832</td>
<td>Figure 6.10</td>
</tr>
<tr>
<td>10</td>
<td>89</td>
<td>1</td>
<td>0.4</td>
<td>5</td>
<td>0.83</td>
<td>Figure 6.11</td>
</tr>
</tbody>
</table>

Figure 6.10: Price series – Modeling of BSE (16%FI; 83%TI; 1%UI)

Figure 6.11: Price series – Modeling of BSE (10%FI; 89%TI; 1%UI)
6.4.5 Inclusion of Sentiments (Optimists and Pessimists) in the Model

A new TI type, called the sentiment TI is described by using a fuzzy set connective to model both optimists and pessimists. Sentiment TI use generalized aggregation operator to estimate future returns, using the rolling window of size m. The prediction of the next period mean return $\bar{\mu}_{t+1}$ is calculated as follows.

$$\bar{\mu}_{t+1} = \left( \frac{1}{m} \sum_{j=1}^{m} (R_{t-j})^s \right)^{\frac{1}{s}} \quad (6.12)$$

The predicted deviation of the next period return $\bar{\sigma}_{t+1}$ is calculated from the $\ddot{\sigma}$ of the sample of past returns $R_{t-1}, ..., R_{t-m}$ and the level of confidence $c$:

$$\ddot{\sigma}_{t+1} = c \times \bar{\sigma} \quad (6.13)$$

In each period of the simulation, TI i predicts next period return by the following discrete probability distribution that incorporates the effects of investor sentiment and confidence:

$$Pr_i(\bar{R}_{t+1} = R_{t-j}) = \frac{pdf(R_{t-j}|\bar{\mu}_{t+1},\ddot{\sigma}_{t+1})}{\sum_{k=1}^{m} pdf(R_{t-k}|\bar{\mu}_{t+1},\ddot{\sigma}_{t+1})} \quad (6.14)$$

Where pdf is the probability density function of a normal distribution. Figure 6.12 depicts the value at which maximum correlation (0.856) has been attained between the simulated price series and the market price series. The best correlation has been achieved for the fuzzy connective factor $s = 0.9$. The ratio of investor composition in the BSE remains unaltered. Inclusion of optimistic and pessimistic behavior into the model generated poor correlation (figures 6.13 and 6.14), thereby leading to the inference that Indian investors may not be swayed by sentiments (Table 6.3).

Table 6.3: Modeling of Sentiments in the behavior bias (BSE)

<table>
<thead>
<tr>
<th>Srl No</th>
<th>FI (%)</th>
<th>TI (%)</th>
<th>Sentiment</th>
<th>OC</th>
<th>Memory Length (Quarters)</th>
<th>Correlation Coefficient</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15</td>
<td>84</td>
<td>0.9</td>
<td>0.4</td>
<td>4</td>
<td>0.856</td>
<td>Figure 6.12( Best correlation )</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>84</td>
<td>2</td>
<td>0.4</td>
<td>4</td>
<td>0.6571</td>
<td>Figure 6.13 (with optimism, poor correlation)</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>84</td>
<td>-2</td>
<td>0.4</td>
<td>4</td>
<td>0.6353</td>
<td>Figure 6.14 (with pessimism, poor correlation)</td>
</tr>
</tbody>
</table>
Figure 6.12: Price Series – Modeling of BSE Investors (s=0.9)

Figure 6.13: Price series – Modeling of BSE Investors (Optimists)

Figure 6.14: Price series – Modeling of BSE Investors (Pessimists)
6.4.6 Inclusion of Recency/Primacy Effects

The recency effect refers to the tendency of TI to give more weight to more recent return observations compared to those farther in the past. This is modelled by assigning decaying probability mass towards the older return values in the rolling window of size $m^i$. In the case of TI investors exhibiting primacy effects, the tendency of investors is to give more importance to the return observations that they encountered first, i.e. the oldest observations in their memory window. The model is implemented by reducing the values by 20% consecutively from the corresponding start points (for the ratio of 15%FI, 84%TI, and 1% UI). The parameters modeled are listed in Table 6.4. In both cases it is seen that the correlation coefficient reduces drastically, thereby leading to an explanation that the recency/primacy behavior bias does not appear to manifest in the behavior of Indian investors.

Table 6.4: Introduction of Recency/Primacy Behavior Bias

<table>
<thead>
<tr>
<th>Srl No</th>
<th>FI (%)</th>
<th>TI (%)</th>
<th>Sentiment</th>
<th>OC</th>
<th>Memory Length (Quarters)</th>
<th>Correlation Coefficient</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15</td>
<td>84</td>
<td>0.9</td>
<td>0.4</td>
<td>4</td>
<td>0.622</td>
<td>Figure 6.15(with recency – poor correlation)</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>84</td>
<td>0.9</td>
<td>0.4</td>
<td>4</td>
<td>0.4730</td>
<td>Figure 6.16(with primacy – poor correlation)</td>
</tr>
</tbody>
</table>

![Simulated Price vs Actual Price](image)

Figure 6.15 : Effect of Recency Behavior Bias
6.4.7 Inclusion of Self Attribution Behavior Bias

The dynamics of investor attitudes based on feedback from the market has been modeled here. The investors look at their return on investment in the last period (the relative change in their own wealth), and based on that change they update their index of optimism. This behavior makes an investor to be surer of future prices of a share, if his current prediction of price comes true and vice versa. This is accomplished by controlling the confidence level of TI. A good prediction subsequently increases his confidence level and vice versa. Here ‘a’ is the factor by which confidence level changes.

\[
\begin{align*}
\text{If } |\bar{\mu}_t - R_t| < 2(c^i_t, \tilde{\sigma}_t) & \text{ then } c^i_{t+1} = \bar{a}.c^i_t, \\
\text{otherwise } c^i_{t+1} = a.c^i_t, \\
\end{align*}
\]

(6.15)

\(a\) is the factor by which his sentiment level changes which has been taken as 1.05 \((\bar{a})\) for increase and 0.95 \((a)\) for decrease. It is seen that, introduction of self–attribution behavior bias had negligible effect on the simulated price series (for the ratio of 15%FI, 84%TI, and 1% UI), since there was no appreciable deviation in the maximum correlation coefficient achieved (Figure 6.17 refers). This implies that the confidence level of investors in BSE does not change even when they make a good or bad prediction.
6.5 ABM of NYSE

In the previous subsection it was demonstrated that the BSE is dominated by technical investors (85%). The designed model is now applied to study the investor behavior on NYSE (CTS stock has been taken to represent NYSE index, its historical beta being close to 1). It has been observed that the investor behavior in NYSE is very different from that of BSE. The parameters modeled and the results obtained are given in Table 6.5 below. Figure 6.18 and Figure 6.19 are illustrative graphs.

<table>
<thead>
<tr>
<th>Srl No</th>
<th>FI (%)</th>
<th>TI (%)</th>
<th>Sentiment</th>
<th>OC</th>
<th>Memory Length (Quarters)</th>
<th>Correlation Coefficient</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>99</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>5</td>
<td>0.921</td>
<td>Figure 6.18 refers</td>
</tr>
<tr>
<td>2</td>
<td>75</td>
<td>24</td>
<td>-</td>
<td>-</td>
<td>6</td>
<td>0.937</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>75</td>
<td>24</td>
<td>-</td>
<td>0.6</td>
<td>6</td>
<td>0.95571</td>
<td>-</td>
</tr>
<tr>
<td>4</td>
<td>75</td>
<td>24</td>
<td>0.9</td>
<td>0.6</td>
<td>6</td>
<td>0.95574</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>75</td>
<td>24</td>
<td>0.9</td>
<td>0.6</td>
<td>6</td>
<td>0.9577</td>
<td>With Self-attribution. Figure 6.19 refers</td>
</tr>
</tbody>
</table>

Figure 6.17: Effect of Self-Attribution Behavior Bias
6.5.1 Observations and Conclusions

The highest correlation obtained between the simulated price series and the market price series indicated that the possible ratio of various categories of investors in NYSE is as follows:

- FI – 75 %
- TI- 25%

It is observed that the investors in NYSE have a memory length of 5 to 6 quarters i.e. they generally tend to reckon the previous year and a half market information for
investments. The investors exhibit overconfidence while investing. The fuzzy connective factor's of the sentiment model has been attained close to 1, which depicts neutral sentiments. These findings are congruent with the scenario prevailing in the developed market of NYSE, wherein lesser volatility prevails than the BSE. The NYSE is populated predominantly with fundamental investors who exhibit maturity in their investment decisions.

6.6 ABM of NASDAQ

A similar study has been carried out in respect of NASDAQ stock market. The designed model has been applied to study the investor behavior on CTSH stock (taken to represent NASDAQ index with historical beta close to 1.0). It has been observed that the investor behavior in NASDAQ is very similar to that seen in NYSE. The highest correlation obtained between the simulated price series and the market price series indicated that the possible ratio of various categories of investors in NASDAQ is:

- FI – 81%
- TI- 19%

Figure 6.20 illustrates the best correlation achieved at this ratio of investor population.

Figure 6.20: The results of NASDAQ (80%FI, 19% TI and 1%UI)
6.7 Limitations of the Model

Few limitations of the model are enumerated below:

- Based on the experimental and empirical studies, DARA and CRRA is assumed with power utility function, with the value of the relative risk aversion parameter in the range of 0.6 to 2.0. However, these are results relating to “typical” investors. Deviations from these values or even from CRRA and DARA may be possible.

- It is assumed that investors have “mental departments” [71], i.e., they invest in one segment of the market while ignoring the other investment components they have. The simulation models assets available in the capital market, ignoring other investment opportunities and assets such as property, commodities such as oil, gold, silver etc.

- The encapsulation of behavior heuristics and biases in the mathematical models displayed above, might seem as an over simplification, and also as an implication of their utmost importance in investor behavior and the dynamics of financial markets. However, this is not necessarily the case. Moreover, one particular behavioral phenomenon can have multiple definitions and manifestations. Therefore, the relevance of each behavioral phenomenon could be treated further as a research question on its own, and addressed using appropriate techniques, whether empirical, experimental, or as agent-based simulations.

- In the mathematical model, Graham’s Intrinsic Value [43] is used, since it is based on parameters that can be measured practically: earnings, dividends, past growth rates, and current interest rates. Studies with respect to estimates other than Graham’s Intrinsic Values could be undertaken.

6.8 Summary

A modified LLS model proposed by Lovric M. [75] has been used to study the general effects of presence of different categories of investors in the BSE. It has been shown that changes in the formation of expectations by technical investors can have a marked impact on the price dynamics. Various behavioral biases have been modeled within the LLS model. The incremental approach has been adopted, wherein an existing computational model is firstly replicated and then new behavior
is introduced into the model one by one [75]. By comparing the results of the original model with the results of the incremented model, the implications of the newly introduced (biased) behaviors of investors have been studied. Investor sentiment and investor over confidence were incorporated in the modified LLS model of the stock market. The over confidence in the model referred to the narrow band of the return distribution around the mean of return observations, while sentiment in the model determined how that mean is chosen (ranging from the minimum observation to the maximum observation in the sample of past returns).

In the experiment, the ASM model of Lovric was duly modified and adopted to represent the BSE/NASDAQ/NYSE. Initial share prices, quarterly dividends and EPS of a company (Infosys, representing BSE with historical beta of one), were given as an input to the ASM, and the different investors were allowed to interact with each other to arrive at the share price. The share price series so obtained has been compared with the actual market price series in order to obtain the possible ratio of different types of investors prevalent in the BSE by comparing their correlation coefficients. It appears that technical investors dominate the BSE stock market (85%), looking into just a year and a half for investing while their confidence levels are mediocre. The study corroborates the scenario prevailing in emerging markets such as the BSE in India, wherein the technical investors hold sway over the fundamental investors, since the market is not as matured as those in the developed financial stock markets, where fundamental investors are expected to dominate. The model was further applied to the NYSE and NASDAQ to study investor behavior therein. It was observed that as expected, these two matured markets of US were seen to be predominantly populated with fundamental investors.

The behavior bias of over confidence; under confidence; sentiments (optimism and pessimism); primacy effects; recency effects and self attribution were also modeled to identify the underlying impact of these characteristics of investors. It has been inferred that the Indian investors may not be overly swayed by sentiments. The recency/primacy behavior bias does not appear to manifest in the behavior of Indian investors. The investors are seen to exhibit overconfidence, however, the confidence level does not change even when they make a good or bad prediction.