Market Timing - Technical Indicators, Portfolio Optimization and Stock Selection

Master's Thesis Project

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ABSTRACT

In this report, I present various types of Moving Averages and Technical Indicators that are widely used by the traders to time the buy or sell of an asset in the market. The advantages and limitations of technical indicators based on moving averages are addressed. However, these indicators help investors in making buy or sell decisions, they don't address the problem of proportion of funds needed to allocate to different assets under portfolio created. For the purpose of capital allocation Mean Variance (Markowitz) Portfolio Optimization model is used. Further combinations of technical indicators were looked upon. The performance of the various strategies will be evaluated using Sharpe Ratio. Also LR, SVR and LSTM models were explored to select the top stocks to be used for portfolio construction.

Keywords: Moving Averages, Technical Indicators, Mean – Variance Model, Market Timing, Portfolio Optimization

CONTENTS

1. INTRODUCTION

Traditionally in finance literature the stock returns were predicted using various financial ratios and macroeconomic variables. Traders shifted to technical analysis and are using it for almost a century now. Technical analysis is a popular technique to decide the timing of buying and selling an asset. One of the basic principles of technical analysis is that "prices move in trends." To determine these trends by smoothing out the fluctuations various types of moving averages are adopted. One of the controversies about market timing with moving averages is over which trading rule in combination with which moving average(s) produces the best performance. This research covers various moving averages and trading rules devised out of them along with some other technical indicators such as MAC, MACD, Stochastic Oscillator (KD Index) and Williams %R.

The buy/sell signal generation is addressed by the technical indicators but investors still face two major problems – 1. Which stocks to select for portfolio construction?, 2. How should their capital be distributed among the stocks in the portfolio? To overcome the first problem LR, SVR and LSTM models were used to get top stocks based upon their average returns. For the second problem a very popular Mean – Variance model pioneered by Harry Markowitz is used. For multiperiod, an optimized portfolio is generated for each period and the adjustments are done by investors at the beginning of each period known as rebalancing. Now while rebalancing based on the signal generated from technical indicator (or combination of indicators) will allow investor to make more structured decision on whether to buy or sell a particular asset from the portfolio and invest the excess amount into risk free asset (here risk-free asset can be taken as Government Securities – GSecs such as 10 Year Bond).

2. LITERATURE REVIEW

2.1 Moving Averages

2.1.1 Simple Moving Average (SMA)

The Simple Moving Average (SMA) is computed as an arithmetic mean of past *n* prices; thus, it is an equally weighted moving average. The mathematical representation of SMA is as below,

$$SMA_t(n) = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i}$$

The recursive formula for SMA can be written as,

$$SMA_t(n) = SMA_{t-1}(n) + \frac{P_t - P_{t-n}}{n}$$

2.1.2 Linear Moving Average (LMA)

Linear Moving Average (LMA) is calculated by giving more weight to the recent prices and the weights for the considered period are linearly decreasing from recent one to past one. LMA can be formulated as below,

$$LMA_t(n) = \frac{\sum_{i=0}^{n-1} (n-i)P_{t-i}}{\sum_{i=0}^{n-1} (n-i)}$$

2.1.3 Exponential Moving Average (EMA)

In the Exponential Moving Average (EMA), the weights are assigned in an exponentially decreasing manner thus overcoming the problem of rigid weights of LMA. EMA is calculated as follows,

$$EMA_t(\lambda, n) = \frac{\sum_{i=0}^{n-1} \lambda^i P_{t-i}}{\sum_{i=0}^{n-1} \lambda^i}$$

2.2 Technical Indicators

In this section various types of technical indicators are defined and the formula to calculate them are described. Some indicators are based on Moving Averages while some are not. These are widely used technical indicators by the investors.

2.2.1 Momentum Rule (MOM)

MOM is a momentum rule which assumes that if market prices have been increasing (decreasing) over the last *(n – 1)* periods, the prices will continue to increase (decrease) over the subsequent period.

$$MOM_t(n) = P_t - P_{t-(n-1)}$$

Buy (Sell) signal is generated when the last closing price is greater (smaller) than the closing price *(n – 1)* periods ago.

2.2.2 Moving Average Crossover Rule (MAC)

In this, two moving averages are employed in generation of trading signal: one shorter average (window size: *s*) and one longer average (window: *l*), *l* > *s*.

$$MAC_t(s, l) = MA_t(s) - MA_t(l)$$

A crossover occurs when a shorter moving average crosses either above (golden cross, buy signal) or below (death cross, sell signal) a longer moving average.

2.2.3 Moving Average Convergence/Divergence Rule (MACD)

This rule is a combination of three EMAs. It is calculated as difference of MACD line and Signal Line, where both are defined below,

$$MACD\ Line = MACD_t(s, l) = EMA_t(s) - EMA_t(l)$$

$$Signal\ Line = EMA_t(n, MACD_t(s, l))$$

$$Indicator = MACD(s, l, n) = MACD\ Line - Signal\ Line$$

Generally, $n < s < l$ *(e.g., n = 9, s = 12, l = 26)*.

When MACD Line crosses above (below) Signal Line the Buy (Sell) signal is generated.

2.2.4 Stochastic Oscillator (KD Index)

The idea behind this indicator is that the price tends to close near the upper (lower) end of an uptrend (downtrend) period.

$$\%K = \left(\frac{Close - Low_n}{High_n - Low_n}\right) \times 100$$

$$\%D = \frac{1}{w} \sum_{i=n-w+1}^{n} K_i$$

Here *n, w* are lookback periods for %K (fast line) and %D (slow line) respectively. Trading rule can be generated as 'Buy' when *(K < 20) & (D < 20) & (K > D)* and 'Sell' when *(K > 80) & (D > 80) & (K < D)*.

2.2.5 Williams %R

This indicator is very similar to the Stochastic oscillator and is used in the same way.

Williams %R:

$$William\ \%R = \frac{Highest\ High_n - Close}{Highest\ High_n - Lowest\ Low_n}$$

where *n (generally taken = 14)* is rolling window period of past data both indicators.

2.3 Portfolio Creation, Optimization and Performance Tools

There have always been many technical indicators with their proper combinations, traders make informed decisions on when to buy or sell an asset or what trend a stock is following. The only thing now left in our total strategy is the proportion of allocation of funds either for rebalancing or buying or selling the assets in the portfolio. In this section we delve into mathematical formulation of Mean – Variance Model and also look into Sharpe Ratio and Sortino Ratio to evaluate our strategies' performance.

2.3.1 LR, SVR, LSTM

LR stands for Linear Regression. LR is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting.

SVR stands for Support Vector Regressor. SVR uses the same basic idea as Support Vector Machine (SVM), a classification algorithm, but applies it to predict real values rather than a class. SVR acknowledges the presence of non-linearity in the data and provides a proficient prediction model.

LSTM stands for Long short-term memory. LSTM is an artificial recurrent neural network (RNN) architecture used in the field of deep learning (DL). Unlike standard feedforward neural networks, LSTM has feedback connections.

For the scope of this research project I have not discussed the mathematics involved in these models and thus omitting the formulas for the same.

2.3.2 Mean – Variance Model (Markowitz)

Expected returns of n risky assets taken as in vector form $\mathbf{r} = (r_1, r_2, \ldots, r_n)$ and their variance – covariance matrix $\boldsymbol{\sigma} = (\sigma_{ij})_{n\times n}$, expected portfolio return is $\mathbf{rw}^\mathbf{T}$ and risk of portfolio is $\mathbf{w\sigma w}^\mathbf{T}$ where $\mathbf{w} = (w_1, w_2, \ldots, w_n)$. Then following optimization is done to get mean – variance model,

$$Minimize\ w\sigma w^T$$

$$s.t.\ \sum_{i=1}^{n} w_i = 1 \ \ and\ \ 0 \le w_i \le 1,\ \ for\ i = 1\ to\ n.$$

2.3.2 Sharpe Ratio

Sharpe Ratio is the average return earned in excess of the risk-free rate per unit of volatility (or total risk). Its formula is as below,

$$Sharpe\ Ratio\ = \frac{R_p - R_f}{\sigma_p}$$

where, R_p = Actual or Expected return of portfolio

R_f = Risk-free rate

σ_p = Standard deviation of portfolio's excess return

3. DATA AND METHODOLOGY

3.1 Data

For the current experiment daily prices data of 4 Fiscal Years have been taken starting from 1st April, 2018 till 31st March, 2022. The stocks under consideration are underlying stocks of NIFTY50. The data is downloaded in an ipython notebook from yahoo finance using the 'yfinance' library with NSE ticker symbols of all the above stocks and NIFTY50.

idxs	Tickers	idxs	Tickers	idxs	Tickers	idxs	Tickers
0	^NSEI	13	BAJFINANCE.NS	26	ICICIBANK.NS	39	TITAN.NS
1	ONGC.NS	14	DIVISLAB.NS	27	TATASTEEL.NS	40	HEROMOTOCO.NS
2	UPL.NS	15	TATACONSUM.NS	28	RELIANCE.NS	41	KOTAKBANK.NS
3	ITC.NS	16	HDFCLIFE.NS	29	HCLTECH.NS	42	BAJAJFINSV.NS
4	SUNPHARMA.NS	17	M&M.NS	30	TECHM.NS	43	POWERGRID.NS
5	IOC.NS	18	INFY.NS	31	BAJAJ-AUTO.NS	44	ASIANPAINT.NS
6	JSWSTEEL.NS	19	GRASIM.NS	32	BPCL.NS	45	EICHERMOT.NS
7	SBIN.NS	20	WIPRO.NS	33	TCS.NS	46	TATAMOTORS.NS
8	SHREECEM.NS	21	COALINDIA.NS	34	NESTLEIND.NS	47	DRREDDY.NS
9	HINDUNILVR.NS	22	BRITANNIA.NS	35	ADANIPORTS.NS	48	HDFCBANK.NS
10	NTPC.NS	23	INDUSINDBK.NS	36	AXISBANK.NS	49	HDFC.NS
11	HINDALCO.NS	24	BHARTIARTL.NS	37	ULTRACEMCO.NS	50	MARUTI.NS
12	LT.NS	25	SBILIFE.NS	38	CIPLA.NS		

Table 1. Tickers of the stocks under consideration for the research work and indices (idxs) of corresponding stock in code or files both for output and input purposes

3.2 Methodology

3.2.1 Technical Indicators

In total 6 strategies are followed for generation of buy/sell signals using technical indicators or combination of technical indicators with the help of 'stock_stats' python library. The indicators are as follows:

- Moving Average Crossover (MAC) Rule
- Moving Average Convergence/Divergence (MACD) Rule
- MACD on Simple Moving Average (SMA) of prices data
- Stochastic Oscillator (KD Index)

- Stochastic Oscillator + MACD (combination)
- Williams %R + MACD (combination)

3.2.2 Stocks Selection

The data was first split into training-validation-testing sets. The size of the split was a hyperparameter and was varied between 1%-10% of the total data size across iterations. Based on the split, predictive models were fit on the training data, such as:

- LSTM
- Linear Regression
- Support Vector Regression

After fitting these models, based on the forecasted prices, the top 'n' (for the scope of this research n = 10 was taken) stocks having the best average returns on predictions were selected to form the portfolio.

3.2.3 Markowitz, Returns, Sharpe Ratio

The hypothesis to be tested was the following : If one uses future forecasts in the process of portfolio allocation and selects assets based on these forecasts, can one get an overall better return (or risk-adjusted return) in future.

To test this, Markowitz models were built over returns for two cases of data:

1. Using the training, validation and predicted values using the forecasting models
2. Using the training and validation data only. This case accounts for the situation when one does not any forecast for the future

Markowitz models optimize the portfolio allocation scheme by solving a Mean – Variance Optimization problem. Based on the weights obtained, metrics of Returns, Risks and Sharpe Ratios were computed on the test data. These were then compared and plotted.

4. RESULTS AND CONCLUSION

4.1 Technical Indicators

Implemented the moving averages and technical indicators on NIFTY50 and stocks individually to check their working. Below are some of the examples of implementation of the technical indicators under consideration.

Fig 1. MAC rule with parameters s = 20, l = 50

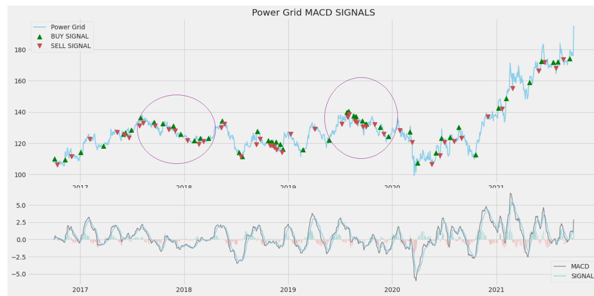

Fig 2. MACD on Stock Price with parameters s = 12, l = 26, n = 9

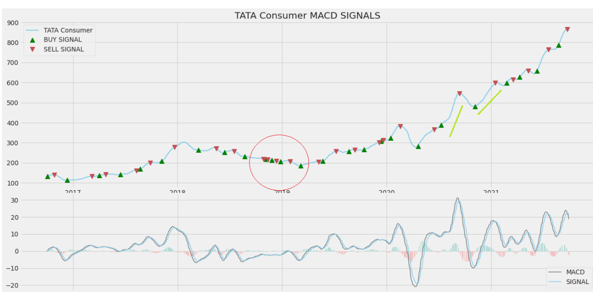

Fig 3. MACD on SMA (20) of stock price with parameters s = 12, l = 26, n = 9

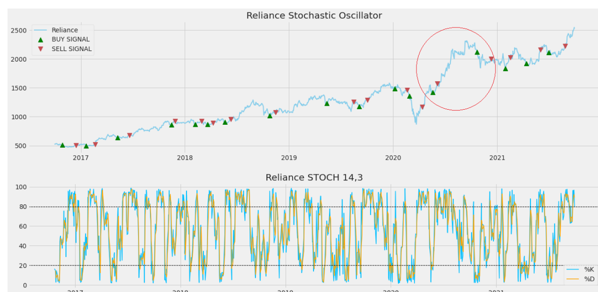

Fig 4. Stochastic Oscillator with parameters n = 14, w = 3

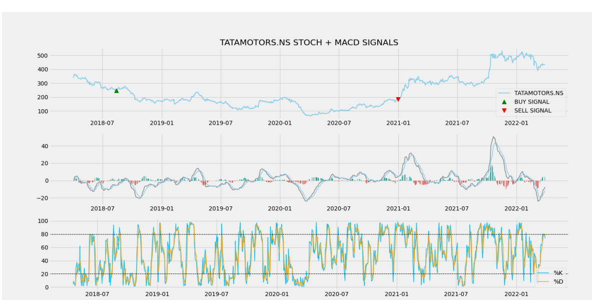

Fig 5. STOCH + MACD of stock price with parameters s = 12, l = 26, n = 9

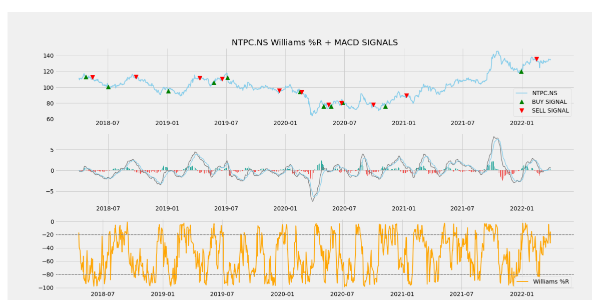

Fig 6. Williams %R + MACD of stock price with parameters s = 12, l = 26, n = 9

Conclusions: It can be observed from the graphs that there are multiple problems faced while using these indicators such as – generation of false signals, delay in the signal intimidation, clustered signals (thus leading to too many transactions in a short period). Similar problems were observed in graphs of other stocks under consideration (these graphs are not attached in the report so that the analysis doesn't become too cluttered). In graphs the upward trend predicted correctly by indicator is marked by an upward moving green coloured line in graphs.

In **Fig 1** and **Fig 4** the false signals are marked with red circles. These are also an example of delayed response of 'buy' signal (marked with green upward arrow). **Fig 2** and **Fig 3** are examples of clustered signal generation. It can be observed that there is a *huge reduction* of signal generation from **Fig 2** to **Fig 3** although the technical indicator used is similar. This difference is the result of using SMA (20) instead of Stock Price directly for applying the MACD rule. In **Fig 5**, it can be seen that there are just 2 signals thus the combination is not able to detect some potentially good buy/sell signals and results in lower performance compared to individual indicators.

4.2 Selected Stocks and Markowitz weights

For the corresponding 3 models used, following are the selected stocks and their Markowitz weights for both the cases of actual and predicted data for test sizes 2% and 10% (experimented for the test sizes 2%, 4%, 6%, 8% and 10%):

LR - 2	TATAMOTORS	KOTAKBANK	TITAN	RELIANCE	INDUSINDBK	COALINDIA	NTPC	IOC	ITC	ONGC
M actual 2	0.14527	0.15846	-0.05749	0.22112	-0.03254	0.2725	0.13528	0.06343	0.14992	-0.05596
M pred 2	0.14063	0.16279	-0.06335	0.21431	-0.03358	0.27053	0.13953	0.06796	0.15221	-0.05103

LR - 10	ASIANPAINT	BAJAJFINSV	TITAN	TECHM	INDUSINDBK	COALINDIA	HCLTECH	TATACONSUM	BAJFINANCE	ONGC
M actual 10	0.1361	0.10245	0.02141	-0.03235	0.19415	0.05837	0.29491	-0.00954	0.00804	0.22646
M pred 10	0.12011	0.09925	0.02729	-0.03176	0.20579	0.07195	0.29829	-0.00745	0.00533	0.2112

SVR - 2	MARUTI	HEROMOTOCO	TATAMOTORS	INDUSINDBK	M&M	COALINDIA	NTPC	ITC	IOC	ONGC
M actual 2	0.16799	-0.05242	0.06976	-0.01459	0.33461	0.09659	0.2599	0.14522	0.05741	-0.06448
M pred 2	0.17561	-0.05524	0.06835	-0.01292	0.33434	0.09819	0.25596	0.14843	0.05215	-0.06486

SVR - 10	MARUTI	HEROMOTOCO	NESTLEIND	BHARTIARTL	INDUSINDBK	COALINDIA	NTPC	ITC	IOC	ONGC
M actual 10	0.12666	0.07463	-0.05022	-0.04183	0.229	0.15593	-0.0164	0.34004	0.09563	0.08655
M pred 10	0.14201	0.08157	-0.06061	-0.03075	0.24475	0.13231	-0.00566	0.31569	0.08328	0.09742

LSTM - 2	RELIANCE	TATAMOTORS	INDUSINDBK	COALINDIA	NTPC	SBIN	IOC	ITC	UPL	ONGC
M actual 2	-0.07041	0.00524	0.16852	0.20977	0.0718	-0.04451	0.03977	0.33922	0.28004	0.00056
M pred 2	-0.07158	0.00583	0.1675	0.20896	0.06874	-0.04196	0.04046	0.34178	0.27924	0.00101

LSTM - 10	EICHERMOT	RELIANCE	TITAN	BAJAJFINSV	BAJFINANCE	COALINDIA	IOC	LT	ITC	ONGC
M actual 10	0.16756	-0.06227	-0.04448	-0.02232	0.31538	0.21768	0.06078	0.06672	0.15387	0.14707
M pred 10	0.1676	-0.07064	-0.03713	-0.02203	0.31255	0.21978	0.0633	0.06464	0.15709	0.14484

Table 2 – 7. Selected stocks under LR, SVR and LSTM models for test sizes 2% and 10% (LR - 2 here means LR model with test size 2%) and Markowitz weights (M actual 2 here means Markowitz weights for test size 2% for actual data and 'pred' means predicted data)

Conclusions: It can be observed that the difference between actual and predicted weights for test size 2% is less compared to test size 10%. This is because the training data is more for 2% test size and the prediction is conducted for small portions of data while for 10% test size the conducting prediction for large portions of data, the error propagates thus it deviates more from actual values and hence the larger difference between weights.

4.3 Backtesting and Performance

Also Backtesting was conducted for these indicators on the selected stocks from all three models – LR, SVR and LSTM, with initial investment amount as **$100,000** over the whole 4 years of horizon under consideration for the project while buying and selling is done as per the signal generated by the technical indicator.

Technical Indicator(s)	TATAMOTORS	KOTAKBANK	TITAN	RELIANCE	INDUSINDBK
MAC	71%	33%	63%	78%	-3%
MACD	87%	-38%	87%	121%	-12%
MACD on SMA	169%	161%	267%	330%	78%
STOCH	-19%	29%	98%	76%	-6%
STOCH + MACD	-46%	77%	112%	207%	-48%
WR + MACD	53%	8%	90%	98%	-12%

Technical Indicator(s)	COALINDIA	NTPC	IOC	ITC	ONGC
MAC	-39%	-13%	-38%	37%	20%
MACD	6%	81%	36%	30%	49%
MACD on SMA	97%	126%	98%	95%	127%
STOCH	4%	17%	12%	21%	-6%
STOCH + MACD	-7%	21%	-6%	13%	10%
WR + MACD	18%	42%	9%	-3%	-12%

Technical Indicator(s)	ASIANPAINT	BAJAJFINSV	TECHM	HCLTECH	TATACONSUM
MAC	89%	188%	150%	75%	180%
MACD	45%	108%	81%	129%	111%
MACD on SMA	258%	348%	258%	272%	273%
STOCH	98%	104%	23%	74%	8%
STOCH + MACD	42%	117%	60%	11%	11%
WR + MACD	73%	98%	59%	127%	25%

Technical Indicator(s)	BAJFINANCE	MARUTI	HEROMOTOCO	M&M	NESTLEIND
MAC	141%	8%	-9%	18%	30%
MACD	260%	-7%	-18%	48%	44%
MACD on SMA	485%	92%	83%	123%	232%
STOCH	26%	13%	-25%	11%	35%
STOCH + MACD	231%	-11%	-39%	10%	38%
WR + MACD	147%	3%	17%	35%	65%

Technical Indicator(s)	BHARTIARTL	SBIN	UPL	EICHERMOT	LT
MAC	34%	37%	69%	-21%	18%
MACD	55%	165%	40%	8%	48%
MACD on SMA	210%	245%	190%	118%	140%
STOCH	74%	46%	18%	39%	19%
STOCH + MACD	118%	70%	29%	-3%	86%
WR + MACD	28%	93%	61%	56%	39%

Table 8 – 12. Percentage returns over 4 years with $100,000 initial investment

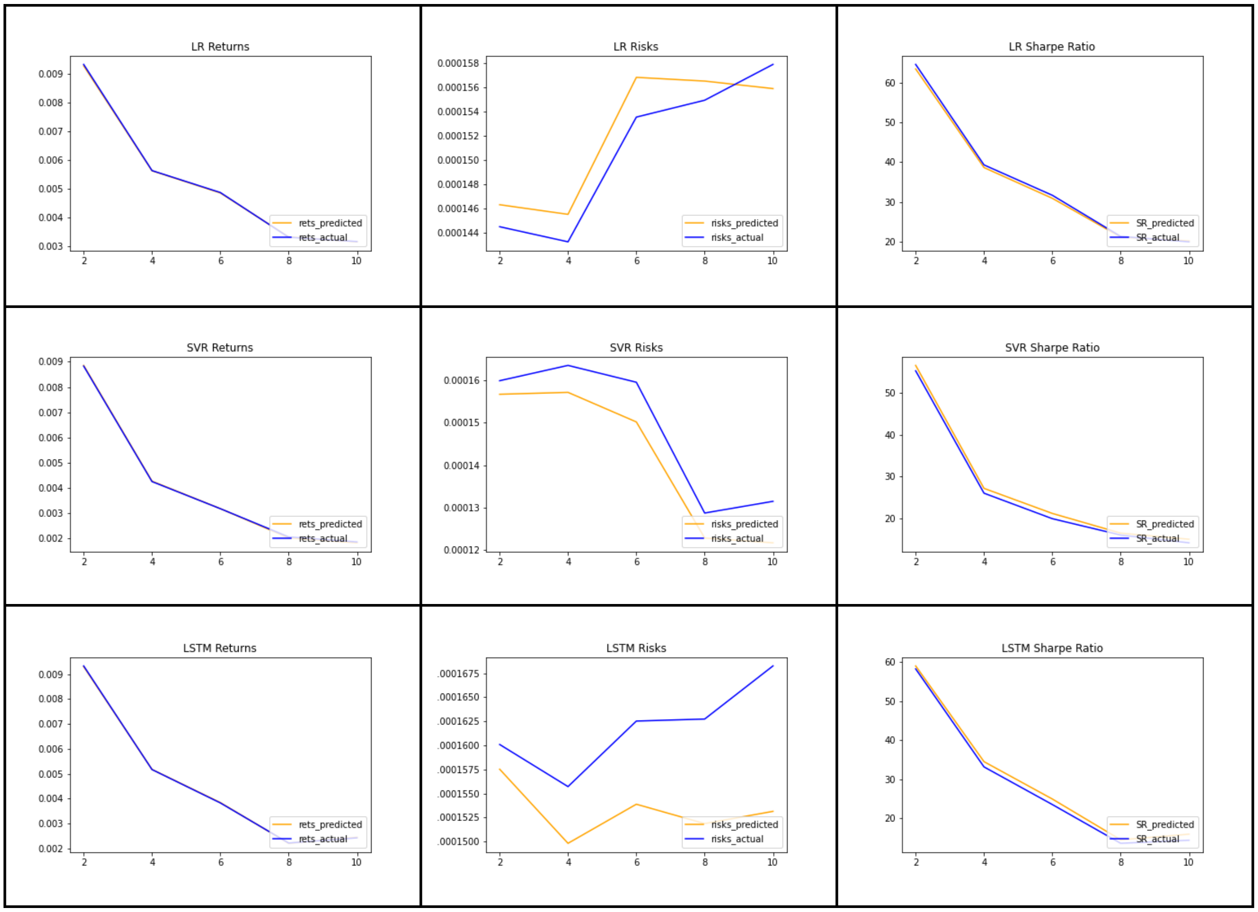

Fig 7 – 15. Plots of returns, variance and Sharpe ratio for test sizes 2%, 4%, 6%, 8%, 10% for each of the three models – LR, SVR and LSTM

Conclusions: Short selling was allowed thus some stocks are repeated in different portfolios created which have negative returns (or least returns) while backtesting using technical indicators. These were considered by the models to be short selled to get the maximum possible portfolio returns.

It can be seen that MACD on SMA (20) of Stock Price is outperforming for all the stock. The reason behind this is the decrease in fluctuations due to use of moving average over stock price. Also the combination of indicators didn't improve the performance much as expected.

A general trend of decreasing returns is observed with increasing test size, the reason behind this can be the training data decreases and thus the model tends to perform better for lesser test size. Also Sharpe Ratios for SVR and LSTM models are better for the data where the predicted portion was also considered for portfolio construction (while the same is not true for LR model).

*** Note –1: Refer Appendix for Correlation plot and Daily returns plot. The drive folder link to more plots, data and some code files – LINK.

*** Note – 2: Link to the three google colab notebook code files – Code-1, Code-2, Code-3.

5. FUTURE WORK …

The following complexities can be acquired for the further research based upon my thesis project to carry forward the automation of stock selection, getting weights and generation of signals. The complexities I propose for future work are transaction costs and combination of all the above discussed models to form investment strategies.

5.1 Transaction Cost:

As observed above the overwhelming profit is generated for most cases. Although there is a discrepancy in calculating those profits. The transaction costs are not accounted for in calculating them. Thus, this can be the first complexity that we can add to the models.

5.2 Investment Strategies:

The **first strategy** is called *conservative strategy* where mean – variance model is used to get optimal weights for the 5 stocks while any technical indicator (in paper they use Stochastic Oscillator) or combination of indicator will provide the signal when to buy or sell an asset.

First Strategy Steps:

1. Get optimized portfolio weights by solving mean – variance model.
2. For each asset i if technical indicator shows a buying signal, then buy it with weight w_i.
3. Invest remaining wealth (considering we are left with any amount from our target investment amount) in risk-free asset (can consider GSec here as risk free investment).

The **second strategy** called as *moderate strategy*, which will use both mean – variance model and technical indicator to choose the asset to be bought. But the equal weight is allocated to chosen assets.

Second Strategy Steps:

1. Get optimized portfolio weights (here remove the constraint of $w_i > 0$).
2. Take a set of all assets for which technical indicator shows a buying signal and also their weights are positive.
3. Buy these assets of the set with equal weight.

The **third strategy** called as *aggressive strategy* relies only on technical indicator to decide which asset to buy, while the weights are allocated equally among all assets under consideration.

Third Strategy Steps:

1. For each asset if technical indicator shows buying signal add it to the set.
2. Buy all assets under the set with equal weight.

Other than these three strategies, some more strategies can be constructed that use the stock selection as the first step, or where selling can be disallowed ('no short selling' can be considered), different technical indicators or combinations of technical indicators can be used, etc.

All strategies can be implemented using a sliding (rolling) window approach for all with a particular lookback period for technical indicators. The performance of different strategies will be evaluated by average returns and Sharpe Ratio over the specific period under consideration.

6. REFERENCES

Van-Dai Ta, Chuan-Ming Liu, Direselign Addis Tadesse (2020) *Portfolio Optimization-Based Stock Prediction Using Long-Short Term Memory Network in Quantitative Trading.* Applied Sciences.

Chao Chen , Xiao Lin and Gabriel Terejanu (2019) *An Approximate Bayesian Long Short-Term Memory Algorithm for Outlier Detection.* International Conference on Pattern Recognition (ICPR), 201-206.

Valeriy Zakamulin (2017) *Market Timing with Moving Averages: The Anatomy and Performance of Trading Rules.* Palgrave Macmillan Publishing.

Jun-Lin Lin, Chien-Hao Wu, Laksamee Khomnotai (2014) *"Integration of Mean–Variance Model and Stochastic Indicator for Portfolio Optimization."* In *Lecture Notes in Electrical Engineering*, 497 – 502. Springer International Publishing.

Talwar Shalini, Shah Pranav, Shah Utkarsh (2019) *Picking Buy-Sell Signals: A Practitioner's Perspective on Key Technical Indicators for Selected Indian Firms.* Studies in Business and Economics Journal.

Terence Tai-Leung Chong, Wing-Kam Ng (2008) *Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30.* Applied Economies Letters, Vol. 15, 1111 – 1114.

Andrew W. Lo (2003). *The Statistics of Sharpe Ratios.* Financial Analysts Journal, Vol. 58, 36 – 52.

APPENDIX

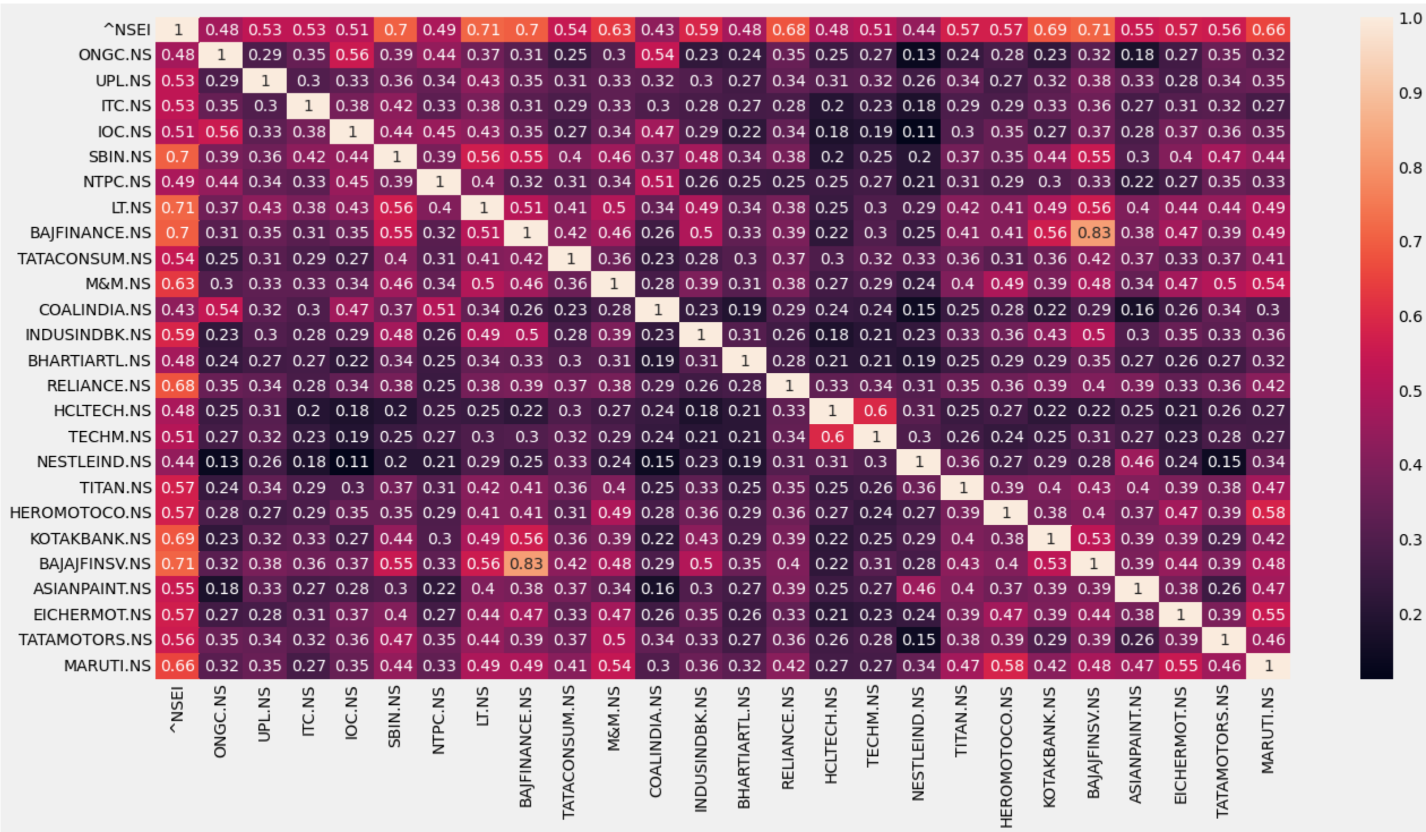

Fig 16. Correlation Matrix

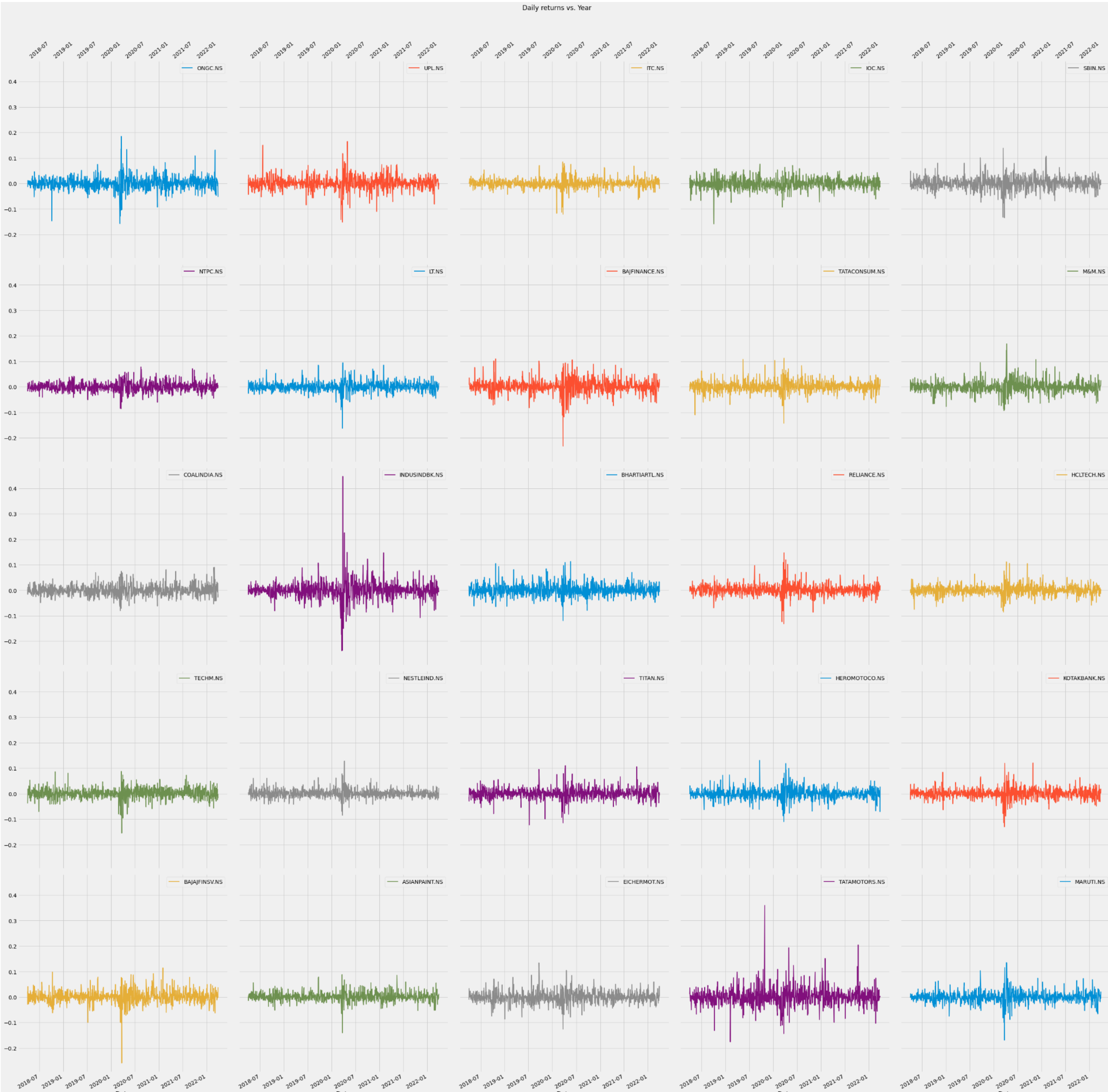

Fig 17. Daily Returns vs Time plot