QF621 QUANT TRADING

Course project report

QUANTMENTAL INVESTING

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Content

1. Introduction

Factors investing has its strong root in finance practices and could be the most widely researched topic in modern finance. Rules-based trading emerged after increased market anomalies published around 1970 that couldn't be explained by CAPM. From the arbitrage pricing theory, Fama French 3 factors then 5 factors model to modern factors investing research, there are hundreds of factors identified that purport to explain equities returns.

One characteristic of factors investing is that the company fundamental information is usually targeted as the crucial source for alphas. Companies that exhibit factors of strong profitability , quality and no sign of financial distress with reasonable value are expected to outperform. Traditionally, fundamental research mainly focuses on companies' financial statements and on-site investigations to value companies and attempts to profit from undervaluation. Currently, the burgeoning of ruled based algorithm investing makes it popular to incorporate fundamental investing characteristics with systematic trading.

The main idea behind Quantmental investing is to utilize fundamental alpha factors, technical indicators and market anomalies to pick stocks and trade. While fundamental factors are the main criteria to select stocks, factor timing and stock momentum are also applied to boost the performance. It is a hybrid strategy that remains defensive by picking stocks with high quality and safe stocks but will become aggressive when timing is right. It is also a strategy that combines the value and momentum style, both of which have been found to have positive historical returns and negative correlations to one another (Ilmanen et al, 2014).

The asset classes for trading are US equities and US bonds. The strategy will be implemented on Quantopian platform and the stock universe used is QTradableStocksUS from the platform. The universe has 1600-2100 members, includes most liquid shares and updates daily. After cleanup, the final universe for this strategy contains the top 1500 stocks in terms of average trading volume, without stocks with no price, no sectors and no recent 5-day returns.

The universe is intended to remain big for the reason that more fundamental data could be available thus more stocks could be included into the portfolio, in addition to reduce the noise from a small sample size.

Based on the same principle, two algorithms have been built. One is long-only (smart beta), the other is long-short equity neutral. Three-factor weighting schemes: equal weighting, factor momentum weighting and correlation weighting have been applied to long short equity strategy. All algorithms are rebalanced weekly to balance between transaction costs and obsolete alpha signals.

Transaction costs for backtesting include commission and slippage. The commission model is as default of Quantopian, at $0.001 per share and no minimum cost per order. The first fill will incur at least the minimum commission, and subsequent fills will incur additional commission. The slippage model is also a default, 5 basis points fixed slippage, but no volume share limit although the algorithm can't fill orders having sizes greater than historical volumes.

2. Factor analysis

The factor selection process starts from a pool of 65 most well-cited factors (Gupta &Kelly, 2019) and other frequently used factors by practitioners (Wiecki,2019). By conducting the alpha factors analysis on Quantopian (Quantopian Alphalens), the list of factors used for the algorithm is summarized in table 1, based on the criteria of information coefficients and data availability. The factor analysis has a period of 9 years so that long enough to cover a full business cycle. The factors for the algorithm should have statistically significant information coefficients, the higher, the better. The automatically generated factor-based quantile portfolios ideally should have distinct performances and no crossover between each other. The Main focus is on 5 days returns spreads and the information coefficient is because the algorithms rebalance weekly. The detailed factor analysis is summarized in appendix 1, and factor correlations in appendix 4.

Table 1 Factors Summary

Spectrum	**Factors**
Quality	The modified version of Piotroski' F_score by Gray et al (2012). It uses financial ratios ROA, Free cash flow to total assets (FCFTA) and accrual to measure profitability, long term debt ratio, liquidity ratio and net equity issuance to measure stability, yearly changes of

	ROA, FCFTA, gross profit margin and asset turnover to measure operational improvements. Each component is capped at 1 if they are positive and 0 otherwise to create a total score from 0 to 10 so that there is no overpay for any outstanding component.
Profitability	Profitability score composed of gross profits over assets (GPOA), return on equity (ROE), return on assets (ROA), cash flow over assets (CFOA), gross margin (GMAR).
Value	Enterprise multiple, earning yield, fcf yield, FREECF (free cash flow to equity)
Efficiency	The composite score contains retained earnings to assets, operating cash flow to assets, EBIT to assets and capital expenditure to assets. Asset Turnover, Cashflows to assets.
Safety	Debt to total assets, total past month Volatility, Altman' Z score for credit strength.
Behavioural heuristic	Composite score by asset growth over 1 year, capital expenditure growth over 1 year and net financing.Analyst revision (earning per share annual revision)

The pool of factors covers a wide range of perspectives in terms of company fundamentals. While the Fscore may already be a comprehensive score for quality, profitability and efficiency are emphasized by including more robust factors. The intention is to pick up the companies with high quality with solid profitability and liquidity at a reasonable value while is not too susceptible financial distresses. For better diversification, the market anomalies as a result of behavioural heuristic are also utilized. Asset growth (Cooper et al, 2008)), capital expenditure growth (Anderson & Garcia-Feijoo, 2006), external financing (Bradshaw et al ,2006), are compressed into one based on similar behavioural reasons: overconfidence, investors over extrapolate past gains to growth. The lookback period for growth is chosen for 1 year due to the data availability issue. Analyst revision (Gleason &Lee, 2003), based on the behavioural finance phenomenon of anchoring and availability, is also utilized.

Factor correlation in appendix 4 shows a debt to assets (account for negative signal), Altman_Z, have a negative correlation with many other factors. Besides, value factors such as earning yield and enterprise multiple are not highly correlated with others and can be negatively correlated with momentum. Accumulate each individual factor' alpha is expected to construct a combined alpha that is robust enough and also diversified enough.

There are some factors other than Fscore, such as profitability and efficiency, are composed of individual factors, which are constructed as $Zscore(\sum_i^n Zscore_i)$, by compressing individual factors Zscore into one. This is consistent with the approach by Asness et al (2019), who states multiple measures of one factor could have superiority over single measure in terms of performance. Hence the composite factor is expected to improve the performance from the individual factor with week signals.

It should be noted that the volatility will be applied factor timing to utilize its regime-switching property, momentum is not an individual factor for ranking stocks in the first stage but is made portable and will be a determining factor to select stocks in the next stage. Altman' Z score will be used in the long-short equity strategy but not long-only strategy, as it has been criticized for lacking predictive power for higher scoring, but it is expected to contribute considerably on the short side if the default happens.

Integrate all those factors together into a one combined alpha is expected to select stocks to perform well in all the specified spectrums in general. It has the superiority in terms of performance over the approach that mixing the factors and selecting stocks sequentially based on individual factors. (Israel et al, 2017). As the latter approach will tend to pick up stocks that are extreme in one dimension but horrible in another.

3. Long only strategy.

3.1 Construction process.

The long-only algorithm is constructed through ranking stocks, stock/factor momentum application and market timing. There is no leverage.

1. Alpha rankings. The above factors are integrated, equal-weighted and winsorized for eliminating the top and bottom 1 percentile outliers (the percentile is chosen to balance between outliers and true high score companies), then are used to rank stocks in the universe by the summed Zscore(normalized by mean and standard deviation).
2. Stock momentum. From the top 30% stocks in terms of alpha factor ranking, 50% of them with best half-year momentum (account for the last 10-day mean reversion) are chosen for the final portfolio. However, when the high momentum portfolio has annualized volatility exceeds 27%, the contrarian approach is taken and stocks with the worst momentum will be selected for the portfolio.
3. Factor timing. Volatility is a negative signal in this case as the intention of the strategy is to be relatively defensive, but high volatility and low volatility factor portfolios have statistically significant positive return spread, it will become a positive signal.
4. Market timing. Trade stocks only when SPY ETF half year return is positive. Otherwise just trade bonds.
5. Portfolio optimization. The stock weights in the portfolio will be optimized to maximize the alpha while meeting certain constraints (exposure and postion).

The reason to separate momentum with other alpha factors for selecting stocks is that momentum is not a robust individual factor to rank stocks. The top quantile momentum portfolio will not consistently outperform the market, as can be seen in figure 1. When the market volatility was very high, the top quantile momentum portfolio underperformed but the bottom quantile momentum portfolio outperformed. Thus Malitskaia (2019) proposes the annualized volatility 27% as the valve for deciding trading momentum or not. By and large, the individual treatment for momentum made it possible to take advantage of the property of momentum by entering into a momentum or contrarian position when the timing is appropriate.

The treatment of volatility stems from the research by Neo&Tee (2019), who demonstrates that hold high volatility portfolio consistently will not reward, but it will outperform when the market enters high volatility regime, as determined by a statistically significant return slope between top quantile volatility portfolio and bottom quantile volatility portfolio. For this strategy, the volatility portfolios are constructed by ranking the universe with past month total volatility, selecting the top 30% of ranked stocks as the equal-weighted top volatility and the bottom 30% as the bottom volatility portfolio. The slope is just the return difference between the two and the standard error will be rolling 20 days standard deviation for the past month. The 5% P-value is used to determine statistical significance.

The volatility timing is consistent with the idea of factor momentum, which is found not strongly correlated with stock momentum, especially the factor momentum formation period is 1 month and could have different sources of returns (Gupta &Kelly, 2019). As a result, the simultaneous application of both factor momentum and stock momentum here is expected to have little overlapping and not jeopardize the performance. It can be indicated that the high volatility regime doesn't necessarily mean the momentum portfolio exceeds the volatility threshold, it only reveals that volatility has positive return momentum. On the other hand, the market timing approach here could be an effective tool to evade market stress events, despite its simplicity.

Figure 1 Momentum portfolios performance

3.2 P&L analysis

As can be seen in the summary statistics in table 2, the strategy generates a very decent annualized return 19%, beat the market significantly (SPY cumulative returns 159.76% for the same period), although its annual volatility is high at 30.8%, which downgrades the Sharpe ratio. The portfolio's CAPM alpha is high but has a close to 1 beta, indicates its sensitivity to market movements. Other than that, the skew, kurtosis and tail ratio all show the returns distribution is close to normal.

Table 2 Performance summary (long only)

Start date	2006-01-04	
End date	2018-12-31	
Total months	155	
	Backtest	
Annual return	19.035%	
Cumulative returns	859.285%	
Annual volatility	30.769%	
Sharpe ratio	0.72	
Calmar ratio	0.45	
Stability	0.95	
Max drawdown	-42.504%	
Omega ratio	1.14	
Sortino ratio	1.01	
Skew	-0.33	
Kurtosis	5.36	
Tail ratio	0.96	
Daily value at risk	-3.788%	
Gross leverage	2.19	
Daily turnover	11.376%	
Alpha	0.14	
Beta	0.92	

Table 3 Drawdowns and stress events (long only)

Worst drawdown periods	Net drawdown in %	Peak date	Valley date	Recovery date	Duration
0	42.50	2007-07-13	2008-07-18	2010-04-15	720
1	33.35	2011-05-10	2011-08-08	2013-02-14	463
2	32.91	2018-09-11	2018-12-24	NaT	NaN

3	29.89	2018-01-23	2018-02-08	2018-05-16	82
4	28.93	2010-04-23	2010-07-06	2010-12-10	166

Stress Events	mean	min	max
Lehman	0.04%	-1.78%	1.90%
US downgrade/European Debt Crisis	0.14%	-12.13%	11.52%
Fukushima	0.77%	-5.44%	5.76%
EZB IR Event	-0.33%	-2.68%	2.65%
Aug07	0.16%	-8.29%	6.22%
Mar08	-0.21%	-4.53%	3.36%
Sept08	0.01%	-1.78%	1.90%
2009Q1	-0.10%	-1.40%	1.64%
2009Q2	0.13%	-1.95%	3.51%
Flash Crash	0.37%	-7.43%	16.52%
Apr14	-0.21%	-3.97%	2.79%
Oct14	0.42%	-4.16%	4.17%
Fall2015	-0.32%	-7.05%	6.64%
Low Volatility Bull Market	0.15%	-8.49%	6.91%
GFC Crash	-0.03%	-8.29%	7.72%
Recovery	0.11%	-12.13%	16.52%
New Normal	0.09%	-12.90%	6.99%

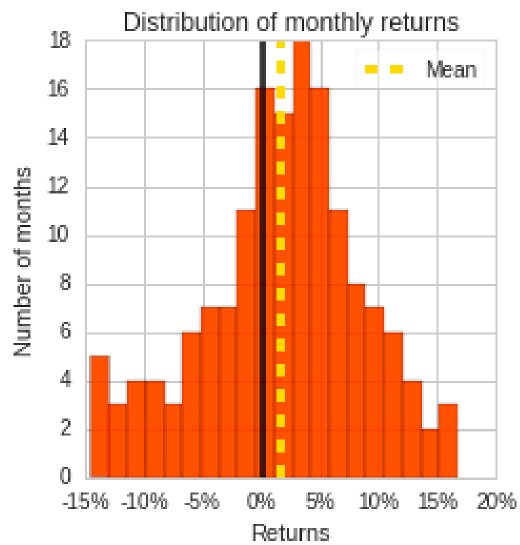
As shown in table 3, The worse drawdown breakdowns show the strategy suffered some significant drawdowns, the top 3 worse drawdowns are close to 40%, especially for the worst drawdowns that lasting for 720 days. The exposure to market stress events were not neutral, although the mean exposure to those events were minimal. Based on the information on holding from figure 2, the market indicators actually effectively voided some impact of stress events, since during global financial crisis, Euro debt crisis and oil price crash, the strategy actually only traded bonds. Thus, those drawdowns may be mainly due to the company specifics.

The long only strategy generally to select stocks from top 15% of stock universe and position concentration is kept at [0, 0.05] during optimization. There are generally around 150 stocks ranked as top 15%, it seems the algorithm picked about 50 stocks on average to maximize the alpha while meeting the concentration constraints as in figure 2. The portfolio size is not so large. The turnover rate is acceptable, the performance summary states a 11.376% average daily turnover and the plotting records a few spikes and most daily turnover at around 0.7, meaning buying and selling on each rebalancing day is kept at acceptable level.

Figure 2 Holdings and Turnover (long only)

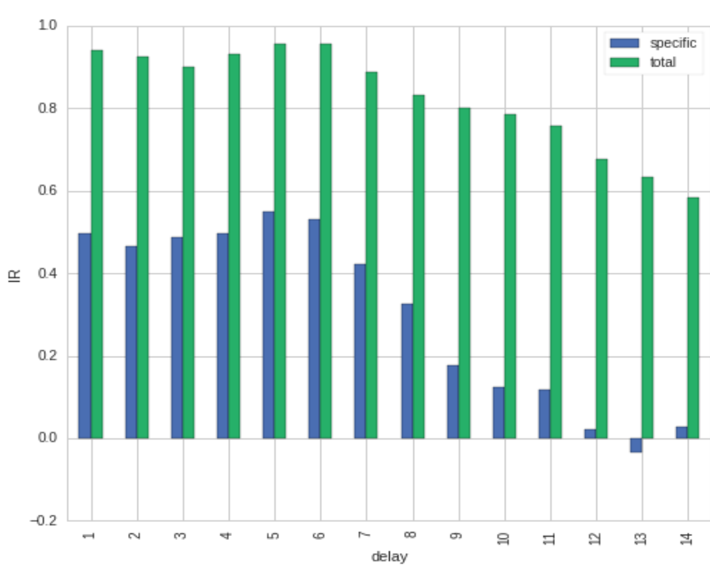
Figure 3 indicates the strategy generated positive returns 12 out 13 years with some considerable returns around 40%, there is no sign of return decays although a sign of ebb and flow. The monthly return distribution is close to normal.

Figure 3 Annual returns and monthly returns distribution (long only)



The information ratio($IR = IC\sqrt{Breadth}$)decay in figure 4 shows the total IR decays very slowly, specific IR doesn't have a sharp decay after first day and it reaches maximum around day 5. This fact implies if the algorithm is not able to enter position on day 1 due to slippage or turnover requirement, the alpha signal will not lose for both total and specific return source, even if delay to day 5 at next rebalancing day.

Figure 4 Alpha decay (long only)



The stock position summary in table 4 shows that most concentrated position is treasury bonds IEF. For stock positions, NFLX provides streaming entertainment service, TRA mainly conducts development of mineral properties, ESRX is a pharmacy benefit management organization. SCCO engages in mining, exploring, smelting, and refining copper, QCOR is pharmaceuticals company, GILD is a research-based biopharmaceutical company, SWKS develops and manufactures proprietary semiconductor products, JAZZ is biopharmaceutical company, APOL is for education business. The position is bit concentrated on energy companies and biopharmaceutical companies.

Table 4 Top 10 stock positions (long only)

Top 10 long positions of all time	**max**
IEF-23870	116.25%
TRA-7561	11.65%
NFLX-23709	11.15%
ESRX-2618	10.87%
SCCO-14284	10.80%
QCOR-20914	10.34%
GILD-3212	9.94%
SWKS-23821	9.92%
JAZZ-33959	9.74%
APOL-24829	9.74%
Top 10 short positions of all time	**max**
IEF-23870	-130.13%

As the strategy adopts market timing to tactically expose to beta, beta and sector exposures are not neutralized when using the built-in optimization. Performance attribution from table 5 and figure 5 reveals the exposure to volatility and momentum were positive as well as significant as by designed. The exposure to volatility were a mean close to 0 and some high exposure occasionally due to the strategy design, but its contribution to common return was minimal or even negative. The strategy had positive exposure to nearly all the common sectors factors, all of which accumulated into the significant 15.83% annualized common return. By contrast, specific return had only 3.13% annually. As expected, most volatility is from common returns, which is not beneficial, as it is difficult to diversify it away and could increase the burdens for risk budgeting from a portfolio perspective.

Combine the information from figure 6, the contribution of returns from sector exposure were all positive, the most noticeable was the contribution from consumer cyclical sector, which didn't match the company sectors from top holdings. It could be due to the strategy picked up some successful stocks that have exposures to those sectors, however, as the strategy actually had no insight into any of the sectors but implicitly took sector bets, this could impose challenges for risk managements.

Table 5 Performance relative to common factors and factor exposure

Summary Statistics			
Annualized Specific Return	3.13%		
Annualized Common Return	15.83%		
Annualized Total Return	19.03%		
Specific Sharpe Ratio	0.30		
Exposures Summary	**Average Risk Factor Exposure**	**Annualized Return**	**Cumulative Return**
basic materials	0.10	0.94%	12.88%
consumer cyclical	0.47	5.19%	92.78%
financial services	0.02	0.31%	4.09%
real estate	0.04	0.51%	6.81%
consumer defensive	0.17	1.27%	17.87%
healthcare	0.15	1.99%	29.21%
utilities	0.02	0.30%	3.94%
communication services	0.03	-0.02%	-0.28%
energy	0.08	0.73%	9.97%
industrials	0.19	2.35%	35.14%
technology	0.25	3.02%	47.08%
momentum	1.17	3.08%	48.26%
size	0.78	-0.56%	-7.05%
value	-0.87	-0.23%	-2.89%
short_term_reversal	-0.26	0.11%	1.40%
volatility	0.13	-1.58%	-18.65%

Figure 5 Factor and sector exposures, returns and volatility (long only)

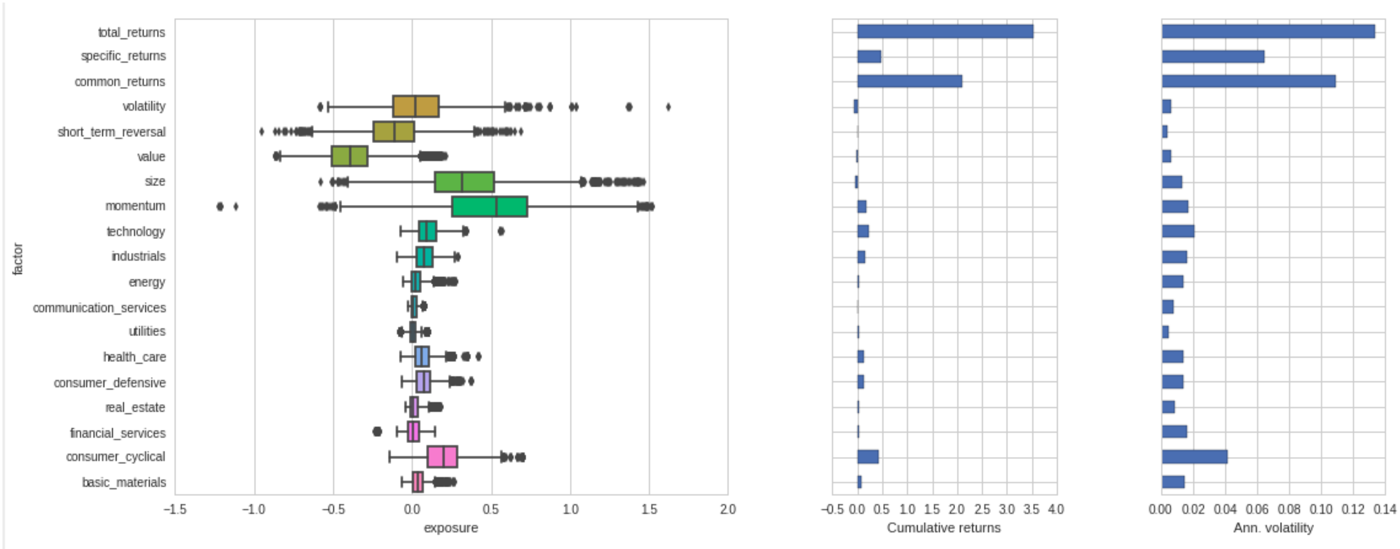


Figure 6 Sector common returns attribution

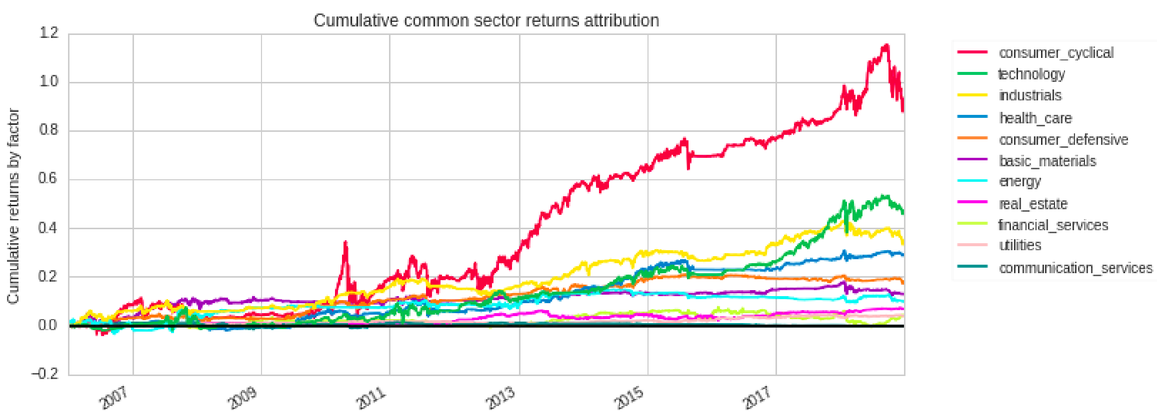


Figure 7 details the daily exposure to sectors and style, there are some spikes for consumer cyclical, and it seems those exposure actually contributed to the higher returns but also higher volatility as in figure 8. Those spikes from momentum and volatility were come from the strategy design, but the contributions were outweighed by consumer sector.

Figure 7 Daily sector and style exposure (long only)

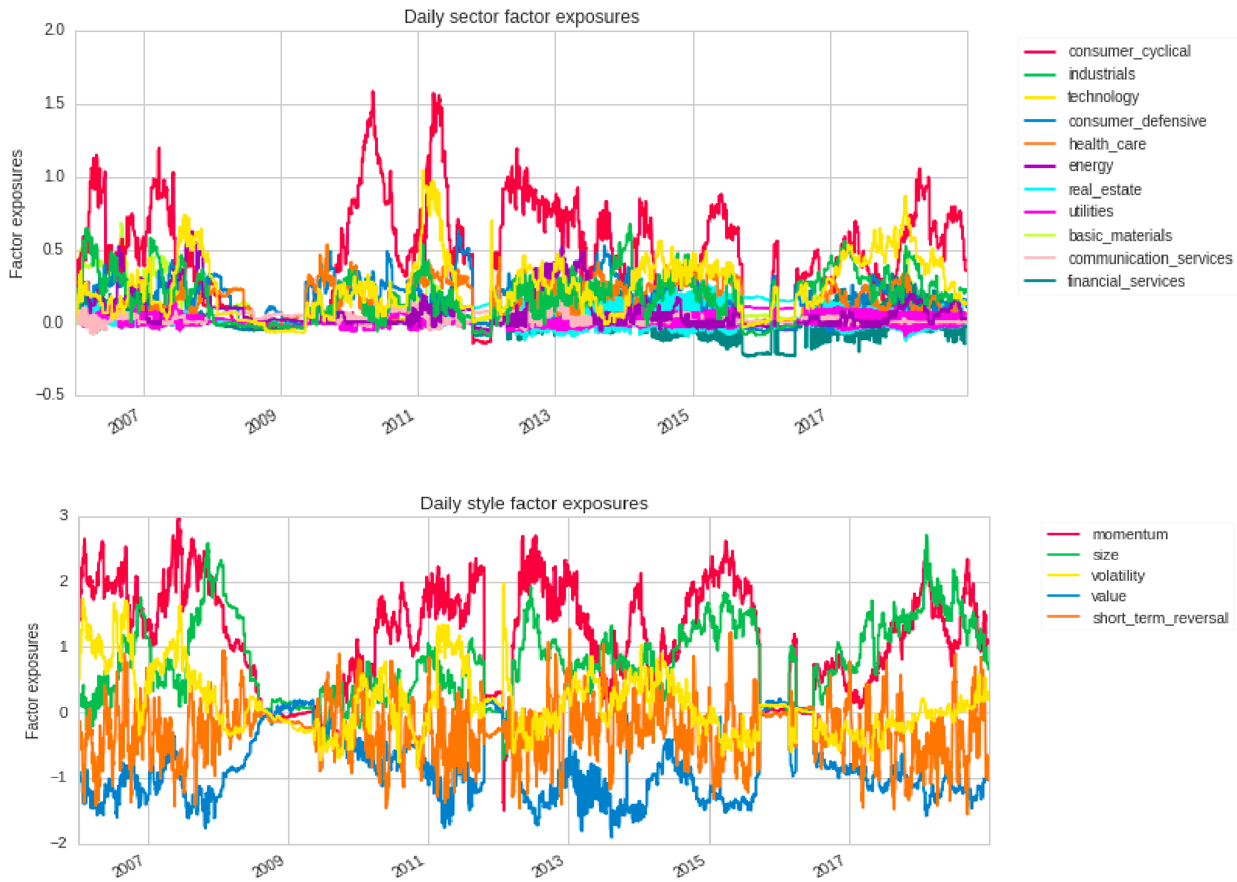
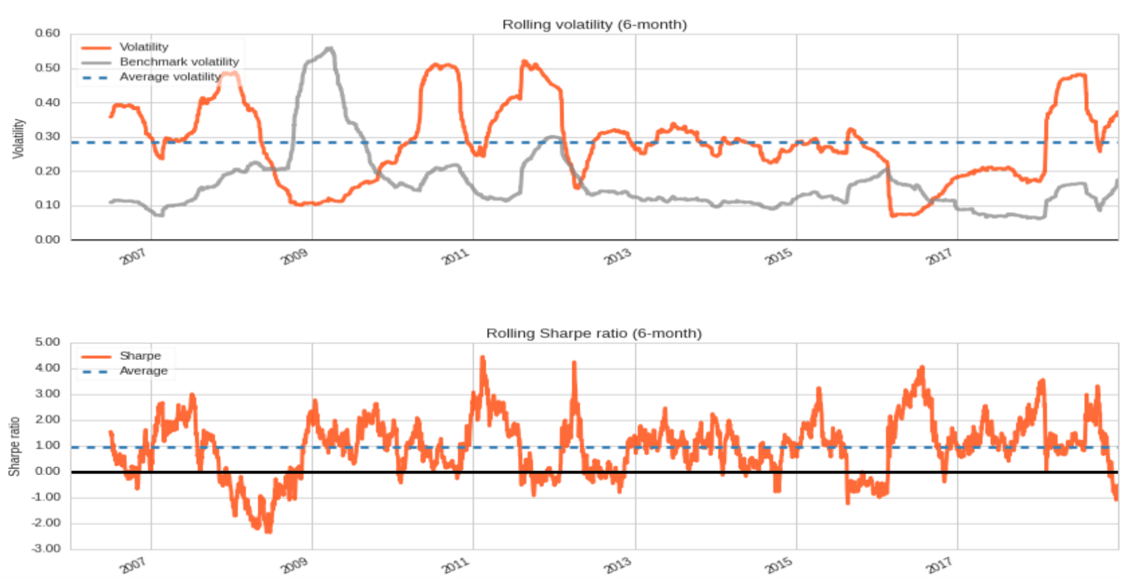


Figure 8 Rolling 6-month volatility and Sharpe ratio (long only)



In summary, the strategy had impressive returns but also high volatility, hence the returns could be attributed to the risk taking. It had some successes in selecting stocks, and tactical momentum exposure, but less so on volatility timing. The specific returns were small so that the strategy is less unique and interesting. The high exposure to certain sectors could also be dangerous.

4. Long short equity strategy.

While long only strategy could be suitable for investors tracking certain benchmarks, long short equity strategy could have its metric of generating higher risk adjusted return and neutrality to market exposure with great diversification gain. In this particular case, the long short equity strategy could be a robustness test to the alpha factors and specific return sources as if without beta and the alphas are not strong enough, it is highly likely that a strategy can't survive after fees. The long short equity algorithm has been deployed into three different types with different factor weighting schemes. The strategies don't use leverage.

Based on law of active investment, $IR = IC\sqrt{Breadth}$, in order to perform well, the strategy needs to forecast accurately for high information coefficient (IC) and forecast frequently, independently for high breadths. It is intended to hedge beta and sector exposure to ensure the strategy's bets are not so correlated and untended risks are avoided. As a result, the stock weights are optimized for maximizing alphas, sector and beta exposure are hedged in the algorithm. Position concentration is kept at [0, 0.05].

4.1 Equal weighting.

The long short equity strategy follows the same principle with long only strategy except SPY market timing has been abandoned. The stocks will be ranked by the equal weighted, combined alpha factors, subsequently top 30% and bottom 30% stocks will be selected. Among those stocks, best 50% of top 30% and worst 50% of bottom regarding momentum are taken for long/ short sides. Reverse the order when high momentum portfolio annualized volatility exceeds 27%, it means still establish long/short positions from highest/lowest fundamental scoring stocks but actually 50% of best contrarian score and best momentum score will be purchased and sold respectively. Volatility is a negative signal in this case but if momentum is positive and significant, it will become a positive signal.

4.1.1P&L analysis (equal weighting)

It can be revealed from the performance summary statistics that the equal weighted long short equity strategy reached total return 306.2% that beat SPY (159.76%) benchmark, achieved a good annualized return 11.4%, had relatively low annual volatility, which is in line with the 0.86 Sharpe ratio. Judge from Sordino ratio, 1.25 indicates it generated returns effectively adjusted by downside risk. Skew, kurtosis and tail ratio all indicate the return distribution is close to normal and the strategy didn't suffer from tail risks. The less than 15% daily turnover shows the strategy was generally stable and alphas of stocks in portfolio could have relatively long-lasting predictive power. It was beta neutral and had 12% CAPM alpha.

As a sanity check, the strategy without volatility timing had 291.83% total returns and 0.83 Sharpe ratio, the strategy without volatility timing, momentum and its timing had only 7.33% and 0.11 Sharpe. As a result, the all the components of this algorithm construction are meaningful.

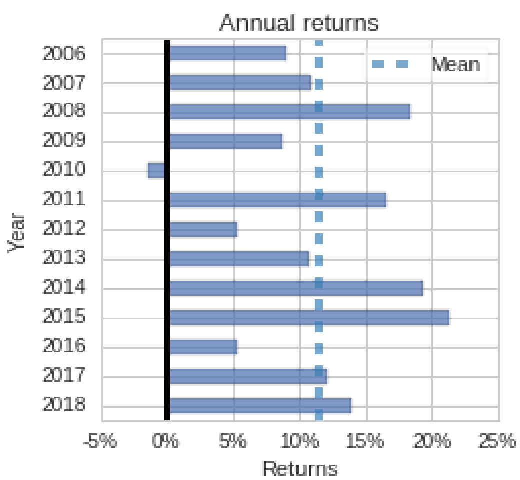
Table 6 Performance summary (LSE equal weighted)

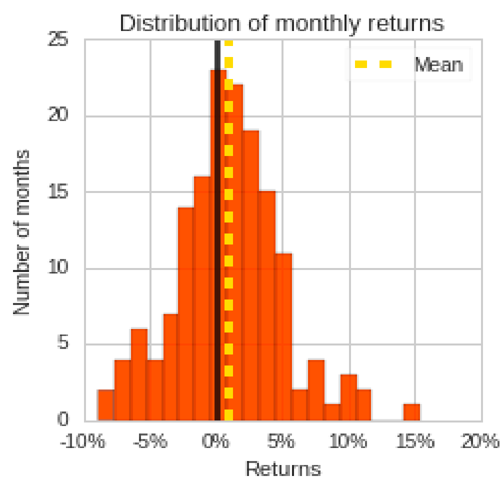
Start date	2006-01-04
End date	2018-12-31
Total months	155
	Backrest
Annual return	11.408%
Cumulative returns	306.235%
Annual volatility	13.668%
Sharpe ratio	0.86
Calmar ratio	0.48
Stability	0.96
Max drawdown	-23.544%
Omega ratio	1.16
Sordino ratio	1.25
Skew	-0.16
Kurtosis	3.59

Tail ratio	1.11
Daily value at risk	-1.675%
Gross leverage	0.96
Daily turnover	14.284%
Alpha	0.12
Beta	-0.03

The monthly returns distribution in table 7 shows strategy returns were close to normal and tended to be positive skewed. Based on the breakdown of annual returns, the strategy had some variations in yearly returns but made postive returns 12 out 13 years, and considerable outperformances in year 2008, 2011, 2014 and 2015.

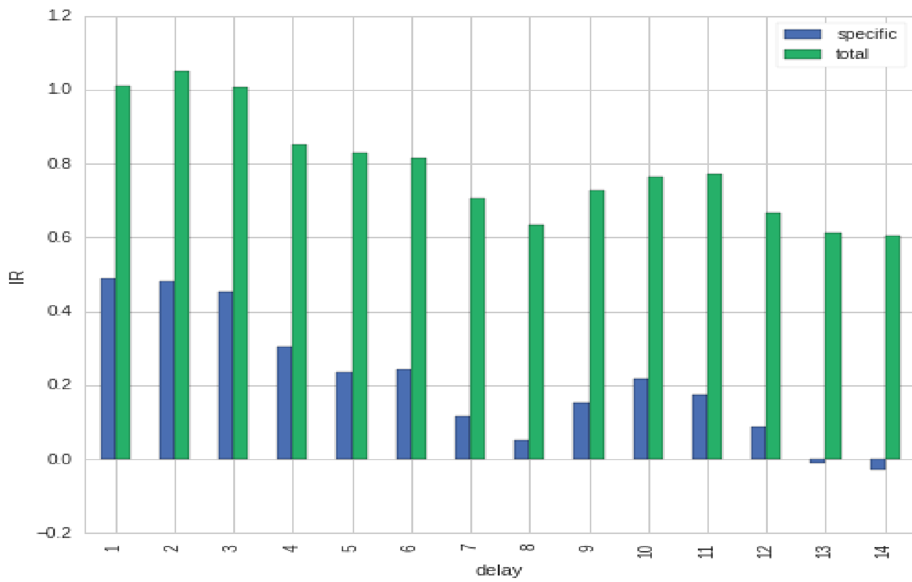
Table 7 Annual returns and monthly returns distribution (LSE equal weighted)





The information coeffiicent decay graph figure 9 shows a slower decay profile for total return source than specific return source. The specific return source shows some sudden drops after 3 days but remain postive for around 12 days. It implies the strategy will lose alpha if it fails to enter postion for the first 3 days, thus it should at least rebalance weekly, in order to extract meanningful infromation from specific alphas.

Figure 9 Alpha decay (LSE equal weighted)



Combine figure 9 box and whisker plot and table 8, it can be found the contribution to the total returns was about 40% from specific sources and about 60% from common factors. It is also desirable to have most volatility coming from specific returns as they could be diversified away easily when including in a portfolio. The negative exposure to volatility and positive momentum is as intended, and they both contribute a large portion of common returns.

Table 8 Performance breakdown and risk exposure (LSE equal weighted)

Summary Statistics			
Annualized Specific Return	4.73%		
Annualized Common Return	6.51%		
Annualized Total Return	11.45%		
Specific Sharpe Ratio	0.44		
Exposures Summary	**Average Risk Factor Exposure**	**Annualized Return**	**Cumulative Return**
basic materials	0.00	0.31%	4.04%
consumer cyclical	0.01	0.23%	3.02%
financial services	0.00	0.04%	0.48%
real estate	-0.00	-0.01%	-0.09%
consumer defensive	0.00	0.01%	0.12%
healthcare	-0.05	-0.88%	-10.82%
utilities	-0.00	0.01%	0.09%

communication services	-0.01	-0.03%	-0.36%
energy	-0.02	-0.30%	-3.82%
industrials	-0.02	-0.19%	-2.44%
technology	-0.00	-0.23%	-2.91%
momentum	0.63	2.62%	39.94%
size	0.53	-0.47%	-5.94%
value	-0.20	-0.13%	-1.73%
short_term_reversal	-0.23	-0.38%	-4.87%
volatility	-0.92	5.94%	111.49%

Table 9 Exposure, returns and volatility (LSE equal weighted)

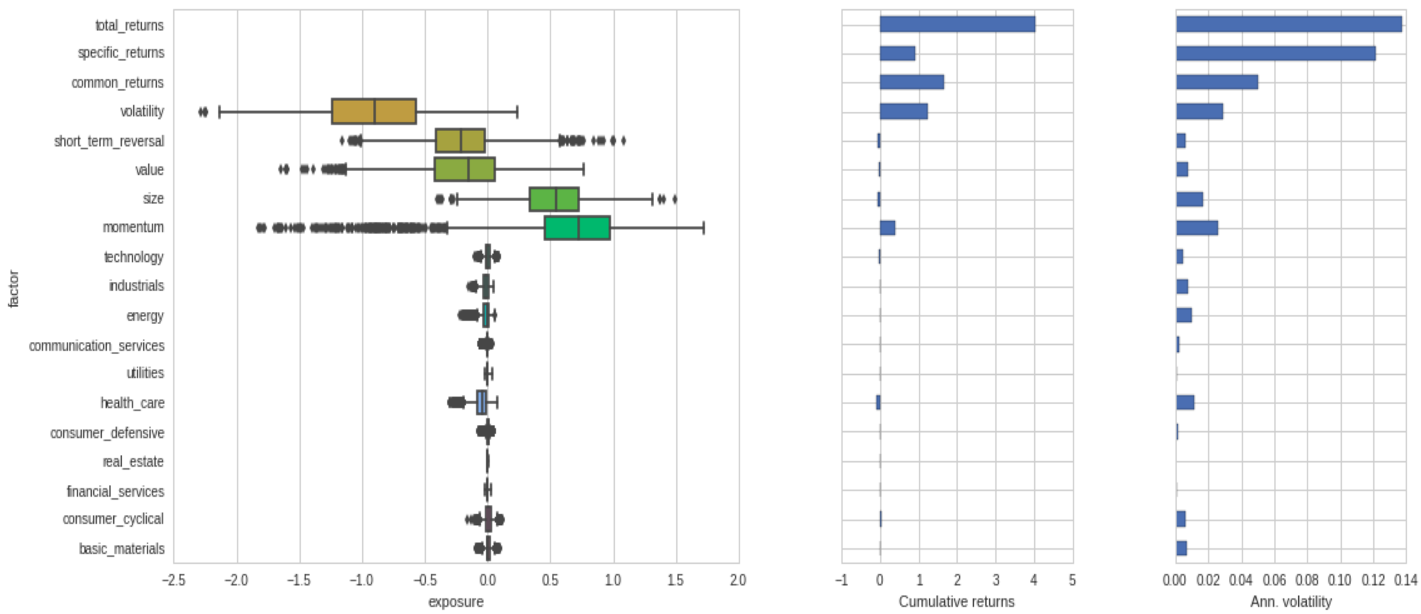


Table 10 shows, the maximum drawdown was 23.54%, happened at second quarter of 2009 and lasts for two years, the other drawdowns were similar in magnitudes. Based on the information about top positions stocks, the strategy had relatively high concentration on energy and resources stocks hence it could be explained that it was the oil price crush in 2016 cause some drawdowns. Besides that, the exposure of the strategy to other stress events are limited, as can be seen in the stress events analysis.

Table 10 Drawdown and stress events (LSE equal weighted)

down periods	Net drawdown in %	Peak date	Valley date	Recovery date	Duration
0	23.54	2009-06-01	2011-01-18	2012-01-20	690
1	16.47	2016-01-19	2016-03-21	2017-03-07	296
2	15.33	2013-11-13	2014-03-03	2014-10-03	233
3	13.72	2008-07-07	2008-07-23	2008-11-05	88
4	13.05	2017-03-22	2017-07-14	2017-10-31	160

Stress Events	mean	min	max
Lehman	-0.08%	-3.01%	2.47%
US downgrade/European Debt Crisis	0.03%	-1.46%	1.97%
Fukushima	0.19%	-0.97%	1.13%
EZB IR Event	-0.06%	-1.65%	1.65%
Aug07	0.11%	-1.75%	1.82%
Mar08	0.30%	-1.51%	2.01%
Sept08	-0.12%	-2.52%	2.47%
2009Q1	0.29%	-1.78%	3.30%
2009Q2	0.29%	-1.72%	3.01%
Flash Crash	0.80%	0.27%	1.28%
Apr14	0.11%	-0.89%	0.90%
Oct14	0.43%	-3.50%	4.79%
Fall2015	0.14%	-4.26%	2.33%
Low Volatility Bull Market	0.03%	-4.59%	2.80%
GFC Crash	0.10%	-3.90%	5.86%
Recovery	0.02%	-5.00%	3.01%
New Normal	0.05%	-5.02%	4.79%

An investigation of the top long and short position in table 11 could explain the performance variations to a certain extent. SDRL offers drilling services for energies, NTRL is a natural sweetener company, SCHN manufactures steel, DAR produces natural ingredients, FRAN offers apparel, CF produces nitrogen fertilizers, SNBR is in furnishings industry, FLR offers services to energy and industrial companies, WPX is independent oil and natural gas exploration and production company, QCOR is a Pharmaceuticals stock. The long positions are generally diversified but tend to slightly hold more companies on energy and industrial sectors. The negative cumulative exposures of the above-mentioned sectors after 2011 could explain some drawdowns during year 2011, 2013 and 2016 as in figure 10.

On the short position, DNR is an oil and natural gas company, CHK is also an energy corporation, HGSI is a biopharmaceutical corporation, UAL provides air transportation services, HOV designs, constructs, markets, and sells residential homes, ITMN is a biotech company, LPI is an energy company, LINE provides communication services, ARNA a biopharmaceutical company. The position on short side is more concentrated on energy and health care biopharmaceutical sector. The biotech companies are generally volatile and lack of financial strength, their outperformance mainly depend on technology breakthrough and FDA approvals. As can be seen, the most significant cumulative exposure was healthcare sector, those companies were not expected to meet the algorithm’s criteria but could have outstanding growth. Thus, the drawdowns could be from shorting those healthcare companies.

Table 11 Top positions (LSE equal weighted)

Top 10 long positions of all time	max
SDRL-39495	16.01%
NTRI-21697	7.13%
SCHN-10268	7.13%
DAR-11908	6.95%
FRAN-41737	6.92%
CF-27558	6.84%
SNBR-19559	6.77%
FLR-24833	6.77%
WPX-42251	6.73%
QCOR-20914	6.62%
Top 10 short positions of all time	**max**
DNR-15789	-14.46%
CHK-8461	-10.21%
HGSI-10409	-9.39%
UAL-28051	-9.33%
HOV-3645	-9.02%
ITMN-21284	-8.76%
LPI-42263	-8.43%
LINE-27993	-8.41%
ARNA-21724	-8.40%
HK-31032	-8.32%

Combine the information from figure 10 and 11, as is consistent with previous results, the negative exposure to volatility and positive exposure momentum at appropriate time leads to some success in performance. Shorting large portions of biotech stocks led to large negative exposure to healthcare, hence missed the healthcare booming after 2017 thus some drawdowns happened.

Figure 10 Sector common return attribution (LSE equal weighted)

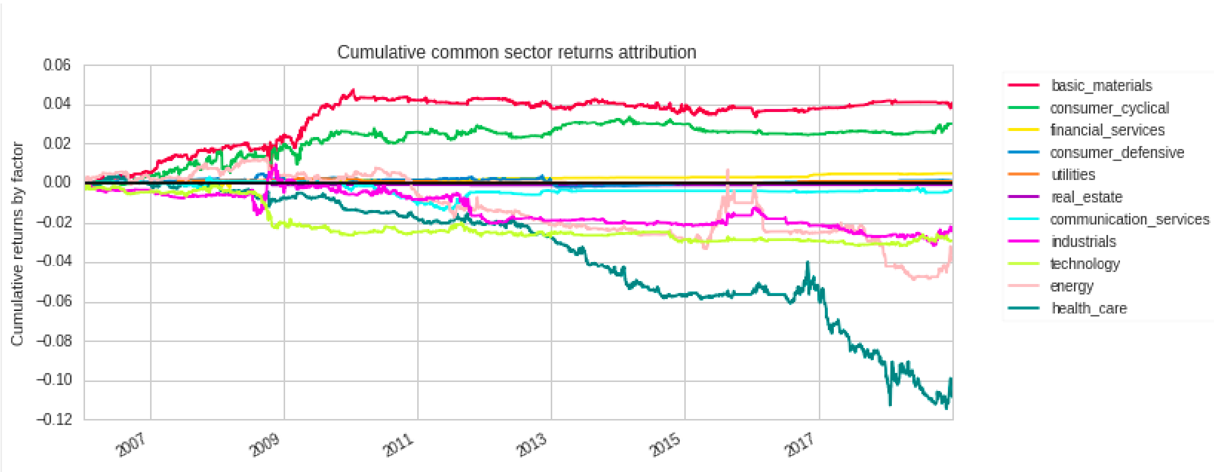


Figure 11 Daily style and sector exposures

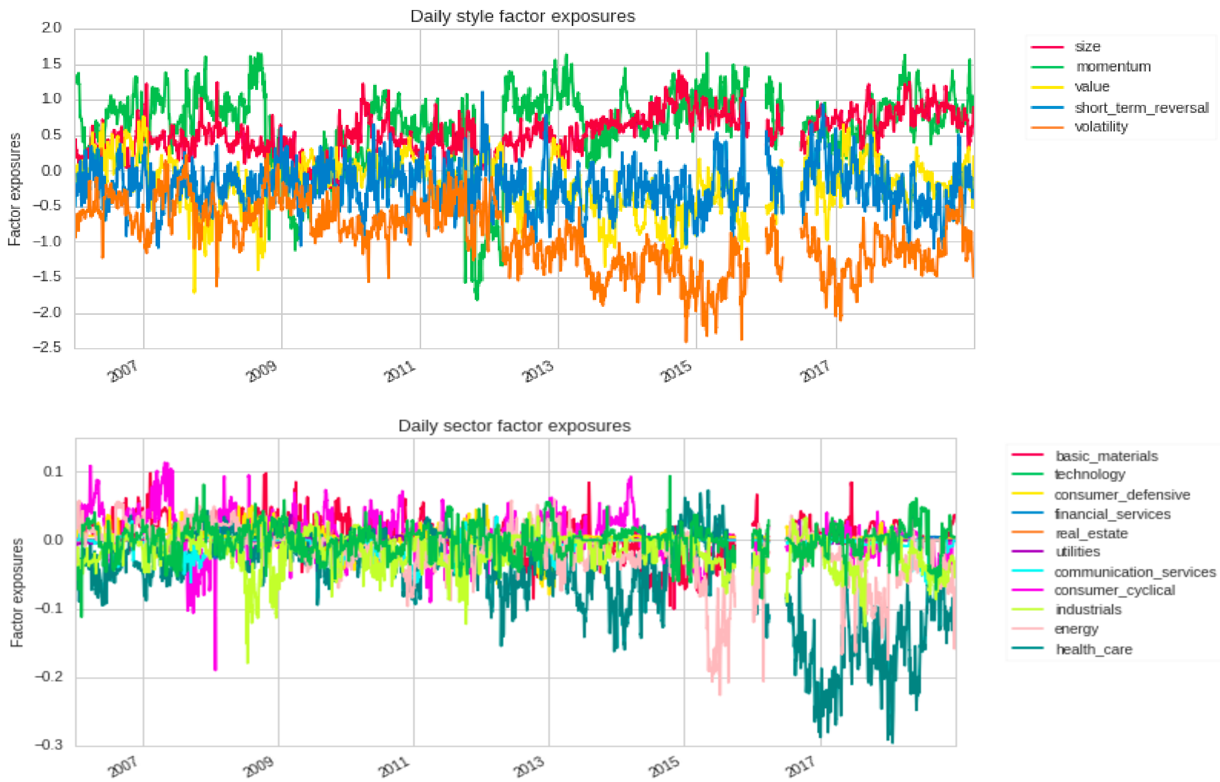
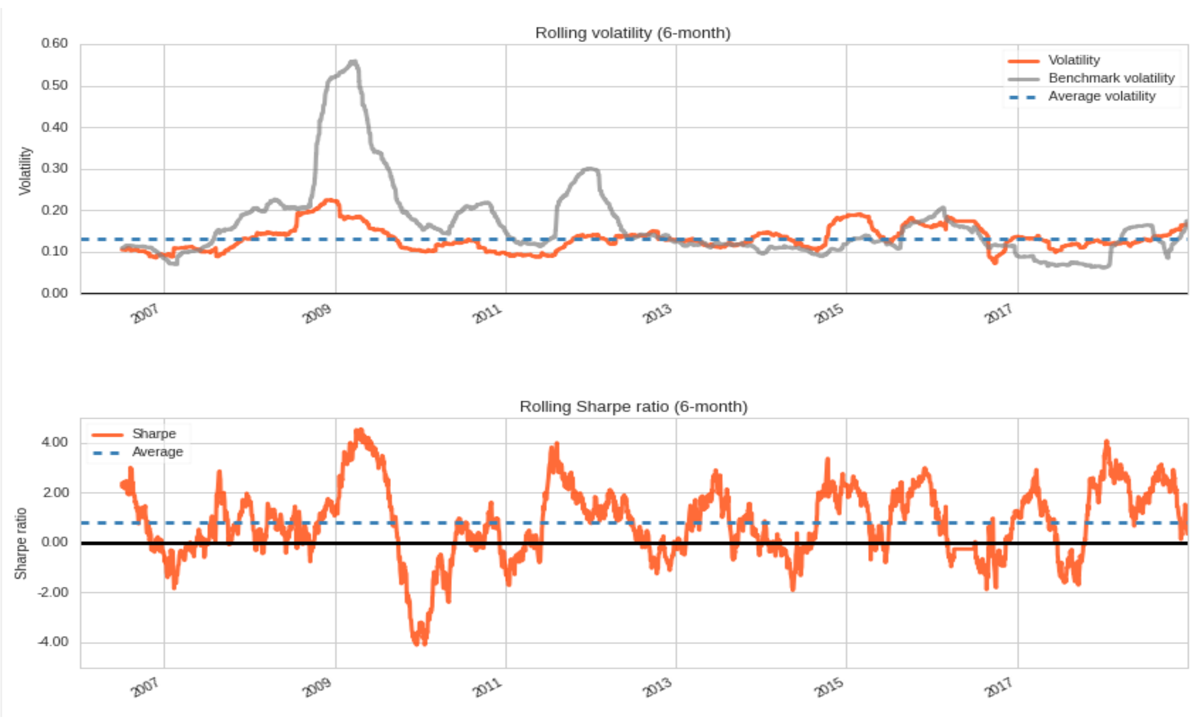


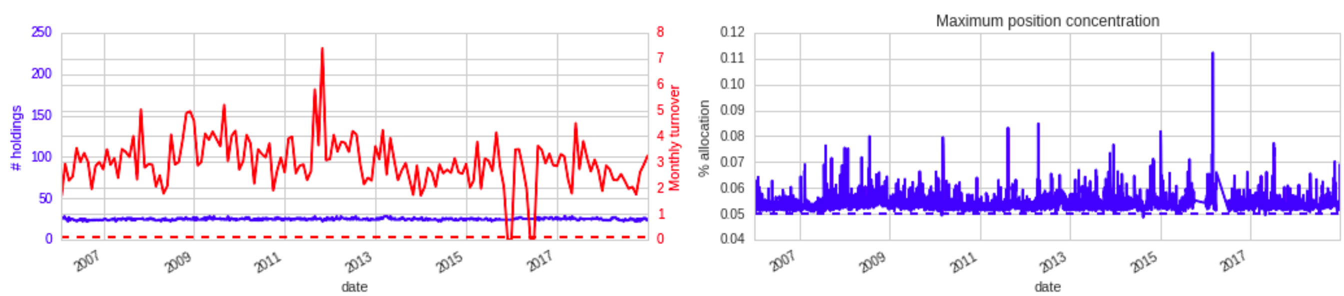
Figure 12 Rolling volatility and Sharpe ratio (LSE equal weighted)



As shown in figure 12, the strategy was sector neutral and beta neutral, had lower volatility than benchmark. Besides some drawdown events, the strategy had some impressive rolling 6 months Sharpe ratios for certain periods.

Figure 13 points out some problems. The universe after filtering and ranking is expected to contain about 200-300 stocks to be included in the portfolio. The holdings position concentration had been capped at plus/minus 0.05, the optimizer just selected the top stocks with maximum position possible, which maked the portfolio size smaller at around 30 all the times and imposed the danger of position concentration risk. Monthly turnover rate in this case is relatively higher as the number implies large switch of positions at each rebalancing week. Moreover, there are certain times in which the holdings have 0 position but jumped back again, it could be partly attributed to data availability issue with many Nans for factors hence the universe is close to empty.

Figure 13 Holdings, positions and turnovers (LSE equal weighted)



4.2 Factor momentum weighting

Gupta &Kelly (2019) presented factor momentum is prevalent and especially strong for past 1 month returns. The results are very robust across different factors and markets.

1. Follow the similar procedure in that research, all the factors including volatility in this algorithm will be dynamically scaled based on past 1-month performance of each factor. The scaling factor is $\min\left(\max\left(\frac{1-month\ factor\ return}{1-month\ factor\ rolling\ voatility}, -2\right), 2\right)$, capped the

Zscore at [-2,2]. The combined alpha after scaling will be normalized to ensure the scaled weighted sum up to 1.

2. To determine the factor momentum, the factor portfolio should be constructed as Israel et al (2017), which is consistent with most academic researches. The stock universe is divided into two size categories (small and big) using market cap medians, in this case 60% market size percentile is chosen. Then split the stocks into three groups based on each factor's value (highest 30%, middle 40%, lowest 30%). The resulting factor portfolio will just be the average of two highs (small high + big high) minus the average of two lows (small low + big low). However, the portfolios are equal weighted in order to save some computational costs. Back testing results show the performance of algorithms based on this factor construction method differs little from that simple top 30%/bottom 30% equal weighted factor portfolio with no size buckets splitting construction method.
3. What conducted differently is that instead of scaling on every rebalancing day, the factor will only be scaled when the factor return is statistically significant at 5% level, the same with treatment towards volatility momentum previously. This approach ensures factor won't be treated more importantly based on past insignificant information.

Thanks to this weighing schemes, during ranking process, the factor with successful past momentum will have higher scored thus stocks achieve high in that particular factor will be more likely selected on the long side, stocks of the factor will also be less emphasized on the short side even if the score is low before scaling and vice versa.

4.2.1 P&L analysis (factor momentum weighting)

As revealed from the performance summary in table 12, the factor momentum weighing algorithm underperformed the equal weighing one with 8.5% annualized return and 0.68 Sharpe ratio, other performance metrics are also lower. The daily turnover in turn becomes higher.

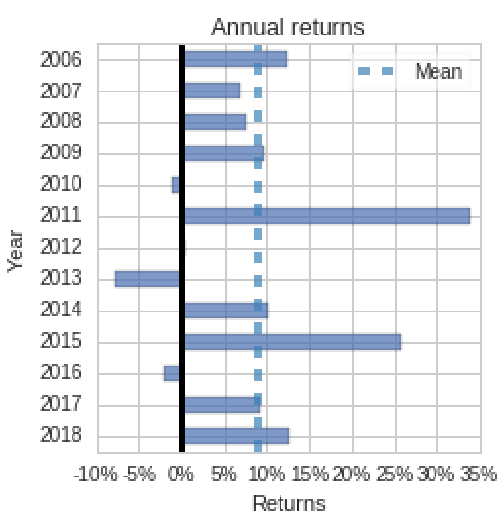
Table 12 Performance summary (LSE momentum weighted)

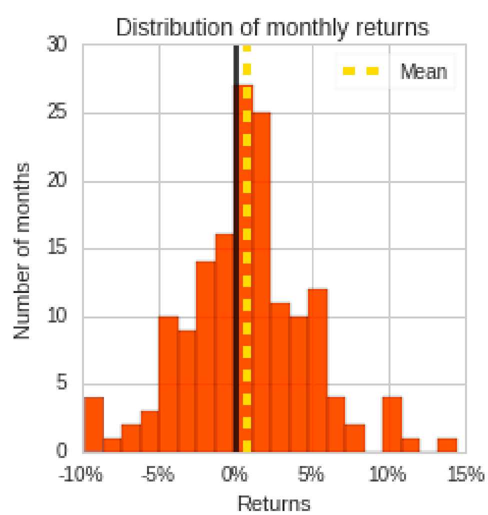
Start date	2006-01-04
End date	2018-12-31
Total months	155
	back test

Annual return	8.552%
Cumulative returns	190.015%
Annual volatility	13.373%
Sharpe ratio	0.68
Calmar ratio	0.34
Stability	0.89
Max drawdown	-24.923%
Omega ratio	1.13
Sortino ratio	0.97
Skew	-0.22
Kurtosis	4.23
Tail ratio	1.07
Daily value at risk	-1.649%
Gross leverage	0.96
Daily turnover	18.536%
Alpha	0.09
Beta	-0.04

The strategy still has close to normal monthly returns distribution which tends to be slightly positive skewed, it made positive returns most of years, but less than equal weighted in terms of magnitudes. The 2011-year return was very impressive, especially when it was the year of Euro debt crisis. It is noted that ebb and flow of annual returns is a bit large.

Table 13 Annual returns and monthly return distribution (LSE momentum weighting)





Regarding drawdown periods in table 14, the strategy had some overlapping with equal weighted, but the most severe drawdowns happened during 2012 to 2014 and the duration was very long.

Table 15 reveals that compare with equal weighted, the factor momentum's common returns didn't decrease, it was the annualized specific returns decreased nearly half. As showed in figure 14, common returns are mainly from volatility and momentum, the factor momentum weighting in fact distorts the signals from specific alphas to some extent.

Table 14 Drawdowns and stress events (LSE momentum weighting)

Worst drawdown periods	Net drawdown in %	Peak date	Valley date	Recovery date	Duration
0	24.92	2012-04-09	2014-07-07	2015-07-15	853
1	22.76	2009-06-01	2011-01-18	2011-07-29	565
2	21.53	2016-01-19	2016-09-22	2018-01-12	519
3	15.97	2008-07-07	2008-07-23	2008-11-12	93
4	12.47	2008-01-09	2008-02-01	2008-06-23	119

Table 15 Return breakdown and risk exposure

Summary Statistics			
Annualized Specific Return	1.98%		
Annualized Common Return	6.58%		
Annualized Total Return	8.61%		
Specific Sharpe Ratio	0.23		
Exposures Summary	**Average Risk Factor Exposure**	**Annualized Return**	**Cumulative Return**
basic materials	0.00	0.31%	4.10%
consumer cyclical	0.00	0.12%	1.55%
financial services	0.00	0.02%	0.20%
real estate	-0.00	0.02%	0.25%
consumer defensive	0.00	0.07%	0.90%
healthcare	-0.05	-0.73%	-9.11%
utilities	-0.00	0.04%	0.51%
communication services	-0.00	-0.05%	-0.67%
energy	-0.02	-0.15%	-1.91%
industrials	-0.02	-0.02%	-0.23%
technology	-0.00	-0.05%	-0.58%

momentum	0.64	2.95%	45.75%
size	0.50	-0.32%	-4.03%
value	-0.22	-0.33%	-4.25%
short_term_reversal	-0.24	-0.42%	-5.31%
volatility	-0.86	5.11%	91.03%

Figure 14 Exposure, returns and volatility (LSE momentum weighting)

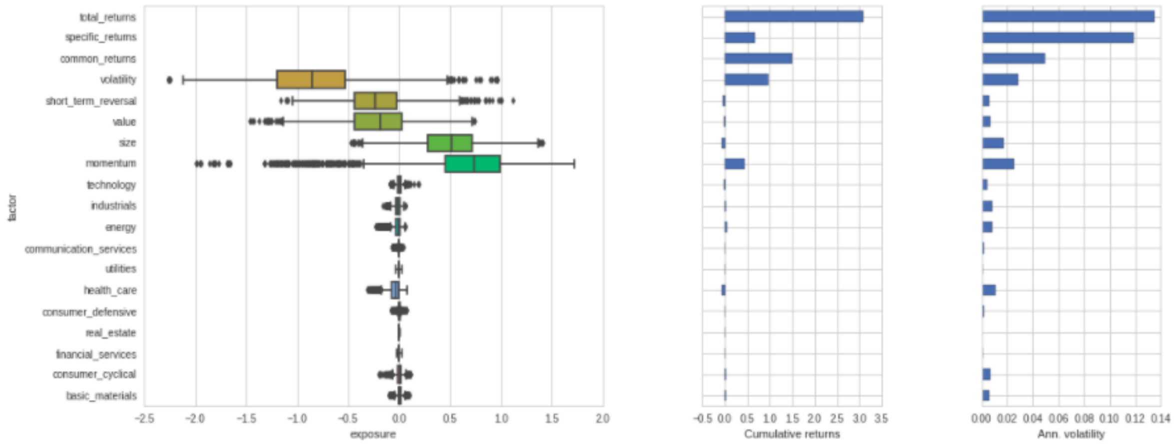


Figure 14 shows volatility achieved higher cumulative returns than specific, but it is desirable to have most volatility coming from specific returns.

In figure 15, alpha decays for specific returns increase to its peak at day 2 and gradually reduce to very small number then rebound again. It also implies the need to enter position as soon as possible and ideally at day 2. Style exposure, sector exposure is also very similar with equal weighted one. Most volatility comes from specific source which is desirable. The top stock positions also basically totally overlapped, despite different weights assigned.

Figure 15 Alpha decays (LSE momentum weighting)

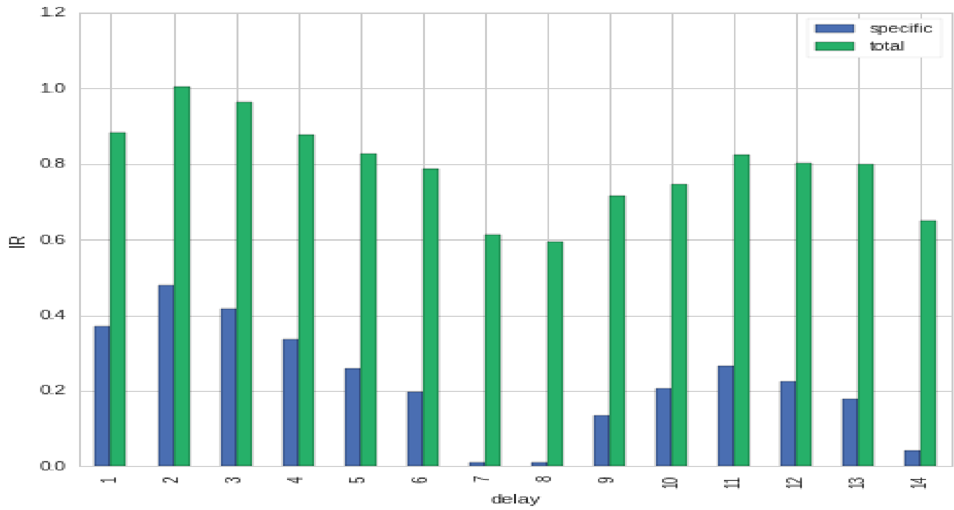
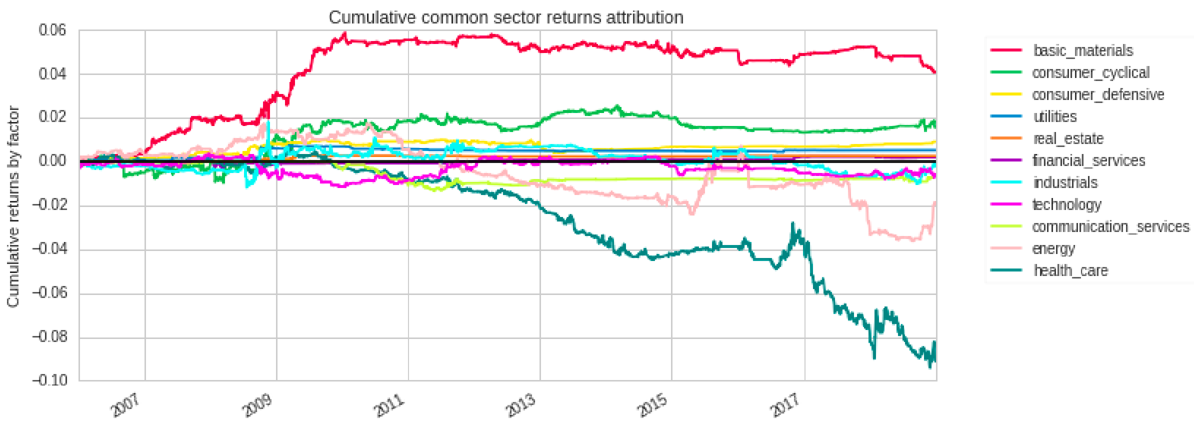


Table 16 Top positions (LSE momentum weighting)

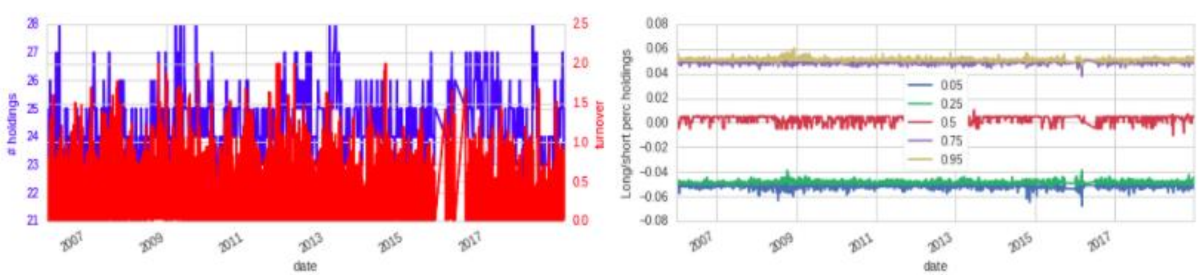
Top 10 long positions of all time	**max**
SDRL-39495	16.02%
SCHN-10268	7.17%
NTRI-21697	7.12%
YRCW-8370	7.05%
FRAN-41737	7.01%
DAR-11908	6.88%
WPX-42251	6.73%
SNBR-19559	6.71%
QCOR-20914	6.62%
SNTS-26164	6.55%
Top 10 short positions of all time	**max**
DNR-15789	-14.47%
CHK-8461	-10.23%
UAL-28051	-9.33%
HOV-3645	-9.01%
ITMN-21284	-8.73%
LPI-42263	-8.44%
ARNA-21724	-8.41%
LINE-27993	-8.36%
ARIA-11880	-8.31%
WFT-19336	-7.91%

Figure 16 common sector returns attribution (LSE momentum weighting)



The position concentration risk and high turnover rate problems still present as in figure 17. The right-hand graph shows the strategy tended to long top two quantiles and short bottom two quantiles, it is acceptable as long as there is clear separation among 0.5 quantile, top and bottom quantiles.

Figure 17 Holdings, turnovers and positions (LSE momentum weighting)



4.3 Factor correlation weighting.

A potential advantage of combining alpha factors from different aspects is the diversification benefits, the advantage could be further strengthened by taking advantage of factor correlation and over-weighting/under-weighting factors that are less correlated/more correlated with other factors.

Although it is straightforward to apply the factor correlation directly into weighting, it could have the issue of look ahead bias, static weighting and data missing. It is because the back-testing period covers the period of alpha factor analysis, the results from factor analysis may not be appropriately to be applied in weighting. Besides, the correlation of some factors (analyst revision) can't be produced due to too many missing values. To overcome those issues, the technique used machine learning, cosine similarity between two factors, has been adopted to weight factors dynamically, following Kiehne, G (2018).

4.3.1 Cosine similarity weighting and P&L analysis.

The intention of cosine similarity is to examine if two vectors are in parallel or actually orthogonal, hence if two factor's Zscore rank stocks very similarly, the cosine similarity is expected to be high and vice versa. It is calculated as $K(X,Y) = \frac{X \times Y}{||X|| \times ||Y||}$, with the nice property of (0,1) bound. The idea is to calculate cosine similarity of factors' Zscores each rebalancing day and summing up the cosine similarity of each factor in the pool, weight each factor as $\frac{1}{\sum cosine\ similarity_i}$, higher similarity, the lower in weighting. The combined alpha after adjustment will be normalized to ensure the adjusted weighted sum up to 1.

It can be concluded from the performance stats in table 17 that the cosine similarity weighting strategy perform better than any other long short equity strategies before, it achieved 12% annualized return and 0.94 Sharpe ratio, Sortino ratio and Omega ratio both improved. The Calmar ratio is more acceptable, which implies that strategy controlled drawdowns while boosting returns. However, the daily turnover was highest among all the LSE strategies.

Table 17 Performance summary (cosine similarity)

Start date	2006-01-04	
End date	2018-12-31	
Total months	155	
	back test	
Annual return	12.032%	
Cumulative returns	336.777%	
Annual volatility	12.909%	
Sharpe ratio	0.94	

Calmar ratio	0.78	
Stability	0.97	
Max drawdown	-15.36%	
Omega ratio	1.18	
Sortino ratio	1.39	
Skew	-0.00	
Kurtosis	3.39	
Tail ratio	1.07	
Daily value at risk	-1.578%	
Gross leverage	0.96	
Daily turnover	24.102%	
Alpha	0.12	
Beta	-0.01	

In Figure 18, the monthly return distribution shows positive skewness, monthly returns heatmap shows very fewer negative returns and the extent of loss was capped. Extreme returns happen more on positive side than negative side. The annual returns profile tells the strategy make profits for 13 years consecutively without loss.

Figure 18 Monthly return heatmap, distribution and annual return breakdown (LSE cosine similarity)

As seen in table 18, while the exposure to stress events were still neutral, the drawdowns were controlled. The magnitudes were lessened while the duration for drawdowns period was reduced.

Table 18 Drawdown and stress events (LSE cosine similarity)

Worst drawdown periods	Net drawdown in %	Peak date	Valley date	Recovery date	Duration
0	15.36	2012-05-17	2012-12-19	2013-06-26	290
1	15.20	2016-01-19	2016-03-14	2017-10-23	460
2	15.07	2008-07-14	2008-09-18	2008-11-20	94
3	14.47	2013-11-13	2014-03-03	2014-10-07	235
4	12.48	2006-07-21	2007-02-22	2007-07-20	261

Stress Events	mean	min	max
Lehman	-0.16%	-2.68%	1.89%
US downgrade/European Debt Crisis	-0.33%	-1.91%	1.06%
Fukushima	0.17%	-0.64%	0.73%
EZB IR Event	-0.05%	-1.60%	1.73%
Aug07	-0.03%	-1.81%	1.67%
Mar08	0.23%	-1.97%	1.71%
Sept08	-0.13%	-1.72%	1.89%
2009Q1	0.12%	-2.27%	2.45%
2009Q2	0.18%	-1.91%	3.47%
Flash Crash	0.37%	-0.12%	1.30%
Apr14	0.05%	-1.26%	1.46%
Oct14	0.46%	-4.24%	5.55%
Fall2015	0.04%	-1.79%	2.27%
Low Volatility Bull Market	0.04%	-2.75%	2.46%
GFC Crash	0.09%	-2.90%	4.00%
Recovery	0.03%	-3.74%	3.47%
New Normal	0.05%	-4.38%	5.55%

Figure 19 Alpha decay (LSE cosine similarity)

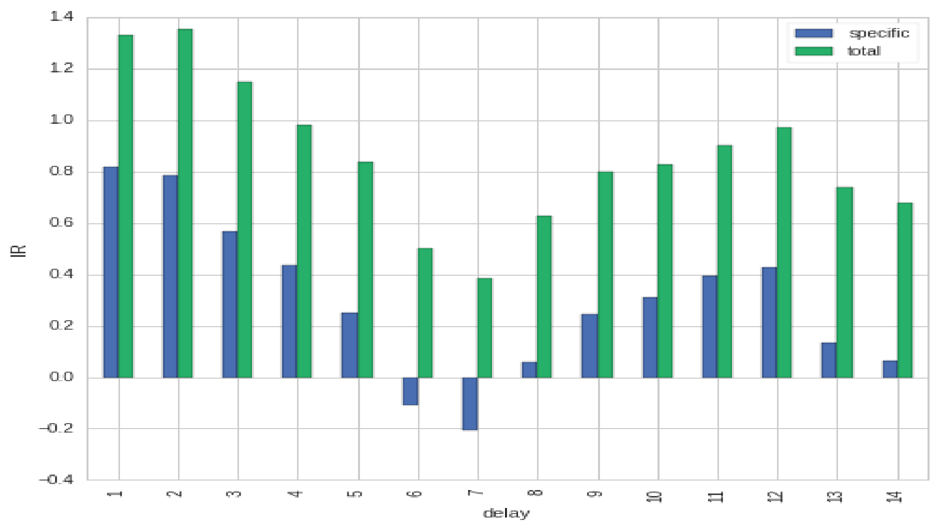


Figure 20 Exposure, returns and volatility (LSE cosine similarity)

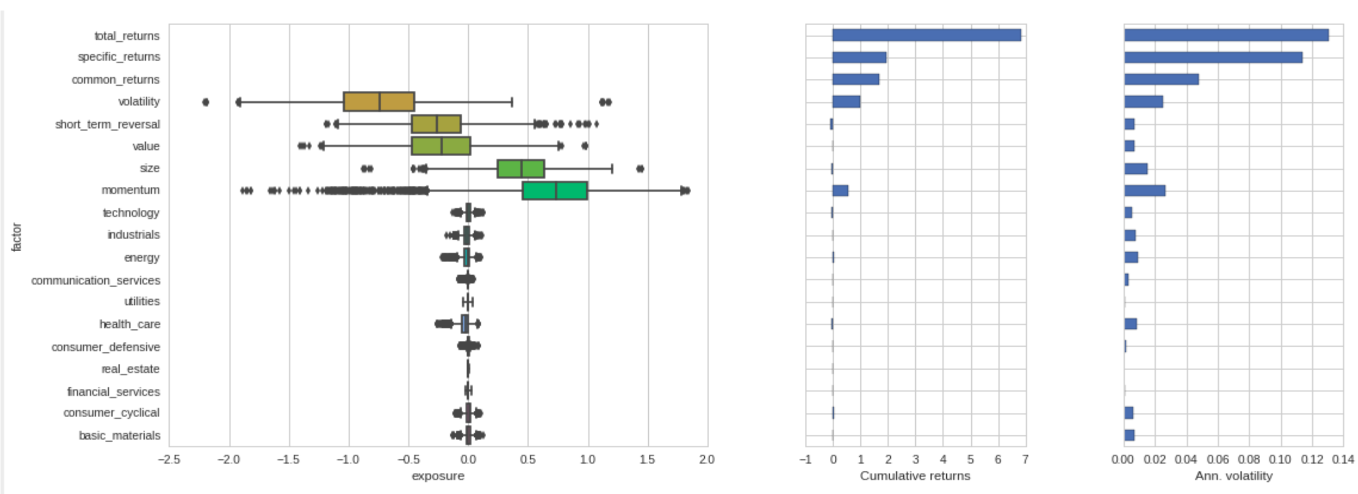


Figure 19 shows the alpha decays will gradually happen after day 2 and can be negative to around day 6,7, this can be challenging for order execution. However, the IR ratios are highest compare with any other strategies in terms of both total and specific. Combine figure 20 and table 19, same as equal weighted, the exposure and contribution from volatility and momentum are most significant, which is consistent with the strategy design. Due to slight calculation discrepancy, the specific return in figure 20 actually occupy higher portion of total returns as well as most volatility, which are desirable properties.

The exposure to short term reversal could be attributed to the contrarian approach when volatility exceeds 0.27 threshold. Value exposure is intended to be positive but actually negative but small, as before. Size exposure is unintended and could be due to the fact that the universe filtering contains no restriction on size hence the exposure is random. Although the impacts from size is minimal, as a way to avoid implicit betting on undesirable styles, it may be advisable to focus on more mid-caps and large-caps stocks only for better investability and less concerns from value exposure.

Table 19 Returns breakdown and risk exposure (LSE cosine similarity)

Summary Statistics			
Annualized Specific Return	5.04%		
Annualized Common Return	6.77%		
Annualized Total Return	12.07%		
Specific Sharpe Ratio	0.49		
Exposures Summary	**Average Risk Factor Exposure**	**Annualized Return**	**Cumulative Return**
basic materials	0.00	0.29%	3.86%
consumer cyclical	0.00	0.32%	4.22%
financial services	0.00	0.05%	0.62%
real estate	-0.00	-0.00%	-0.04%
consumer defensive	0.00	0.01%	0.11%
healthcare	-0.04	-0.64%	-8.04%
utilities	-0.00	-0.00%	-0.04%
communication services	-0.01	0.02%	0.22%
energy	-0.02	-0.04%	-0.57%
industrials	-0.01	-0.13%	-1.61%
technology	-0.00	-0.20%	-2.56%
momentum	0.64	3.11%	48.87%
size	0.44	-0.40%	-5.09%
value	-0.23	-0.08%	-1.05%
short_term_reversal	-0.27	-0.70%	-8.71%
volatility	-0.75	5.16%	92.19%

Table 20 Top position (LSE cosine similarity)

Top 10 long positions of all time	max
SDRL-39495	14.73%
NTRI-21697	7.18%
MDR-4752	7.00%
FRAN-41737	7.00%
CDNS-1385	6.93%
SKS-15019	6.87%
DAR-11908	6.85%
CHS-8612	6.81%
YRCW-8370	6.72%
GERN-15306	6.67%
Top 10 short positions of all time	**max**
UAL-28051	-9.72%
CHK-8461	-9.40%
ITMN-21284	-8.77%
HK-31032	-8.30%
ARIA-11880	-8.29%
LINE-27993	-8.07%
SUNE-13306	-8.01%
WFT-19336	-7.93%
CLWR-33480	-7.77%
ANR-27035	-7.74%

Regardless those same stocks selected by equal weighting strategy, the cosine similarity weighting strategy had less overlapped top positions, as seen in table 20. MDR is another energy service company, CDNS provides software, hardware, services, and reusable integrated circuit (IC) design blocks worldwide, CHS sells women clothing, YRCW provides a range of transportation services, GERN is a late-stage clinical biopharmaceutical company. On the short position, ARIA is a Pharmaceuticals company, SUNE manufactures semiconductors and solar energy technology, WFT provides oil field services and equipment, CLWR provides broadband services, ANR extracts, processes, and markets steam and metallurgical coal. The long and positions still tilted towards energy and healthcare sector but are more diversified than equal weighted.

Concluded from figure 21 and 22, despite being sector neutral in terms of average risk factor exposure, healthcare sector, probably because of heavily shorting those biotech stocks by the algorithm, eroded some noticeable cumulative returns. Daily exposures to energy are also noticeably high after 2015 and 2017, which could also explain some drawdowns when both long and short positions contained large value of energy stocks.

Figure 21 common sector returns attribution (LSE cosine similarity)

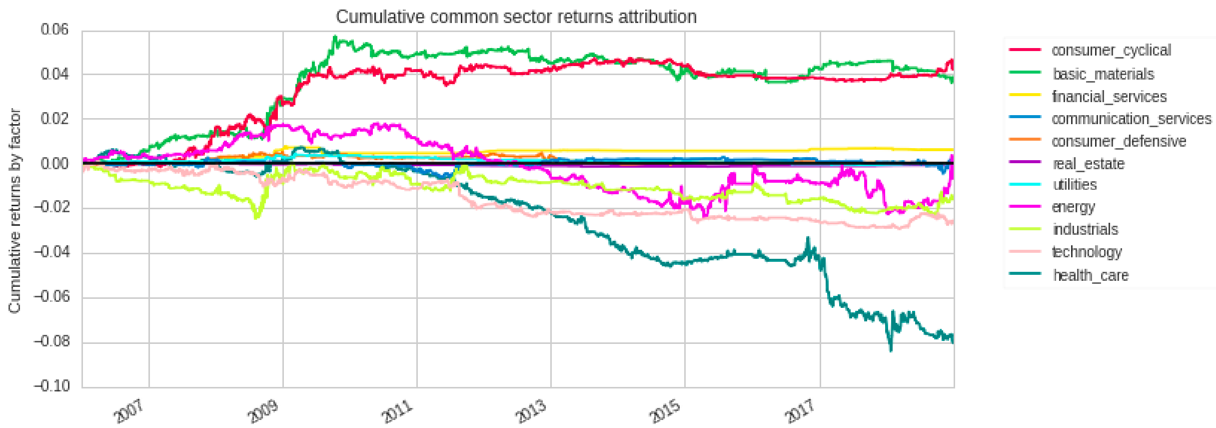
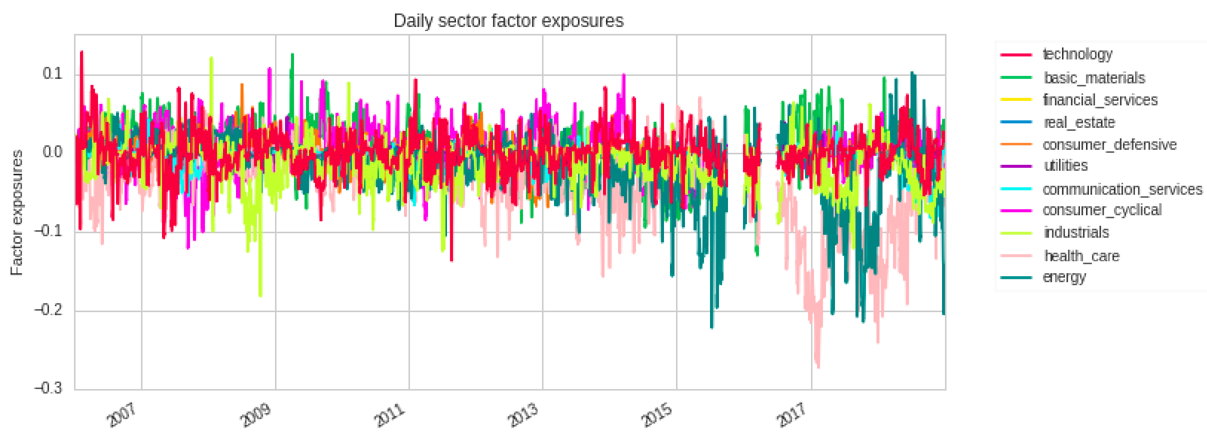
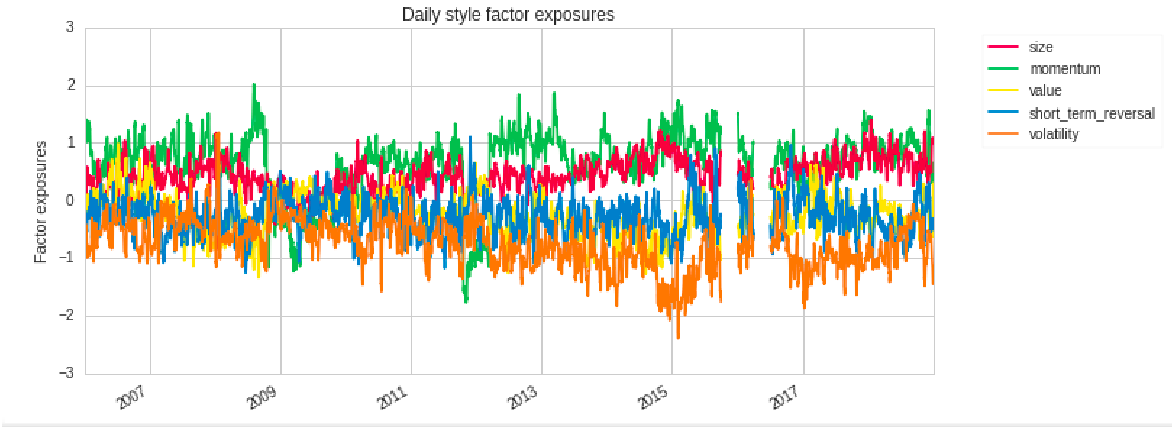


Figure 22 Sector and style daily exposure (LSE cosine similarity)





Rolling volatility and rolling Sharpe ratio plotting presents a similar profile with that of equal weighting in figure 23.

Figure 23 Rolling volatility and Sharpe ratio (LSE cosine similarity)

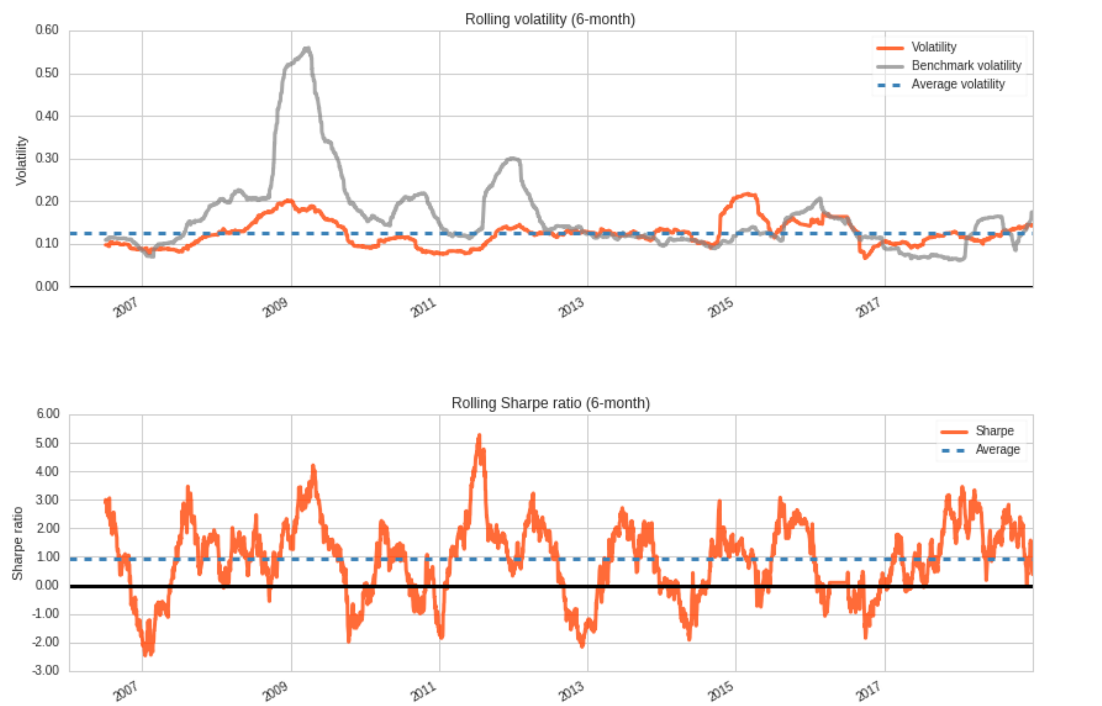
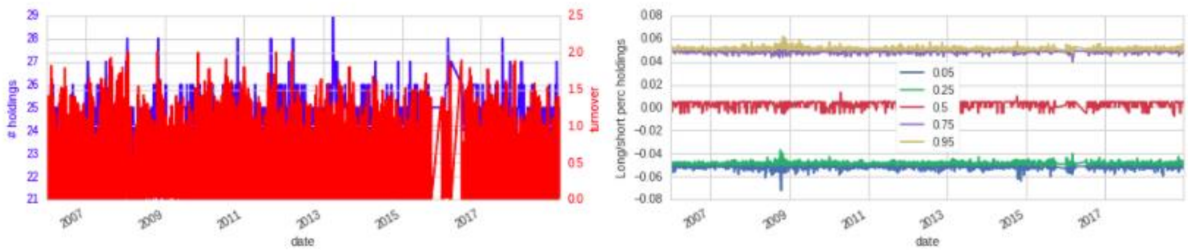


Figure 24 Holdings and turnover (LSE cosine similarity)



As noted in figure 24, the position concentration risk was still there, and turnover rates were higher. This creates some challenges for risk managements and incentives to revise the hyperparameters and constraints setting. It also unveils the necessity to locate or strengthen alpha factors so that the short term (weekly in this case) predictive power is high, which will naturally lower the turnover rates.

Overall, the cosine similarity weighted algorithm utilized the correlations of factors in the way that optimize the benefits of factor diversification to a certain extent.

5. Conclusion

In conclusion, long-only strategy and 3 long short equities are designed for this practice. The long-only strategy obtained impressive returns but is vulnerable to risks issue. The other 3 LSE strategies, momentum weighted, equal weighted and cosine similarity(correlation) weighted in ascending order regarding performances, are also presented. The best performing strategy, cosine similarity LSE, exhibited the best Sharpe ratio and highest IR ratios but still suffered from position concentration risks. The basket was small hence could be seen from the top positions tables, the strategy tended to pick up stocks from energy and healthcare sectors, if there are systematic risks in those sectors, large drawdowns could happen, as can been seen from the previous drawdown information table. Besides, small sizing could hinder large scale money injection due to volume limitation. It might be natural to adjust the position concentration bound, however, if the bound is set too low, the optimizer for maximizing alphas will crash the signal generated from factors and crumble the algorithm into equal weighed one. If too wide, it tends to allocate most capitals into certain high scoring stocks while meeting constraints. This again emphasizes the importance of factor diversification, and calls for better optimization strategies.

Many hyperparameters set in the algorithms were based on reasonable justifications, the universe was set to be big enough to have less noises, top/bottom percentiles splitting was based on academic practices and some thresholds were based on previous researches, but overfitting is always an issue. Not to mention the setting of position concentration bounds and other constraints, for the selections of alpha factors, which are based on academic researches and reasonable economic rationale, have been frequently used by the industry hence could suffer from alpha decay inevitably. The alpha factor analysis aims to locate the factors with solid predictive powers thus test using 9 years to cover a complete business cycle. Meanwhile, the backtestings were also intended to be long enough to test the robustness of algorithms. This could cause time frame overlapping by using factor analysis results from future into backtestings. Hence real life trading application result will not be guaranteed. The cross-validation methods could be applied to test the robustness of factors. Moreover, tuning hyperparameters in the optimization process requires more economic justifications to avoid overfitting.

The insights from this practice are: Firstly, factor diversification could be optimized by weighting factors using correlations. Secondly, those factors that have regime-switching property, if taken advantage of appropriately, could increase performances. The two important factors volatility and momentum, whose return profile could be found in appendix 1,2, both have well researched variabilities in behaviors. The top quantile of those factors portfolios doesn’t always outperform bottom quantile, but if timing appropriately, the results could be fruitful. Thirdly, factor momentum weighting results are not optimal, besides the reasons of discrepancies between academic researches and practices or alpha decays, it was possible the small sizing bucket constrained the performances of factor momentum.

Despite the variability of factors and combination methods, as can be seen from the factor analysis, there are some factors having high correlations thus could create noises when combing them. The backtesting result shows common returns outweigh specific returns most of the time, which implies the strategies are not so unique and sought-after. There are more robust factors need to be founded, more combination methods such as nonlinear combination and factor clustering could be applied for further improvements. Other signal-weighting method such as risk adjusted information coefficient weighting or blending (50/50 for correlation and IC) could also be attempted.

Appendix

Appendix 1 Alpha fctors statistics summary

Factors (Alphalens Test for 9-year period)	**Description**	**5day return spread between Top and bottom quantile**	**cumulative returns for quantile portfolios**	**5day mean Information coefficient**
Fscore	It uses financial ratios ROA, Free cash flow to total assets (FCFTA) and accrual to measure profitability, long term debt ratio, liquidity ratio and net equity issuance to measure stability, yearly changes of ROA, FCFTA, gross profit margin and asset turnover to measure operational improvements. Each component is capped at 1 if they are positive and 0 otherwise. It values financial strength comprehensively.	2.36 bps	Significant return spread between top and bottom quantile. Factor weighted long short portfolio archive 135% returns for 9 years	0.017(P value =0)

Enterprise multiple	EBIT divided by enterprise value. Its values cheapness.	1.036 bps	Significant return spread between top and bottom quantile. Some crossovers for high quantiles	0.012(P value =0)
Earning yield	Earnings per share for the most recent 12-month period divided by the current market price per share. Its values cheapness.	1.402bps	Significant return spread between top and bottom quantile. Some crossovers for high quantiles	0.011(P value =0)
Free cash flow yield	free cash flow per share divided by the current share price. Its values cheapness.	3.692bps	Significant return spread between top and bottom quantile. Factor weighted long short portfolio achieve 180% returns for 9 years	0.019(P value =0)
Asset growth 5y	Total asset growth over past 5 years. It is a reverse sign that companies with high asset growth tend to underperform.	-1.207bps	Significant return spread between bottom and top quantile. Clear reverse return profile for quantile portfolios Bottom quantile achieve achieve 113.4% for 9 years.	-0.001(P value =0.49)
CEGTH Capital expenditure growth Capital Spending - 5Yr Growth Rate	The capital expenditure growth rate over past 5 years, it is also a reverse sign.	-0.959bps	Significant return spread between bottom and top quantile. Clear reverse return profile for	-0.003(P value =0.013)

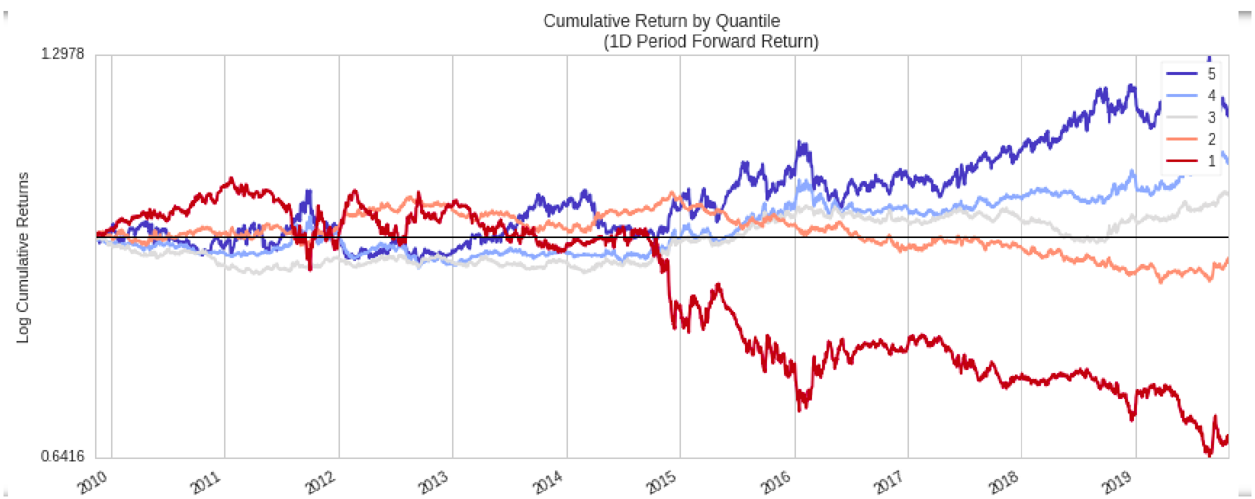
			quantile portfolios Bottom quantile achieve 119% for 9 years.	
Asset anomalies	Includes 5year asset growth rate, 5-year capital expenditure growth and net financing. It is a negative sign	-1.251bps	Significant return spread between bottom and top quantile. Clear reverse return profile for quantile portfolios Bottom quantile achieve achieve 119% for 9 years.	-0.005(P value =0)
Debt to asset ratio	A sum of long term and current portion of debt to total assets. It is a reverse sign which indicates high risks for high ratio companies.	-0.690bps	Significant return spread between bottom and top quantile. Some crossover for low quantile portfolios.	-0.003(P value =0.155)
Asset turnover	the ratio of total sales or revenue to average assets. This metric helps investors understand how effectively companies are using their assets to generate sales.	1.458bps	Higher quantile portfolio always outperforms lower quantile. But 4th quantile outperform 5 th quantile.	0.014(P value =0)
FREECF	Free cash flow to equity, as a value measure	2.308bps	Significant return spread between bottom and top quantile. Clear reverse return profile for quantile portfolios Bottom quantile achieve achieve	0.015(P value =0)

			134.9% for 9 years.	
Profitability score	Measure profitability as composite score includes gross profits over assets (GPOA), return on equity (ROE), return on assets (ROA), cash flow over assets (CFOA), gross margin (GMAR).	2.360bps	Significant return spread between bottom and top quantile. Clear reverse return profile for quantile portfolios Bottom quantile achieve achieve 143.5% for 9 years.	0.017(P value =0
CapEx Vol	Capital Expenditure Volatility over the last 6 months. It is often considered a proxy for uncertainty at a firm level, thus a reverse sign.	0.579bps	Significant return spread between top and bottom quantile. Some crossovers for high quantiles	-0.003(P value =0)
ACC Accruals	The accrual records free cash flow earned on assets and deduct ROA. It rates actual cash flows to company assets without being affected by income recognition or income measurements.	2.149bps	Quantile 5 have the highest returns while quantile 1 have the lowest returns Some crossovers for high quantiles	0.002(P value =0)
GRPROF	Gross profitability. It measures profit a company makes after deducting the costs associated with making and selling its products.	1.654bps	Significant return spread between top and bottom quantile. Some crossovers for high quantiles	0.013(P value =0
GS5	Sales growth is the 5-year percent growth in the net sales of a business	0.043bps	Significant return spread between top and bottom	-0.001(P value =0.307)

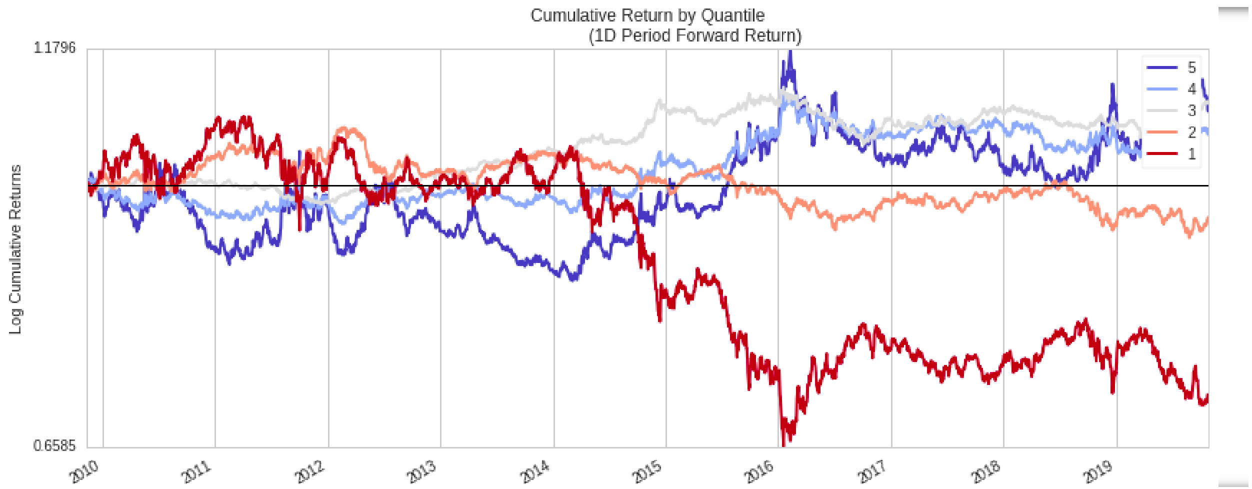
	from one fiscal period to another.		quantile. Some crossovers for high quantiles	
52-week high price	52 weeks high as an anchoring point that has Benn founded has predictive power for future returns	2.349bps	Significant return spread between top and bottom quantile. Some crossovers for high quantiles. High quantile achieves 122.5 % for 9 years.	0.016(P value =0)
Efficiency score	Composite score contains retained earnings to assets, operating cash flow to assets, EBIT to assets and capital expenditure to assets.	2.244bps	Significant return spread between bottom and top quantile. No crossovers. High quantile achieves 120.7% for 9 years.	0.018(P value =0)
Cash flow to assets	Free cash flow to total assts per share. It measures how efficiently assets generate cash flows.	1.488 bps	Significant return spread between top and bottom quantile. Some crossovers for high quantiles. High quantile achieves 118.4% for 9 years.	0.013(P value =0)
Asset turnover	The ratio of total sales or revenue to average assets. This metric measure how effectively companies are using their assets to generate sales.	1.219 bps	Significant return spread between top and bottom quantile. The second highest quantile portfolio sometimes	0.012(P value =0)

			outperform the highest one.	
Altman Z score	The Altman Z-score is the output of a credit-strength test that gauges a publicly traded manufacturing company's likelihood of bankruptcy. The Altman Z-score uses profitability, leverage, liquidity, solvency, and activity to predict whether a company has a high probability of becoming insolvent	1.747 bps	The bottom quantile significantly underperforms but not distinct performances among higher quantile portfolios	0.014(P value =0)

Appendix 2 Momentum quantile portfolios returns



Appendix 3 Volatility quantile portfolio returns (negative sign)



Appendix 4 Factor correlation matrix

	Asset anomalies	Altman Z	Efficiency	frees	Earning yield	Fcf yield	Asset Turnover	Fscore	Vol_1M	Cashflows To Assets	Enterprise Multiple	Debt to asset
Asset anomalies	1	-0.695465	0.699819	0.801345	0.634575	0.803201	0.923366	0.770423	0.850529	0.753364	0.831415	-0.781126
Altman Z	-0.695465	1	-0.45111	-0.447341	-0.219491	-0.475707	-0.580005	-0.493101	-0.36696	-0.567495	-0.42074	0.756425
Efficiency	0.699819	-0.45111	1	0.782084	0.329844	0.944178	0.870919	0.942261	0.797456	0.704702	0.599214	-0.377965
freecf	0.801345	-0.447341	0.782084	1	0.553817	0.862556	0.879118	0.766808	0.866486	0.646578	0.725827	-0.51901
Earning yield	0.634575	-0.219491	0.329844	0.553817	1	0.437925	0.59645	0.433139	0.731058	0.425506	0.872958	-0.525768
Fcf yield	0.803201	-0.475707	0.944178	0.862556	0.437925	1	0.948395	0.942735	0.885933	0.759444	0.719275	-0.45413
Asset Turnover	0.923366	-0.580005	0.870919	0.879118	0.59645	0.948395	1	0.902645	0.912782	0.80869	0.84687	-0.65238
F_score	0.770423	-0.493101	0.942261	0.766808	0.433139	0.942735	0.902645	1	0.85133	0.833086	0.720144	-0.423078
Vol_1M	0.850529	-0.36696	0.797456	0.866486	0.731058	0.885933	0.912782	0.85133	1	0.679865	0.890664	-0.483855
Cashflows To Assets	0.753364	-0.567495	0.704702	0.646578	0.425506	0.759444	0.80869	0.833086	0.679865	1	0.681784	-0.548978
Enterprise Multiple	0.831415	-0.42074	0.599214	0.725827	0.872958	0.719275	0.84687	0.720144	0.890664	0.681784	1	-0.653265
Debt to asset	-0.781126	0.756425	-0.377965	-0.51901	-0.525768	-0.45413	-0.65238	-0.423078	-0.483855	-0.548978	-0.653265	1

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