PORTFOLIO PERFORMANCE & PREDICTIVE RELEVANCE THROUGH TECHNO-FUNDAMENTAL ANALYSIS- A HYBRID ARIMA APPROACH

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ABSTRACT

Purpose: The primary purpose of this paper is to understand the portfolio performance & predictive relevance of Techno-Fundamental analysis through Hybrid ARIMA. Can we leverage the portfolio selection, investment optimisation & predictive relevance through Techno-fundamental analysis?

Design /Methodologies/Approach: In this paper, we have selected the National Stock Exchange selected shares & apply fundamental analysis for selecting portfolio & technical analysis along with algorithmic trading for superior earning optimization, furthermore, Hybrid ARIMA to validate predictive relevance. The empirical analysis includes the chosen portfolio from Jan 2014 to May 2020.

Originality & Value: This paper is written primarily for those financial enthusiasts who want to take leverage of synergy i.e., Technical analysis & Fundamental analysis to optimise their portfolio.

Results & Practical implication: The successful application of "L- FANTAM" approach will encourage the practitioners & academicians of Financial markets to research & explore further uses & practical impact of the present study.

KEYWORDS: Technical Analysis, Fundamental Analysis, Hybrid ARIMA, Backtest, Nifty Index, Portfolio, Expert System, Algorithmic Trading/Investment

JEL Classification: F37 "International Finance Forecasting & Simulation: Models & Application"

Received: Jun 10, 2020; **Accepted:** Jun 30, 2020; **Published:** Jul 27, 2020; **Paper Id.:** IJMPERDJUN2020471

INTRODUCTION

In the past, Fundamental analysis & Technical analysis has been used separately for understanding the phenomena of the stock market. Both schools of thought have been practice without interacting, as well. Understanding the strength & weaknesses of both the analysis may give an evident strategy building competence & may fulfil the dream of "Beat the market" through the proposed fusion of two different schools of thought. i.e. L-FANTAM Frontier Predictive Model (Leveraging Fundamental& Technical Analysis Model).

The aim of this study to test the performance & predictive effectiveness of "Leveraging Fundamental & Technical analysis" on the National Stock Exchange selected valued shares, during the sample period 2014-2020 with the help of Hybrid ARIMA.

The combination & synchronization of fundamental & technical analysis demonstrates that an investor may get a higher rate of return than the return of the benchmark (Nifty50) or fixed deposit.

The first important task is to create a diversified portfolio with defined rules of Fundamental Analysis value investing by Benjamin Graham, second optimize returns with the help of a Technical analysis & then use

Hybrid ARIMA to understand the significance of prediction of selected valued stock. The research is based on the authors' own methods of producing a sequence of stages in a specific time range.

This Paper Consists of Five-Part:

- Theoretical concept building.
- Description of research methods.
- Selection of Stock.
- Optimisation of Stocks.
- Validate performance & predictive relevance.

LITERATURE REVIEW

In the context of trading & investing, both Fundamental & Technical analysis strategies (in isolation) have been dominating the stock market for long (**Fama 1965; Leigh, Purvis & Ragusa 2002; Malkiel 2007; Sharpe 1985; Sharpe, Alexander & Bailey 1999; Spritzer & Freitas 2006; Sternberg & Lubart 1992; Vanstone 2006**). Both investing school of thought i.e. Fundamental & Technical analysis uses trends but in a different way altogether. The fundamental analysis focus on historical information like net profit, sales, revenue, etc. whereas Technical analysis focus on past prices & volume, etc. (**Thomsett, MC 1998**).

Murphy (1999) outlines three philosophies behind the strategy:

- Prices move in trends
- The market discounts everything and
- History tends to repeat itself.

Now a day, many professional traders use a combination of both the investment strategies to give an edge in the investment world (**Bernstein 1998**)

With the help of several survey many researchers support the combination of fundamental & technical analysis strategies for investment. For example, the study done by **Arnold and Moizer (1984)** and **Taylor and Allen (1992)** in the United Kingdom (UK), **Menkhoff (2010)** in the US Germany, Switzerland, Italy, advocates that professional trader & investors mainly uses fundamental & technical analysis over any other strategy like portfolio analysis.

Burton Malkiel (2003, pp.113-116) describing in their research that P/E ratio is a good fundamental tool, as well as a technical signal, is also very useful to identify the best possible time to buy-sell stocks. He suggests that both the analysis is widely used in the market.

William O'Neill (2000, pp.19-24) his long experience in the market proves that an investor not only wants to get the information regarding the strength, quality, management & the controlling condition of a company but also interested in to know about the stock price behave in the market.

Romain Belair (2010), "The impact of volatility on the implementation of RSI, this paper reveals the importance of volatility over the trading rule, by using RSI in the Chinese Stock Exchange. They investigate how sensitive is the

choice of RSI boundaries to different volatility regimes. **Adrian Taran-Morosan (2011)**, "The relative strength index revisited" They revealed that RSI is very popular among investors to get a consistent return. They revelled the importance between RSI classic form & adjusted RSI with trading volume, after compare both the form they find out classic way of RSI doing pretty good job, but if we use adjusted RSI with some additional variables, can get an outstanding result. According to **Wilder (1978)** the most appropriate value to compute the best RSI for value N is 14 as this is half of the lunar cycle. Though the value 14 is not best always or is not the only value to compute the RSI as it depends and varies concerning the market, company and any other factor. **Lev and Thiagarajan (1993)** show a total fundamental score is approaching with consistent earnings growth of a firm. According to **Park and Irwin (2004)**, "among a total of 92 modern studies, 58 studies found optimistic results regarding technical trading strategies, while 24 reviews obtained undesirable effects. **Chan et al. (1996)** and **Griffin et al. (2005)** reveals that a zero-investment portfolio with almost double returns and earnings astonishments can generate higher profits.

In the past literature, when the critics of technical analysis appeared to gain ground, since the middle of the last century (Alam, 2009) **Fama (1965a)** asserts that two different approaches of the stock market try to predict the future market movement .i.e. the chartist approach & fundamentalist approach. Both assume that the stock price can be estimated within a particular time frame, but the technique used in these theories is different altogether. If chartists study the behavior of prices in the past to determine how they will evolve in the future, the advocates of fundamental analysis attempt to resolve the intrinsic value of the shares according to their capacity to generate returns and if the current price is below or above their intrinsic value (**Alam et al., 2009, 2010**). The hypothesis from which fundamental analysis departs is that in time, the price of stocks tends to their intrinsic value.

Most in recent times, **Piotroski and So (2012)** examine the performance of the fundamental strategy in the US for the period 1972 to 2010 on the portfolios of firms with high, medium and low PBV. This strategy of stock selection produces high yield of returns 24.64%. Furthermore, by taking inspiration from Piotroski (2000), **Dorantes (2013)** explores the trading performance of FSCORE-sorted portfolios in the Mexican market. The author finds that the fundamental strategy works well for predicting returns one year ahead.

Wong, Manzur and Chew (2003) analyzed the use of technical analysis as an entry and exit from the security. The two most common methods i.e. MA and RSI were followed on the Singapore Stock Exchange (SSE). The results were enthusiastic. The investor profited by using the above indicators in the SSE market.

Kwon and Kish (2002) gave more importance to technical analysis. He proved this by using the New York Stock Exchange (NYSE) data. He further recommended that investors should use technical analysis while buying and selling of the stock.

Ticknor (2013) advocated the importance of technical analysis with artificial intelligence to build an expert system for trading system design. It has been detecting that technical analysis is an essential instrument in timing the market. Many of the researchers do research using this aspect (**Taylor and Allen, 1992**). Technical analysis can be used in analysing the quantitative and qualitative data (**Menkhoff and Taylor, 2007**) **Alexakis, Patra and Poshakwale (2010)** advocate that portfolios designed based on financial ratios return higher than average returns.

Darvas (1960) encapsulates the development of his techno-fundamental strategy and provides subjective evidence on how it has profited him in the 1950s. His technique combines several indicators, inter alia, increased in firm's earning power, and his invention called the Box Theory.

There is sufficient literature (in isolation) available based on Fundamental & Technical analysis, but less documentation available on the combined approach of both phenomena. Few researchers have considered this combined approach like **Fama 1965; Leigh, Purvis & Ragusa 2002; Malkiel 2007; Sharpe 1985; Sharpe, Alexander & Bailey 1999; Spritzer & Freitas 2006; Sternberg & Lubart 1992; Vanstone 2006**.

In a nutshell, the availability of using the information in the form of Fundamental & Technical analysis (as a combination) may provide a piece of useful information to select good stocks & also the timing of buy & sell. In this research paper, we test Fundamental & Technical analysis tools & techniques on the Indian stock market, & with the help of our results, we draw "**Investment Methodological Framework**.", furthermore, with the help of these performance results, we validate the predictive relevance through Hybrid ARIMA.

Kashei et al, 2009 suggest that the use of hybrid ARIMA is a good attempt to predict the future price movement of gold & US dollar/ Iran rial financial markets. In addition to Zhang, 2003 applied a combination of ARIMA & ANN to various data sets including British pound/US dollar exchange rate.

RESEARCH OBJECTIVE

- Fundamental analysis & Technical Analysis complementary or competitive in terms of optimization & prediction of share markets.
- Leveraging Fundamental & Technical analysis be used to make a competitive portfolio& outperform the investment returns as compared to B&H strategy?
- Understanding the predictive relevance of L-FANTAM (Leveraging Fundamental & Technical analysis) through Hybrid ARIMA.

HYPOTHESIS

- **Null Hypothesis (H₀):** Fundamental analysis and Technical analysis cannot be leveraged together.
- **Null Hypothesis (H₀):** The mean returns through Techno-fundamental analysis equal to B&H strategy.
- **Null Hypothesis (H₀):** The predictive relevance of L-FANTAM is not significant.

RESEARCH DESIGN & METHODOLOGY

To reach out the predefined objectives of the study first we need to select the stocks on the basis of valued investing (Benjamin Graham). Value investing utilising a traditional fundamental approach in selecting stocks for investment portfolio (Ahmed, 2008). The origin of value investing started dated back 1930, when the crashes of 1929 prompted the Columbia Business School professor Benjamin Graham & Dodd had created a significance support for stock market investment. In 1934, both develops value investing by using a sound principles of company fundamental.

Intrinsic Valuation of Stocks –Benjamin Graham

The original formula shared by Graham in 1962 was

$$V = \text{EPS}(8.5 + 2g)$$

Here,

V= Intrinsic value of stock

EPS= Trailing twelve months' earnings per share

8.5= PE of a stock at 0% growth rate

g = Growth rate of the company

Later, it was revised in 1974 revised edition of “The Intelligent Investor” as

$$V = [\text{EPS}(8.5 + 2g) * 4.4] / Y$$

In this formula, United states risk free return was 4.4% & Y represent AAA corporate bond yield. Graham includes Y because of minimum required rate of return for investing in stock. As we know bond rates affect the valuation, lower the yield higher the price. Since, all intrinsic value calculations based upon opportunity cost relative to the risk free interest, so we need to modified the formula for Indian market & US market.

For Indian Market (2014):

$$\text{Intrinsic value} = [\text{EPS}(8.5 + 2G) * \text{FD rate}] / Y$$

Here, fixed deposit rate (risk free rate) is 8.5 & Nifty AAA Corporate bond is 8.3.

After selecting stocks through value investing (fundamental analysis), we need to validate return optimisation through technical analysis (EMA), & we validate predictive relevance through Hybrid ARIMA.

LEVERAGING FUNDAMENTAL & TECHNICAL ANALYSIS

Stock Selection (Step 1)

In this section, we first filtered out the valued stocks with the help of value investing developed by Benjamin Graham. Graham recommended that the stock that meets all the principles of stock selection should have bought by investor, but the stock selection rules of Benjamin Graham have considered quite stringent, that if all the rule of Graham are applied simultaneously on the stock, not even a single stock will qualify for the portfolio (Klerch & Maritz, 1997)

Table 1: Stock Selection(Portfolio) through Fundamental Analysis

Sr. No.	Company	Current Price(2014)	Intrinsic Value
1	Axis Bank	207	866
2	HDFC Bank	293	891
3	HDFC	749	1301
4	ICICI Bank	138	543
5	SBI Bank	126	529
6	Indusind Bank	326	1148
7	Kotak Bank	330	363

Source: Author Computed

These are the selected stocks based on value investing proposed by Benjamin Graham in the book “The intelligent investor”. The market prices of 2014 of all the stocks are undervalued as compare to intrinsic value. So, we select these stocks for sample as these are the main representative of Bank nifty too.

B&H Strategy

During the sample period (Jan 2014 to May 2020), we buy all the suggestive stocks at the initial out of sample period. We kept stock all through the whole period. This is passive strategy so it ignores risk management, timing & other active strategy variables. This strategy we use as a benchmark is in line with prior literature (Dryden 1970; Fama & Blume, 1966; Vanstone 2006; Thawornwong et al 2003).

Return Optimisation (Step 2)

Table 2: Technical Analysis-Primary Inputs for Expert System

Initial Equity	Commission	Sample Time Range	Long Trade	Stop Loss	Profit Target
1,00,000	1%	01-01-2014 - 06-06-2020	Buy	6%	30%

Source: Author Computed

Here, after valued stock selection is based on fundamental analysis, we now concentrated towards return optimization is based on technical analysis, which includes risk analysis too. Fundamental analysis includes Benjamin Graham stock selection value investing model, technical analysis includes historical adjusted closing stock data, exponential moving average which include “dead cross & golden cross” strategy for buying & selling (Zhu & Zhou, 2007) (Fifield et al, 2014).

Table 3: Investment Performance through Technical Analysis (2014-2020)

Sr. No.	Company	B&H Annual Return %	L-FANTAM Annual Return %
1	Axis Bank	7.6	45
2	HDFC Bank	19.3	35.5
3	HDFC	12.7	20.94
4	ICICI Bank	10	41.7
5	SBI Bank	1.4	49
6	Indusind Bank	0.32	44
7	Kotak Bank	22.8	43

Source: Author Computed

Table 3 depict the comparative investment performance of Axis bank, HDFC Bank, HDFC, ICICI Bank, SBI Bank, Indusind Bank, Kotak bank. The mean return of B&H strategy is 10.58% as compare to the L-FANTAM mean return is 39.87 respectively. The performance of L-FANTAM outperforms the B&H strategy in all the stocks during the sample time frame. Below the monthly returns generated by L-FANTAM model. These are the Returns of Selected Stocks

Table 4: AXIS BANK Profit/Loss Results (Month & Year Wise)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yr%
2014	-1.50%	10.00%	15.40%	4.80%	19.80%	4.00%	4.50%	1.00%	1.30%	12.50%	9.50%	2.80%	120.80%
2015	18.90%	-3.60%	0.80%	3.80%	3.70%	-2.00%	2.20%	0.20%	0.00%	1.00%	0.00%	0.00%	26.10%
2016	0.00%	0.00%	9.20%	8.30%	8.50%	-0.10%	6.80%	7.40%	0.70%	0.00%	0.00%	0.00%	47.90%
2017	3.30%	11.70%	-4.30%	3.00%	0.40%	1.30%	0.30%	0.60%	1.10%	0.70%	10.10%	3.40%	35.00%
2018	9.20%	-6.60%	0.00%	5.30%	0.00%	-0.70%	5.80%	17.40%	-4.20%	0.00%	8.50%	0.10%	37.70%
2019	7.20%	4.80%	11.20%	-2.70%	5.70%	0.50%	-1.90%	0.00%	2.50%	2.50%	4.30%	3.00%	43.00%
2020	-2.70%	0.50%	0.00%	0.20%	0.00%	1.80%	N/A	N/A	N/A	N/A	N/A	N/A	-0.30%
Avg	4.90%	2.40%	4.60%	3.30%	5.40%	0.70%	2.90%	4.40%	0.20%	2.80%	5.40%	1.50%	

Source: Author Computed

Table 5: HDFC BANK Profit/Loss Results (Month & Year Wise)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yr%
2014	-0.10%	2.70%	11.30%	-2.40%	9.30%	3.00%	2.50%	2.00%	3.30%	4.60%	5.00%	-0.90%	47.50%
2015	13.60%	-2.20%	0.10%	0.00%	4.60%	1.60%	4.60%	-1.80%	1.00%	4.60%	-0.90%	0.50%	27.70%
2016	0.00%	0.00%	4.20%	7.90%	4.80%	-2.10%	7.30%	0.90%	1.70%	0.10%	0.20%	0.20%	27.70%
2017	7.30%	7.90%	3.50%	7.20%	5.10%	1.60%	7.70%	-0.90%	2.50%	0.80%	2.20%	1.10%	56.20%
2018	5.50%	-2.90%	1.20%	2.00%	4.40%	5.00%	4.40%	-2.80%	0.00%	0.00%	8.00%	-0.30%	26.60%
2019	-0.80%	0.30%	9.80%	-0.90%	6.30%	0.80%	-0.80%	0.00%	10.50%	-1.20%	3.70%	0.10%	30.30%
2020	-0.20%	0.00%	0.00%	5.10%	-0.20%	8.60%	N/A	N/A	N/A	N/A	N/A	N/A	13.70%
Avg	3.60%	0.80%	4.30%	2.70%	4.90%	2.60%	4.30%	-0.40%	3.20%	1.50%	3.00%	0.10%	

Source: Author Computed

Table 6: HDFC Profit/Loss Results (Month & Year Wise)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yr%
2014	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2015	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2016	-3.30%	-5.60%	7.20%	-2.60%	13.00%	-2.60%	12.40%	-0.60%	2.10%	2.00%	-1.10%	0.00%	20.80%
2017	10.00%	0.90%	8.40%	2.30%	0.70%	4.30%	10.60%	-1.60%	-0.20%	0.30%	0.50%	0.50%	42.30%
2018	11.60%	-3.70%	0.00%	1.50%	0.80%	3.50%	7.30%	-4.10%	0.00%	0.00%	13.50%	-0.50%	33.30%
2019	-0.10%	-0.50%	2.20%	2.20%	10.80%	0.40%	1.40%	1.60%	-1.00%	2.80%	9.30%	6.40%	40.80%
2020	-1.20%	0.00%	0.00%	9.60%	-6.60%	3.80%	N/A	N/A	N/A	N/A	N/A	N/A	5.00%
Avg	2.40%	-1.30%	2.60%	1.90%	2.70%	1.30%	5.30%	-0.80%	0.20%	0.80%	3.70%	1.10%	

Source: Author Computed

Table 7: ICICI Bank Profit/Loss Results (Month & Year Wise)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yr%
2014	-1.80%	3.10%	20.60%	0.90%	11.60%	-0.80%	6.60%	5.60%	-1.40%	9.30%	7.90%	0.00%	78.60%
2015	3.40%	-1.20%	0.40%	4.00%	-2.90%	1.80%	0.00%	0.20%	0.00%	2.40%	0.00%	0.00%	8.40%
2016	0.30%	0.00%	12.00%	1.60%	4.00%	-1.70%	11.00%	-3.30%	5.40%	9.10%	-3.10%	0.40%	40.10%
2017	5.20%	4.60%	-3.40%	1.40%	15.50%	-0.70%	2.10%	1.20%	-0.90%	9.80%	5.30%	-0.50%	45.40%
2018	14.90%	-7.70%	0.00%	0.00%	3.60%	-0.10%	6.20%	16.80%	-5.10%	0.30%	8.20%	1.60%	42.60%
2019	1.00%	0.00%	13.10%	1.70%	3.70%	3.20%	-2.60%	0.20%	10.40%	4.80%	9.30%	7.20%	64.30%
2020	-3.20%	1.50%	0.00%	3.00%	-5.60%	6.30%	N/A	N/A	N/A	N/A	N/A	N/A	1.60%
Avg	2.80%	0.00%	6.10%	1.80%	4.30%	1.10%	3.90%	3.50%	1.40%	5.90%	4.60%	1.50%	

Source: Author Computed

Table 8: SBI Bank Profit/Loss Results (Month & Year Wise)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yr%
2014	0.00%	0.00%	22.60%	9.60%	21.90%	3.80%	-2.10%	0.70%	2.40%	9.00%	18.90%	-4.30%	113.10%
2015	1.70%	0.10%	0.00%	1.10%	1.50%	0.00%	1.90%	0.50%	0.00%	2.30%	2.60%	-1.90%	10.20%
2016	0.00%	0.00%	13.60%	-2.30%	6.60%	7.80%	8.60%	7.50%	1.90%	2.80%	2.70%	1.00%	61.80%
2017	5.40%	1.50%	8.70%	-1.20%	1.60%	0.00%	5.30%	-1.70%	0.00%	20.70%	6.90%	-5.20%	47.80%
2018	1.20%	-0.90%	0.00%	0.10%	8.60%	-0.20%	9.70%	8.00%	-4.50%	0.00%	7.60%	4.00%	37.60%
2019	-0.50%	0.00%	14.80%	-2.00%	12.80%	2.50%	-1.80%	0.00%	0.80%	3.10%	21.40%	-1.30%	58.10%
2020	-2.10%	0.40%	0.00%	0.00%	0.00%	8.30%	N/A	N/A	N/A	N/A	N/A	N/A	6.40%
Avg	0.80%	0.10%	8.50%	0.80%	7.60%	3.20%	3.60%	2.50%	0.10%	6.30%	10.00%	-1.30%	

Source: Author Computed

Table 9: Indusind Bank Profit/Loss Results (Month & Year Wise)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yr%
2014	0.40%	0.40%	26.20%	-1.20%	8.10%	7.10%	-2.90%	7.00%	6.70%	15.50%	4.20%	4.50%	102.60%
2015	10.90%	-0.70%	1.90%	2.50%	3.20%	1.40%	12.50%	-4.30%	4.70%	1.30%	0.30%	2.70%	41.50%
2016	-0.20%	-0.20%	7.20%	13.00%	5.30%	-0.80%	7.30%	-1.00%	3.00%	1.10%	0.30%	0.60%	40.70%
2017	13.10%	7.00%	6.30%	1.40%	2.70%	0.10%	10.10%	2.40%	0.90%	0.80%	0.80%	-0.40%	54.50%
2018	4.20%	-1.20%	7.30%	4.90%	1.60%	0.60%	3.00%	-0.60%	0.00%	0.00%	5.00%	-2.80%	23.60%
2019	-0.20%	0.00%	21.10%	-6.00%	3.40%	-1.30%	0.90%	0.00%	6.90%	-4.20%	18.50%	-2.80%	37.80%
2020	-2.30%	0.00%	0.00%	0.00%	0.00%	0.00%	N/A	N/A	N/A	N/A	N/A	N/A	-2.30%
Avg	3.70%	0.80%	10.00%	2.10%	3.50%	1.00%	5.10%	0.60%	3.70%	2.40%	4.80%	0.30%	

Source: Author Computed

Table 10: Kotak Bank Table: Profit/Loss Results (Month & Year Wise)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yr%
2014	0.10%	1.00%	13.70%	3.90%	7.40%	2.30%	7.80%	9.80%	-0.90%	10.30%	7.50%	4.20%	90.40%
2015	5.50%	2.10%	0.10%	2.80%	3.70%	0.30%	2.60%	0.50%	0.00%	5.20%	2.00%	1.00%	28.80%
2016	-0.80%	0.20%	1.90%	8.70%	3.50%	-1.00%	3.90%	2.30%	1.80%	4.30%	-2.30%	0.00%	24.30%
2017	7.70%	3.30%	7.60%	3.40%	7.00%	-0.20%	5.40%	-2.40%	1.90%	3.90%	0.70%	-0.20%	44.60%
2018	7.90%	-0.50%	-1.00%	12.40%	9.00%	3.60%	0.10%	0.00%	0.00%	0.50%	6.60%	0.60%	45.50%
2019	2.20%	-0.10%	7.50%	2.90%	10.40%	-3.00%	2.40%	-0.40%	11.80%	-3.30%	2.00%	4.40%	41.80%
2020	0.80%	-0.70%	0.00%	4.10%	-3.80%	8.10%	N/A	N/A	N/A	N/A	N/A	N/A	8.30%
Avg	3.30%	0.70%	4.30%	5.50%	5.30%	1.40%	3.70%	1.60%	2.40%	3.50%	2.80%	1.70%	

Source: Author Computed

Hybrid ARIMA

ARIMA model combined with other techniques like ANN, Expert system, Support vector machine etc. to upgrade the forecasting results (Wang et al, 2012, Khashei & Bijari, 2012, Aladag et al, 2009). A model is one in which variables of the stationary dataset (non-stationary data set becomes stationary through differenced) are combined with the data mining learners other than regression (Allen Steel, 2014). Whereas, Artificial neural network (ANN) is the piece of a computing system design to stimulate the way the brain analyses & process information, in addition to Expert system defined as computer based decision making system that can solve complex decision making problem using both facts & heuristics (learn something for our self). Khashei et al, 2009 suggest that the use of hybrid ARIMA is a good attempt to predict the future price movement of gold & US dollar/ Iran rial financial markets. In addition to Zhang, 2003 applied a combination of ARIMA & ANN to various data sets including British pound/US dollar exchange rate. The Hybrid ARIMA is more accurate & performs better than artificial neural network (Khashei & Bijari 2011)

We use Hybrid ARIMA model for this section to predict the closing prices of stocks by incorporating L-FANTAM model expert system (based on AFL language) results (output) & variables. We need to follow these steps:

- Monthly returns, moving average & volume of FANTAM model expert system of selected valued stocks. These are independent variables for predicting closing stock price (dependent variable).
- Make them stationary after taking difference.
- Apply automatic ARIMA forecasting.
- Apply forecasting evaluation.

PERFORMANCE & PREDICTION EVALUATION CRITERIA FOR HYBRID ARIMA (COMBINATION OF ARIMA & EXPERT SYSTEM)

- **Dependent variable:** It is D (ADJ_CLOSE), also it is the outcome variable.
- **Independent variable:** Monthly returns (FANTAM model), Moving average, Volume

- **Method:** The Hybrid ARIMA model i.e. the mix of ARIMA & Expert system
- **Date:** Jan 2014 to June 2020
- **Sample:** Monthly data split into training 75% & 25% testing
- **Standard Error:** it explains that how much deviation occurs from predicting the slope coefficient estimates.
- **T- stat:** A value is more than 2 is sufficient evidence of null hypothesis.
- **P value:** Low P value gives higher confidence in rejecting the null hypothesis at the level of 1%, 5% ,10%.
- **R squared:** the higher the R^2 better the model & more predictive power the variable has.
- **Adjusted R^2 :** This increases the viability of explanatory variables & reduce as more explanatory variables added.
- **S.E. of regression:** the summary measure based on the estimated variance of the residuals.
- **F statistic:** it captures that the explanatory variable is significant in explaining the outcome variable, higher the f statistic better the model.
- **Prob.** (F statistic): If the probability value is .00000 that indicates the significance of F statistic, we prefer the prob. Value less than .05
- **Akaike/Schwartz/Hannan-Quinn info. Criteria:** lower the value of these criteria better the model.
- **Durbin Watson Stat.:** $DW < 2$ equals evidence of positive serial correlation.
- **MAPE:** Mean absolute percentage error signifies the average of absolute percentage amount by which forecast differ from outcome.
- **Theil U:** When U is closer to 0 zero, predictive model is efficient, also it measures the forecast quality (Theil H,1958) (Theil,1966) (Bliemel, F 1973)

Table 11: ADF Test of Selected Stocks

S. No.	Company	ADF Test
1	AXISBANK.NS	-7.5
2	HDFCBANK.NS	-8.5
3	HDFC.NS	-10.05
4	ICICIBANK	-9.8
5	SBIN	-7.73
6	INDUSINDBK.NS	-9.31
7	KOTAKBANK.NS	-4.1

Source: Author Computed

Table 11 shows the ADF test result, the first phase of ARIMA prediction model is Identification stage, Augmented Dickie Fuller Test is used to ensure the level of data is stationary or not. If the T- statistics value is less than critical value at 95% level i.e. -2.87, then it is considered as stationary. In the present research work, all the companies are greater than that of critical values at 5% level of significance (table1). All the independent variables are stationary at 5% level. Further, we discuss model identification, model estimation, data forecasting & forecasting evaluation of selected stocks.

Table 12: Summary of Automatic ARIMA Forecasting(Hybrid)

S. No.	Company	Model	R Square	AIC	BIC	HQ	F stat	Durbin Watson	MAPE	Theil U
1	AXIS B.	(0,1)	71.5	8.951	9.163	9.034	26.69	1.96	14.9	0.074
2	HDFC B.	(2,5)	83	10.983	11.405	11.147	22.39	1.97	5.4	0.033
3	HDFC	(3,5)	76	11.045	11.503	11.224	12.18	1.89	5.17	0.032
4	ICICI B.	(0,0)	53	8.3434	8.519	8.4121	21.05	2	12.3	0.086
5	SBI B.	(2,1)	79.12	8.932	9.214	9.042	27.6	2.08	20.24	0.011
6	Indusind B.	(3,3)	80.7	10.499	10.886	10.651	20.18	1.85	88	0.22
7	Kotak B.	(5,2)	70.21	9.8700	10.292	10.034	10.07	2	4.04	0.02

Source: Author Computed

Table 12 shows the summary of Hybrid ARIMA model, the predictive relevance of all the stocks are significant except ICICI Bank (53%), rest of all the stocks have more than 70% R square, which signifies that variables can predict more than 70% of closing prices. Theil U signifies that the value is closer to 0, the model has more forecasting accuracy, except Indusind Bank, all the models have sig. value is close to 0. F stat signifies that the explanatory variable is significant in explaining the outcome variable, higher the value better the model, here all the values more than 10. So, we can conclude that L-FANTAM have a reasonably good forecasting & optimizing ability.

CONCLUSIONS

- **Null Hypothesis (H0):** We can reject the null hypothesis (H01) because our results show that “Leveraging fundamental & technical analysis” is possible with significant level of performance & predictive acceptability as per table 3 & 12.
- **Null Hypothesis (H0):** We can reject the null hypothesis (H02) since the mean returns of techno-fundamental analysis is more than B&H strategy as per table 3
- **Null Hypothesis (H0):** We can reject the null hypothesis(H03) since the significant predictive relevance have shown by Hybrid ARIMA model, average R square of the portfolio is more than 70% as per table 12. **Below the pictorial diagrammed of selected shares actual & forecasted values with residuals.**

Axis Bank

Figure 1.1: Actual & Forecasting

Figure 1.2: Residual, Actual & Fitted.

HDFC Bank **Figure 2.1: Actual & Forecasting** **Figure 2.2: Residual, Actual & Fitted.****HDFC** **Figure 3.1: Actual & Forecasting** **Figure 3.2: Residual, Actual & Fitted.****ICICI Bank** **Figure 4.1: Actual & Forecasting** **Figure 4.2: Residual, Actual & Fitted.**

SBI **Figure 5.1: Actual & Forecasting** **Figure 5.2: Residual, Actual & Fitted.****Indusind Bank** **Figure 6.1: Actual & Forecasting** **Figure 6.2: Residual, Actual & Fitted.** **Figure 7.1: Actual & Forecasting** **Figure 7.2: Residual, Actual & Fitted.**

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