FBE 551: Quantitative Investing
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Synergistic Effect Among Strategies

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1. Executive Summary

Ever since Edward Oakley Thorp's first quantitative investing in 1969, trading strategies has gone through significant development. Nowadays there exist numerous trading strategies along with different variants. Different strategies have different assumptions and emphases on different features of stocks, some of which share certain degree of agreement while some collide with each other. We therefore would like to find out the best possible way of combining different strategies.

This project is aimed at exploring the synergistic effect among strategies by developing the best combination method of individual strategies. Specifically, we explored three combination methods, Assigned Weights, Set Methods, and Linear Regression, to combine four individual strategies, Reversal, Payout Yield, Volatility, and Momentum. The final strategy would perform better than any of the four individual strategy.

We used crspm.feather from the Center for Research in Securities Prices in the university of Chicago as our dataset. And the whole strategy was divided into 2 phases. The first phase is individual strategy tunning, and the second phase is the combination process.

At the first phase, we conducted parameter tunning for each individual strategy to find out their best combinations of quantiles and lags that yield highest returns:

- For Reversal, we tested the quantiles ranged from 2 to 10 with lags ranged from 1 to 3. The combination of 10 quantiles and 1 lag yielded the highest returns.
- For Payout Yield, we tested 3, 6, 9, 12 lags with 3, 5, 10 quantiles. The combination of 12 lags with 3 quantiles yielded the highest returns.
- For Volatility, we tested 12, 24, 36 lags with 3, 5, 10 quantiles. The combination of 12 lags with 10 quantiles yielded the highest returns.
- For Momentum, we tested through 1, 2, 3 min lags, 10, 13, 20 max lags, 'VE' & 'EW' weight types, and 5 and 10 quantiles. The combination of 3 min lags, 13 max lags, VE and 5 quantiles yielded the highest returns.

As a result, our output contained original data with 4 different quantiles generated from above individual strategies were produced, whose detailed implementation could be found in the 'Individual_Strategies' notebook.

At the second phase, we conducted 3 types of combination method:

- For Assigned Weights, we assigned weights to each strategy based on their return rates. If the strategy yielded the highest return, the strategy was granted the highest weight, vice versa. We calculated final scores for stocks by applying the weights and made long or short decisions based on the final scores. The final average monthly return was 0.016091.
- For Set Methods, we conducted two different types of combination, Union and Intersection. The first one, Union, ignored the stocks that got conflicted signals from the 4 individual strategies simultaneously. The second one, Intersection, only longs the stocks got 4 longs signals and shorts the stocks got 4 shorts signals. The final average monthly returns were 0.005495 and 0.024473 respectively.
- For Linear Regression, we calculated weights for each individual strategy by building a regression model. The final average monthly return was 0.009347.

The final result was produced at this phase, whose detailed implementation could be found in the 'Combined_Strategies' notebook. Among three combination strategies, the Intersection Set Method yielded the highest average return of 0.024473 per month, and therefore was selected as our final strategy.

The rest of the report will present our strategy in detail and discuss our further concerns.

2. Data Description

The dataset for our final project is crspm.feather, which originally came from the Center for Research in Securities Prices in the university of Chicago. Containing 4,395,321 observations with 10 features, this dataset provides stock trading information for 33,942 stocks, started from 01/29/1960 to 12/31/2020. We mainly used the following features in our final project:

- PERMNO: a unique security identifier
- DATE: the date
- PRC: closing price; if negative, then the midpoint of the closing bid-ask spread
- SHROUT: number of shares outstanding
- VOL: trading volume in shares
- RET: rate of return
- DIVAMT: amount of any dividend paid

3. Individual Strategies

To build a solid foundation for combined strategy, we implemented four individual strategies to produce accurate return predictions. In determining individual strategies, we chose Reversal Strategy, Payout Yield Strategy, Volatility Strategy, and Momentum Strategy as their empirical performance are well recognized.

3.1 Data Preprocess

First, as the dataset has transaction data back to 1960, we set a time range of 01/27/1993 - 12/31/2020 for considerably new data and got 2,582,186 observations.

When conducting data quality examination, we found 24,315 duplicated rows in this dataset, that shared same PERMNO and DATE yet had different other trading information. In order to remove the duplicates, we selected the ones with highest market value, defined as the product of shares outstanding and closing price.

3.2 Reversal Strategy

At its simplest, a reversal strategy aims to profit from the reversal of trends in markets[1]. Reversal portfolios are typically constructed by taking a long position in loser stocks and short position in winner stocks based on past returns[2].

On this dataset, we explored reversal strategy by specifying different quantiles based on past returns. Specifically, we back-tested reversal strategy with respect to two key hyperparameters: (1) q-quantiles and (2) moving average of past-N-day returns.

We first examined reversal strategy with common hyperparameter settings, and the results are shown in Table 3.1. In terms of past returns, time window of moving average affected the statistical significance of strategy performance. Large time window led to insignificant results, indicating the necessity of back testing on small time windows. On the other hand, q-quantile setting had a great influence on strategy returns. With more quantiles, stocks were further separated and thus resulted in a better performance.

Table 3.1 Reversal Strategy Hyperparameter Exploration

q	N	Mean	Sharpe_Annual	t-stat	significance
2	1	0.003487	0.363527	1.920741	FALSE
2	2	0.002155	0.206336	1.088574	FALSE
2	3	0.000306	0.029382	0.154778	FALSE
3	1	0.005337	0.404563	2.137558	TRUE
3	2	0.003081	0.214593	1.132133	FALSE
3	3	0.000591	0.040947	0.215701	FALSE
4	1	0.006962	0.447410	2.363945	TRUE
4	2	0.004360	0.258138	1.361867	FALSE
4	3	0.001218	0.071905	0.378783	FALSE
5	1	0.008643	0.499201	2.637589	TRUE
5	2	0.005562	0.296939	1.566568	FALSE
5	3	0.002175	0.116258	0.612424	FALSE

With insights gained from hyperparameter exploration, we rigorously tuned the hyperparameter and showed the results in Table 3.2.

Table 3.2 Reversal Strategy Hyperparameter Tuning

q	N	Mean	Sharpe_Annual	t-stat	significance
5	1	0.008643	0.499201	2.637589	TRUE
5	2	0.005562	0.296939	1.566568	FALSE
6	1	0.010087	0.541796	2.862645	TRUE
6	2	0.006886	0.341215	1.800157	FALSE
7	1	0.011707	0.589320	3.113744	TRUE
7	2	0.008210	0.384911	2.030687	TRUE
8	1	0.012910	0.621360	3.283030	TRUE
8	2	0.009419	0.421283	2.222576	TRUE
9	1	0.014300	0.659345	3.483729	TRUE
9	2	0.010485	0.451481	2.381890	TRUE
10	1	0.015685	0.696764	3.681437	TRUE
10	2	0.011464	0.477525	2.519296	TRUE

Therefore, for the reversal strategy, we chose the setting of {q:10, N:1} as the result and created quantile labels accordingly for further use in combination methods. However, we did observed the increasing trend of average return with increasing number of quantiles, which is further discussed in the Future Discussions section.

3.3 Payout Yield Strategy

The "conservative formula" of van Vliet and Blitz (VVB) combines three ingredients: Low risk, High past returns and High payout ratio. Since our four individual strategies already included volatility and momentum, we mainly focused on the third ingredient, payout yield, to avoid redundancy.

As VVB's strategy, we focused on common stocks whose SHRCD is 10 or 11. Then Dividends and Net repurchases were used to calculate the Payout yield. In payout yield strategy, we explored two hyperparameters: number of lags of payout yield as well as number of quantiles. The following table shows the result of hyperparameter tuning.

Table 3.3 Payout Yield Strategy Hyperparameter Tuning

Lags	q	Long	Short	Long-Short
3	3	0.011796	0.012658	-0.000862
3	5	0.012586	0.015711	-0.003125
3	10	0.012806	0.023379	-0.010573
6	3	0.012208	0.012316	-0.000108
6	5	0.012527	0.014845	-0.002318
6	10	0.012998	0.021581	-0.008583
9	3	0.012264	0.011759	0.000505
9	5	0.012684	0.014033	-0.001349
9	10	0.013435	0.020032	-0.006596
12	3	0.012480	0.011676	0.000805
12	5	0.013198	0.013449	-0.000251
12	10	0.014004	0.019292	-0.005288

Based on the result of different combinations of lags and quantiles, {lag:12, q:3} was selected as the final result, for it yielded the highest Long-Short return. However, the strategy failed to differentiate good and bad portfolios. Moreover, the difference between the highest and lowest quantile was more likely to be negative. We could expect that when we combine all strategies together, payout yield strategy would be assigned with a low weight.

We also noticed some interesting facts in the payout yield strategy whose details are illustrated in the Future Discussions section.

3.4 Volatility Strategy

The volatility strategy preferred stocks with low volatility based on the assumption of high volatility related to high risks. Volatility portfolios are typically constructed by taking a long position in stable stocks and short position in volatile stocks based on past returns standard deviations.

On this dataset, we explored volatility strategy by specifying different quantiles based on past volatility. Specifically, we back-tested the volatility strategy with respect to two key hyperparameters: (1) q-quantiles and (2) past-N-month standard deviations of prices. The following table shows the top 10 results of hyperparameter tuning.

Table 3.4 Volatility Strategy Hyperparameter Tuning

Lags	q	Long	Short	Long-Short
12	10	0.010581	0.010351	0.000230
24	10	0.010988	0.012058	-0.001070
36	10	0.010366	0.011744	-0.001378
12	3	0.011040	0.012692	-0.001652
12	5	0.010824	0.012619	-0.001795
36	5	0.010491	0.013496	-0.003005
36	3	0.011108	0.014464	-0.003357
24	3	0.011174	0.014666	-0.003492
24	5	0.010925	0.014501	-0.003576

The result was ranked in descending order based on average returns. The combination of {lag:12, q:10} was our final selection because it generated the highest Long-Short return. Besides, it's the only combination that had positive Long-Short return. Further discussions about the long/short differentiation are included in the Future Discussions section.

3.5 Momentum Strategy

Momentum investing is a trading strategy in which investors buy securities that are rising and sell them when they look to have peaked[3]. Although it does not look like a complicated investing strategy, there are lucrative profits to be made from momentum investing. There are two important components in momentum investing: the formation periods and different methods to compute momentum, showed as 'pastrettypes'. It is obvious that different formation periods led to different input data and then may get a different result. The variable of 'pastrettypes' can help us to discern whether this stock was winners or not in the past period. Therefore, in this momentum part, we mainly examined several different combinations in multiple formation periods and the methods computing momentum, trying to find the one with the highest return.

We examined the different formation periods such as 9 and 12 months by setting different start dates and end dates. We also tried three methods to compute momentum: mean, cumulative return, sharp ratio. By iterating different combinations and fine-tuning parameters, we selected optimal combination: {minlags:3, maxlags:13, weighttype:'VW', pastrettypes:'sharpe', numbinses:5}.

Table 3.5 Momentum Strategy Hyperparameter Tuning (Top 20)

minlags	maxlags	weighttypes	types	numbinses	shorts	longs	long-short
3	13	VW	sharpe	5	0.009624	0.014982	0.005359

3	13	EW	sharpe	5	0.009624	0.014982	0.005359
3	10	VW	sharpe	10	0.010390	0.015730	0.005340
3	10	EW	sharpe	10	0.010390	0.015730	0.005340
3	13	VW	sharpe	10	0.010515	0.015525	0.005010
3	13	EW	sharpe	10	0.010515	0.015525	0.005010
2	13	VW	sharpe	5	0.010229	0.015204	0.004976
2	13	EW	sharpe	5	0.010229	0.015204	0.004976
3	10	VW	sharpe	5	0.010013	0.014850	0.004837
3	10	EW	sharpe	5	0.010013	0.014850	0.004837
2	10	VW	sharpe	5	0.010577	0.015268	0.004691
2	10	EW	sharpe	5	0.010577	0.015268	0.004691
2	10	VW	comp	5	0.011077	0.014892	0.003815
2	10	EW	comp	5	0.011077	0.014892	0.003815
2	10	VW	sharpe	10	0.012648	0.016212	0.003564
2	10	EW	sharpe	10	0.012648	0.016212	0.003564
2	13	VW	sharpe	10	0.012292	0.015712	0.003420
2	13	EW	sharpe	10	0.012292	0.015712	0.003420
3	10	VW	comp	5	0.010788	0.014177	0.003390
3	10	EW	comp	5	0.010788	0.014177	0.003390

Based on this result, the quartile 5 has the highest return and Sharpe ratio. Therefore, according to the guidance of momentum strategy, we went long the stocks located in quartile 5 and went short the stocks located in quartile 1.

4. Combined Strategy

With four quantiles produced by four individual strategies, we further explored different combination methods: Assigned Weights, Set Methods, Linear Regression. We applied backtest to find the optimal combination method with best strategy performance.

4.1 Data Preprocess

To combine all the strategies together, we first merged the quantiles to the original data set. Next, we created RET_lead column to get the data ready for Linear Regression method. Finally, NAs were dropped. There are three possible sources of NAs:

- For each strategy, we dropped records whose RET is null.
- Some records were dropped due to lagging.
- In Volatility and Payout Yield strategy, small companies were removed.

On the other hand, as RET_lead was only used for Linear Regression method, NAs resulted from RET_lead would be handled only in the Linear Regression method.

For quantile labels produced by four individual strategies, we long-short stocks according to their underlying properties.

Table 4.1 Long-Short Strategies

	Reversal	Payout Yield	Volatility	Momentum
long	min quantile	max quantile	min quantile	max quantile
short	max quantile	min quantile	max quantile	min quantile

4.2 Assigned Weights

For Assigned Weights method, we assigned weights to each individual strategy based on their average returns in proportion to the sum of four average returns. As we conducted data cleaning for combined strategies, average returns of each individual strategies were slightly different from those from tunning tables. Detailed calculation was shown below.

Table 4.2 Long Returns and Weights

	Reversal	Payout Yield	Volatility	Momentum	Sum
return	0.023064	0.012527	0.010372	0.014930	0.060893
weight	0.378764	0.205727	0.170327	0.245181	1

Moreover, we transferred four columns of quantiles to four columns of trading signals by replacing long quantiles with 1, short quantiles with -1 and the rest with 0. Finally, we calculated an individual score by multiplying weight with trading signal and then summed up four scores to get the final score for each stock on each date. As for our trading strategy, we went long stocks whose final scores are larger than 0.5 and went short stocks whose final scores are smaller than -0.5. The Assigned Weights method eventually gained a 0.016712 average monthly return under long-only strategy and a 0.016091 average monthly return under long-short strategy.

Table 4.3 Assigned Weights Performance

	short	long	long-short
count	323	323	323
mean	0.000620	0.016712	0.016091
std	0.084763	0.058166	0.062586
min	-0.244185	-0.267678	-0.429051
25%	-0.043467	-0.007323	-0.014268
50%	0.001517	0.018152	0.014814
75%	0.044602	0.043241	0.048429
max	0.493329	0.310396	0.301760
sharpe_annual	0.025358	0.995259	0.890634
tstat	0.131561	5.163529	4.620723

4.3 Set Methods

To combine results of individual strategies, we reckoned various quantile labels as sets and applied two set methods below.

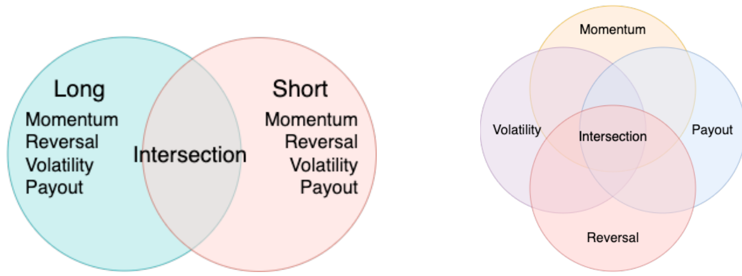

Figure 4.1 Union Method(left) and Intersection Method(right)

4.3.1 Union Method

In union method, we united all stocks and removed the intersection part. Specifically, to found out the combined long/short set, we first created the union set based on all long/short sets of individual strategies. The union method made the advantage of diversity among different strategies and produced a robust portfolio from market crashes. However, the union method automatically relaxed the criterion for long/short sets and brought about overlap in long and short sets. Hence, we further removed the intersection part and long-short the rest. The backtest result is shown below, with an average long-short strategy return of 0.005495 per month. Yet the t-statistic of union method was 2.5317, which was statistically significant.

Table 4.4 Union Method Performance

	short	long	long-short
count	323	323	323
mean	0.007670	0.013165	0.005495
std	0.070797	0.046763	0.039005
min	-0.238110	-0.228271	-0.185460
25%	-0.030612	-0.008792	-0.011536
50%	0.010436	0.016678	0.006388
75%	0.042251	0.040727	0.026061
max	0.280725	0.174821	0.134633
sharpe_annual	0.375305	0.975240	0.487989
tstat	1.947131	5.059670	2.531749

4.3.2 Intersection Method

In intersection method, we simply created the intersection set of four individual strategies for both long and short sets. Different from the relaxation effect of union method, the intersection method, on the other hand, restricted the criterion for long/short sets and separated the stocks even further.

However, since we set different criterions for long and short portfolios, some dates only contained long or short portfolios, and the traditional long-short strategy was not applicable. In this case, we only went long for long portfolios and only went short for short portfolios.

The backtest performance of intersection method was much better compared to the union method, with an average long-short strategy return of 0.016380 per month. Though the average return was considerably high, the t-statistic of the intersection method was 1.6451. Since the result was not statistically significant, we further explored an updated version of intersection method.

Table 4.5 Vanilla Intersection Method Performance

	short	**long**	**long-short**
count	320	70	320
mean	-0.014056	0.010621	0.016380
std	0.174854	0.082460	0.178113
min	-0.479381	-0.467748	-1.147094
25%	-0.109232	-0.016631	-0.052007
50%	-0.035951	0.010401	0.040352
75%	0.052007	0.046627	0.116209
max	1.147094	0.195833	0.479381
sharpe_annual	-0.278474	0.446190	0.318565
tstat	-1.438032	1.077651	1.645062

To update the portfolio, we relaxed the restriction of integrated portfolio. Specifically, as the number of quantiles of payout yield and momentum only covered three and five quantiles respectively, we relaxed the quantiles of reversal and volatility by two quantiles. With the relaxed portfolio, we gained an average monthly return of 0.024473 with a t-statistic of 4.5110.

Table 4.6 Relaxed Intersection Method Performance

	short	**long**	**long-short**
count	323	321	323
mean	-0.007963	0.016613	0.024473
std	0.105319	0.042312	0.097503
min	-0.277732	-0.175995	-0.358753
25%	-0.067486	-0.004375	-0.018901
50%	-0.013680	0.018900	0.028237
75%	0.051575	0.041123	0.078334
max	0.321109	0.192282	0.308044
sharpe_annual	-0.261917	1.360079	0.869470
tstat	-1.358857	7.034385	4.510919

4.4 Linear Regression

For this combination method, we built a linear regression model to determine the weights of each individual strategy. As mentioned in 4.1 Data Preprocess, the lead of return was created as the target variable, and the input variables contained four quantiles returned by the four strategies. Thus, if a strategy performed poorly, its negative impact will be minimized in the stacking model. Similarly, if a strategy performed well, its effect would be enlarged.

For implementation, like Fama-Macbeth regression, we grouped data by DATE and performed a linear regression to fit RET_lead by four quantiles. The in-sample R-Squared is 0.13, while none of the input variables are statistically significant, which indicates the poor performance of this model. However, we still conducted the backtest to see if it can outperform other combination strategies.

Table 4.7 Linear Regression Model Summary

	lambda	Beta_Payout	Beta_Vola	Beta_Mom	Beta_Reversal
mean	0.011382	-0.000294	0.000223	0.000524	-0.000300
std	0.061125	0.009744	0.009270	0.010095	0.003966
min	-0.196528	-0.043894	-0.029080	-0.085128	-0.038498
25%	-0.020424	-0.004641	-0.004355	-0.002837	-0.001956
50%	0.012151	0.000339	-0.000389	0.001555	-0.000067
75%	0.039911	0.005321	0.003987	0.005172	0.001800
max	0.561260	0.035268	0.042162	0.036599	0.009961
stderr	0.003406	0.000543	0.000517	0.000563	0.000221
tstat	3.341524	-0.541497	0.432255	0.931200	-1.357122
significance	TRUE	FALSE	FALSE	FALSE	FALSE

The linear regression returned a predicted return based on all four individual strategies. For each portfolio and each date, a new quantile was formed. If we long the stocks with top 20% predicted return and short the bottom 20%, the average long-short difference would be 0.9262% per month (11.14% annually). And the difference is statistically significant (t-stat = 2.023).

Table 4.8 Linear Regression Method Performance

	short	long	long-short
count	322	322	322
mean	0.007087	0.016434	0.009347
std	0.076251	0.076063	0.082731
min	-0.253872	-0.262396	-0.534203
25%	-0.025655	-0.012687	-0.022976
50%	0.012423	0.015807	0.006791
75%	0.037864	0.044227	0.045195
max	0.580301	0.400134	0.335305
sharpe_annual	0.321955	0.748457	0.391398
tstat	1.667756	3.877075	2.027476

4.5 Final Strategy

As shown in Table 4.9, the Relaxed Intersection Set Method yielded the significantly highest monthly return of 0.024473 among all three combination methods and therefore was chosen as our final strategy. A complete comparison table containing all individual strategies and combined strategies could be found in Appendix.

Table 4.9 Combination Method Summary

	Assigned Weights	Set Method - Union	Set Method - Intersection	Set Method – Relaxed Intersection	Linear Regression
mean	0.016091	0.005495	0.016380	0.024473	0.009347
std	0.062586	0.039005	0.178113	0.097503	0.082731
min	-0.429051	-0.185460	-1.147094	-0.358753	-0.534203
25%	-0.014268	-0.011536	-0.052007	-0.018901	-0.022976
50%	0.014814	0.006388	0.040352	0.028237	0.006791
75%	0.048429	0.026061	0.116209	0.078334	0.045195
max	0.30176	0.134633	0.479381	0.308044	0.335305
sharpe_annual	0.890634	0.487989	0.318565	0.869470	0.391398
tstat	4.620723	2.531749	1.645062	4.510919	2.027476
significance	TRUE	TRUE	FALSE	TRUE	TRUE

Individual strategies have different underlying assumptions as well as focuses, and they lead to either similar or opposite portfolios when conducted separately. Therefore, we would like to explore the synergistic effect among those strategies, where we could make advantage of diversity, reinforcement, and avoiding unnecessary transactions.

In our final project, we made no assumptions about the strategies and let data found pattern itself. While aiming at developing the best combination method of base strategies, Relaxed Intersection Set Method of combining Reversal, Payout Yield, Volatility and Momentum strategy was proven to be our final choice. The following reasons justified the process:

- By combining individual strategies, we diversified the portfolio with various merits of different strategies. As diversity leads to robustness, the long-short strategy helped eliminate the risk of market crashes.
- By selecting the intersection set of different strategies, we restricted the long/short criterion and allowed them to reinforce each other to form an integrated portfolio.
- By combining individual strategies, we took several strategies into account and avoided the contrast trades to reduce transaction costs.

We also decomposed different strategy performance on the trading date level, whose details were illustrated in Appendix.

Figure 4.2 Final Strategy Performance

After determining our final strategy, we made a comparison of its performance with other benchmarks. The above figure compared our cumulative returns with cumulative returns of risk-free assets and S&P 500 during the past ten years. The strategy outperforms the market before 2020. However, there was a steep decline after 2020, which might be caused by COVID-19. We discussed this issue in the Future Discussions section.

5. Future Discussions

In this part, we further elaborated several interesting facts found in implementation, and left the work for future discussions.

5.1 Reversal Strategy

When conducting hyperparameter tuning, we found the increasing trend of average return with respect to the increasing number of quantiles. For instance, the combination of {q:16, N:1} yielded a higher average monthly return of 0.021399, which is also statistically significant and incredibly impressive. Nevertheless, a large number of quantiles would automatically leave few stocks in each quantile, which might undermine the diversity of portfolio and cause difficulty for combination methods, especially the intersection set method. Therefore, regardless of the promising average return, we eventually chose the combination of {q:10, N:1} that yielded an average monthly return of 0.015685. Possible improvement, such as conducting hyperparameter tuning during the combination phase, may lead to a better performance. We leave such work for future discussions.

5.2 Payout Yield Strategy

As shown in Table 3.3, the top quantile portfolios shared similar returns with the bottom quantile portfolios. If we reverse the strategy by longing the bottom quantile and shorting top quantile, the optimal return will increase from 0.000805 to 0.010573. Moreover, if we only long the top quantile, the monthly return would be 0.014004. Similarly, if we only long the bottom quantile, the monthly return would be 0.023379. All the scenarios outperform original strategy. This implies that vanilla Payout Yield strategy did not fit this dataset and more attempts are needed for a better performance.

5.3 Volatility Strategy

The problem of indifference between the top quantiles and the bottom quantiles also appeared in the Volatility Strategy. As shown in Table 3.4, the top quantile portfolios shared similar returns with the bottom quantile portfolios. If we only long stocks, we could get higher average return.

5.4 Momentum Strategy

About momentum strategy, it needs to be known that reversal strategy may conclude opposite results compare with momentum strategy because the reversal strategy typically took a long position in loser stocks and short position in winner stocks. Therefore, there is a conflict between momentum strategy and reversal strategy in some situations.

5.5 Intersection Set Method

In Intersection Set Method, we accidentally found that if we long the maximum quantile for Volatility Strategy and short the minimum quantile, we would instead get a higher average monthly return of 0.033550. Opposite to the common practice, this strategy should fail to produce an impressive return. However, in our implementation, it did yield the highest return, mainly resulted from the long portfolio with a considerably high return. Possible reasons may derive from the reinforcement from combining different strategies. We would leave it for future work to explain this phenomenon.

Table 5.1 Performance of Opposite Volatility

	short	long	long-short
count	42	255	265
mean	0.002915	0.035346	0.033550
std	0.091123	0.256411	0.243963
min	-0.280702	-0.372276	-0.372276
25%	-0.032353	-0.101247	-0.101258
50%	-0.006829	-0.001217	0.000446
75%	0.034235	0.134040	0.132441
max	0.311475	2.707547	2.501156
sharpe_annual	0.110832	0.477521	0.476387
tstat	0.207348	2.201264	2.238680

6. Conclusions

To explore the synergistic effect among strategies, we applied three combination methods, Assigned Weights, Set Methods, and Linear Regression, to combine four individual strategies, Reversal, Payout Yield, Volatility, and Momentum. With rigorous tuning for individual strategies and detailed comparison among combination methods, we selected the Relaxed Intersection Set Method as our best combination method of individual strategies.

For implementation, we chose crspm.feather from the Center for Research in Securities Prices in the university of Chicago as our dataset and applied a two-stage strategy. In the first phase, we examined the four individual strategies, Reversal, Payout Yield, Volatility, and Momentum, separately and conducted hyperparameter tuning for each strategy. We backtested different combinations of hyperparameter settings and produced quantile labels with the combination yielding the highest return. The output of the first phase was four corresponding quantiles.

In the second phase, we utilized three approaches to combine the quantiles together: Assigned Weights, Set Methods (Union Method & Intersection Method) and Linear Regression. Eventually, the Relaxed Intersection Set Method yielded the highest average monthly return of 0.024473. This champion trading strategy outperformed all individual strategies, which indeed revealed the synergistic effect among Reversal, Payout Yield, Volatility, and Momentum strategies.

7. References

[1] https://www.warriortrading.com/reversal-trading-strategy/
[2] de Groot, Wilma & Huij, Joop & Zhou, Weili, 2012. "Another look at trading costs and short-term reversal profits," Journal of Banking & Finance, Elsevier, vol. 36(2), pages 371-382.
[3] https://www.investopedia.com/trading/introduction-to-momentum-trading/

8. Appendix

Table 8.1 Strategy Summary

	mean	std	min	25%	50%	75%	max	sharpe_annual	tstat
Reversal	0.016882	0.080303	-0.384148	-0.016433	0.008319	0.036585	0.815640	0.728243	3.778217
Payout Yield	0.000827	0.036973	-0.201621	-0.015954	0.001867	0.021849	0.125037	0.077484	0.401998
Volatility	0.000470	0.098234	-0.489526	-0.045272	0.000396	0.054069	0.312614	0.016566	0.085946
Momentum	0.005460	0.055015	-0.422896	-0.016017	0.009470	0.032091	0.195583	0.343827	1.783820
Assigned Weights	0.016091	0.062586	-0.429051	-0.014268	0.014814	0.048429	0.301760	0.890634	4.620723
Union Set Method	0.005495	0.039005	-0.185460	-0.011536	0.006388	0.026061	0.134633	0.487989	2.531749
Intersection Set Method	0.016380	0.178113	-1.147094	-0.052007	0.040352	0.116209	0.479381	0.318565	1.645062
Relaxed Intersection Set Method	0.024473	0.097503	-0.358753	-0.018901	0.028237	0.078334	0.308044	0.869470	4.510919
Linear Regression	0.009347	0.082731	-0.534203	-0.022976	0.006791	0.045195	0.335305	0.391398	2.027476

The above table showed a complete comparison for all individual strategies and combined strategies. Furthermore, to find out the reason of high average return of our final strategy, we checked strategy performance on each trading date.

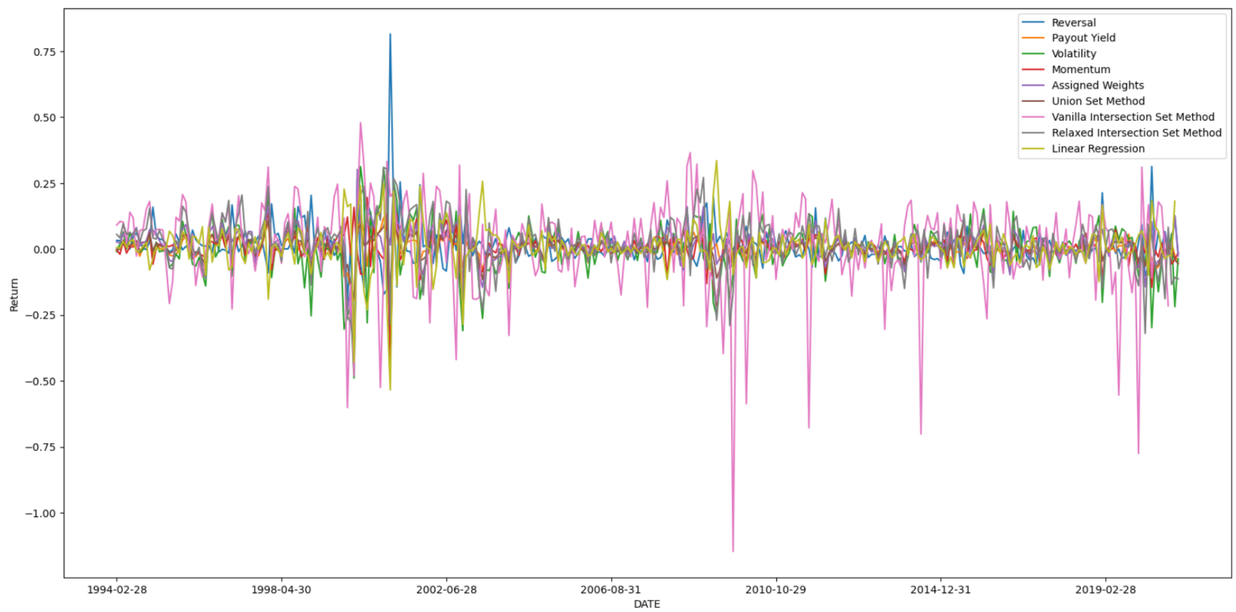

Figure 8.1 Strategy Performance

As shown in the figure, the vanilla intersection set method yielded highest return for most dates. However, it yielded lowest return for most dates in the meanwhile, which led to a lower average return (0.016380 per month) compared to the relaxed intersection set method (0.024473 per month).

Table 8.2 Count of Maximum & Minimum Returns

	# max RET
Vanilla Intersection Set Method	131
Reversal	49
Linear Regression	45
Relaxed Intersection Set Method	37
Volatility	32
Assigned Weights	13
Momentum	11
Payout Yield	5

	# min RET
Vanilla Intersection Set Method	76
Reversal	70
Volatility	58
Linear Regression	58
Momentum	22
Payout Yield	18
Relaxed Intersection Set Method	15
Assigned Weights	6

The above table also explained the higher average return of the relaxed intersection set method. Among all strategies, it yielded highest return for a considerable number of dates (ranking fourth) and yielded lowest return for considerably few dates (ranking second).