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RSI and Quantile Trading Strategies with Markowitz Portfolio

Jinlang Gao (jg2335)
Jiulong Zhang (jz983)
Ruoyu Chen (rc855)
Zhihao Tang (zt222)

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Abstract

The overall purpose of our project is to analyze the performance and feasibility of combining momentum technical indicators and Markowitz theory in equity trading. We begin our pipeline by setting up a benchmark for comparison. Then we continuously added in momentum technical indicators with various parameters to test out our ideas. More specifically, we utilized RSI as our trading signal, and re-balance the portfolio every 30 trading days. Apart from that, we used quantile trading with RSI and the difference of RSI, and tested the performance of portfolios using different trading signals and parameters. Each time we re-balance our portfolio, we utilize Markowitz theory as our primary method of optimization.

In our paper, we analysed why some parameters for some technical indicators work well with the selected time horizon, as well as why some indicators perform badly. We also found that, using pure Markowitz may not beat the benchmark in real trading, however, during our back-testing period, the strategy using quantile trading on the difference of RSI and combined quantile trading re-balanced using Markowitz theory outperformed the market. Furthermore, we came into conclusion that our strategies are sensitive to parameter changes, which requires effort to choose optimized parameters to be successful in real life markets.

1. Introduction and Motivation

A large number of variables are tested by researchers to explain the future stock returns. Popular variables include size, book-to-market ratio, market beta, and the net income ratio. Momentum, as one of the most powerful explanatory variables for future stock price prediction, has been used as a trading strategy by hedge funds since the early 2000's. Many researchers investigate whether past stock returns can be possible explanatory variables for future stock returns.

Empirically, there is evidence for both continuation and reversal movement in the equity market. There are two main types of continuation. The first one is unconditional positive serial correlation at horizons on the order of three to twelve months, while the second type is conditional on observable public events. Stocks tend to experience post-event drift in the same direction as the initial event impact [1]. However, it is also found that stock returns have negative correlation at long horizons firstly noted by DeBondt and Thaler(1985).

Based on the above findings, practitioners implemented both trend-following momentum trading strategies and mean-reversion trading strategies in the equity market. Using trend-following momentum trading, traders believe that an asset price that is moving strongly in a given direction will continue to move in that direction until the trend loses strength [2]. Jegadeesh, N. and Titman, S. examined the profitability implementing momentum trading strategy in US stock market from 1965 to 1989 in their research [3], and concluded that momentum strategies is profitable with past winners outperforming past losers by about one percent per month over 3-to-12-month holding period [4]. At the same time, stock prices also show mean-reversion patterns. There are several momentum indicators that are frequently used in momentum trading, including exponential moving average(EMA) [5], relative strength indicator(RSI) and Moving Average Convergence/ Divergence(MACD). However, in our report, we will focus on RSI and investigate how RSI could serve as a trading signal.

2. Dataset Description

2.1 NASDAQ 100 Dataset

To create our dataset, we collected NASDAQ 100 stock price data from 2010.03.01 to 2020.02.28. We used the data starting from 2010 so as to avoid the financial crisis period. The huge volatility of the stock market during that period could and would possibly affect the results of our study. Therefore, we decided to exclude this period to reduce the bias of our results. Our portfolio constructions are based on stock prices from 2015.03.01 to 2020.02.28.

To obtain the covariance between stocks, and the average return of each individual stock within our data-set, we split the 10-year data from 2010 to 2020 into two parts. The first five years' data, 2010.03.01 - 2015.02.27, was used to calculate the covariance matrix and average return, and the next five years of data starting from 2015.03.01 is used to construct our portfolio under Markowitz theory.

A minor problem that we identified is that NASDAQ 100 re-balances itself every year in December, and the current constituents of the index is somewhat different from the constituents of that in 2010. Some of the 103 listed stocks (in NASDAQ 100 as of February 2020) do not exist in the market back then. To tackle this problem, we decided to drop those stocks that only entered the market after 2010. The modified portfolio ended up with 95 stocks (including some stocks that exists at the 2010 timestamp, but was listed as a component under NASDAQ 100 sometime between 2010 and 2015). After taking a close look in to these stocks, we found out that some of these excluded companies are either merged or have small weight in the index, thus we assume this change would not influence the overall performance of the portfolio significantly.

CHTR	MXIM	TTWO	AMD	...	AAPL	TMUS	XLNX
30.100000	13.469389	9.440000	8.21	...	25.915976	9.822725	20.995541
30.400000	13.455107	9.280000	8.38	...	25.898617	10.131718	20.979637
30.750000	13.355122	9.030000	8.35	...	25.958138	10.294346	20.836487
31.020000	13.412257	10.020000	8.50	...	26.129267	10.359397	20.852386
31.750000	13.583657	9.990000	8.61	...	27.151081	10.375660	21.242085
...	...	...	...	...	...	...	...
167.460007	27.007601	28.600000	2.65	...	102.673050	26.174040	39.308846
168.169998	26.737272	28.990000	2.65	...	104.488007	26.527346	39.157272
169.229996	26.576765	28.709999	2.66	...	104.414688	26.978790	39.041374

Table 1: sample data of stock prices

In our trading strategy, as we will be using RSI as our trading signal, we designed a python function to calculate the RSI for each stock at each day in our portfolio as our pre-processing step. We allowed the function to take in a parameter N(i.e. How many days do we look back) so that we could find an optimal N in our further studies. After generating the RSI dataset as a comma-separated-file (CSV), we passed the it to MATLAB and used it as constraints of our portfolio optimization at each rebalancing date(details to be discussed in the following section).

CHTR	MXIM	TTWO	AMD	...	AAPL	TMUS	XLNX
55.692669	58.068578	56.974414	43.770223	...	49.713182	48.531210	48.848730
49.217608	55.043083	54.820944	43.409440	...	45.716290	47.030956	46.021153
45.362586	54.191194	55.933722	42.326696	...	45.730987	46.788321	43.980131
45.865078	57.676193	56.540966	40.581509	...	47.898955	52.605949	44.062896
51.747083	60.843409	57.814458	42.064195	...	53.265392	55.419276	47.812595
...	...	...	...	...	...	...	...
60.301044	45.662854	42.805178	52.143097	...	49.399837	67.849649	41.405314
55.535826	42.794895	41.303129	49.852211	...	45.485316	64.379716	40.261476
55.569752	44.332954	40.234449	49.735545	...	47.435017	62.657454	39.159593

Table 2: sample data of stock RSIs

2.2 Risk-Free Rate Of Return

Our choice of the risk-free rate of return comes from the 3-month treasury data. We obtained the time series price data from Yahoo-finance, and after a few pre-processing steps, we have our CSV file containing the desired risk-free rate of return for each trading day.

3. Trading Strategies

3.1 Introduction to Relative Strength Index(RSI)

The relative strength index (RSI) is a momentum indicator that measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock or other asset. The RSI is displayed as an oscillator (a line graph that moves between two extremes) and can have a ranging from 0 to 100.

The formula for RSI is:

$$RSI = 100 - \frac{100}{1 + \frac{Average\ Loss}{Average\ Gain}}$$

It has been a long time since RSI was used for trading signals regarding stocks and indices. A common and traditional interpretation and usage of the RSI is that values of 70 or above indicate that a security is becoming overbought or overvalued and may be primed for a trend reversal or corrective pullback in price. An RSI reading of 30 or below indicates an oversold or undervalued condition.

The common standard is to use 14 periods to calculate the initial RSI value. We will be 30-day periods to realize backtest on our selected dataset and compare the differences between parameters and different models.

Figure 1: Nasdaq 100 index daily close price with 14 days RSI

Figure 1 shows the Nasdaq 100 index daily close price with the 14 days RSI curve below it for the past 1 year (May 2019 - April 2020). We can tell that once the 70 threshold is bypassed, i.e. when the stock is considered overbought, there is often a price downfall trend in the following period, while RSI below 30, i.e. oversold, often indicates a rebounce of the index price in the future. Therefore, RSI could be a useful indicator of mean reversion to be implemented in our trading strategy. This figure also tells that the peak or valley time period is roughly a month or so, so our rebalancing frequency could be monthly based on the initial.

Figure 2: Apple stock daily close price with 14 days RSI

Figure 2 above shows the Apple Inc. stock price with the RSI curve below it for the past 12 months (May 2019 - April 2020). Compared to Figure 1, we see more often overbought or oversold occasions. This phenomenon is probably because the index is composed of about 100 stocks and many of the gains and losses of individual stocks get averaged out rather than solely itself.

Given the ideas and facts above, our main algorithm is to select the stocks that go into the portfolio based on their RSI scores. If a stock's RSI>70, the portfolio would include a short position of the stock, which has a constraint of its weight to be negative. If a stock's RSI<30, the portfolio would include a long position of the stock, which has a constraint of its weight to be positive. A Markowitz portfolio would be generated under those additional constraints. Besides, we will create some other portfolios for comparison to prove the effect of the RSI indicator and the Markowitz optimization.

3.2 Introduction to Quantile Trading

Quantile trading is regarded as one of the most useful rule of thumb in portfolio management. Some of the results derived from pure mathematics are highly unreliable so instead of compund our errors by torturing these reliable predictions, we can use ranked trading or quantile trading. Thus, we rank our key indicators, and choose long and short quantiles $Q_{l,s}$ and we take long and short positions respectively. There is also a modified quantile trading strategy, that is we will add two new "hold" quantile variables $H_{L,S}$, where $H_L < Q_L$ and $H_S > Q_S$. Now, in any given period, we do not enter a position until it is in the top Q_L, but if we already in position, then we will exit the position once it is no longer in the top H_L, and similarly for shorts.

However, in our trading strategy that will be specified below, we will only use the traditional quantile trading, given that our trading period is relatively long, we will not consider position changes other than the rebalance time window.

4. Portfolio Construction

4.1 Baseline Portfolio

Firstly, we consider to construct a baseline portfolio, which is initiated with 1/(n+1) fraction of allocation to each different stock along with 3-month US bonds. It would be periodically rebalanced to regain the equal weights of every asset. This is different to the NASDAQ 100 index because we have dropped certain stocks for data cleaning purposes. Thus, the weights among the selected stocks between NASDAQ 100 and our baseline are different. Our expectation for this portfolio is to be outperformed by the following portfolios.

4.2 Markowitz Portfolio

This portfolio is initiated according to Markowitz, based on the parameters calculated from the historical data before the initialization date of our backtest. Then we rebalance the portfolio periodically according to Markowitz.

4.3 Markowitz Portfolio Using RSI

This portfolio is initiated according to our RSI constraints and Markowitz. For stocks whose RSI is higher than the upper threshold, we will regard them as overbought and short these stocks. For those stocks with RSI that is lower than the lower threshold, we will regard them as oversold and long these stocks. A major part of the component stocks would not be included since their RSI signal is not significant enough to surpass the thresholds. The stock pool is updated each period of 30 trading days based on their RSI as well as their weights, using Markowitz.

4.4 Markowitz Portfolio Using Quantile of RSI

This portfolio is initiated with a similar strategy as the last portfolio. Instead of using designed RSI thresholds to determine long and short which stocks, we use quantiles of RSI to make the decision. We long the five stocks which have the lowest RSI values, and short the other five which have the largest RSI values. The stock pool is updated each period of 30 trading days, and the weights are determined based on Markowitz.

4.5 Markowitz Portfolio Using Quantile Difference of RSI

Different from the last strategy, this quantile difference strategy is based on the difference of RSIs in two periods. We calculate the difference of the RSI values between this period and the last period, and select the stocks based on the percentile of the calculated difference. We long the stocks which have the lowest differences of RSI, and short the others which have the largest differences. The portfolio is updated each period of 30 trading days by using this strategy and Markowitz.

4.6 Markowitz Portfolio Using Combined RSI Quantile Strategy

This portfolio is initiated with a strategy combined with quantile of RSI and quantile difference of RSI. The stocks are selected by both quantile and quantile of differences of their RSI values. We will long the stock if:

1. Its quantile difference of RSI is larger than the upper bound of percentile.
2. Its percentile of RSI is smaller than the lower bound of percentile.

We will short the stock if:

1. Its quantile difference of RSI is smaller than the lower bound of percentile.
2. Its percentile of RSI is larger than the upper bound of percentile.

This strategy is combined with Markowitz to update the portfolio each period of 30 trading days.

5. Results Analysis

5.1 Baseline Portfolio

The baseline portfolio is an equal-weighted portfolio. The weights of each stock and the risk free asset are the same during each of the period. We expect that this portfolio will have positive return because there has been an upward trend for NASDAQ 100 index from 2015 to 2020. The portfolio return is based on the growth of each of the stocks in our pool. As expected, the portfolio generates 220.46% cumulative return.

5.2 Markowitz Portfolio

This portfolio was rebalanced each period of 30 trading days based on the basic Markowitz portfolio. Apparently, this basic strategy performed badly, because we did not include any constraints during stock selection for our portfolio when running the optimization procedure. The overall cumulative return is close to 0, so we almost lost all of our initial wealth.

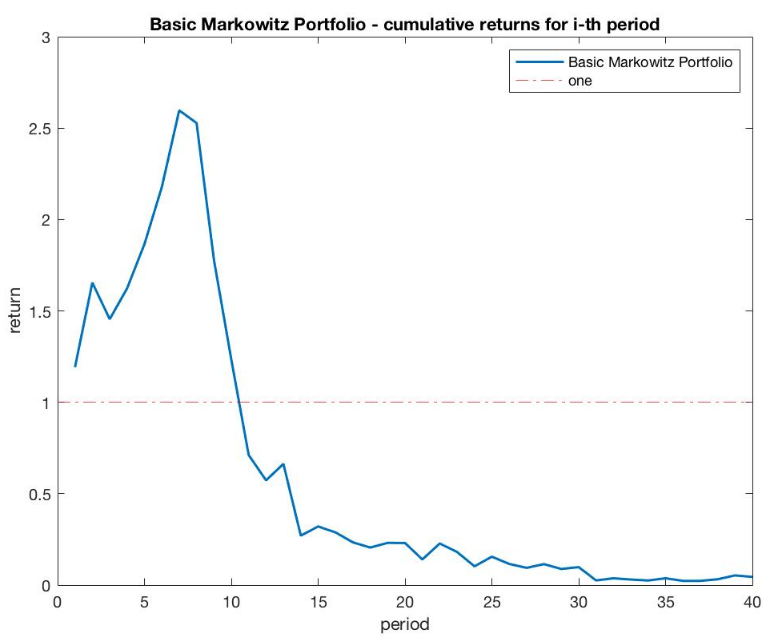

Figure 3: Cumulative return of strategy using basic Markowitz

5.3 Markowitz Portfolio Using RSI

In this trading strategy, we use fixed RSI threshold as trading signals. However, the performance of different parameters seems to have significant variations.

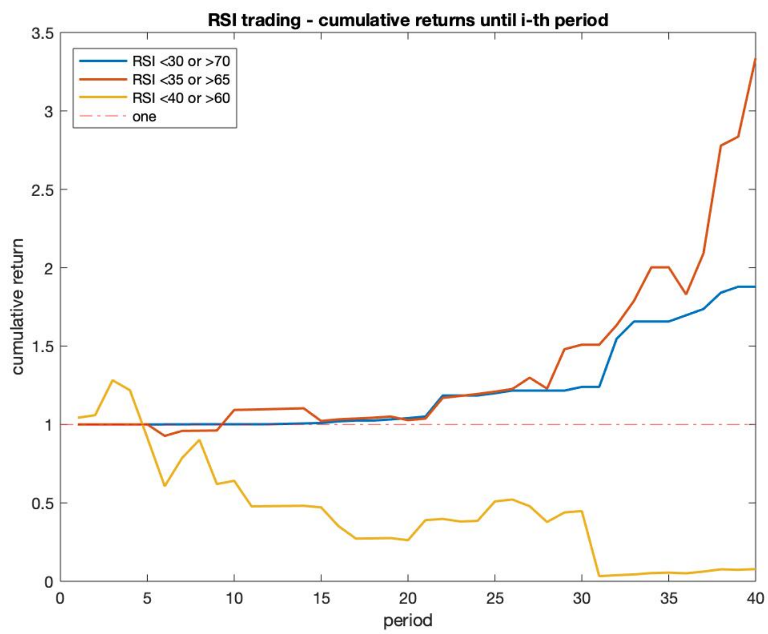

Figure 4: Cumulative return of trading strategy using RSI

From the plot, we observe that the trading strategy that uses RSI $>$ 60 as short signal and RSI $<$ 40 as long signal performed badly. We think this is because many stocks in this chosen region (RSI $>$ 60 or RSI $<$ 40) were not overbought or oversold, therefore the trading model became very volatile and does not work very well.

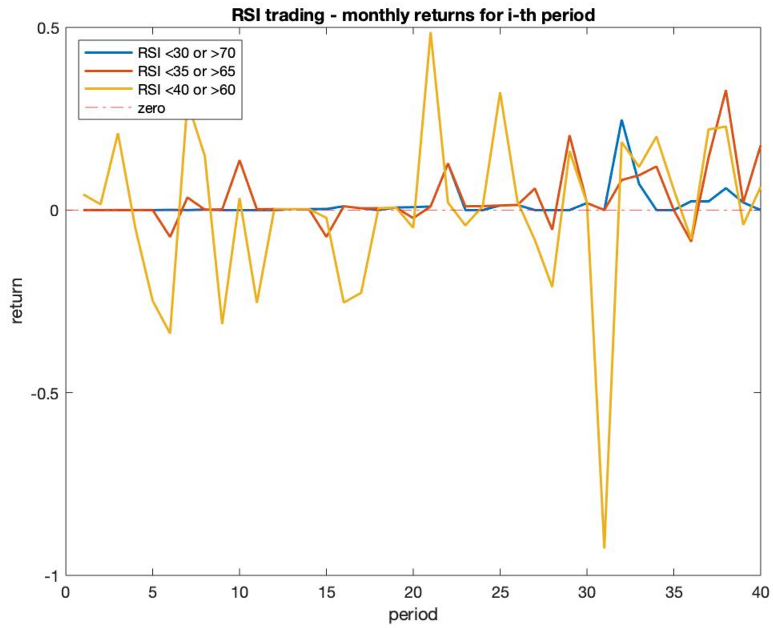

Figure 5: monthly return of trading strategy using RSI

Both the other strategies have positive returns. The >70/<30 strategy have a relatively lower return compared with the >65/<35 strategy, but the former strategy is less volatile and has a smaller draw-down in comparison

5.4 Markowitz Portfolio Using Quantiles of RSI

From the above trading strategy, we realized there was a problem that if we use a fixed threshold as the trading signal, there will be some time that we don't buy or short any stocks which may miss some opportunities. Thus, instead of fix the threshold, we use the idea of quantile trading on RSI. We don't want to include too much stocks in our portfolio at each re-balancing time, so we would test quantiles range from 1% to 7%.

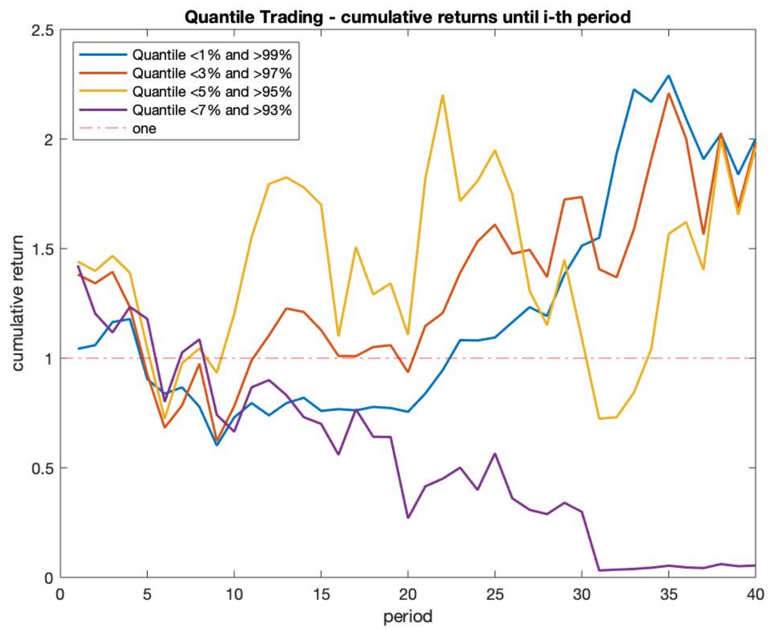

Figure 6: Cumulative return of strategy using RSI quantile trading strategy

We found that except the 7% strategy that has an upset result, all other three strategies ends up at roughly the same point, though the variation of these strategies are different along its path.

5.5 Markowitz Portfolio Using Quantile Difference of RSI

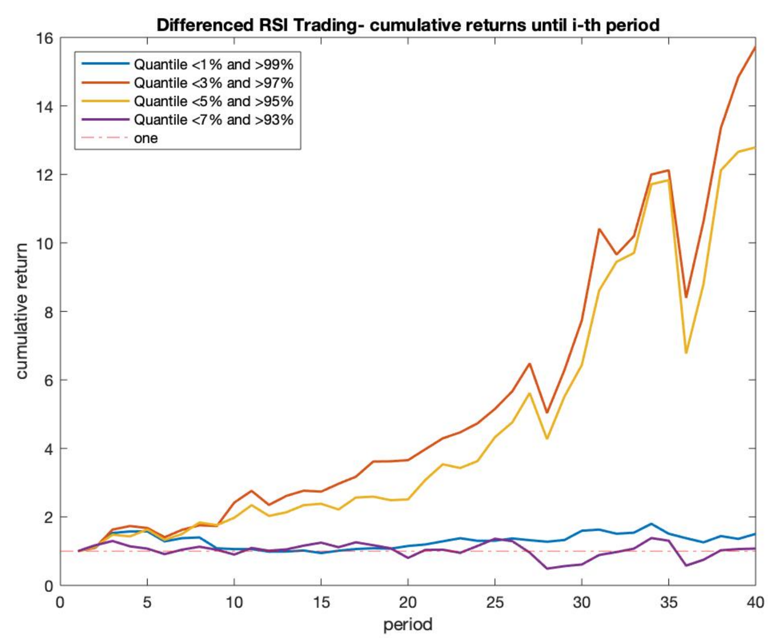

Figure 7: Cumulative return of strategy using differenced RSI quantile trading strategy

In this strategy, unlike the above strategy, we used the quantile of the differenced RSI as the trading signal. The 3% strategy and 5% strategy have cumulative returns that are higher than 1000%. However, if we choose a smaller quantile(1%) or larger quantile(7%), there is only barely positive returns. So this strategy is very sensitive to the change of parameters, but we would like to make our strategy more rubust, thus we thought of combining the above two quantile trading strategies.

5.6 Markowitz Portfolio Using Combined RSI Quantile Strategy

In this trading strategy, we have two parameters to test, the quantile of RSI and the quantile of the differenced RSI. Unlike the above strategies, if we choose both quantile less than 0.1, we would end up with no tradings in most of the periods, since it is hard to fulfill both requirement. Thus, we loosed our requirement in generally. We chose 10%, 20% and 30% as the testing quantile of diffrenced RSI while we chose 20%, 30% and 40% as the testing quantile of the RSI.

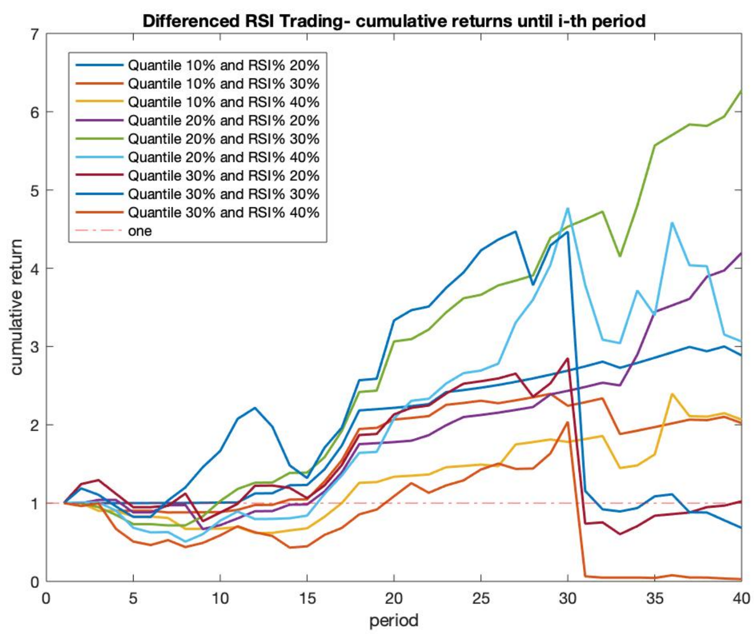

Figure 8: Cumulative return of strategy using combined quantile trading strategy

Not surprisingly, the cumulative return results varies tremendously, ranging from -97.14% to 526.26%. We looked at the best performance and the worst performance strategy. The worst performance strategy chose 30% and 40% respectively as the quantile of differenced RSI and RSI, thus two many stocks will be included in each period and some of the stocks does not have convincing signal to have a strong performance in the following period. In other words, since we used 40% as the quantile of RSI, some stocks with an RSI of 50 may be regarded as overbought and sending us an sell signal which is not reliable. Besides, from the plot, we observe a huge drawdown in three lines, all of which are using 30% as the threshold of quantile of differenced RSI, and it gives another instance that some bad selections are made because of the loose requirement.

However, the best performance strategy is not the strategy with narrowest quantile. That is because, as stated above, if the quantile is too narrow, we will not trade enough stocks to generate high return. That is to say, we have a trade-off here, and it is tricky to determine which quantile to use will have a best result in the future trading, and we are only able to present an empirically result.

5.7 Performance Comparison

In this section, we will compare the performance of different strategies with the optimized parameter that we test above. The cumulative return and Sharpe ratio comparison is as below.

Portfolio Type	Cumulative Return	Sharpe Ratio
Baseline	2.2046	0.8576
Basic Markowitz	0.0448	-0.4430
RSI (Threshold = 35)	3.3367	0.8334
Quantile of RSI (RSI Quantile = 1)	2.0012	0.3053
Quantile Difference of RSI (Difference Quantile = 3)	15.7282	1.3105
Combined RSI Quantile (Difference Quantile = 20, RSI Quantile = 30)	6.2726	1.2378

Figure 9: Summary statistics for portfolio strategies with no transaction costs

Based on the cumulative return and Sharpe ratio, three of the portfolios with different RSI strategies outperform the baseline portfolio and Markowitz portfolio. Only the portfolio using the quantile of RSI strategy has relatively low return. Thus, RSI can be an useful indicator of trading to improve the performance of our portfolio by using the appropriate parameters.

Although all of our strategies use RSI as the main signal to determine the trading of stocks, different structures of the strategies cause the cumulative return of portfolios to vary a lot, ranging from 2.0012 to 15.7282. For the quantile strategy, which is the worst-performing, the quantile structure forces the portfolio to long or short one stock each period. For some periods, RSIs of the stocks in our portfolio are not large enough or small enough to indicate overbought or oversold. However, the portfolio still includes these stocks which don't have the significant signals. This could be the main reason why quantile strategy performs badly. Compared to the quantile strategy, the basic RSI strategy sets a stricter threshold when determining the trading of stocks. Thus, the basic RSI strategy generates higher return than the quantile strategy.

There is a concern about using the basic RSI strategy. The RSI value of certain stocks may continuously stay high or low during several periods. However, it doesn't mean that these stocks are overbought or oversold all that time. In this case, the quantile difference strategy can be useful to solve this problem. After choosing an appropriate parameter, the quantile difference strategy generates 15.7282 cumulative return, which is much higher than the return of other strategies.

5.8 Transaction Cost

In order to better resemble the performance of the trading strategy in the real markets, we introduced transaction costs into our Markowitz portfolio optimization progress. And it turned out that the transaction cost parameter in the optimization progress could deeply influence the outcome of the weights and thus, the performance of the backtesting.

For a transaction cost set close to the real world scale, e.g. 0.0005, the overall return and sharpe ratio would significantly outperform the one of the backtesting with no costs. On the one hand, the existence of transaction cost could prevent weights from making large changes, then filtering out the stocks with relatively bad performance for a short period of time. On the other hand, we have found out that CVX could return the original input weights if optimized weights is not achievable under the certain constraints. Parameter tuning within the same scale could also lead to vast change in the backtesting performance.

For a transaction cost set relatively high, e.g. 0.1, the optimization results would put most weight into the bank and basically no weights on the risky assets, therefore, the plot looks like an exponential growing curve with fair overall return and no drawdowns.

In a nutshell, the performance of the trading strategy is parameter-sensitive regarding the transaction costs. And we need to carefully choose the parameter for the results to make sense in the real markets.

6. Limitation and Discussion

6.1 Selection Bias

In our backtesting procudure, we used the stock price from 2015 to 2020, when the market is in the middle of a bull market, and the NASDAQ index has doubled during the past five years. We could only conclude that our best-performance parameter or even our strategy will work in such a market, but we are not confident on how the strategy will perform if it is implemented in real trading.

6.2 Strategy Robustness

From the results above, all strategies are sensitive to the parameter changes. for example, in quantile differenced RSI trading strategy, if we choose the threshold to be 5% we will have huge profit, however, if we use 7% as the threshold, we would end up losing all money. Thus, it is important to improve the strategy robustness.

6.3 Technical Issue

As stated above, the CVX function is not able to give us an reasonabe results when we included transaction cost into the backtesting procedure. Besides, the result weight we got from CVX did not have a high precision. Further works need to be done to find a better optimization technique.

6.4 High Variation

We realized the monthly return has a large variance which in some circumstances lead to a huge drawdown. That may be result from the usage of just an single technical indicator. RSI was a mean-reversion indicator, thus we are not able to catch the trend-following patterns in the equity market. Some other technical indicators especially trend-following momentum indicators should be taken into consideration, so that we may be more confident about the future trend of stocks.

Bibliography

[1] H. Harrison and C. S. Jeremy. A unified theory of underreaction,momentum trading, and overreaction in asset markets. *The Journal of Finance*, 54, 1999.

[2] What is momentum trading. `https://www.fxcm.com/markets/insights/what-is-momentum-trading/`. Accessed: 2020-02-20.

[3] N. Jegadeesh and S. Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48, 1993.

[4] Cheng-Few Lee and Alice C. Lee. Encyclopedia of finance. pages 600–703, 2006.

[5] *International MultiConference of Engineers and Computer Scientists 2016*, Hong Kong, 2016.