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Assessing and Predicting Returns of Equity Portfolio using the ARIMA Model

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Abstract: Predicting the Stock prices has always attracted the attention and interest of researchers and analysts worldwide and has led to the development of better prediction models. Share Market is unpredictable, since there are no significant rules to estimate or predict the prices of shares. Famous methods like technical analysis, fundamental analysis, etc. are all used to attempt to predict the price in the share market but none of these have proved as an accurately correct and consistently acceptable prediction tool.In recent years, the banking industry of India has been seeing many ups and downs due to world economic depression and it has impacted the stock prices of many banks. A smart investor can take the benefits of high volatility of NSE bank stock prices. Through time series analysis and statistical analysis, this research has tried to forecast the stock returns of banking industry. Results obtained revealed that statistical analysis by using efficient frontier and capital allocation line through Sharpe ratio has potential for short term prediction and can compete favorably with the existing techniques like technical analysis for stock prediction. Also, the Autoregressive Integrated Moving Average (ARIMA) model has been used which uses the historical data points which further enhances the accuracy in comparison to the fundamental analysis, as it considers the share prices and analyses the historical trend of the extracted data and then forecasts the prices.

***Index Terms**: Modern Portfolio Theory, Portfolio Management, Capital Allocation Line, Frontier Graphs, Covariance matrix, ARIMA, Risks, Returns.*

I. INTRODUCTION

Life is a series of trade-offs and risk is an inevitable part of life. Risk and reward go hand in hand. Taking risk may give you higher returns, while risk aversion may lead to compromises on the returns. Modern Portfolio Theory (MPT) serves as a guideline to generate the maximum possible profits involving the least amount of risk. This paper has been designed to examine the relationship between the risk and return of an investment and how diversification helps in maximising returns with minimum risks and also the role MPT can play in a portfolio. Portfolio may consist of any element of securities, it may be mutual funds or the equity, and there is always some risk associated with each and every security.

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Performance evaluation plays a crucial role and is challenging as well. Decisions taken can affect the investment objectives and also provide feedback on the investment policy of a firm. From the perspective of an investment manager, it permits the investigation of the effectiveness of the elements of the investment process and their contributions to the investment results [9].

Harry Markowitz's pioneering theory, on Portfolio Selection, in 1952 was the beginning of an era when investment theory discussed the risks of investing. Prior to that there were only suggestions for maximizing returns. Markowitz, in his thesis, mathematically inferred that there is a direct relationship between the risks and rewards of an investment. He argued that investors must manage the sensitive relation between the two and should measure, monitor and control risk at the portfolio level instead of the individual security level. This in turn will affect the choice of securities as they will be chosen not only on their merits but also on their associated effect on the portfolio as a whole.

According to Modern Portfolio Theory, investors can contain the volatility of their portfolios by distributing the risks among different types of investments. This will create a basket of risky stocks, and would actually reduce the overall risk of the portfolio than would be observed for the individual stocks [5]. Diversification is dependent on the relative performance of the securities and not the number of securities owned by an individual. Markowitz in his work did a comparative analysis of a portfolio comprising 60 railway securities with another of the same size that included railroads, utilities, mining and manufacturing companies. His results proved that the later was better diversified and had better performance. He reasoned that it is generally more likely for firms within the same industry perform poorly at the same time than for firms in dissimilar industries [1].

The perfect diversification requires that the compiled securities behave differently and have least correlation in their price movements. Correlation is the degree at which two securities behave in the same pattern. A correlation value ranges from -1.0, indicating exactly opposite securities, to 1.0 depicting securities moving in tandem. Therefore to diversify the risk, securities with correlation -1.0 are more preferable than those with 1.0. As suggested by Markowitz, the goal may be to create an "efficient" portfolio, which can either be offering highest expected return for a given level of risk or offering the given expected return with the lowest level of risk.

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The line connecting all the efficient portfolios is the Efficient Frontier, which represents the set of portfolios that have the maximum rate of return for every given level of risk. The Efficient Frontier serves as a guide for Investors to examine their own risk/return preferences for choosing wisely where to invest thereby allowing the investors to reduce the risk with fixed returns or increase return at any particular level of risk [1].

II. APPLYING MODERN PORTFOLIO THEORY TO THE INVESTMENT REALITY

We have discussed the concepts of an efficient portfolio and the efficient frontier graphs, but the question is, how they can be applied to real investment situations. Determination of an efficient portfolio is a challenge as the market prices keep changing, and therefore the risk associated with the asset classes is dynamic. Therefore finding an efficient portfolio or creating an efficient frontier graph are not the pronounced by the MPT. Rather, the takeaways from the MPT are listed below:

1. Risk and return are directly related. Taking a chance at greater returns, needs taking on more risks.
2. Diversification across securities that behave differently reduces the overall risk of the portfolio. For example For example, the stock and bond markets don't usually move in the same direction. Hence having them both in a portfolio creates a more diversified and less risky portfolio

These two concepts are used by investors to build portfolio.

III. PORTFOLIO MANAGEMENT

“Portfolio management is the art and science of making decisions about investment mix and policy, matching investments to objectives, asset allocation for individuals and institutions, and balancing risk against performance”. It is about performing the SWOT analysis of the diversified portfolio in the choice of debt vs. equity, domestic funds vs. international funds, growth perspective vs. safety measures, and many other trade-offs that needs to be encountered while attempting to maximize the investor’s expected return at a given level for risk [4].

The efficient frontier is the set of optimal portfolios where the portfolios that assimilate to the right are sub-optimal as they have a higher level of risk for the specified rate of return.

Efficient frontier comprises investment of diversified and undiversified portfolios that offer the maximum return for a specific level of risk. Returns are dependent on the investment combinations that make up the portfolio. The standard deviation of a security is synonymous with risk. So, to calculate the level of risk being appetite with the investment made, we need to calculate the standard deviation. Lower correlation between portfolio securities results in lower portfolio standard deviation. Successful optimization of the return versus risk paradigm should place a portfolio along with the efficient frontier line. Optimal portfolios that comprise the efficient frontier tend to have a higher degree of diversification [4].

IV. CAPITAL ALLOCATION LINE - CAL

The Capital Allocation Line (CAL), also referred to as the Capital Market Link (CML), defines the graphical representation of all possible combinations of risk-free and risky assets. CML displays the returns that would be earned by the investors by assuming a certain level of risk by making a marginal investment in their portfolio. It is basically a reward to vulnerability ratio.

A. *Slope of the CAL*

CAL measures the return in the form of trade-off between risk and return. Higher slope of Capital allocation line signifies that the investor receives higher return in exchange of taking higher risk and vice versa. The calculation of capital allocation line is based on Sharpe ratio.

Nobel laureate William F. Sharpe is the person who has developed the Sharpe ratio and it is being used by the investors to understand the expected return on an investment in comparison to the risk taken by the investor. Sharpe ratio is the average of return earned in comparison to the total risk taken.

V. PERFORMANCE MEASUREMENT AND EVALUATION

The Evaluation of the performance measurement is necessary for both the investors and portfolio managers, though the need for evaluating may differ. Performance evaluation surfaces the areas of effectiveness as well as improvements in the investment scheme [6].

Broadly, the measurement and assessment of the outcomes of the investment management decisions is referred to as performance evaluation. In this paper, the focus is on exploring the analytical techniques representing best practices that can lead to valid insights about the sources of past returns, and such insights can be useful inputs for evaluation of the equity portfolio. Here an attempt has been made to summarize the understanding with the aim to provide an overview of current performance evaluation concepts and techniques. The focus is on how the institutional investors—both fund sponsors and investment managers—conduct performance evaluation. Individual investors use variations of the performance evaluation techniques employed by institutional investors. [6]

VI. ASSESSING RETURNS OF EQUITY PORTFOLIO MANAGEMENT

The broad subject of performance evaluation is divided into three components:

- **Performance Measurement**: The return performance of the investment.
- **Performance Attribution:** How the observed performance is attained.
- **Performance Appraisal:** If the performance is due to the investment decisions.

A. *Performance Measurement:*

There are several methods of calculating portfolio performance. The approaches can be broadly categorized into two approaches—

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- *Conventional Methods—*

Performance Evaluation through the conventional method doesn't take into account the risks taken by the portfolio manager. Here, the performance of a portfolio is evaluated by comparing the portfolio returns to the returns of a considered benchmark, which can be a market index, such as S&P 500, or any another similar portfolio [7].

- *Risk-adjusted Methods—*

In these methods, the returns of the portfolio are compared to the returns of the benchmark, considering the difference in their risk levels.

1) Calculation of Portfolio Returns

Let us assume that the period of evaluation is *t*, market value at the start of the time period was MV_0 and at the end of this time period is MV_t. Further, the cash inflows at the start and end of the time period *t* are CF_0 and CF_t. The return from the portfolio for this period can be computed as:

$$r_t = \frac{(MV_t - CF_t) - (MV_0 + CF_0)}{MV_0 + CF_0}$$

- *Time-Weighted Rate of Return (TWRR)*

If there are *n* time periods within our analysis period *t* and $r_{t,i}$ denotes the return from the sub-period *i*, then the time-weighted rate of return can be computed as:

$$TWRR = (1 + r_{t,1})(1 + r_{t,2}) \ldots (1 + r_{t,n}) - 1$$

***2)** Risk-adjusted Methods*

- *Sharpe's Measure*

The Sharpe's Index measures the total risk by calculating the standard deviation. This method was adopted to rank the portfolios on the basis of the measure of their performance evaluation. Reward i.e. risk premium, is taken as the numerator. Total risk is taken as the denominator in the form of the standard deviation of its return. It helps measure the total risk of the portfolio and variability of return in relation to the risk premium. The following formula helps in measuring the portfolio:

$$SI = (R_t - R_f)/\sigma_f$$

where:
SI = Sharpe's Index
R_t = Average return on portfolio
R_f = Risk free return
σ_f = Standard deviation of the portfolio return.

The results from the Sharpe ratio can be generalized to present a comparative analysis of the performance of an account with that of a specific benchmark. The general form of the Sharpe ratio is called information ratio [7].

B. *Performance Attribution:*

Having calculated the return from the portfolio, we analyze various components of the return. These returns can be divided into three components.

$$P = M + S + A$$

where:
P is the return from the Portfolio
M is the Market Return
$S = B - M$, where *B* is the Benchmark Return. *S* signifies Excess Return due to investing style
$A = P - B$, is the Active Return generated by the manager over the Benchmark

The active return or the value-added return (*return of the portfolio – benchmark return*) can be attributed or broken into three components:

- Pure sector selection: Pure sector selection assumes that the manager holds the same sectors in the portfolio as in the benchmark but in different proportions. The proportion of each security within each sector is also held the same as in the benchmark. The active performance is due to the selection of the weights of the sector only. [7,8]

- Within-sector selection return: This assumes that the portfolio manager holds all the sectors in the same proportion as the benchmark and the returns are generated by adjusting the weights of securities in each sector. [7, 8]

- Allocation/selection interaction return: This involves the joint effect of changing the weights of both the securities and the sectors in the portfolio. Any increase in the weight of a security will also increase the weight of that sector.

$$R_v = \sum_{j=1}^{S}(w_{P,j} - w_{B,j})(R_{B,j} - R_B) + \sum_{j=1}^{S}(w_{P,j} - w_{B,j})(R_{P,j} - R_{B,j}) + \sum_{j=1}^{S} w_{B,j}(R_{P,j} - R_{B,j})$$

where:
R_V = Value added return
$W_{P,j}$ = Portfolio weight of sector *j*
$W_{B,j}$ = Benchmark weight of sector *j*
$R_{P,j}$ = Portfolio return of sector *j*
$R_{B,j}$ = Benchmark return of sector *j*
R_B = Return of Portfolio's Benchmark
S = Number of Sectors.
In the above equation, the first term refers to the Pure Sector Allocation, the second term refers to the Selection Interaction Return while the third term refers to the Within-Sector Selection Return.
The sum of all the three components add-up to the active returns from the portfolio (also known as **alpha**).

VII. METHODOLOGY

The ARIMA model for stock price forecasting is explained further. The data used is the historical daily stock prices obtained from stock exchanges. The data has four elements: open price, low price, high price and close price respectively. The current paper, choses closing price for prediction, as it reflects all the activities of the index in a trading day.

Published stock data of two previous year obtained from National Stock Exchange (NSE) has been used with stock price predictive model developed (1st January 2017 to 31st December 2018).

To determine the stock return and risk involved in it, the authors extracted the data of eight banks' share prices of Banking industry.

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Correlation has been calculated to depict the dependency of one's stock on the other.

The Banks which have been used for forecasting the return are:-

1. Punjab National Bank
2. IDFC First Bank Limited
3. IDBI Bank Limited
4. Yes Bank
5. State Bank of India
6. HDFC Bank
7. Bank of Baroda
8. Union Bank of India

The stock data used in this study covers the period from 1st January 2017 to 31st December 2018 having a total of 493 observations.

VIII. RESULTS AND DISCUSSIONS

A. *Statistical Analysis By Using Efficient Frontier And Capital Allocation Line Through Sharpe Ratio*

The Sharpe ratio, developed by Nobel laureate William F. Sharpe, helps investors understand the return of an investment compared to its risk. The ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk.

$$\text{Sharpe Ratio} = \frac{Rp - Rf}{\sigma p}$$

where:

Rp = Return of portfolio

Rf = Risk-free rate

σp = Standard deviation of the portfolio's excess return

Different combinations of securities produce different levels of return. The efficient frontier represents the best of these securities combinations -- those that produce the maximum expected return for a given level of risk. The efficient frontier is the basis for modern portfolio theory. Table 1 and 2 show the expected return from various combination of two stock.

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Name of securities	**Return**	**Standard Deviation**	**Correlation**
PNB	20.09%	51%	0.35816158
IDFC	11.43%	33%	
IDBI	-5.94%	43%	0.079577222
Yes Bank	21.11%	123%	
Union Bank	-19.41%	47%	0.775080533
Bank of Baroda	11.76%	44%	
SBIN	24.18%	23.14%	-0.034423524
HDFC	24.62%	21.69%	

TABLE 1: REPRESENTING 8 STOCKS' RETURN, STANDARD DEVIATION AND CORRELATION

	Weight PNB	Weight IDFC	Return	SD	Sharpe ratio
	0%	100%	11.43%	33.37%	0.2826
	10.00%	90%	12.29%	30.46%	0.3380
	20.00%	80%	13.16%	28.56%	0.3908
	30.00%	70%	14.03%	27.89%	0.4313
	40.00%	60%	14.89%	28.52%	0.4520
	50.00%	50%	15.76%	30.38%	0.4528
	60.00%	40%	16.62%	33.27%	0.4396
	70.00%	30%	17.49%	36.93%	0.4194
	80.00%	20%	18.35%	41.17%	0.3972
	90.00%	10%	19.22%	45.83%	0.3757
	100.00%	0%	20.09%	50.79%	0.3561
Sharpe ratio	46.41%	53.59%	15.45%	29.59%	0.4545

TABLE 2: REPRESENTING WEIGHTED RETURN AND RISK ASSOCIATED WITH SHARPE RATIO

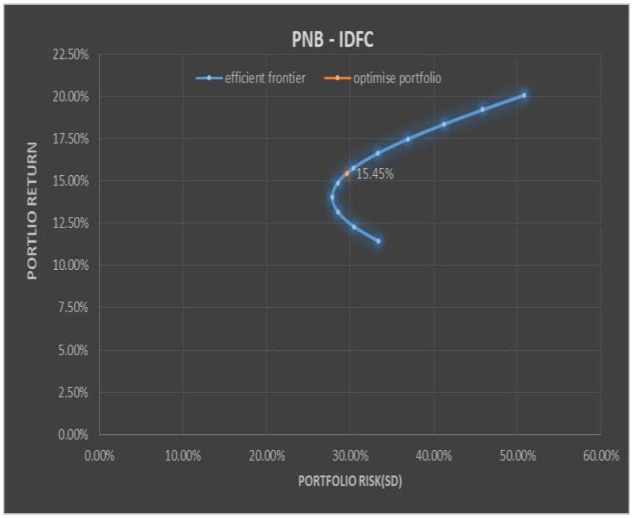

Figure 1: Graphical representation of PNB- IDFC efficient frontier with expected return

Weight SBIN	WEIGHT HDFC	Return	SD	Sharpe Ratio
0%	100%	24.62%	21.69%	1.0429
10.00%	90%	24.58%	19.58%	1.1532
20.00%	80%	24.53%	17.81%	1.2656
30.00%	70%	24.49%	16.48%	1.3649
40.00%	60%	24.45%	15.71%	1.4288
50.00%	50%	24.40%	15.59%	1.4373
60.00%	40%	24.36%	16.12%	1.3870
70.00%	30%	24.31%	17.25%	1.2935
80.00%	20%	24.27%	18.87%	1.1800
90.00%	10%	24.22%	20.87%	1.0650
100.00%	0%	24.18%	23.14%	0.9583
48.41%	51.59%	24.41%	15.56%	1.4401

TABLE 3: REPRESENTING WEIGHTED RETURN AND RISK ASSOCIATED WITH SHARPE RATIO

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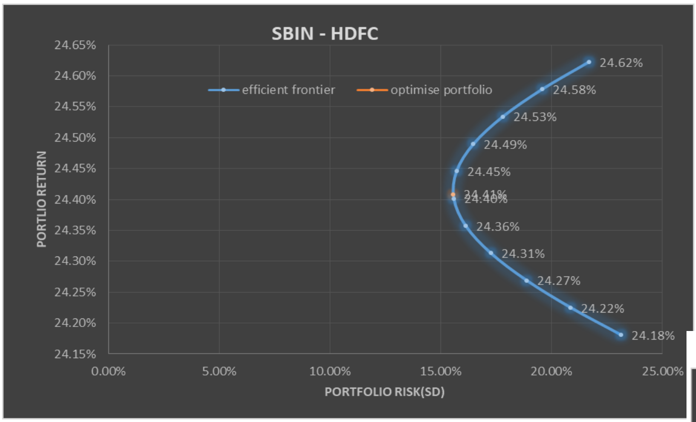

Figure 2: Graphical representation of SBIN- HDFC efficient frontier

Weight IDBI	WEIGHT Yes Bank	Return	SD	Sharpe ratio
0%	100%	21.11%	123.25%	0.1551
10.00%	90%	18.41%	111.35%	0.1474
20.00%	80%	15.70%	99.66%	0.1375
30.00%	70%	13.00%	88.24%	0.1246
40.00%	60%	10.29%	77.24%	0.1074
50.00%	50%	7.59%	66.86%	0.0836
60.00%	40%	4.88%	57.42%	0.0502
70.00%	30%	2.18%	49.49%	0.0036
80.00%	20%	-0.53%	43.86%	-0.0576
90.00%	10%	-3.23%	41.51%	-0.1260
100.00%	0%	-5.94%	42.97%	-0.1847
42.41%	57.59%	9.64%	74.67%	0.1023

TABLE 4: REPRESENTING WEIGHTED RETURN AND RISK ASSOCIATED WITH SHARPE RATIO

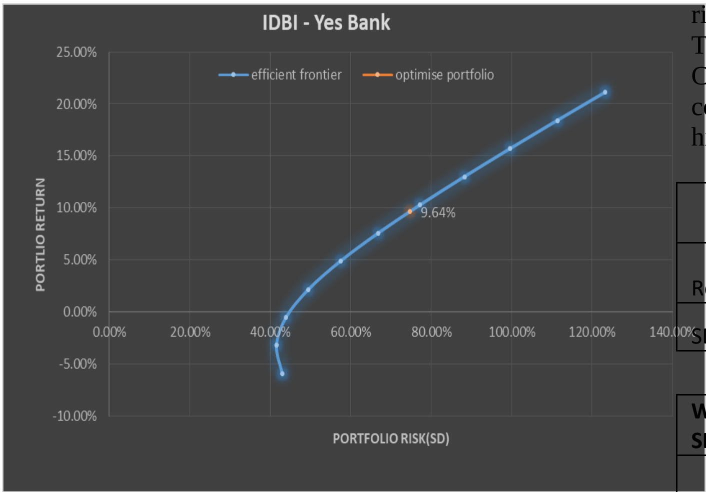

Figure 3: Graphical representation of IDBI- Yes Bank efficient frontier

Weight Union Bank	WEIGHT BOB	Return	SD	Sharpe ratio
0%	100%	11.76%	43.86%	0.2226
10.00%	90%	8.64%	43.21%	0.1538
20.00%	80%	5.53%	42.77%	0.0825
30.00%	70%	2.41%	42.54%	0.0096
40.00%	60%	-0.71%	42.54%	-0.0636
50.00%	50%	-3.82%	42.75%	-0.1362
60.00%	40%	-6.94%	43.18%	-0.2071
70.00%	30%	-10.06%	43.82%	-0.2752
80.00%	20%	-13.17%	44.66%	-0.3398
90.00%	10%	-16.29%	45.69%	-0.4004
100.00%	0%	-19.41%	46.90%	-0.4565
46.41%	53.59%	-2.71%	42.65%	-0.1103

TABLE 5: REPRESENTING WEIGHTED RETURN AND RISK ASSOCIATED WITH SHARPE RATIO

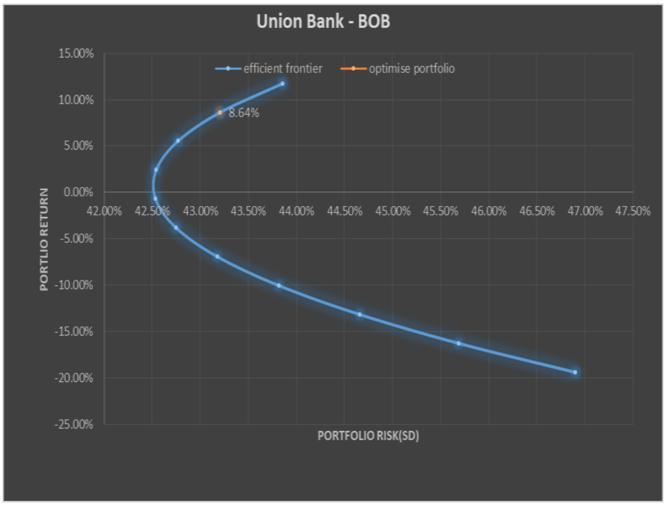

Figure 4: Graphical representation of Union Bank - BOB efficient frontier

Figure 4 and Table 6 shows that if an investor wants to get lesser risks & maximize the return then capital allocation line will be better predicting tool in case of two securities (HDFC – State Bank of India) selected from banking industry. This graphical representation shows the risk and reward profile of risky assets and can be used to find the optimal portfolio.
The optimal risky portfolio is found at the point where the CAL is tangent to the efficient frontier. This asset weight combination gives the best risk-to-reward ratio, as it has the highest slope for capital allocation line.

	ANNUAL				
Return	SBIN	24.18%	HDFC	20.50%	Correlation
SD	SBIN	23.14%	HDFC	21.69%	-0.034423524

Weight SBIN	Weight HDFC	Return	SD	Sharpe ratio
0%	100%	20.50%	21.69%	0.852876006
10.00%	90%	20.87%	19.58%	0.963658364
20.00%	80%	21.24%	17.81%	1.080365737
30.00%	70%	21.60%	16.48%	1.189764082
40.00%	60%	21.97%	15.71%	1.2713243
50.00%	50%	22.34%	15.59%	1.305081705
60.00%	40%	22.71%	16.12%	1.284696272

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70.00%	30%	23.08%	17.25%	1.221806306
80.00%	20%	23.44%	18.87%	1.136357198
90.00%	10%	23.81%	20.87%	1.045238864
100.00%	0%	24.18%	23.14%	0.958344521
46.41%	53.59%	22.21%	15.55%	1.299278823

TABLE 6: REPRESENTING WEIGHTED RETURN AND RISK ASSOCIATED WITH SHARPE RATIO

Risk free rate (RFR)			
	Return	2%	
	SD	0%	
Best Portfolio as per Sharpe ratio			
	Return	22.21%	
	SD	15.55%	
Correlation between risky asset & RFR			
0			

Weight PORTFOLIO	Weight RFR	Return	SD
0%	100%	2.00%	0.00%
10.00%	90%	4.02%	1.56%
20.00%	80%	6.04%	3.11%
30.00%	70%	8.06%	4.67%
40.00%	60%	10.08%	6.22%
50.00%	50%	12.10%	7.78%
60.00%	40%	14.12%	9.33%
70.00%	30%	16.15%	10.89%
80.00%	20%	18.17%	12.44%
90.00%	10%	20.19%	14.00%
100.00%	0%	22.21%	15.55%

110.00%	-10%	24.23%	17.11%
120.00%	-20%	26.25%	18.66%
130.00%	-30%	28.27%	20.22%
140.00%	-40%	30.29%	21.77%
150.00%	-50%	32.31%	23.33%
160.00%	-60%	34.33%	24.89%
170.00%	-70%	36.35%	26.44%
180.00%	-80%	38.37%	28.00%
190.00%	-90%	40.40%	29.55%
200.00%	-100%	42.42%	31.11%

TABLE 7: REPRESENTING ESTIMATED WEIGHTED RETURN AND WEIGHTED RISK

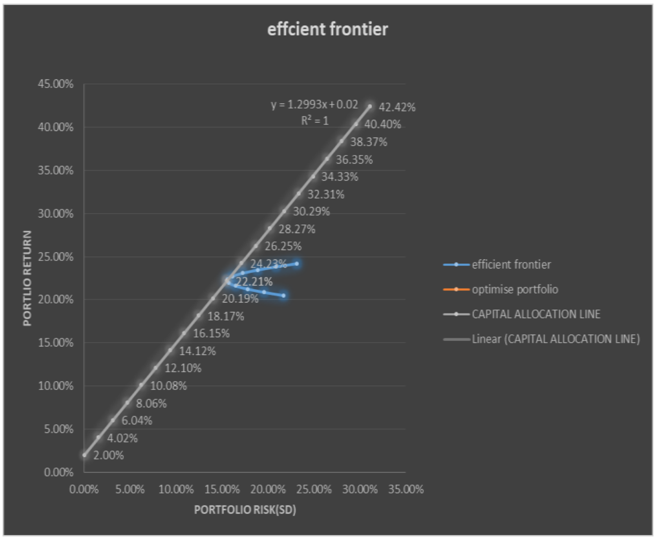

Figure 5: Graphical representation of SBIN – HDFC linear capital allocation line

B. *Statistical Analysis Using Variance- Covariance Matrix of All The Selected Stocks*

TABLE 8: VARIANCE – COVARIANCE MATRIX OF EXPECTED RETURNS OF 8 COMMERCIAL BANKS

Stock Name	PNB	IDFC	IDBI	Yes Bank	Union Bank	Bank of Baroda	SBIN	HDFC
PNB	0.0504	0.0118	0.0231	0.0128	0.0367	0.0320	-0.0002	0.0019
IDFC	0.0118	0.0217	0.0087	0.0127	0.0129	0.0107	-0.0011	0.0023
IDBI	0.0231	0.0087	0.0360	0.0082	0.0202	0.0180	-0.0003	0.0011
Yes Bank	0.0128	0.0127	0.0082	0.2966	0.0132	0.0096	-0.0027	0.0010
Union Bank	0.0367	0.0129	0.0202	0.0132	0.0429	0.0311	-0.0005	0.0017
Bank of Baroda	0.0320	0.0107	0.0180	0.0096	0.0311	0.0376	-0.0005	0.0018
SBIN	-0.0002	-0.0011	-0.0003	-0.0027	-0.0005	-0.0005	0.0105	-0.0003
HDFC	0.0019	0.0023	0.0011	0.0010	0.0017	0.0018	-0.0003	0.0092

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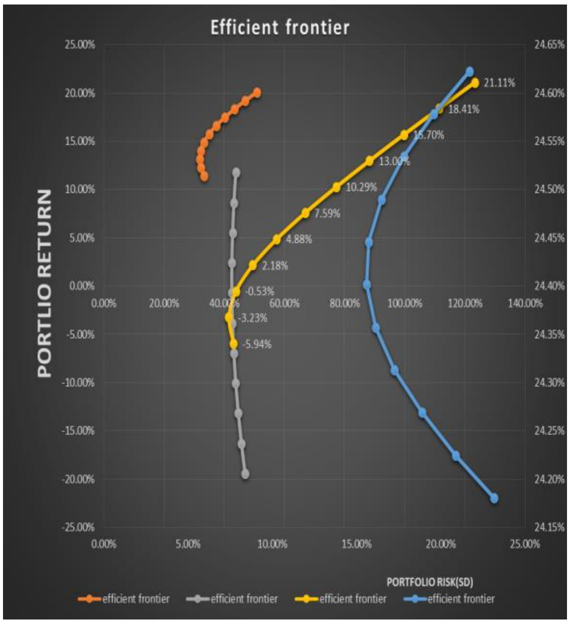

Figure 6: represents the consolidated efficient portfolio of eight securities

After statistical analysis, the short-term prediction will be done by time series modelling through ARIMA model, a robust and efficient method for financial time series forecasting, specially for short term forecasts [10].

C. Statistical Analysis Using ARIMA Model

ARIMA model, also known as Box-Jenkins approach after the name of its developer, has been applied on the stock prices of Punjab National Bank taken from NSE website starting from 1st January 2017 to 31st December 2018.
The model claims that data that is stationary can be converted to stationary data by differentiating the series, Yt. The general equation for Yt can be written as,

$$\emptyset Y_{t-1} + \emptyset Y_{t-2} \dots \emptyset Y_{t-p} + \in_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots \theta_q \epsilon_{t-q}$$

Y_t is the differentiated time series value, ϕ and θ are parameters which are not known and ϵ are the independent identically distributed error terms with zero mean. In this equation Yt is specified in terms of its older values and the present and older values of error terms.

ARIMA (p,d,q) Forecasting Equation:

These have 3 parameters:

P: number of autoregressive terms – this is the number of lag observations included in the model. So, in the model an observation would be dependent on ‘p’ previous observations.

d: degree of differencing needed for making series stationery (a time series is stationery if its statistical properties are all constant over time. For example, no trend, variations around the mean has constant amplitude etc.). Differencing means subtracting an observation from an observation at the previous time step.

q: size of moving average window – Size ‘q’ means that in the model, an observation depends on residual error of moving average model applied to previous ‘q’ observations.

In Ideal scenario - plots, statistical tests are studies to identify the best parameters for any given time series.

In-built functions available in standard libraries can directly be used to estimate the model parameters for a given time series.

Special cases:

ARIMA (0,1,0): Random Walk

ARIMA (1,1,0: Differenced first-order Auto Regressive model

ARIMA (1,1,2): Damped Trend linear Exponential Smoothing

Before applying the ARIMA model, we have shown the close prices of SBIN and Yes Bank to see the trend of fluctuations of stock prices of these correlated stocks. Below figure shows the trend analysis in terms of volatility of stock prices (Yes Bank and State Bank of India) by using R coding.

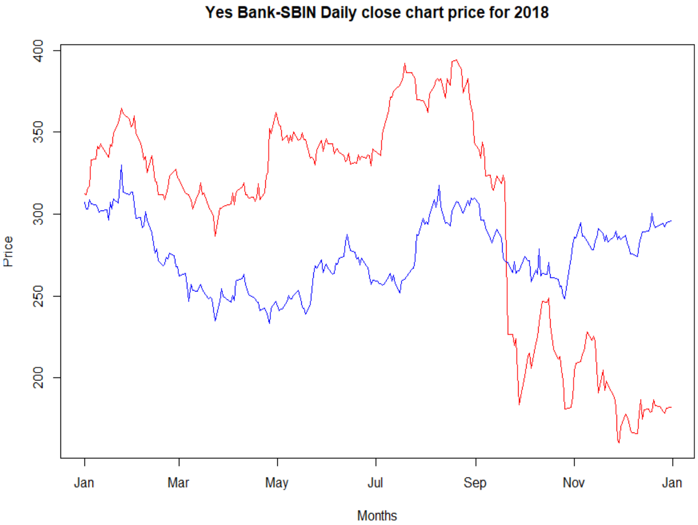

Figure 7: Yes Bank-SBIN Daily close chart price for 2018

The steps of applying the ARIMA model on PNB stock closing prices from 1st January 2017 to 31st December 2018.

Step 1: Testing and Ensuring Stationarity

For modelling a time series with ARIMA, it must be be stationary i.e. it should not have any trend and should have a constant mean and variance over time. This would make it useful for predicting values.

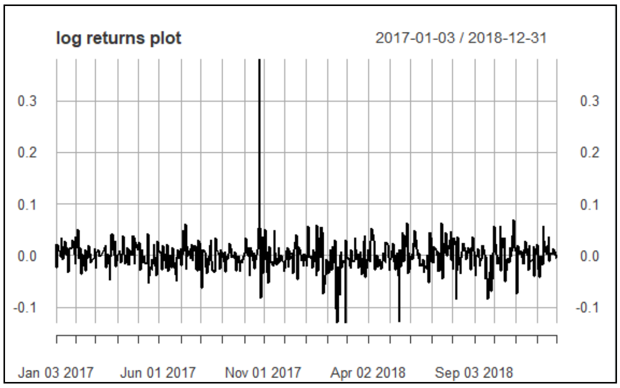

Figure 8: Plot showing the log returns for 2017 and 2018

Testing for stationarity – Augmented Dickey-Fuller unit root test is used for testing stationarity. p-value less than 0.05 or 5% suggests stationary time series, while that greater than refers to a non-stationary process.

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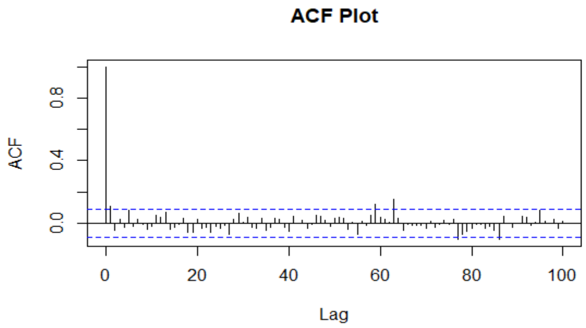
```
Augmented Dickey-Fuller Test

data:  stock
Dickey-Fuller = -7.491, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

Step 2: Identification of p and q

Order of Auto Regressive (AR) and Moving average (MA) processes with the help of the Autocorrelation function (ACF) and Partial Autocorrelation function (PACF) are identified here.



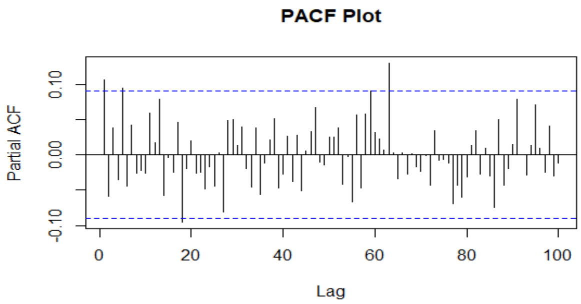


Figure 9: ACF and PACF Plots

In case of the AR Model, the ACF will exponentially reduce and the PACF will be used to estimate the order (p). While in MA model, the PACF will diminish and the ACF will help in identifying the order (q). Thus on the basis of these plots the chosen ARIMA parameters are (1, 0, 1)

The ARIMA function is executed on the training dataset with parameters (2, 0, 2). This model, with the forecast function, is the used to forecast the next data point. The function, set at 99% confidence, predicts the next day returns [11].

```
Call:
Arima (x = stock_train, order = c(2, 0, 2), include. me
an = FALSE)

Coefficients:
          ar1      ar2     ma1     ma2
      -0.1636   0.4845   0.288   -0.52
s.e.      NaN      NaN     NaN     NaN

sigma^2 estimated as 0.000996:  log likelihood = 1002.1
3, aic = -1994.27

Training set error measures:
                        ME         RMSE         MAE MPE MA
PE      MASE         ACF1
Training set -0.0006901337 0.03155875 0.02033281 NaN
Inf 0.6930836 0.004324858
```

The Return equation is as follows:

$$Y_t = -0.1636 * Y_{(t-1)} + 0.4845 * Y_{(t-2)} + 0.288\varepsilon_{(t-1)} - 0.52\varepsilon_{(t-2)}$$

The equation accepts standard error within acceptable limits. The Akaike information criterion (AIC) score indicates the accuracy of the ARIMA Model, lower the AIC, better is the model. The ACF Plot of the residuals can also be used. We can also view the autocorrelations from the ACF plot of the residuals, a good ARIMA model has its autocorrelations below the threshold. The forecasted value is -0.0006901337, listed in the last row of the output.

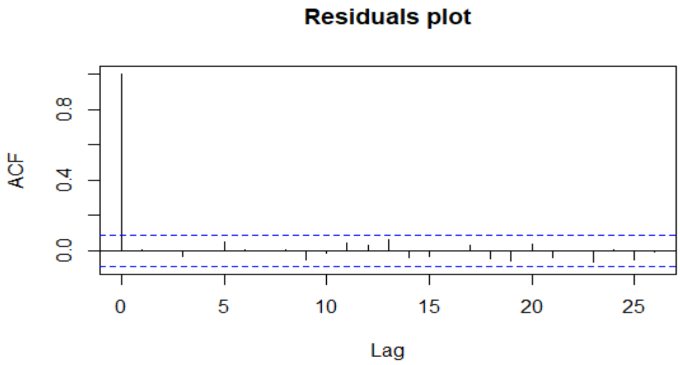


Figure 10: Residual Plot

Above figure depicts the residual values in our model to check the null values in the forecasted returns.

Step 3: Estimation and Forecasting

Once the parameters of (p,d,q) have been determined, the accuracy of the model is known on the historical data. Thereafter this model is used to forecast the values of the returns in the future using a forecasting function. Finally the forecasted values will be compared with the actual values to verify the results.

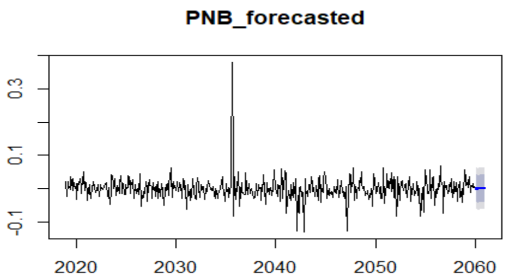


Figure 11: Forecasted log returns of PNB NSE close price

Figure 11 predicts the variations in the log returns of Punjab national Bank on its shares for the upcoming years.

Figure 17shows the predicted values for the years 2019 and 2020 using ARIMA (1, 0, 1). This model is deemed best for PNB stock index after several adjustments of the parameters (p) and (q).

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```
         Point Forecast       Lo 80      Hi 80       Lo 95      Hi 95
Feb 2019 -4.322663e-03 -0.04483263 0.03618730 -0.06627731 0.05763198
Mar 2019   3.286290e-03 -0.03745560 0.04402818 -0.05902306 0.06559564
Apr 2019 -2.498391e-03 -0.04337373 0.03837695 -0.06501183 0.06001505
May 2019   1.899394e-03 -0.03905288 0.04285167 -0.06073170 0.06453049
Jun 2019 -1.444008e-03 -0.04244068 0.03955266 -0.06414301 0.06125499
Jul 2019   1.097802e-03 -0.03992451 0.04212011 -0.06164041 0.06383601
Aug 2019 -8.346004e-04 -0.04187172 0.04020252 -0.06359546 0.06192626
Sep 2019   6.345022e-04 -0.04041118 0.04168018 -0.06213945 0.06340845
Oct 2019 -4.823782e-04 -0.04153301 0.04056825 -0.06326389 0.06229914
Nov 2019   3.667264e-04 -0.04068676 0.04142021 -0.06241916 0.06315261
Dec 2019 -2.788025e-04 -0.04133394 0.04077633 -0.06306722 0.06250961
Jan 2020   2.119587e-04 -0.04084413 0.04126805 -0.06257792 0.06300183
Feb 2020 -1.611409e-04 -0.04121778 0.04089550 -0.06295186 0.06262958
Mar 2020   1.225068e-04 -0.04093446 0.04117947 -0.06266870 0.06291371
Apr 2020 -9.313542e-05 -0.04115028 0.04096401 -0.06288462 0.06269835
May 2020   7.080589e-05 -0.04098645 0.04112806 -0.06272084 0.06286246
Jun 2020 -5.382995e-05 -0.04111115 0.04100349 -0.06284557 0.06273791
Jul 2020   4.092404e-05 -0.04101643 0.04109827 -0.06275088 0.06283272
Aug 2020 -3.111236e-05 -0.04108848 0.04102626 -0.06282294 0.06276072
Sep 2020   2.365307e-05 -0.04103373 0.04108104 -0.06276820 0.06281550
Oct 2020 -1.798217e-05 -0.04107537 0.04103941 -0.06280984 0.06277388
Nov 2020   1.367088e-05 -0.04104372 0.04107106 -0.06277819 0.06280554
Dec 2020 -1.039324e-05 -0.04106779 0.04104700 -0.06280226 0.06278148
```

Figure 12: Predicted Log returns of PNB stock

Figure 13 is the graph of predicted returns against actual stock returns of PNB stock to demonstrate the correlation of accuracy. It can be seen from the graph, that the model's performance is exemplary and the predicted and actual values have pretty close at some points.

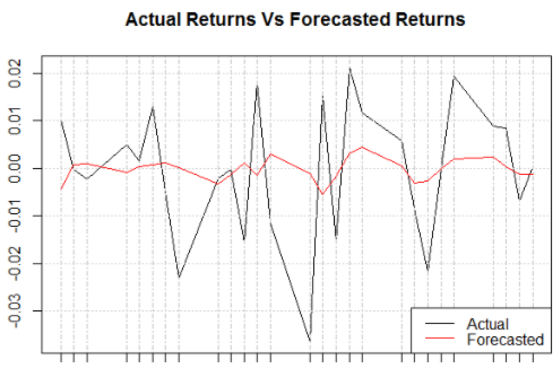

Figure 13: Graph of Actual returns v/s forecasted returns

X. CONCLUSION

This paper presents the techniques of predicting the returns of stock prices through statistical and time series modelling. The results obtained from the ARIMA model to predict the stock prices are at a satisfactory level for short term period. This can be used to guide the investors to assess their portfolio through various channels of analysis to make profitable investment decisions.

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AUTHORS PROFILE

Ms. Riya Agarwal, born and brought up in Delhi, India, is has completed her PGDM from New Delhi Institute of Management, with specializations in Finance and Business Analytics. She has graduated from Deen Dayal Upadhyaya College, Delhi University.

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She has over 18 years of rich experience in Industry and Academics. She has been associated with organizations as Prosix Softron and HCL Infosystems as a Software Engineer. She was awarded the Faculty Excellence Award 2016 by Infosys. She has guided a number of M. Tech and MBA projects and dissertations.

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Prof. (Dr.) Rinku Sharma Dixit, born and brought up in Delhi, India. She has completed her Ph.D (Computer Science) with specialization in Artificial Neural Networks for Pattern Recognition. She has completed her MCA, M. Tech (IT) and B.Sc (H) from Delhi, India.

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