Advanced Intraday trading strategies

Mean reversion, Momentum, Seasonality

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Abstract— In this paper the authors explore and demonstrate 'Advanced Intraday Trading Strategies'. The topic was selected by authors as a part of the Capstone project research track in the MSc Financial engineering program at WorldQuant University. The authors aim to explore the effectiveness of various technical indicators leveraging minute level Open, High, Low, Close, Volume and open interest data in the Indian equity futures market. The authors specifically demonstrate mean reversion, momentum and seasonality strategies that have short holding periods ranging from one minute to five minutes and have sharpe ratios ranging from 0.5 to over 5, excluding any transaction costs.

Keywords—Nifty, mean reversion, momentum, seasonality, futures, equity futures, sharpe ratio, technical, World Quant

I. Introduction

The rapid advancement in the global technology industry has enabled an explosion of data and its availability to corporations, institutions - financial and non-financial, regulators and other entities. The technology boom has either transformed or at least touched various points of the value chain of other industries including financial and securities. The developments along with the regulatory changes have led to proliferation of securities and exchanges which consequently has made data available on a more frequent basis than traditionally monthly or quarterly.

"When we look at the security price dynamics with respect to market microstructure, our focus has shifted from monthly or daily to minute or tick level with more features such as bid price, ask price, bid size, ask size, trade price and trade volume among others" (Omoruyi, Aigbovo & Isibor,. 2017).

The hedge funds, proprietary trading firms and other asset managers aim to maximize returns, given an agreed level of risk, for their clients and investors by utilizing various strategies. The advanced intraday trading strategies are often one of their key focus points given availability of data, technology and top talent to harness it. The sell side, on the other hand, provides their market making services, which is to put it simply to provide liquidity to the market.

The advanced intraday strategies are highly relevant to traders and investors. These strategies enable them to create a high competitive edge in the market by exploiting price discrepancies, providing liquidity and optimizing execution. "These strategies support real-time decision-making, reduce transaction costs, and promote better price discovery, enhancing overall market efficiency." Journal of Financial Markets

II. PURPOSE & OBJECTIVES

Our purpose is to develop an intraday trading strategy that identifies inefficiencies while effectively sizing our trade and managing risk. This strategy will utilize short term price fluctuations within a trading (business) day to create a signal or algorithm. Ideally we would like to leverage high frequency data on the security prices and volumes.

Within intraday, our focus will likely be on either the mean reversion strategy or the momentum strategies depending whether we are in a range (non-trending) market or a trending market. Although there are a few other strategies such as strat-arbitrage, seasonality, etc that could be of lower interest to us. Our initial exploratory work using Hurst exponent on US treasury bond futures shows broadly, there are more instances of mean revision in its security price on an intraday level than momentum.

We will develop quantitative signals by leveraging the technical features derived from price and volume such as RSI, Hurst exponent, Bollinger bands, etc. The machine learning techniques will be applied to create better accuracy at prediction. The signal can go long and/or short based on the prediction on multiple assets. We will evaluate different techniques for sizing the bets. Further, we also aim to have clearly defined trading rules in-built in the signal algorithm for effective risk management of the overall strategy.

Our coding design will focus on six main components. First, data pre-processing in importing and cleaning the data for any missing values, outliers, etc. Second, the exploratory research component will help us in not only visualizing but also creating an important understanding of the characteristics of the intraday market in various assets. Third, the feature creation component will utilize the data to create features crucial for identification of trend, seasonality, mean reverting behaviour of the time series. Fourth, strategy (signal) creation will utilize statistical and machine learning methods to make realistic time series predictions. Fifth, we will also build the risk management functionalities to make the strategy follow certain real world rules around drawdown, take profit, stop loss, etc. Sixth, the back-testing component will assess the strategy performance historically and in different regimes and scenarios.

III. CONTRIBUTION OR EXTENSION OF THE TOPIC

There are numerous pain points in the current intraday high-frequency trading business.

Firstly, intra-day trading is viewed as a zero-sum game. There are especially a lot of short term fluctuations lacking fundamental or economic sense and full of noise. Overall market may not rise as it does in the medium to long term creating wealth for most investors. The point is there is a limited pie to compete for among a school of sharks/competitors. Hence it takes a very high skill financially engineered strategy to be successful.

Secondly, intraday trading demands constant attention and quick decision-trading, which may create psychological pressure for a trader. The continuous monitoring of the market also requires a high-level of time commitment. For a systematically engineered strategy, it may require close attention to various aspects of trade sizing, drawdowns, macro events and unexpected volatility.

Thirdly, intra-day trading is becoming more competitive and sophisticated, as the arm-race of AI, big data, HFT and Algo trading escates. The traditional financial engineered strategies have focussed on leveraging technical features. However, given evolution of real time alternative data like twitter (X) sentiment, disinformation campaigns by rogue elements and other sentiment features can add a lot of value that is currently missing and often can be a cause of drawdowns and volatility in the market.

Fourthly, there are regulatory concerns on whether intra-day trading (especially HFT) triggers more market volatility. Regulatory regimes have evolved over time and enabled by technology they have allowed zero day options and a boom in intraday trading. There is genuine concern that unnecessary market volatility might be created by such instruments and HFT market players which can increasingly make it difficult for traditional intra-day trading strategies to be profitable.

Fifthly, there are concerns for market noise from short-term price movements and if traders or algorithms wrongly pick them as real patterns or trends, it can create quick losses in short-time. There are quite a few cases of algorithms wrongly trading and creating unnecessary volatility spikes such that exchanges have had to shut down for a brief period. Such corner cases however present can cause huge issues for financially engineered strategies.

Last but not the least, transaction costs erode alpha. It is a delicate balance between choosing high win ratio but lower alpha trades and low win ratio but higher alpha trades. The number of trades tend to be higher in the former case and the transaction costs can eat up a lot of the margins further. Hence HFT players have no option but to be really low latency to increase the margins. Low win ratio, higher alpha trades tend to suffer more drawdowns given low win ratio but lottery like payout. Overall, financially engineering strategies need to take into account bid-ask spreads that are dynamic and difficult to model hence a realistic net sharpe ratio tends to be lower than the expected one.

IV. METHODOLOGY

First, as briefly mentioned above, we aim to create an algorithm to reliably identify mean reversion and trend in the price time series. For such purposes we will need to deeply explore various technical features. Currently, we have studied following features - Bollinger bands, Z score, RSI, William's R, Commodity channel index (CCI), MACD, VWAP, exponential moving average, simple moving average, Chaikin Money Flow Indicator, Price volume trend (PVT), volume spike, average true range, Donchian channel, Keltner channel, ichimoku cloud, Money flow index, On balance volume, SAR indicator, Force index, Stochastic oscillator, Directional Movement Index, Chande Momentum Oscillator , Average Directional Index, VWMA, Price spike, etc. We created the above feature signals in our github repo jupyter notebook for further analysis and creating a robust strategy.

We will create technical features using Open, High, Low, Close, Volume and Open Interest data that was kindly shared by our Professor and mentor Ritabrata Bhattacharya. The data frequency is minute-ly and covers around 186 assets in total. Most of them are single name equity futures and four of the 186 are equity index futures. All of the assets are traded in the Indian market on the National Stock Exchange.

Second, based on the above technical signals, we aim to create a smart bet sizing measure and compare it with a simple and discrete strategy like sell (-1), hold (0) and buy (+1). The bet sizing could be done in various ways such as score-based, kelly criterion or more a formal approach like Markowitz optimization. For example score based methodology could be based on the differential between closing price and Bollinger upper band (or lower band). Such a continuous score, when calculated across sufficient breadth of assets, could enable us to go long and short simultaneously with a further cross sectional scoring method to spread the bets. According to Grinold, Richard C. and Kahn, Ronald N (2019) [16], alpha = IC x volatility x score. Hence with alpha forecasts and a variance covariance estimation, we could look to optimize the portfolio for holdings and bet sizing.

Lastly, Machine Learning methods including ensemble learning techniques could enhance the prediction accuracy of the above identified technical signals. During our current efforts, we have tested predicting next hour (positive, negative or hold) returns i.e. a classification problem using ML methods with fair accuracy. Further risk management techniques will be important in order to scale manage stop losses and strategy drawdown limits.

V. LITERATURE REVIEW

In the theme of intraday trading models the mean reversion trading strategy is popular both among academic researchers and practical applications. In the literature review we are going to overview the main articles regarding mean reversion strategy for different financial markets and assets which include stocks, forex, commodities and futures. There are a lot of articles that provide the existence of mean reversion, but in these articles usually daily and monthly prices are considered while during the project shorter periods will be considered.

The pioneers in the theme of mean reversion in stock prices are Poterba and Summers (1988) [11], in their work they examined if stock prices follow mean reversion behaviour, which means that the price fluctuations from their historical average are temporal and prices return to the long-run balance. To check the hypothesis authors have used monthly and annual data from NYSE in the period 1926-1985. Researchers applied statistical tests like variance ratio one and regression tests. In their work it was shown that there are positive correlations over short horizons and negative correlation over long horizons. This behaviour cannot be explained by discount rate changes and as a result market inefficiency can take a place.

The next significant article in the field of mean reversion could be Chaudhuri and Wu (2003) [3] paper. In their research authors analyze if the stock prices in emerging markets follow the mean reversion strategy. To do this authors collect the data of 17 emerging markets like Argentina, Brazil and Mexico in the period from 1985 to 2002 and use dollar denominated stock price indexes. In analysis they apply panel-based, ADF and PP tests for every data series and in the final step the seemingly unrelated regression is used. In the article authors conclude that there is significant evidence that mean reversion exists with a half-life of about 30 months in the data series and this fact can be helpful for traders to create trading opportunities.

Another important article that proves that mean reversion strategy works is the paper of Bali, Demirtas, and Levy (2008) [1]. In their work authors suggest a nonlinear test to prove or decline the existence of mean reversion, they focus on extreme daily returns and the probability to improve predicted values based on these rare events. The data that is used in the paper include different indexes like SP500, Dow Jones Industrial Average and others in the period from 1926 to 2005. In the article authors also check the relationship between size decile portfolios and mean reversion. To find the connections between past and future data authors use a regression to estimate the relationship between past extreme daily returns and future monthly returns. In the article authors have found that there is a negative relationship between extreme daily returns in the past and stock market returns in the future.

If we step away from the stock prices, we can consider the paper of Lubnau and Todorova (2015) [7] where the authors applied mean reversion trading strategies (the Bollinger Bands) to energy futures markets. The data in this paper consists of WTI Crude Oil, Natural Gas and Heating Oil Futures in the period from 1992 to 2013 from the New York Mercantile Exchange (NYMEX). The authors applied mean reversion trading strategies to identify the buy and sell moments, the hedge ratio was calculated based on Kalman Filter. This method provided better results than random trades, so the authors concluded that this approach is profitable.

Another meaningful paper about comparison of mean reversion and momentum strategies was published by Chaves and Viswanathan (2016) [4]. In this article authors compare the performance of these strategies for commodity spot and future markets. Researchers use two datasets in the analysis, the first one is spot prices for 46 commodities from 1946, the second one is future prices for 27 commodities from 1965. The authors divide commodities into three groups based on the prices and past performance, the Fama MacBeth approach is also used in the article to analyse relationships between basis, future returns and spot price fluctuations. Authors show that momentum strategies are more suitable for future markets while mean reversion strategies provide good results on spot markets.

We believe that one of the most meaningful and relevant work was done by Stübinger and Endres (2018) [13], where the authors represented a mean reverting jump diffusion model for minute-by-minute data. In paper the data is called high-frequency data, but it is just a minute one, authors have considered pair trading in the article. To do this the minute-by-minute trading data was collected for the SP500 oil sector from 1998 to 2015. The model suggested by authors include mean reversion and jumping components to catch sudden jumps in stock prices, to model mean reversion spread the Ornstein-Uhlenbeck process is used. The suggested model works better than traditional strategies and as a result provides 60.61% annualized return after transaction costs.

In another paper Serban (2010) [12] the momentum and mean reversion strategies were combined to create profitable trading strategies in foreign exchange markets. The data for the research include one month forward and spot exchange rates from 1978 to 2008 with such currencies as Belgian Franc, Canadian Dollar, UK Pound and many others, the equity market data was collected from MSCI Barra equity market price indexes. Authors combined mean reversion and momentum and used a parametric test to evaluate UIP deviations. The strategy suggested by authors generates higher returns than traditional FX strategies.

Aside from practical approaches there is also a theoretical article by Leung and Li (2015) [6] where the authors experimented with optimal trading strategies to estimate the buy and sell periods based on mean reverting price spreads. In the paper authors also consider such important points as transaction costs and stop-loss mechanisms. To model the price dynamics authors use the Ornstein Uhlenbeck process. The paper mostly considers theoretical approaches but also provides a useful example based on exchange-traded funds. The most profitable trading strategy depends on transaction costs and stop-loss levels, for example the higher stop-loss level is the reason for earlier liquidations.

There is also a useful article with daily data for foreign exchange market by Popović and Đurović (2014) [10]. Authors work with hourly time-series of EUR/USD exchange rate for Swiss FOREX market in period from 2004 to 2014. The statistical and econometric tests were used to identify anomalies. Authors collected the data about EUR/USD spot anomalies based on statistics and found trading opportunities on Fridays and suggested to sell USD at 12 a.m. and sell EUR at 3 a.m. while the market is liquid it cannot be fully efficient and anomalies can take a place.

If we move away from mean reversion and momentum using traditional methods, we can consider Paspanthong et al. (2019) [9] where the authors apply various machine learning techniques to predict prices on intraday data. Authors suggest LSTM, CNN, SVM techniques to predict the future price movements. The one minute interval data from March to May 2019 for SPY index is used, despite the fact that the index authors also suggest such variables as trading volume, Simple Moving Average and Exponential Moving Average to improve the prediction results. Authors suggest that SVM works better than other techniques but as they notice they do not consider transaction costs.

The literature reviewed above shows that the mean reversion, momentum and machine learning based strategies can be applied to various markets such as equities, commodities and Foreign exchange markets. While in the early stages they were used for long run data like daily and monthly, the modern articles suggest that it can be applied for intra day data also. The machine learning techniques can make a significant impact on the predictive power of the strategies. However in practice most papers do not consider the transaction costs and stop loss mechanism while they can play a crucial role in the profitability of these strategies.

VI. RESULTS & CONCLUSION

We have focused our analysis on the Bank Nifty futures for which the strategies and indicators are discussed below. The in-sample represents the first 80% of the full sample data - January 2022 to early August 2023. Out of the sample is the rest 20% - August 2023 to December 2023.

A. SEASONALITY

We observed significant autocorrelations occurring at regular intervals in the minute level return series. There are both positive as well negative autocorrelations occurring, however small in absolute magnitude but are statistically significant using 95% confidence interval. For example, positive autocorrelation occurs at lag 1,15,30,45,60, etc. It is not demonstrated here, but most significant autocorrelations persist even if we increase the confidence interval to 99%.

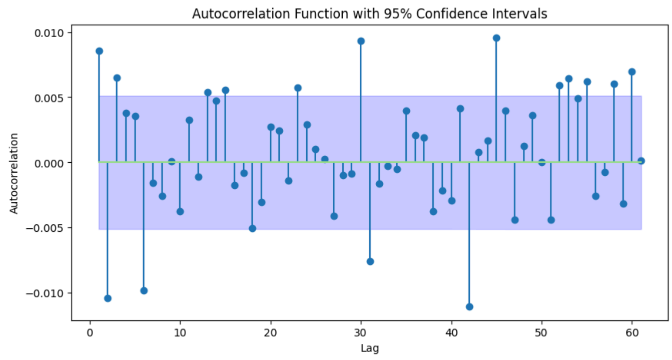

Fig.1 Bank Nifty returns Autocorrelation at various lags

We create a seasonality strategy by betting at various regular intervals based on the sign of the significant autocorrelation. For example lag 2 has a significant negative autocorrelation, hence we bet on the reversal of $t-2$ period return. If $t-2$ return was positive, we go short in the current period. Similarly, lag 3 has significant positive autocorrelation hence we bet on the same direction of $t-3$ return. If $t-3$ return was positive, we go long in the current period betting that the returns will be positive.

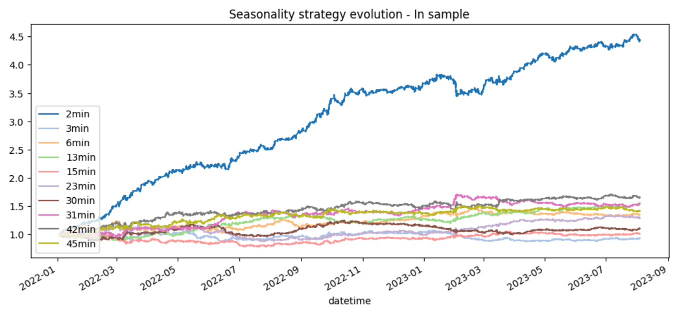

Fig.2 In sample Seasonality strategy evolution for various intervals

The in-sample strategies in general do fairly well but the 2 min seasonality does exceedingly well with a gross sharpe ratio (excluding any transaction costs) above 5.

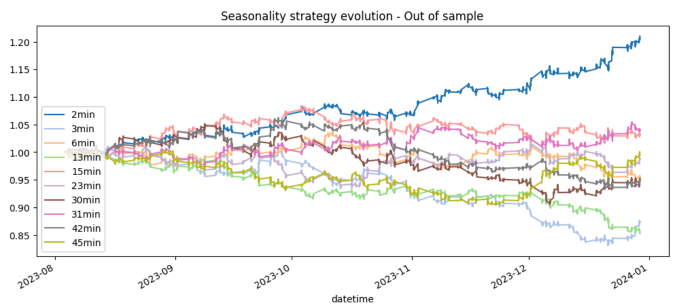

Fig.3 Out of sample Seasonality strategy evolution for various intervals

The strategy holds well out of sample too with almost a 4 gross sharpe ratio. Max drawdown is also quite low at 1.4%. We find many other strategies that did very well during the in-sample period, they struggled during out of sample. While we believe the 2 min seasonality strategy looks very promising, given a holding period of one minute we also recognize a need to look deeply into the transaction costs that could add up significantly with a round trip (buy and sell) fixed cost and any market impact.

TABLE 1. Seasonality strategies performance comparison

Period	In-sample Sharpe ratio	Out of sample Sharpe ratio	OOS Max drawdown
2	5.1	4.0	1.4%
6	1.0	-1.2	5.8%
13	1.5	-3.5	16.7%
23	0.8	-0.4	7.7%
30	0.3	-1.3	10.7%
31	1.5	0.7	3.6%
42	1.7	-1.2	7.9%
45	1.2	-0.3	11.1%

B. BOLLINGER BANDS

Bollinger bands are calculated as a fixed standard deviation away from a price series that is generally (exponential or simple) smoothed with a given lookback period.

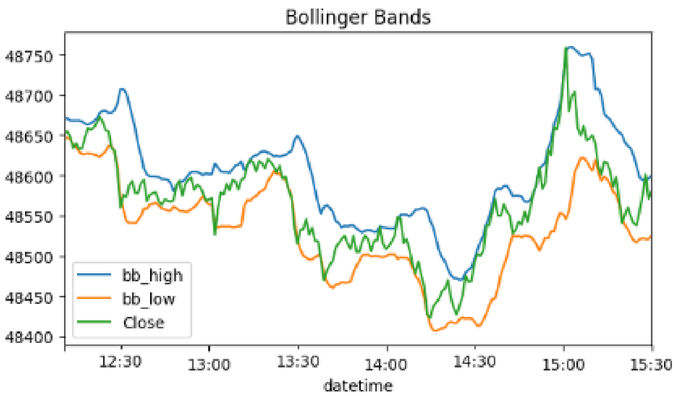

Fig.4 Bollinger bands (1 std dev) for Bank Nifty futures

We create a mean reversion strategy that bets on price reversal if the price moves beyond the bands. To specify our holding period, we stay long or short while the price does not correct back to within the bands.

We did a thorough robustness test for varying lags, look back windows and band tolerances. The lags varied from 1 to 4, look back windows varied from 5 mins to 65 mins increasing in 10 min steps and band tolerance varied from 1 to 4 standard deviations.

The general observation is that the strategy seems to do well for small look back windows, small band tolerance. The alpha seems to decay quickly with increasing lags which is consistent with our understanding of such strategies. It also decays with the increasing look back windows and it performs best with a small look back window of 5mins. The in sample versus out of sample performance is fairly consistent for various lookback and with the lag 2. This is reassuring given it shows a good robustness in our strategy.

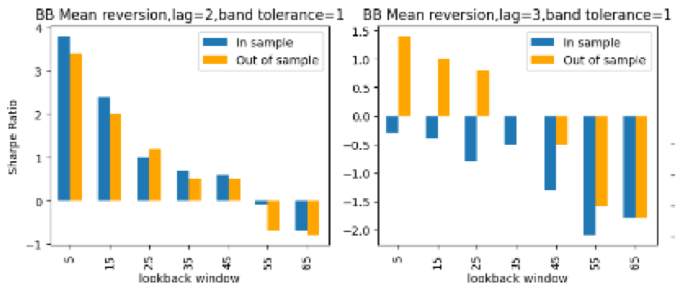

Fig.5 Bollinger bands mean reversion strategy performance comparison for different lags

We plot the top 10 percentile, based on cumulative performance during out of sample, of all the combinations of the strategies tested below. The gross sharpe ratio for the strategy with lag as 2 mins, lookback window as 5 mins, band as 1 standard deviation, achieved was well above 3 during out of the sample period. The holding period on average for the strategy is around 2 minutes.

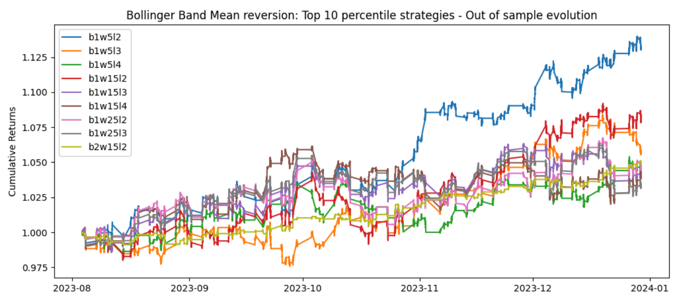

Fig.6 Bollinger bands mean reversion strategy evolution during out of sample period

We also create a momentum strategy based on the bollinger bands by betting with the price trend (rather than the reversal) when the price goes above or below the bands. To specify our holding period, we stay long or short while the price stays outside the bands.

Here we observe that when the price breaks out above the higher bands (more than 2 standard deviations), there is a significant opportunity to capitalize on the momentum. Another key observation is that the strategy generally works on the higher lookback windows (>90mins) and higher lags like 3 and 4. Also the holding period is generally longer than the mean reversion strategy. This makes the strategy quite implementable.

The strategies having band tolerance as 3, lag as 3 and lookback window having 45 mins or more generally achieved strong gross sharpe ratios well above 1.5. The holding period is generally higher than 3 mins for such strategies.

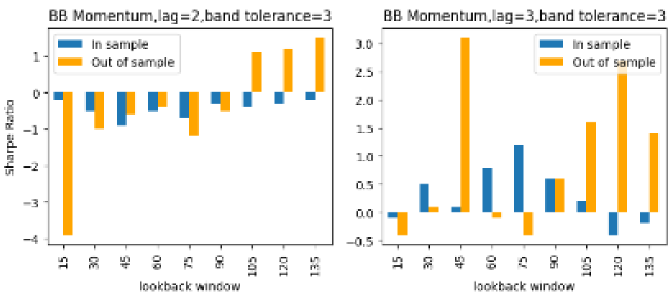

Fig.7 Bollinger bands momentum strategy performance comparison for different lags

The above observation is quite well demonstrated below in the evolution of the Top 10 percentile strategies. The three strategies that avoided the drawdown are the ones with higher bands 2 and 3, look back windows 45 mins or above and lags 2 or more.

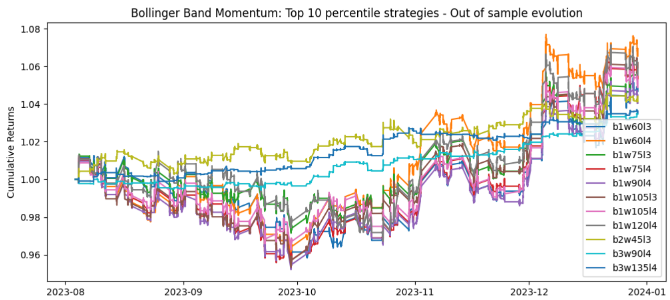

Fig.8 Bollinger bands momentum strategy evolution during out of sample period

Overall, we feel confident with betting on the Bollinger band dynamics and our approach taken to create signals. The results are well aligned with our understanding. The short lookback works well for the mean reversion strategy as there's short term oscillation in the prices per our literature study while the longer lookback is logical for detecting and trading momentum. Shorter lags are associated with trading mean reversion effectively while longer lags works well for the momentum. Smaller deviations or bands are suited to the mean reversion strategy while the higher deviation or bands around the prices are logical for confirming and trading momentum.

C. Z-Score

The Z-Score measures the number of standard deviations a data point is from the mean. In our project, we are modifying the formula slightly to accommodate the dynamic nature of the stock market, i.e., using moving average instead of mean. We are using the following formula for Z-Score calculation:

$$Z_t = \frac{P_t - MA_t}{\sigma_t}$$

Where:

- P_t is the current price at time t.
- MA_t is the moving average of prices over the lookback_window period.
- σ_t is the standard deviation of the price over the same lookback_window.

When we compared various lookback window lengths (5, 15, 25, 35, 45, 55), window length 5 gave the best cumulative returns.

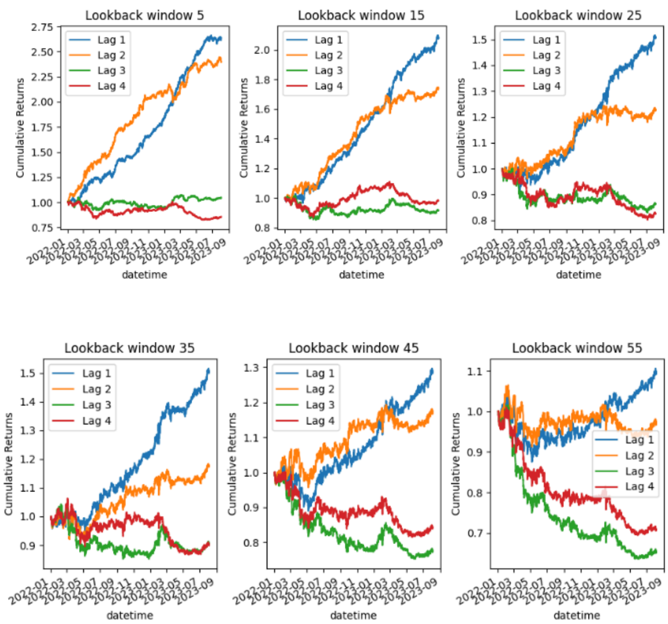

Fig.9 Z score strategy: Comparison of returns for different lookback windows and lags

We have tested different Z-Score thresholds for mean-reversion strategy versus cumulative returns, and the results suggest smaller thresholds from 0.25-0.75 generate best cumulative returns.

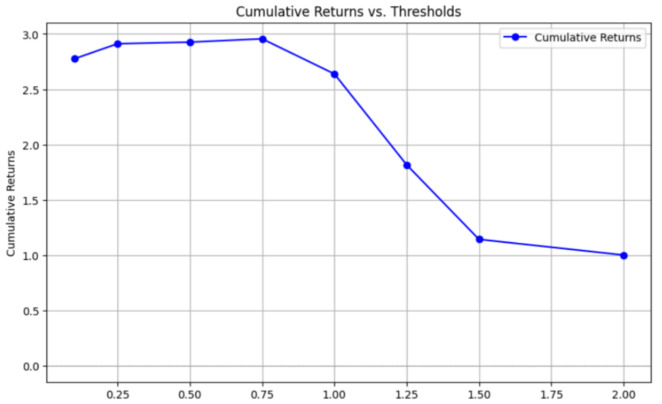

Fig.10 Comparison of cumulative returns for different thresholds for Z-score

However, the smaller the threshold, the more trading signals the model will generate, which can in turn translate into more transaction cost (although we assume "0" transaction cost in backtesting, there will be transaction costs for real implementation). As there is almost no material difference in terms of cumulative returns between using threshold of 0.25 vs. 0.75, but the number of transactions drops three folds by using threshold of 0.75, our test recommends using a larger threshold of 0.75.

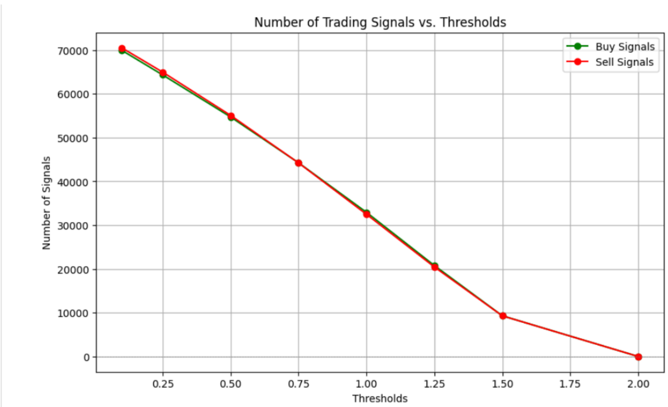

Fig.11 Dependency of number of trading signals on thresholds

D. Relative Strength Index (RSI)

Relative Strength Index (RSI) is in the oscillator category, and it can be calculated in two steps: first step is to calculate the relative strength (RS) using average gain over N periods divided by average loss over N periods.; the second step is to calculate RSI using the formula "100-100/(1+RS)" (Fernando, 2024).

Instead of using default parameters, we have used grid-search machine learning technique to find the best RSI parameters, which suggest a window of 10, buy threshold of 40 and sell threshold of 60. The cumulative returns over the testing period is 89% with a sharpe ratio of 0.138.

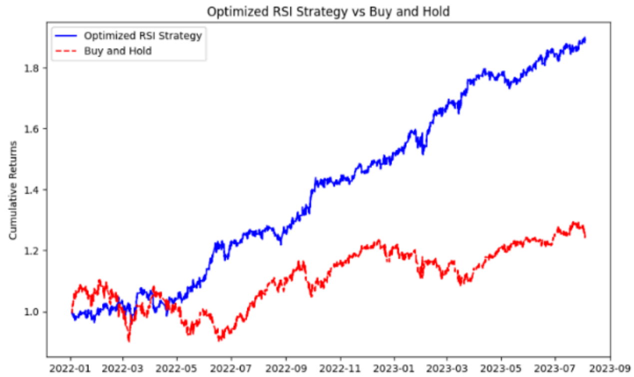

Fig.12 Comparison of RSI strategy cumulative return and buy and hold strategy

E. Williams %R

William %R, also known as Williams percent range, is in the oscillator category, similar to RSI we have discussed previously. William %R can be used to identify overbought and oversold conditions in the market and therefore can be used to aid mean-reversion strategy. According to Mitchell (2024), Williams percent range can be calculated using the following formula:

$$Williams\ \%R = \frac{Highest\ High\ over\ N\ periods - Close}{Highest\ over\ N\ periods - Lowest\ over\ N\ periods} * (-100)$$

where:

- N is the number of periods
- Highest is the highest price over the lookback period
- Lowest is the lowest price over the lookback period

We have split the dataset into 70:30 as in-sample versus out-of-sample, and from the in-sample dataset, we derived best parameters for Williams %R with a window of 10, overbought threshold of "-20" and oversold threshold of "-70".

For the in-sample test, we have a cumulative return of 98.66% with sharpe ratio of 0.18, max drawdown of -5.84%.

For the out-of-sample test, we have a cumulative return of 26% with sharpe ratio of 0.24, max drawdown of -2.54 %, but it still outperforms the buy and hold strategy.

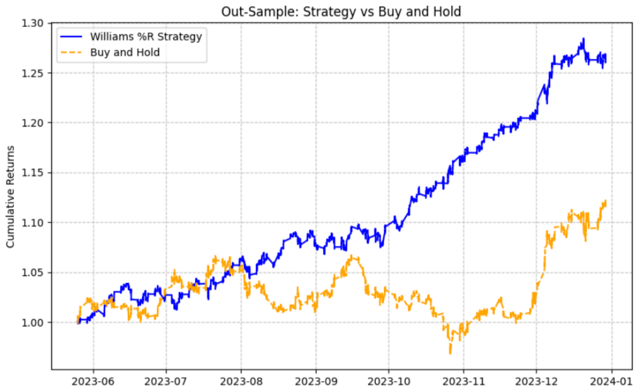

Fig.13 Comparison of Wiliams %R strategy cumulative return and buy and hold strategy

F. AVERAGE TRUE RANGE

The average true range measures volatility of the price series. The indicator is calculated as the maximum of current high minus current low, absolute of current high minus previous close and absolute of current low minus previous close.

Fig.14 Average True Range bands around the Bank Nifty futures close prices

The indicator is plotted below to demonstrate how the volatility is elevated during the first couple of hours after open before it comes down and then rises once again before the close in this instance.

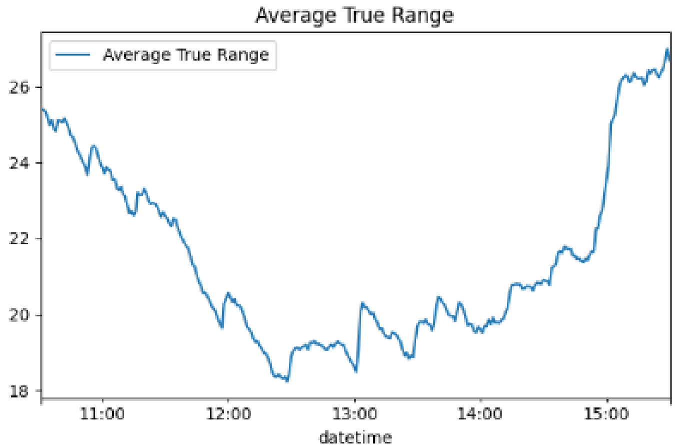

Fig.15 Average True Range indicator for Bank Nifty futures

The out of sample performance of the ATR indicator took us by surprise when compared to the in-sample performance. It is possible that there happened to be a strong mean reversion in the out of sample period by chance. However, many aspects of the results make sense to us. The alpha decays slightly when the lookback window is increased. Similarly alpha also seems to decay with increasing lags.

Overall, there is strong performance in the mean reversion strategy. However we could not achieve interesting results for the momentum strategy using Average True Range hence we skipped sharing them here.

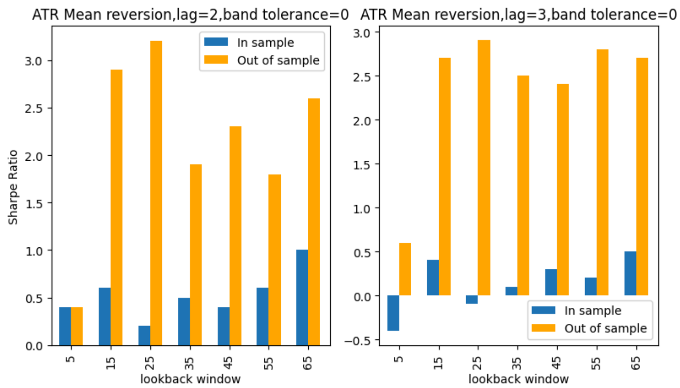

Fig.16 Average True Range strategy performance comparison for different lags and lookback windows

G. KELTNER CHANNEL

Keltner channel leverages Average True Range (ATR) to determine and bet on the trend. Like ATR it is also a volatility based indicator and plots high and low bands around the price series.

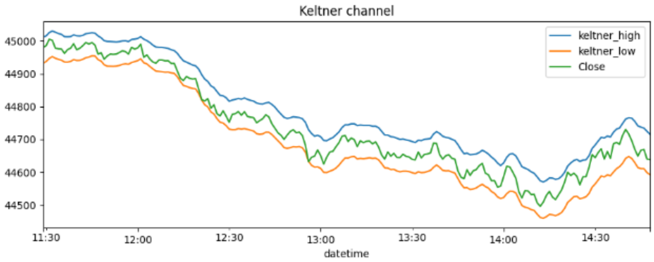

Fig.17 Keltner channel indicator around the Bank Nifty futures close prices

We create a momentum strategy with the Keltner channel, going long as the price moves above the higher band and short when it goes below the lower band. Out of sample performance with smoothing using a 5 minute window achieves robust results across the lookback windows. Overall we felt encouraged by Keltner channel based momentum strategy, however given high contrast versus the in sample performance we feel this needs a little more study similar to the Average True Range.

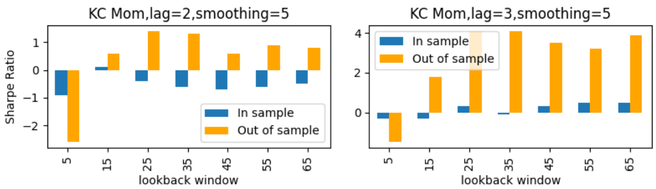

Fig.18 Keltner channel momentum strategy performance comparison for different lags and lookback windows

H. MACD

Moving average convergence divergence (MACD) is calculated by subtracting a slow exponentially weighted price series from a fast exponentially weighted price series. 'MACD signal' is arrived at by exponentially smoothing the calculated MACD.

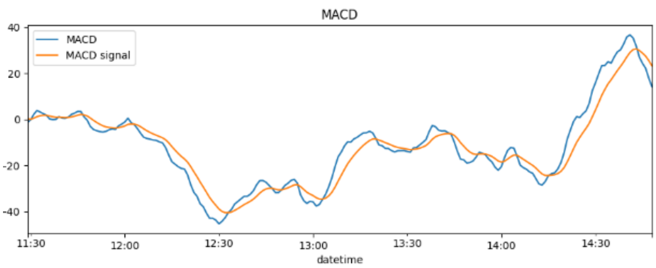

Fig.19 MACD and MACD signal for the Bank Nifty futures close price

We create a momentum strategy with MACD by going long when the MACD line goes over the signal line and we go short in the opposite scenario.

The performance of the strategy is encouraging and robust across both samples. Below we demonstrate the robustness of the strategy to variation in the parameters such as slow window, fast window and lags. We are able to achieve over 1.5 sharpe ratio in both the samples with strategy doing better higher lags (more than 2). Overall we feel confident in this strategy due to robustness and stable performance across the market scenarios and broad sample range.

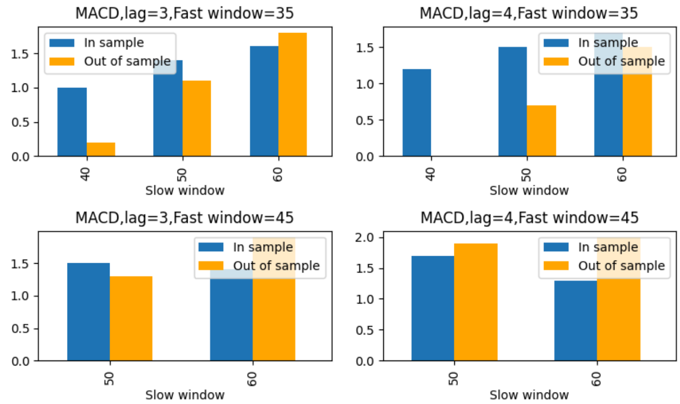

Fig.20 MACD channel momentum strategy performance comparison for different lags and lookback windows

I. OSCILLATORS

Another important part of our work was to use oscillators to estimate the momentum, trend and possible trend changes. Oscillators play an important role in estimating oversold and overbought moments in the market and as a result they can show market inefficiency and provide buy and sell signals. As oscillators we have used five common types of oscillators: Stochastic oscillator, Commodity Channel Index (CCI), Chaikin Money Flow (CMF), Average Directional Index (ADI) and Force Index (FI).

Stochastic oscillator is a type of momentum indicator which compares asset closing price and the price over some period of time, after which we compare two lines: the closing price of the moment with its relationship to the price over period and moving average of the line discussed before.

Commodity Channel index is also a type of momentum indicator where the typical price is compared with its moving average. If the value is higher than sell parameter we sell the asset, if lower than buy parameter we buy an asset.

Chaikin Money Flow is an oscillator based on buying and selling volume, it varies from -1 to 1, where 1 means that there is maximum possible buying pressure, and -1 indicates selling pressure.

Average Directional Index is the indicator that estimates the strength of the thread, the indicator is based on two other indicators the Positive Directional one and Negative Directional one.

Finally, the Force Index indicator is also a momentum indicator that estimates the importance of market movements and shows whether buyers or sellers dominate the market.

To apply these oscillators we have tuned hyperparameters at the same time we have also tuned signals on the training dataset to find the most profitable strategy. The idea was not just to tune and apply the oscillator and its parameters, we have also assumed that the price can move in the opposite direction as the parameter suggests. In the table below the main information about models is provided.

TABLE 2. The comparison of income for oscillators trading and buy and hold strategy

Indicator	Hyperparameters	Training return	Testing return	Success in training testing
Stochastic oscillator	period (95 minutes), buy/sell thresholds (5, 95)	0.088	-0.002	No/No
CCI	period (10 minutes)	0.945	0.107	Yes/Yes
CMF	period (5 minutes), buy/sell thresholds (0.1, 0.05)	1.27	0.361	Yes/Yes
ADX	period (40), buy/sell thresholds (10,10)	0.278	0.083	Yes/No
FI	period (2), buy/sell thresholds (4000, -3000)	4.004	0.206	Yes/Yes

From the table above we can conclude that oscillators can outperform buy and hold strategy, but we have to note that transaction costs are not considered in these strategies yet. The main feature of successful indexes is that the optimal period is short and does not exceed 10 minutes. The buy and hold return for training and testing data equals 0.246 and 0.088 respectively. The comparison of the indexes trading and buy and hold strategy is provided on the pictures below.

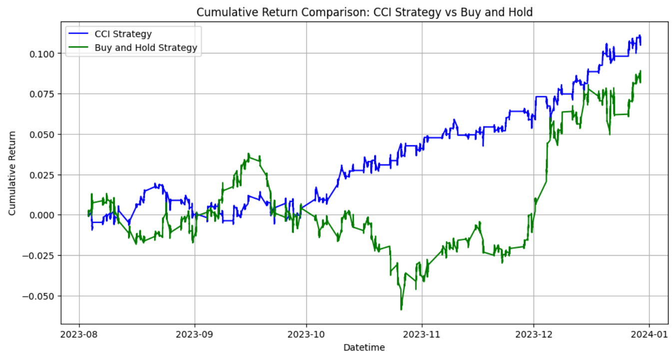

Fig.21 Comparison of CCI strategy with buy and hold strategy on testing set

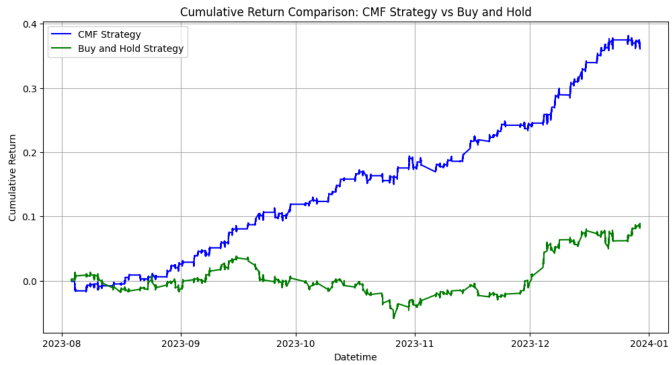

Fig.22 Comparison of CMF strategy with buy and hold strategy on testing set

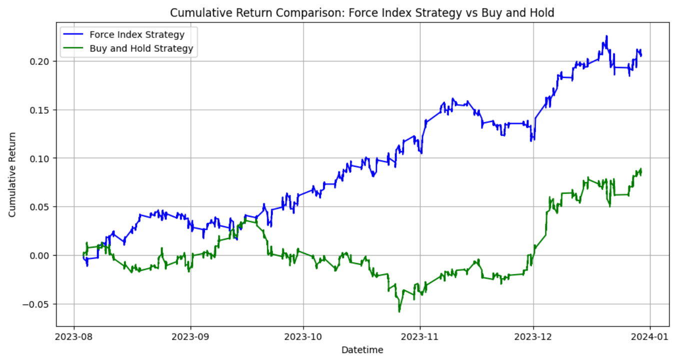

Fig.23 Comparison of FI strategy with buy and hold strategy on testing set

J. Cross sectional reversal/mean reversion

The cross sectional strategies take a universe of single name equity futures and create a relative value strategy using reversal/mean reversion or momentum indicators. Here we use the provided data on single name Indian equity futures, a total of 182 price series.

We use a simple ratio of the last closing price to the closing price before the lookback window, this is called raw score. At each time step, we take the mean and standard deviation of the raw score created in the last step to create a z score of each ticker. We clip the scores at +/-3. Further, we time series score the metric in the last step by taking the mean and standard deviation of each ticker's z-score.

In case of momentum strategies, we exclude the last few observations, this is captured by 'ignore period'. We test these systematic strategies by varying ignore period, lookback period, rebalance frequency and the lags. Below we plot the gross sharpe ratio which has a lookback of 240 mins, we ignore the last 30 mins prices and the signal is lagged by 3 mins for implementation.

While there is no clear trend on gross sharpe ratio due to changing rebalance frequency, we find that results are robust (in sample vs out of sample) at certain rebalance frequencies like 45 mins, 90 mins and 120 mins.

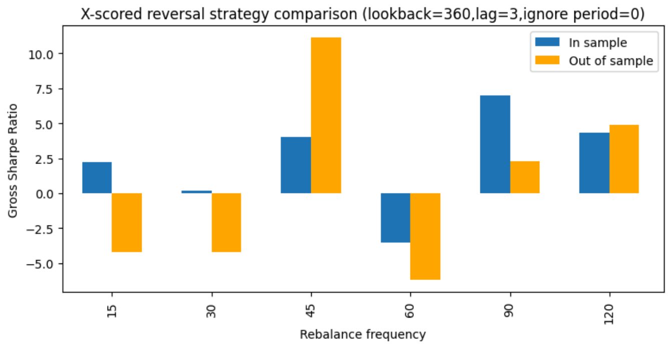

Fig.24 Cross sectional reversal strategy Sharpe ratio vs rebalance frequency

We test the robustness of the strategy to the lookback window. Below we set the rebalance frequency at 120 mins and lag by 3 mins .The cross sectional reversal strategy works at the higher lookback window. This is in contrast to our previous work on Bank Nifty index futures that showed reversal worked at a shorter lookback window.

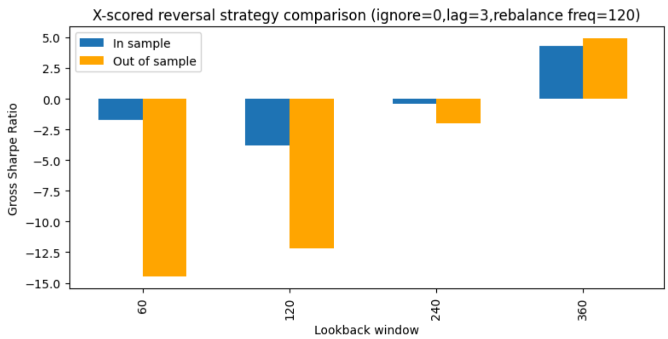

Fig.25 Cross sectional reversal strategy Sharpe ratio vs lookback window

K. Cross sectional momentum

There is clear empirical evidence of high sharpe momentum strategy from our test results. Below we plot the gross sharpe ratio which has a lookback of 360 mins and the signal is lagged by 3 mins for implementation. While there is no clear trend on gross sharpe ratio due to changing rebalance frequency, we find that results are robust (in sample vs out of sample) at shorter rebalance frequencies like 15 mins and 30 mins. The signal does not seem to work at lower rebalance frequency from 45 mins to 120 mins.

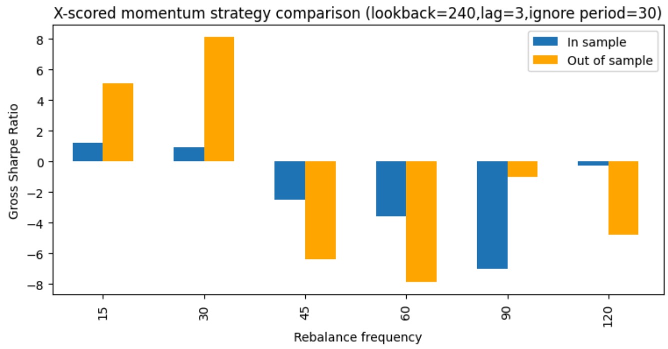

Fig.26 Cross sectional momentum strategy Sharpe ratio vs rebalance frequency

As mentioned briefly before in the literature study, empirical evidence shows successful momentum strategies in the stocks usually ignore some past period to filter out noise related to mean reversion. Here we introduce a parameter which ignores the certain immediate past period. However, we find there is mixed evidence of its effectiveness. During the in-sample period, the gross sharpe ratio increases as we offset the lookback window by ignoring past 15 mins or 30 mins prices. However, during the out of sample period the gross sharpe ratio comes down with the 'ignore period'.

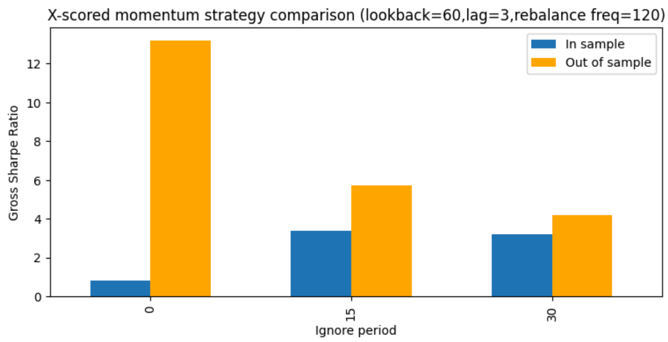

Fig.27 Cross sectional momentum strategy Sharpe ratio vs Ignore period

Transaction costs

Our analysis on the transaction costs is as follows. With respect to the fixed costs for the buying and selling of futures on NSE, total taxes and charges include brokerage, exchange fees, GST, SEBI charge, stamp duty.

At 1 million INR notional, futures buy fixed costs come down to 0.66 bps. This drops further to 0.45 bps at 10 million INR notional and further down to 0.43bps at the next notional multiple of 10 and keeps roughly constant at that rate.

The sell fixed costs are comparatively higher. At 1 million INR notional, futures sell fixed costs are c.2.5 bps. At 10 million INR notional, futures sell fixed costs goes down to c.2.25 bps. At the next multiple of 10, it goes down to 2.23 bps but roughly stays there for bigger notionals.

The round trip including a buy and a sell transaction, costs for a 1 million INR notional is c.3.13 bps. For a 10 million INR notional, round trip cost drops down to 2.7 bps. It drops further to 2.66bps on the next tens multiple of notional and stays roughly constant rate there for bigger notionals.

VII. CONCLUSION & NEXT STEPS

We analyzed various strategies such as seasonality, mean reversion and momentum with the help of well recognized and proven technical indicators. There were quite a few exciting results discovered.

One of them being, mean reversion strategy tends to work in the short term for example using 5 min lookback Bollinger Bands whereas momentum works on the opposite end as the breakouts or trends are confirmed on longer windows. The gross sharpe ratios achieved in the working strategies ranged from 0.5 to 4. At the same time oscillators, based on the momentum also can provide useful results if tuned hyperparameters have a period which does not exceed 10 minutes.

Second, given our very short holding periods ranging from 1 minute to 5 minutes, we will need to be very conscious of transaction costs given the number of trades but also any market impact costs. Any risk adjusted returns like sharpe ratio will be best adjusted to arrive at a net number. From our analysis after referring to National Stock exchange (NSE) and brokerage platforms like Zerodha, the fixed round trip costs tend to be fairly low.

Third, we created two cross sectional and time series scored strategies based on the universe of 182 single name equity futures. We noted an added advantage of the breadth as information ratio is directly proportional to the square root of the breadth. In contrast to the above strategies based on single future, the cross sectional reversal works better on longer lookback windows in the strategy. The opposite is found true for the cross sectional momentum strategy. For momentum, the faster rebalance frequency from 15 to 30 mins was more successful than slower ones. We found mixed evidence for skipping or ignoring immediate past periods in the momentum strategy.

Further work could be done to combine all the working strategies to form a single strategy. This could allow us to diversify significantly and leverage upon the different return characteristics of seasonality, mean reversion and momentum. The holding periods of these strategies also tend to be different from our experience. While many of the technical indicators used to form strategies by us tend to be similar, we believe the diversity of indicators picked and strategies formed should allow us to have attractive return and risk characteristics on the final strategy.

Lastly, we did not have the data on the bid-ask spreads to estimate market impact costs. We attempted to model these costs using previous academic work, however it was not effective in realistically capturing costs. We also tried to adjust the strategies for the fixed costs, however given the scale of the problem we leave this exercise for the future work to analyze in depth. The transaction costs work could help us better assess strategies that are on different frequency spectrum (high vs medium) on a comparative scale such as net sharpe ratio.

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