Importance of Technical and Fundamental Analysis and Other Strategic Factors in the Indian Stock Market

Naveen Kumar
IIPM Hyderabad,
India
Email: naveenkumar.isb@gmail.com

Sanjay Mohapatra
Xavier Institute of Management,
Bhubaneswar, India
Email: sanjay_mohapatra@yahoo.com

Gaurvinder Sandhu
IIPM Hyderabad,
India
Email: ISB.Gary@gmail.com

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ABSTRACT

This paper presents findings of an online questionnaire survey on the perceived importance of chartist/technical and fundamental analysis and the different strategic factors in the stock price forecasting by stock brokers of Bombay Stock Exchange, India. Stock brokers rely more on technical analysis vis-à-vis fundamental analysis at shorter forecasting horizons and rely more on fundamental analysis at longer forecasting horizons.
Regarding the use of chartist/technical and fundamental analysis on seven forecasting horizons, four distinct forecasting styles among stock brokers could be identified through cluster analysis. Also, our results suggest that Company Specific Factors was rated the most important and Other Factors was rated the least in stock price forecasting in the long term by brokers.

Keywords: stock brokers; technical analysis; fundamental analysis; strategic factors.

INTRODUCTION

As in all financial markets, the primary question in the stock market is how market participants and stock traders forecast future market prices. How we forecast stock market prices now and in the future influences major economic and social policy decisions that affect not only investors but also society at large.

The two general techniques for predicting stock market prices used by market professionals are “chartist” or "technical" analysis and fundamental or intrinsic value analysis. Technical, or chartist, analysis of financial markets involves providing forecasts of asset prices or buy/sell advice on the basis of visual observation and examination of the past history of price movements (Edwards et al., 1967), perhaps with the aid of certain quantitative techniques such as momentum indicators and moving averages (Murphy, 1986), without considering any fundamental factors. Fundamental Analysis is a method of evaluating a stock by attempting to measure its intrinsic value. Fundamental analysts study everything from the overall economy and industry conditions, to the financial condition and management of companies. In other words, fundamental analysis
is about using real data to evaluate a stock's value. The method uses revenues, earnings, future growth, return on equity, profit margins and other data to determine a company's underlying value and potential for future growth.

Despite the increasing professional interest in non-fundamental factors, there is little empirical evidence on the prevalence and usage of such techniques in the Indian stock market. Goodman (1980) examines the performance of technical analysts, but does not provide evidence on the importance and usage which markets attaches to their advice. Mitra (2009), Kakani et al., (2006) and Pampana et al., (2005) analyses the profitability of different technical trading rules in the Indian stock market but, has not directly compared the usage of technical and fundamental analysis tools and the importance given to strategic factors by brokers in the Indian stock market.

This is the first study concerned with how professional traders forecast stock rate movements in India. Given that India is the 2nd largest stock exchange market in terms of market capitalisation among emerging and developing countries and the fact that brokers’ views are an important factor driving stock price movements, this study may enhance understanding of stock price analysis and forecasting.

This study tries to extend the results of previous works done on the use of technical analysis and fundamental analysis among foreign exchange traders in London (Taylor et al., 1992) and work done in Hong Kong (Lui et al., 1998) and work done in the European foreign exchange market (Oberlechner, 2001) and work done by Menkhoff (Menkhoff, 2010) to a new geographic location and to a new financial market. This is the first study which determines the usage and perception of technical and fundamental analysis and importance given to strategic factors by brokers in the Indian stock market.
To examine the importance that brokers’ personally give to fundamental and technical analysis over seven forecasting horizons: intraday, 1 week, 1 month, 3 months, 6 months, 1 year and beyond 1 year.

To investigate the importance of Risk Factors, Liquidity Factors, Financial Factors, Technical Factors, Economic Factors, Industry Specific Factors, Company Specific Factors and Other Factors on stock price forecasting in long term.

The first objective was to examine the importance that brokers’ personally give to fundamental and technical analysis over seven forecasting horizons: intraday, 1 week, 1 month, 3 months, 6 months, 1 year and beyond 1 year. Attempt was made to understand the relative importance brokers attach to chartist / technical analysis versus fundamental analysis of stocks over seven forecasting horizons.

The second objective was to investigate the importance of Risk Factors, Liquidity Factors, Financial Factors, Technical Factors, Economic Factors, Industry Specific Factors, Company Specific Factors and Other Factors on stock price forecasting in long term. Attempt was made to understand the importance of the above factors that brokers take into consideration, while making investment in the stock market in long term.

LITERATURE REVIEW

The two general techniques for predicting stock market prices used by market professionals are “chartist” or "technical" analysis and fundamental or intrinsic value analysis.

“The technical approach to investment is essentially a reflection of the idea that prices move in trends which are determined by the changing attitudes of investors toward a variety of economic, monetary, political and psychological
forces…Since the technical approach is based on the theory that the price is a reflection of mass psychology ("the crowd") in action, it attempts to forecast future price movements on the assumption that crowd psychology moves between panic, fear, and pessimism on one hand and confidence, excessive optimism, and greed on the other.” (Pring, 1991)

Another approach which is rather different from technical approach is fundamental analysis or the intrinsic value method. The assumption of the fundamental analysis approach is that at any point in time an individual security has an intrinsic value which depends on the fundamentals of the security (earning potential of the security). The future earning potential of the security depends on factors like quality of management, outlook for the industry and the economy. Through a careful study of these fundamental factors the analyst should, be able to determine whether the actual market price of a security is above or below its intrinsic value (Fama, 1965).

Since the early 1980s, models based on economic fundamentals have been poor at explaining the movements in the exchange rates (Meese, 1990). Post world war, many of the financial economists believed technical analysis with skepticism (Malkiel, 1985; Sharpe, 1985). This skepticism might have developed from the efficient markets hypothesis, which says that speculators who do not concentrate on underlying economic fundamentals when trading will be quickly driven out of the market by smart money.

Prices can exhibit substantial short-run deviations from fundamentals due to the role of market sentiment, noise traders and limits to arbitrage. The novel time-series framework reveals that the recognition of asymmetric dynamics over the cycle (bull and bear markets) is crucial for reconciling such apparently persistent deviations and the overall mean reversion in valuation
ratios. Thus, the results not only underline the importance of noise trading and market sentiment in the short run but also corroborate that prices reflect fundamentals in the long run (Coakley et al., 2006).

As per Keynes (Keynes, 1936) financial markets are also influenced by non-fundamental factors. Any general analysis of exchange rates examines underlying economic fundamentals to explain the movements in the exchange rates, but there were situations where current fundamentals based models fail to explain the past completely, or forecast the future reliably (Dornbusch, 1976, 1987; Frankel et al., 1986, 1990a), suggest that technical analysis could have largely been responsible for the overvaluation of US dollar during the 1980's, during which period, pressure in the opposite direction was signaled by the economic fundamentals. Because of such failures, academicians and researchers have started to look into the role of non-fundamental factors influencing financial markets.

Allen et al. (1990) in their paper provides some empirical evidence concerning the nature and perceived importance of one particular kind of non-fundamentalist analysis namely chartism, in the London foreign exchange market. In questionnaire survey conducted in Germany among professional foreign exchange market participants found that rational participants use non-fundamental analysis to exploit less rational noise traders (Menkhoff, 1998). Frankel et al., (1988) developed a model that uses two approaches to forecast the exchange rate: the fundamentalist approach, which bases the forecast on economic fundamentals, and the chartist approach, which bases the forecast on the past behaviour of the exchange rate.

That 90% of the foreign exchange dealers based in London give some importance on this type of non-fundamental analysis (technical analysis) when forecasting exchange rates. Traders
rely more on technical analysis vis-à-vis fundamental analysis at shorter forecasting horizons and rely more on fundamental analysis at longer forecasting horizons. Most of the traders view technical analysis as complementary to fundamental analysis and a significant number of them suggest that technical analysis may be self-fulfilling (Taylor et al., 1992).

In a questionnaire survey conducted among foreign exchange dealers in Hong Kong on the usage of fundamental and technical analysis, more than 85% of them said that they use both fundamental and technical analysis for forecasting exchange rate movements at different time horizons. Traders rely more on technical analysis vis-à-vis fundamental analysis at shorter forecasting horizons and rely more on fundamental analysis at longer forecasting horizons. Technical analysis is considered somewhat more useful in forecasting trends than fundamental analysis, but significantly more useful in predicting turning points. Interest rate related news is found to be relatively important fundamental factor in exchange rate forecasting, while moving average and other trend-following systems are most useful technical techniques. Nevertheless, they are both given less weight than news about central bank intervention in influencing intraday exchange rate movements. Their results also imply that the two analyses are complementary to each other (Lui et al., 1998).

In a questionnaire and an interview survey on the perceived importance of fundamental and technical analysis among foreign exchange traders and financial journalists in London, Frankfurt, Vienna, and Zurich finds that most of the traders use both forecasting approaches and shorter the forecasting horizon, the more important technical analysis is. Financial Journalists place more importance on fundamental analysis than do foreign exchange traders on all forecasting
horizons investigated. Four distinct clusters of traders can be identified when you analyze over seven forecasting horizons (Intraday trading to more than 1 year) regarding use of technical and fundamental analyses (Oberlechner, 2001).

Surveys conducted later also confirm many of these early findings that traders use both technical and fundamental analysis and the usage of technical analysis is much more frequent than they do fundamental analysis at shorter horizons. Cheung et al., (2001) find that 30% of U.S. foreign exchange traders could best be characterised as technical analysts and that an increasing percentage use technical analysis. Cheung et al., (2004) confirm previous findings that traders pay more attention to non-fundamental factors at shorter horizons.

Investor sentiment and limited arbitrage do play role in determining asset prices (Shleifer et al., 1990). Neely et al., (2003) examine the out-of-sample performance of intraday technical trading strategies selected using two methodologies, a genetic program and an optimised linear forecasting model. Trading rules discover some remarkably stable patterns in the data but when transaction costs and trading hours are taken into account, they find no evidence of excess returns to the trading rules derived with either methodology.

In survey evidence from 692 fund managers in five countries, found the vast majority rely on technical analysis. When the forecasting horizon was very short, technical analysis was the most important form of analysis and thus more important than fundamental analysis. Technical analysts were found to be as experienced, as educated, as successful in their career as others. Technical analysis was found to be more popular in smaller asset management firms. What they found most significant is the relation of technical analysis with the view that prices are heavily determined by psychological influences.
Consequently, technicians apply trend-following behaviour (Menkhoff, 2010).

Irrational investor behaviour resulted in excess bond and stock market volatility (Shiller, 1984). In a study conducted in U.S. equity market to test whether intraday technical analysis is profitable, it was found that market participants place more emphasis on technical analysis (and less on fundamental analysis) the shorter the time horizon. They found that using two bootstrap methodologies, that none of the 7846 popular technical trading rules tested are profitable after data snooping bias is taken into account. There is no evidence that the market is inefficient over this time horizon (Marshall et al., 2008). Kakati’s (2005) work done examines the four aspects of valuation process. Factors/variables considered, sources of information, forecasting techniques used and valuation methodology. Each respondent was also asked to indicate the current performance of his/her portfolio against his/her expectation level and the Sensex or any other index they use as benchmark. The Cluster analysis reveals three distinct styles which are active style, passive style and balanced style. While active and balanced style seems to surpass both the investors’ own expectations and Sensex return, the passive style performs below expectation and Sensex. Step-wise regression shows that none of the economic, industry and firm variables considered in the study could lead to variation in the portfolio performance. It appears that the performance of portfolio does not depend on what variables are considered in the valuation of stocks. The most influencing aspect appear to be use of dividend discount model of expected stock returns driven by the top management forecast data.

Mitra (2009) in his paper analyses the profitability of moving average based trading rules in the Indian stock market using four stock index series. The results indicate that most
technical trading rules are able to capture the direction of market movements reasonably well and give significant positive returns both in long and short positions however these returns cannot be exploited fully due to the presence of transaction costs. Kakani et al., (2006) in their study used the Simple Moving Average (SMA) and the Displaced Moving Average (DMA) trading rules to test the weak form of efficiency on Indian stock market indexes Standard and Poor (S & P) CNX Nifty, BSE Sensex as well as multiple individual stocks for a time period of 15 years (1991–2005). Their results indicate that even after adjusting for transaction costs there was sufficient evidence that the DMA indicator is a highly successful trading rule that generates profitable signals. Pampana et al., (2005) in their study observed the profitability of applying technical trading rules using single moving averages of 5, 10, 30, 50, 100, 150 and 200 days, and dual moving averages (of various combinations) to the daily closing values of the S&P CNX Nifty index of the National Stock Exchange of India. Their results indicate that in spite of presence of transaction costs, making trading decisions based on moving average rules leads to significantly higher returns than the buy-and-hold policy. Another observation was that the shorter period single moving averages (5, 10, 30 days) and dual moving averages give better returns than longer period single moving averages.

In the study conducted for evaluating the economic feasibility of technical analysis in the Indian stock market, it was found that technical indicators do not outperform Simple Buy and Hold strategy on net return basis for individual stocks. Even though technical indicators seem to do better during market upturns compared to market downturns, technical based trading strategies are not feasible vis-à-vis passive strategy irrespective of market cycle conditions. Technical indicators also do not provide economically significant profit for industry as well as
economy based data (Sehgal et al., 2007).

Lo et al., (2000), propose a systematic and automatic approach to technical pattern recognition using non-parametric kernel regression, and applied this method to a large number of U.S. stocks from 1962 to 1996 to evaluate the effectiveness of technical analysis. They find that over the 31-year sample period, several technical indicators do provide incremental information and may have some practical value. Wong et al., (2003) in their paper say that technical analysis has a role in signaling the timing of stock market entry and exit. Moving Average and Relative Strength Index were used on Singapore Straits Times Industrial Index (STII) data and the results indicate that the indicators can be used to generate significantly positive return. It is found that member firms of Singapore Stock Exchange (SES) (No transaction costs for members) tend to enjoy substantial profits by applying technical indicators and found that most member firms do have their own trading teams that rely heavily on technical analysis.

How we forecast stock market prices now and in the future influences major economic and social policy decisions that affect not only investors but also society at large, even the world. (Shiller, 2000).

RESEARCH METHODOLOGY

After the selection and formulation of research problem, the researcher has worked out the following research design. Research design covers the following aspects.

Primary data for finding importance of chartist/technical analysis and the usage of chartist methods and services and valuation techniques was collected through conducting a well-structured online questionnaire survey.
Table 1-1. Research Methodology Framework

<table>
<thead>
<tr>
<th>Number</th>
<th>Topic</th>
<th>Sub-topic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1.1</td>
<td>Sources of data</td>
<td>Primary data</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Secondary data</td>
</tr>
<tr>
<td>1.1.2</td>
<td>Sampling Plan</td>
<td>Sampling units</td>
</tr>
<tr>
<td></td>
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<td>Sample size</td>
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<td></td>
<td></td>
<td>Sampling procedure</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sampling contact method</td>
</tr>
<tr>
<td>1.1.3</td>
<td>Methods of data collection</td>
<td>Design of Questionnaire</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Testing of Questionnaire</td>
</tr>
<tr>
<td>1.1.4</td>
<td>Data analysis tools and</td>
<td>One way ANOVA</td>
</tr>
<tr>
<td></td>
<td>techniques</td>
<td>t-test</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Chi-square test</td>
</tr>
</tbody>
</table>

Sources of data: The study was based on both Primary data and Secondary data.

Secondary data is the data which already exists in various sources like, newspapers, magazines, journals, company brochures, Census reports, Government reports, etc. Internet has emerged as a major source of collecting secondary data. Sources of secondary data for the current research were as follows:

- Research works of various scholars.
- Journals and Magazines.
- Websites of regulators like SEBI, RBI.
- Databases like Science Direct.
- Journals and Magazines.
- Websites of stock exchanges like NSE and BSE.
- Books and other literature in the following related areas: Corporate Finance, Technical Analysis, Valuation, Research Methodology, etc.
- Newspapers and Articles.
Sampling Plan

The sampling plan for the current thesis consisted of sampling units, sample size, sampling procedure and sampling contact method.

The sampling units contacted were corporate brokers registered with Bombay Stock Exchange.

Sample comprised of 262 respondents selected using probability random sampling technique. The sample size of 262 is justified using the most popularly used equation based on precision rate and confidence level (Kothari, 2004). To calculate the sample size ‘n’, size of the population ‘N’ is required. From the regulator of stock market, Securities and Exchange Board of India website, the total corporate broker population (N) in the Bombay Stock Exchange for the year ending 2009-10 was identified as 826. Thus sample size is calculated as below (Table 1.2):

Table 1.2. Determination of Sample Size

\[
\begin{align*}
n &= \left\{ \frac{Z^2(pq)N}{e^2(N-1) + Z^2(pq)} \right\} \\
n &= \left\{ \frac{(1.96)^2(0.5 \times 0.5)826}{(0.05)^2(826 - 1) + (1.96)^2(0.5 \times 0.5)} \right\} \\
n &= \frac{793.2904}{(0.0025)(826 - 1) + 0.9604} \\
n &= 262
\end{align*}
\]

Source: Kothari (2004)

Probability random sampling technique was used for the p
purpose of collecting the sampling units. Sample units of 262 were, then selected using simple random sampling technique using random number generation method and rand between function.

The selected sampling units (corporate brokers in this case) were approached via online survey through their email addresses. Survey Monkey was used to conduct the online survey.

Methods of Data collection

The current research required primary data. For this purpose, questionnaire was used.

First of all information needed for research work was specified. Required demographic data included was age, gender, location of the office, email address, relevant work experience.

For objective one, brokers were asked to indicate on the 10 point Likert scale the relative importance they attach to technical analysis versus fundamental analysis of stocks over seven forecasting horizons: intraday, 1 week, 1 month, 3 months, 6 months, 1 year and beyond 1 year. A score of zero would indicate the use of pure chartist (technical) analysis alone at that horizon and a score of ten would indicate the use of pure fundamental analysis and an intermediate score would indicate a weighted mix of technical analysis and fundamental analysis.

For objective two, brokers were asked to rate on the 5 point Likert scale the importance of the different factors that they take into consideration while making investment in the stock market in the long term. Scale indicating very important at one end to very unimportant at the other end was used.

We sent respondents the link to the questionnaire through email, thus conducting online web based survey for collecting primary data.
Testing of questionnaire

It was decided to test the validity and reliability of the questionnaire. For this purpose, firstly the researcher has identified different approaches available. There are various methods of testing a questionnaire like Test/Retest approach, Test of face validity, conducting pilot study, etc. (Malhotra, 2007). Pilot study was conducted.

Data analysis tools and techniques

In order to extract meaningful information from the raw data collected, the data analysis was carried out by the researcher. The data were first edited, coded and tabulated for the purpose of analysing them. The analysis was conducted by using simple statistical tools like percentages, averages and measures of dispersion. Diagrams, graphs, charts and pictures were used.

One way ANOVA, t-tests and Chi-square analysis were used for the purpose of testing the hypotheses. Data analysis software SPSS (version 19) package was used to conduct, one way ANOVA, t-tests and Chi-square tests.

Data Analysis & Interpretation

For conducting the research on the use of technical and fundamental analysis among corporate brokers of Bombay Stock Exchange, a sample of 262 respondents (Table 1.2) were selected using probability random sampling technique. The sample size of 262 was justified using the most popularly used equation based on precision rate and confidence level (Kothari, 2004). Among 262 corporate brokers 152 corporate brokers participated in the survey. Response rate was 58%.

Out of 152 responses males were 142 (93.4%) and the rest 10 were females (6.6%). Following table and subsequent Chart present this data:
Table 1-3. Age Groups of the Respondents

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Response Percent</th>
<th>Response Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under 25</td>
<td>7.9%</td>
<td>12</td>
</tr>
<tr>
<td>26 to 35</td>
<td>50.7%</td>
<td>77</td>
</tr>
<tr>
<td>36 to 45</td>
<td>25.0%</td>
<td>38</td>
</tr>
<tr>
<td>46 to 55</td>
<td>13.2%</td>
<td>20</td>
</tr>
<tr>
<td>56 to 65</td>
<td>3.3%</td>
<td>5</td>
</tr>
<tr>
<td>66 to 75</td>
<td>0.0%</td>
<td>0</td>
</tr>
<tr>
<td>Over 75</td>
<td>0.0%</td>
<td>0</td>
</tr>
<tr>
<td>TOTAL</td>
<td>100%</td>
<td>152</td>
</tr>
</tbody>
</table>

AGE GROUPS

Next important demographic information of the respondents was their age group.

Table 1-4. Age Groups of the Respondents

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<td>0</td>
</tr>
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<td>0</td>
</tr>
<tr>
<td>TOTAL</td>
<td>100%</td>
<td>152</td>
</tr>
</tbody>
</table>
The above table and Chart present the age groups of the respondents who participated in the survey. Out of 152 respondents, 7.9% were less than 25 age, 50.7% in the age group of 26-35, 25.0% in the age group of 36-45, 13.2% in the age group of 46-55, 3.3% in the age group of 56-65 and 0% in the age group of 66-75 and over 75. Most of the respondents were in the age group of 26-35.

RELEVANT WORK EXPERIENCE

Next important demographic information of the respondents was the relevant work experience they had. We categorised them into three groups based on the work experience they had. These categories were Junior Level, Middle Level and Senior Level.

<table>
<thead>
<tr>
<th>CATEGORY</th>
<th>Relevant Work Experience</th>
<th>Response Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Junior Level</td>
<td>19.74%</td>
<td>30</td>
</tr>
<tr>
<td>Middle Level</td>
<td>40.13%</td>
<td>61</td>
</tr>
<tr>
<td>Senior Level</td>
<td>40.13%</td>
<td>61</td>
</tr>
<tr>
<td>TOTAL</td>
<td>100%</td>
<td>152</td>
</tr>
</tbody>
</table>

The above table present the categorisation of relevant work experience of the respondents who participated in the survey. Out of 152 respondents, 19.74% were in the Junior Level category, 40.13% were in the Middle Level category and 40.13% were in the Senior Level category. Most of the respondents were in the Middle and Senior Level category.
Objective 1: Time Period Analysis

ANOVA One Way Using SPSS

First objective of the current research was to examine the importance that brokers’ personally give to fundamental and technical analysis over seven forecasting horizons: intraday, 1 week, 1 month, 3 months, 6 months, 1 year and beyond 1 year. Hence it was decided to conduct means test using one way ANOVA (Oberlechner, 2001). For this purpose, basing on the literature available, following hypotheses were set up and further tested.

HYPOTHESIS

H₀: Mean Importance ratings over seven forecasting horizons are equal i.e.

H₀: \( \mu_{\text{intraday}} = \mu_{\text{1 week}} = \mu_{\text{1 month}} = \mu_{\text{3 months}} = \mu_{\text{6 months}} = \mu_{\text{1 year}} = \mu_{\text{> 1 year}} \)

Hₐ: Mean Importance ratings over seven forecasting horizons are not equal i.e.

Hₐ: \( \mu_{\text{intraday}} \neq \mu_{\text{1 week}} \neq \mu_{\text{1 month}} \neq \mu_{\text{3 months}} \neq \mu_{\text{6 months}} \neq \mu_{\text{1 year}} \neq \mu_{\text{> 1 year}} \)

<table>
<thead>
<tr>
<th>Table 1-6. One Way ANOVA of Time Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of Squares</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>Between Groups</td>
</tr>
<tr>
<td>Within Groups</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>


A one way ANOVA was used to test the influence of Time Period (Hypothesis), on importance ratings in stock price forecasting.

Table 1-7. Robust Tests of Equality of Means-Time Period

<table>
<thead>
<tr>
<th>Statistic</th>
<th>df1</th>
<th>df2</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Welch</td>
<td>120.722</td>
<td>6</td>
<td>469.203</td>
</tr>
<tr>
<td>Brown-Forsythe</td>
<td>126.138</td>
<td>6</td>
<td>1009.821</td>
</tr>
</tbody>
</table>

One way ANOVA of Time Period was found to be significant at p<.05, (F (6, 1057) = 126.138, p=.000). Welch test of Homogeneity of Variances was also found to be significant at p < .05, (Welch (6, 469.203) =120.722, p=.000) and Brown Forsythe test of Homogeneity of Variances was also found to be significant at p < .05, (Brown-Forsythe (6, 1009.81) =126.138, p=.000). These two tests say that variances among groups are Homogeneous.

As One way ANOVA of Time Period was significant, we then conducted Post Hoc Tests to find out between which pairs’ of Time Period significance exists.

Tamhane post-hoc comparisons of the seven forecasting horizons indicate that the Intraday (M = 2.92, SD= 3.168) is statistically significant with respect to the 1Month (M =4.82, SD=2.812, p=.000), 3 Months (M = 5.74, SD=2.654, p=.000), 6 Months (M = 7.14, SD=2.437, p=.000), 1 Year (M = 8.54, SD=2.350, p=.000) and > 1 Year (M = 9.43, SD=2.666, p=.000). Comparisons between the Intraday and 1 Week was not statistically significant at p< .05.

Tamhane post-hoc comparisons of the seven forecasting horizons indicate that the 1 Week (M = 3.25, SD= 3.152) is statistically significant with respect to the 1Month (M =4.82, SD=2.812, p=.000), 3 Months (M = 5.74, SD=2.654, p=.000), 6 Months (M = 7.14, SD=2.437, p=.000), 1 Year (M = 8.54, SD=2.350, p=.000) and > 1 Year (M = 9.43, SD=2.666, p=.000).
SD=2.350, p=.000) and > 1 Year (M = 9.43, SD=2.666, p=.000). Comparisons between the Intraday and 1 Week was not statistically significant at p<.05.

Tamhane post-hoc comparisons of the seven forecasting horizons indicate that the 1Month (M = 4.82, SD=2.812) is statistically significant with respect to the Intraday (M = 2.92, SD= 3.168), 1 Week (M = 3.25, SD= 3.152, p=.000), 6 Months (M = 7.14, SD=2.437, p=.000), 1 Year (M = 8.54, SD=2.350, p=.000) and > 1 Year (M = 9.43, SD=2.666, p=.000). Comparisons between the 1Month and 3 Months were not statistically significant at p<.05.

Tamhane post-hoc comparisons of the seven forecasting horizons indicate that the 3 Months (M = 5.74, SD=2.654), is statistically significant with respect to the Intraday (M = 2.92, SD= 3.168), 1 Week (M = 3.25, SD= 3.152, p=.000), 6 Months (M = 7.14, SD=2.437, p=.000), 1 Year (M = 8.54, SD=2.350, p=.000) and > 1 Year (M = 9.43, SD=2.666, p=.000). Comparisons between the 3 Months and 1 Month were not statistically significant at p<.05.

Tamhane post-hoc comparisons of the seven forecasting horizons indicate that the 6 Months (M = 7.14, SD=2.437) is statistically significant with respect to the Intraday (M = 2.92, SD= 3.168, p=.000), 1 Week (M = 3.25, SD= 3.152 p=.000), 1Month (M =4.82, SD=2.812, p=.000), 3 Months (M = 5.74, SD=2.654, p=.000), 1 Year (M = 8.54, SD=2.350, p=.000) and > 1 Year (M = 9.43, SD=2.666, p=.000).

Tamhane post-hoc comparisons of the seven forecasting horizons indicate that the 1 Year (M = 8.54, SD=2.350) is statistically significant with respect to the Intraday (M = 2.92, SD= 3.168, p=.000), 1 Week (M = 3.25, SD= 3.152 p=.000), 1Month (M =4.82, SD=2.812, p=.000), 3 Months (M = 5.74, SD=2.654, p=.000), 6 Months(M = 7.14, SD=2.437,p=.000) and >
1 Year (M = 9.43, SD=2.666, p=.000).

Tamhane post-hoc comparisons of the seven forecasting horizons indicate that the > 1 Year (M = 9.43, SD=2.666) is statistically significant with respect to the Intraday (M = 2.92, SD= 3.168, p=.000), 1 Week (M = 3.25, SD= 3.152 p=.000), 1Month (M =4.82, SD=2.812, p=.000), 3 Months (M = 5.74, SD=2.654, p=.000), 6 Months M = 7.14, SD=2.437,p=.000) and 1 Year (M = 8.54, SD=2.350, p=.000)

Table 1-8. Overall Means of Time Period

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Overall Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intraday</td>
<td>2.92</td>
</tr>
<tr>
<td>1 Week</td>
<td>3.25</td>
</tr>
<tr>
<td>1 Month</td>
<td>4.82</td>
</tr>
<tr>
<td>3 Months</td>
<td>5.73</td>
</tr>
<tr>
<td>6 Months</td>
<td>7.14</td>
</tr>
<tr>
<td>1 Year</td>
<td>8.53</td>
</tr>
<tr>
<td>&gt; 1 Year</td>
<td>9.43</td>
</tr>
</tbody>
</table>

From overall means of seven forecasting horizons (Table 1.8) it can be interpreted that at shorter horizons the skew is towards use of Pure Chartist Analysis and with increase in duration the skew shifts towards use of Pure Fundamental Analysis.

**Cluster Analysis**

Brokers’ overall forecasting approaches were determined by the mean value of their individual ratings given on the seven forecasting horizons. Cluster analysis was done to arrive at different classification of forecasting styles. This statistical method determines homogeneous groups of brokers using similar forecasting styles across the different time horizons examined. Cluster analysis is able to differentiate between brokers who
arrived at same mean value of ratings by the use of different forecasting styles across the seven forecasting periods.

A hierarchical cluster analysis using Ward’s clustering method and squared Euclidean distance measures suggested a solution of four relatively homogeneous clusters of forecasting styles. Then k-means, non-hierarchical cluster analysis was conducted to divide brokers optimally into the four clusters. Chart 1.4 gives a picture of the four identified forecasting styles.

The largest cluster (54.60%) of brokers represents the forecasting profile termed ‘chartist, ascending’ which starts with a very technical (chartist) approach at intraday and 1 week forecasts (1 on the scale from 1= pure chartist analysis to 11= pure fundamental analysis).

Chart 1-4. Forecasting Styles
The longer the forecasting period, the more fundamental this forecasting approach becomes, and brokers in this cluster progress to a purely fundamental forecasting approach in forecasting periods greater than 1 year (Mean=10 on the 1-11 scale). Brokers in the ‘fundamental, ascending’ cluster (21.05%) have a forecasting profile which looks like the ‘chartist, ascending’ profile described above. However, brokers in this cluster begin with a relatively more fundamental forecasting approach in intraday forecasts (Mean=3 on the 1-11 scale) and with increasingly longer forecasting horizons, apply a progressively more fundamental approach, ending with purely fundamental approach in forecasting horizons greater than 1 year (Mean=10 on the 1-11 scale).

Brokers in the ‘constant chartist’ cluster (13.81%) apply a constantly chartist forecasting approach across all time periods (Mean=4 over all forecasting periods on the 1-11 scale). The last category of brokers (10.52%) is termed as ‘constant fundamental’ apply a constantly fundamental forecasting approach across all time periods (Mean=10 mostly over all forecasting periods on the 1-11 scale).

Detailed analyses of these four forecasting styles and brokers’ demographic variables show that like the overall chartism versus fundamentalism approaches, these forecasting styles do also not correlate with brokers’ age ($\chi^2=11.020$, $p=.527$), gender ($\chi^2=4.941$, $p=.176$) and experience ($\chi^2=11.386$, $p=.250$).

**OBJECTIVE 2-IMPORTANCE FACTORS' ANALYSIS ANOVA ONE WAY USING SPSS**

Second objective of the current research was to investigate the importance of Risk Factors, Liquidity Factors, Financial Factors, Technical Factors, Economic Factors, Industry Specific Factors,
Company Specific Factors and Other Factors on stock price forecasting in long term. Hence it was decided to conduct means test using one way ANOVA (Oberlechner, 2001). For this purpose, basing on the literature available, following hypotheses were set up and further tested.

**Ho:** Means of importance ratings of all Factors are equal i.e.
\[ \mu_{\text{Risk Factors}} = \mu_{\text{Liquidity Factors}} = \mu_{\text{Financial Factors}} = \mu_{\text{Technical Factors}} = \mu_{\text{Economic Factors}} = \mu_{\text{Industry Specific Factors}} = \mu_{\text{Company Specific Factors}} = \mu_{\text{Other Factors}}. \]

**Ha:** Means of importance ratings of all Factors are not equal i.e.
\[ \mu_{\text{Risk Factors}} \neq \mu_{\text{Liquidity Factors}} \neq \mu_{\text{Financial Factors}} \neq \mu_{\text{Technical Factors}} \neq \mu_{\text{Economic Factors}} \neq \mu_{\text{Industry Specific Factors}} \neq \mu_{\text{Company Specific Factors}} \neq \mu_{\text{Other Factors}}. \]

A one-way ANOVA was used to test the importance given to eight different factors: Risk Factors, Liquidity Factors, Financial Factors, Technical Factors, Economic Factors, Industry Specific Factors, Company Specific Factors and Other Factors in stock price forecasting by brokers in long term.

**Table 1.9. One way ANOVA of importance factors**

<table>
<thead>
<tr>
<th></th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Groups</td>
<td>155.102</td>
<td>7</td>
<td>22.157</td>
<td>37.915</td>
<td>.000</td>
</tr>
<tr>
<td>Within Groups</td>
<td>705.947</td>
<td>1208</td>
<td>.584</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>861.049</td>
<td>1215</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 1·10. Robust Tests of Equality of Means-Importance Factors

<table>
<thead>
<tr>
<th>Importance Rating</th>
<th>Statistica</th>
<th>df1</th>
<th>df2</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Welch</td>
<td>35.109</td>
<td>7</td>
<td>517.342</td>
<td>.000</td>
</tr>
<tr>
<td>Brown-Forsythe</td>
<td>37.915</td>
<td>7</td>
<td>1165.048</td>
<td>.000</td>
</tr>
</tbody>
</table>

A one-way ANOVA was used to test the importance given to eight different factors: Risk Factors, Liquidity Factors, Financial Factors, Technical Factors, Economic Factors, Industry Specific Factors, Company Specific Factors and Other Factors in stock price forecasting in long term. The analysis showed significant difference across these eight factors at the p<.05, (F (7, 1208) =37.915, p = .000).

Welch test of Homogeneity of Variances was also found to be significant at the p < .05, (Welch (7, 517.342) = 35.109, p=.000) and Brown Forsythe test of Homogeneity of Variances was also found to be significant at the p < .05, (Brown Forsythe (7, 1165.048) =37.915, p=.000). These two tests say that variances among groups are Homogeneous.

As one way ANOVA of importance factors was significant, we then conducted Post Hoc Tests to find out between which pairs’ of importance factors significance exists.

**Post Hoc Tests**

Tamhane post-hoc comparisons of the eight factors indicate that the Risk Factor (M = 4.47, SD= 0.745) is statistically significant with respect to the Liquidity Factor (M = 4.09, SD=0.772, p=.000), Technical Factor (M = 3.73, SD=0.876, p=.000), Economic Factor (M = 4.03, SD=0.736 p=.000), and others (M = 3.53, SD=0.861, p=.000). Comparisons between the
Risk Factor and the other three factors: Financial, Industry Specific and Company Specific was not statistically significant at p< .05.

Tamhane post-hoc comparisons of the eight factors indicate that the Liquidity Factor (M = 4.09, SD=0.772) is statistically significant with respect to the Risk Factor (M = 4.47, SD= 0.745, p=.000), Financial Factor(M=4.51, SD=0.661, p=.000), Technical Factor (M = 3.73, SD=0.876, p=.006), Industry Specific Factor (M = 4.40, SD=0.766, p=.011), Company Specific Factor (M = 4.52, SD=0.671, p=.000), and others (M = 3.53, SD=0.861, p=.000). Comparison between the Liquidity Factor and the Economic Factor was not statistically significant at p< .05.

Tamhane post-hoc comparisons of the eight factors indicate that the Financial Factor (M=4.51, SD=0.661) is statistically significant with respect to the Liquidity Factor (M = 4.09, SD=0.772, p=.000), Technical Factor (M = 3.73, SD=0.876, p=.000), Economic Factor (M = 4.03, SD=0.736, p=.000), and others (M = 3.53, SD=0.861, p=.000). Comparisons between the Financial Factor and the other three factors: Risk, Industry Specific and Company Specific was not statistically significant at p< .05.

Tamhane post-hoc comparisons of the eight factors indicate that the Technical Factor (M = 3.73, SD=0.876) is statistically significant with respect to the Risk Factor (M = 4.47, SD= 0.745, p=.000), Liquidity Factor (M = 4.09, SD=0.772, p=.006), Financial Factor(M=4.51, SD=0.661, p=.000), Economic Factor (M = 4.03, SD=0.736, p=.043), Industry Specific Factor (M = 4.40, SD=0.766, p=.000) and Company Specific Factor (M = 4.52, SD=0.671, p=.000). Comparison between the Technical Factor and the others was not statistically significant at p< .05.

Tamhane post-hoc comparisons of the eight factors indicate that the Economic Factor (M = 4.03, SD=0.736), is statistically
significant with respect to the Risk Factor ($M = 4.47$, $SD= 0.745$, $p=.000$), Financial Factor($M=4.51$, $SD=0.661$, $p=.000$), Technical Factor ($M = 3.73$, $SD=0.876,p=.043$), Industry Specific Factor ($M = 4.40$, $SD=0.766$, $p=.001$), Company Specific Factor ($M = 4.52$, $SD=0.671$, $p=.000$) and others ($M = 3.53$, $SD=0.861$, $p=.000$). Comparison between the Economic Factor and the Liquidity Factor was not statistically significant at $p< .05$.

Tamhane post-hoc comparisons of the eight factors indicate that the Industry Specific Factor ($M = 4.40$, $SD=0.766$), is statistically significant with respect to the Liquidity Factor ($M = 4.09$, $SD=0.772$, $p=.011$), Technical Factor ($M = 3.73$, $SD=0.876$, $p=.000$), Economic Factor ($M = 4.03$, $SD=0.736$, $p=.001$), and others ($M = 3.53$, $SD=0.861$, $p=.000$). Comparisons between the Industry Specific Factor and the other three factors: Risk, Financial and Company Specific was not statistically significant at $p<.05$.

Tamhane post-hoc comparisons of the eight factors indicate that the Company Specific Factor ($M = 4.52$, $SD=0.671$), is statistically significant with respect to the Liquidity Factor ($M = 4.09$, $SD=0.772$, $p=.000$), Technical Factor ($M = 3.73$, $SD=0.876$, $p=.000$), Economic Factor ($M = 4.03$, $SD=0.736$, $p=.000$), and others ($M = 3.53$, $SD=0.861$, $p=.000$). Comparisons between the Company Specific Factor and the other three factors: Risk, Financial and Industry Specific were not statistically significant at $p< .05$.

Tamhane post-hoc comparisons of the eight factors indicate that the Others ($M = 3.53$, $SD=0.861$), is statistically significant with respect to the Risk Factor ($M = 4.47$, $SD= 0.745$, $p=.000$), Liquidity Factor ($M = 4.09$, $SD=0.772$, $p=.000$), Financial Factor($M=4.51$, $SD=0.661$, $p=.000$), Economic Factor ($M = 4.03$, $SD=0.736$, $p=.000$), Industry Specific Factor ($M = 4.40$, $SD=0.766$, $p=.000$) and Company Specific Factor ($M = 4.52$, $SD=0.671$, $p=.000$) and others ($M = 3.53$, $SD=0.861$, $p=.000$).
p= .000). Comparison between the Others Factor and the Technical Factor was not statistically significant at p< .05.

Specifically our results suggest that Company Specific Factor was rated the most important (M = 4.52) and Others Factor was rated the least (M = 3.53) in stock price forecasting. (Greater the mean greater the importance attached (Table 4.59). Rest of the factors in the order of rating importance were Financial Factor (M=4.51), Risk Factor (M = 4.47), Industry Specific Factor (M = 4.40), Liquidity Factor (M = 4.09), Economic Factor (M = 4.03) and Technical Factor (M = 3.73).

Table 1-11. Means of Importance Factors

<table>
<thead>
<tr>
<th>Importance Factor</th>
<th>Mean Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company Specific Factors</td>
<td>4.52</td>
</tr>
<tr>
<td>Financial Factors</td>
<td>4.51</td>
</tr>
<tr>
<td>Risk Factors</td>
<td>4.47</td>
</tr>
<tr>
<td>Industry Specific Factors</td>
<td>4.40</td>
</tr>
<tr>
<td>Liquidity Factors</td>
<td>4.09</td>
</tr>
<tr>
<td>Economic Factors</td>
<td>4.03</td>
</tr>
<tr>
<td>Technical Factors</td>
<td>3.73</td>
</tr>
<tr>
<td>Others</td>
<td>3.53</td>
</tr>
</tbody>
</table>

Taken together these results suggest that Risk Factor, Liquidity Factor, Financial Factor, Technical Factor, Economic Factor, Industry Specific Factor, Company Specific Factor and Others Factor do play important role in stock price forecasting even though intra-significance level is varying.
Table 1-12. Homogeneous Subsets of Importance Factors

<table>
<thead>
<tr>
<th>Factors</th>
<th>Subset for alpha = 0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
</tr>
<tr>
<td>Company Specific Factors</td>
<td>152</td>
</tr>
<tr>
<td>Financial Factors</td>
<td>152</td>
</tr>
<tr>
<td>Risk Factors</td>
<td>152</td>
</tr>
<tr>
<td>Industry Specific Factors</td>
<td>152</td>
</tr>
<tr>
<td>Liquidity Factors</td>
<td>152</td>
</tr>
<tr>
<td>Economic Factors</td>
<td>152</td>
</tr>
<tr>
<td>Technical Factors</td>
<td>152</td>
</tr>
<tr>
<td>Others</td>
<td>152</td>
</tr>
<tr>
<td>Sig.</td>
<td></td>
</tr>
</tbody>
</table>

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 152.000.

Company Specific Factor, Financial Factor, Risk Factor and Industry Specific Factor gave significantly higher importance ratings than the Liquidity Factor, Technical Factor, Economic Factor and Others Factor. Liquidity Factor and Economic Factor gave significantly higher importance ratings than the Technical Factor and Others Factor.

Company Specific Factors, Financial Factors, Risk Factors and Industry Specific Factors are grouped into one homogeneous set. Liquidity Factors and Economic Factors are grouped into one homogeneous set. Technical Factors and Others Factor are grouped into one homogeneous set.
PRACTICAL IMPLICATIONS

These findings have some practical implications. First, as professional traders do not trade purely on the basis of the economic fundamentals, but also take into account market movements generated by other factors (noise trading), knowledge of technical analysis is important to anyone who would like to participate successfully in the stock market. Second, the existence of a skew towards reliance on fundamental analysis at longer horizons suggests that models based on economic considerations will be more important on the long run. Third, the existence of a skew towards reliance on technical analysis at shorter horizons
suggests that models based on short term considerations (noise) will be more important in the short term.

Fourth, the identification of different investment styles of brokers would help in understanding functioning of stock market better. Fifth, with respect to long term investment in the stock market, investors need to note that brokers pay special attention to company specific factors and financial factors.

CONCLUSIONS & RECOMMENDATIONS

Objective 1· Time Period
A one-way Analysis of Variance of Time Period to examine the importance that brokers’ personally give to fundamental and technical analysis over seven forecasting horizons: intraday, 1 week, 1 month, 3 months, 6 months, 1 year and beyond 1 year reveal that Time Period did had a significant effect (Hypothesis testing, Table 1.6).

As one-way Analysis of Variance of Time Period was found to be significant (Hypothesis testing, Table 1.6), we then conducted Post Hoc Tests of Time period to find out between which pairs’ of Time period significance exists. Post Hoc Tests of Time period was also found to be significant. Thus it could be interpreted that the importance that brokers’ personally give to fundamental and technical analysis over seven forecasting horizons: intraday, 1 week, 1 month, 3 months, 6 months, 1 year and beyond 1 year is not the same. Brokers’ rating differed depending on the forecasting horizon. From the overall means of seven forecasting horizons (Table 1.8) it can be interpreted that at shorter time periods (Intraday, 1 week and 1 month), there exists a skew towards reliance on technical analysis as compared to fundamental analysis, but as the length of time period increases (6 months, 1 year and > 1 year) the skew shifts to fundamental
analysis. This suggests that models that focus on fundamentals may perform poorly over short horizons because they miss the effect of technical analysis based decision on the market in the short period.

As professional traders do not trade purely on the basis of the economic fundamentals, but also take into account market movements generated by other factors (noise trading), hence it is recommended that knowledge of technical signals is important to anyone who would like to participate successfully in the stock market. It is also recommended that Technical analysis tools should be taught in Management Programmes along with fundamental analysis tools. The existence of a skew towards reliance on technical analysis at shorter horizons, suggest that models based on short term considerations (noise) will be more important in the short term hence, it is suggested that technical analysis should be used mainly for short term stock price prediction.

The existence of a skew towards reliance on fundamental analysis at longer horizons suggests that models based on economic considerations will be more important on the long run hence; it is recommended that fundamental analysis should be used mainly for long term stock price prediction.

Objective 2: Importance Factors

A one-way Analysis of Variance (Oberlechner, 2001) was conducted to test the importance given to eight different factors: Risk Factors, Liquidity Factors, Financial Factors, Technical Factors, Economic Factors, Industry Specific Factors, Company Specific Factors and Other Factors in stock price forecasting by brokers in long term. The analysis showed significant difference across these eight factors (Hypothesis testing, Table 1.9).

As One way Analysis of Variance of importance factors
was significant, we then conducted Post Hoc Tests and found out that significance exists between different pairs’ of importance factors. Thus it could be interpreted that brokers clearly perceive different factors differently. They gave more importance to few factors than others when they forecast stock prices in long term.

Company Specific Factors, Financial Factors, Risk Factors and Industry Specific Factors are grouped into one homogeneous set. Liquidity Factors and Economic Factors are grouped into one homogeneous set. Technical Factors and Others Factor are grouped into one homogeneous set (Table 1.12). Specifically our results suggest that Company Specific Factor was rated the most important and Others Factor was rated the least in stock price forecasting (Table 1.11). As company specific factors were rated as most important hence, it is recommended that investors need to look into company specific factors like quality of management, quality of audit report / auditors, bonus issues which effect the investment decision. As others factor was rated the least important hence, it is recommended that, the factors which investors need to concentrate less are political factors, astrology, dispersion of analyst forecast etc.

Company Specific Factor, Financial Factor, Risk Factor and Industry Specific Factor gave significantly higher importance ratings than the Liquidity Factor, Technical Factor, Economic Factor and Others Factor (Table 1.12). Liquidity Factor and Economic Factor gave significantly higher importance ratings than the, Technical Factor and Others Factor, (Table 1.12).

SCOPE AND LIMITATIONS OF THE STUDY

The first objective was to examine the importance that brokers’ personally give to fundamental and technical analysis over seven forecasting horizons: intraday, 1 week, 1 month, 3 months, 6
months, 1 year and beyond 1 year. For this purpose researcher has conducted online questionnaire survey among corporate stock brokers registered with Bombay Stock Exchange in India only. Online survey was conducted for this purpose as the brokers were geographically distributed all over India and the cost and time involved in reaching them personally was huge. Attempt was made to understand the relative importance brokers attach to chartist/technical analysis versus fundamental analysis of stocks over seven forecasting horizons.

The second objective was to investigate the importance of Risk Factors, Liquidity Factors, Financial Factors, Technical Factors, Economic Factors, Industry Specific Factors, Company Specific Factors and Other Factors on stock price forecasting in long term. Attempt was made to understand the importance of the above factors that brokers take into consideration, while making investment in the stock market in long term.

The study was limited to only select approaches namely technical approach and fundamental approach and the study was limited to only select strategic factors. Another limitation of the study was economic conditions might have varied over time as the survey was taken quite some time to complete.

**SCOPE FOR FURTHER RESEARCH**

Further study can be done by comparing developed stock markets with emerging and developing stock markets across countries investigating the differences in usage of technical and fundamental analysis among different players in the stock market like Mutual Fund Managers, Brokers, Investment Bankers, Financial News Reporters, and Financial Analysts etc and also investigate other strategic factors which influence brokers decisions.
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