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Style Rotation on Swiss Long-Only Equity Factors

Quantitative Asset & Risk Management II

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Abstract

The purpose of this paper[1] is to investigate whether it is valuable to time factors in a portfolio that combines a set of different factors. Our investment universe are Swiss equities and we build eight long-only well-known factors. We first construct an equal-risk contribution (ERC) portfolio, which does not include any tilting in the factors. We then construct three different strategies aiming to tilt the factors, by proceeding with a Ridge regression, a momentum of factors and parametric weights using several macro variables. We demonstrate that tilting the different factors does improve the performance compared to the benchmark and even compared to the ERC portfolio. The most promising approaches are the portfolios with parametric weights using the VIX as only macro variable and the portfolio using a momentum of factors. When trying to control for the tracking error, we find that the parametric weights portfolio based on the VIX provides a lower tracking error than the momentum of factors for comparable performance in terms of raw and risk-adjusted returns. Moreover, our results are robust when it comes to the sensitivity analysis of various parameters of our model.

[1] Both code and data set are available in our **Github repository**.

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1 Introduction

In 1992, Fama and French (2021b) are the first to publish a paper on *Cross-Section of Expected Stock Returns* that aims to explain the cross-sectional returns of equities by looking at other risk premia than market excess return, only determinant of return according to the Capital Asset Pricing Model (CAPM). This paper gives rise to the well-known Fama and French three factors model, where the two other factors that explain cross-sectional returns are size and value. The following year, Fama and French (2021a) published another paper on *Common Risk Factors in the Returns on Stocks and Bonds*, giving rise to the Fama and French five factors model, adding *profitability* and *investment*.

Factor investing has gained increasing interest over the last decade. Since the 1990's, many other risk premia such as momentum, dividend yield, volatility or the low beta anomaly have been found and can therefore be added to Fama and French's five factors model to improve predictability of cross-sectional returns. However, the multitude of risk premia gives raise to another question: How can we optimally combine several factors in a portfolio? The answer is not trivial.

The first step could be to try to combine the different factors in a portfolio using a risk-based approach. The advantage is that it does not require to have a view on the different factors, but rather to control the risk inherent to them, investing using multiple risk premia.

Another approach could be to try to tilt factors at a given period to select the most profitable factor exposure. This approach is more challenging as it requires the ability to predict the profitability of the different factors in advance. Although challenging, this approach is essential for investors seeking to obtain better risk-adjusted performances using risk premia.

In this paper, we first created eight different factors. We then constructed four different portfolios of these aforementioned risk premia: the first one, which does not tilt the factors, is simply an Equal-Risk Contribution (ERC) portfolio. The three others are tilting the factors and are the following: Ridge Regression portfolio, a momentum of factors portfolio and parametric weights portfolio. Then we perform a sensitivity analysis on different variables: liquidity constraint on the Swiss market, factor construction quantile, and finally combination between the different portfolios and the benchmark aiming to reduce the tracking error.

In terms of performance, as expected the ERC portfolio is the most tempered one, while the others exhibit interesting risk-adjusted returns, and manage to beat the benchmark, which is based on a simple cap-weighted portfolio of all the available equities at a given time. Ridge regression portfolio allows to attain the lowest level of risk and tracking error. The parametric weights portfolio, when accounting for the VIX as a factor tilt, attains the highest Sharpe ratio, and the momentum of factors is the most aggressive strategy by achieving the highest annualized returns, while being the most risky as well. We therefore find that factor timing can indeed improve the performance of a given portfolio. Moreover, all the results are robust to the parameters when we perform a sensitivity analysis.

2 Review of literature

Although factor investing is well-known in the literature, the question of factor timing is another one. It is also subject of vast literature, notably in the case of equities, even though predicting factor returns is a challenging task.

Indeed, Chincoli and Guidolin (2017) could not find evidence that multivariate econometric models are statistically significant at predicting factor returns. However, they show that it is possible to exploit factors' return predictability by using a Markov-Switching model to forecast returns combined with different asset allocation strategies. The result of the latter model shows that it is possible to exploit factors predictability in asset allocation strategies, leaving room to factor timing.

In fact, Hodges et al. (2017) show that using different predictive variables to time factors adds value compared to a single predictor. They also find low or even negative correlations among factors (correlation of -0.23 between value and momentum) which indicates that combining several factors offers diversification benefits. They also find negative correlations among predictors, which explains why it is important to combine several predictors when timing factors.

Our paper starts by exploring the methodology of Ulloa et al. (2012), who put weights to different factors based on an allocation scheme that consists in maximizing the portfolio's information ratio. In their approach, they use a Ridge regression, which consists in imposing a penalty on weights that deviate from the equally-weighted portfolio of factors. This approach is interesting since it leads to a more stable allocation, especially when many factors that may be highly correlated are considered.

Then, we use the result of Brandt and Santa-Clara (2006), who give a methodology for market timing using parametric portfolio weights. Parametric weights are expressed as the product between the unconditional weights and a set of time-varying explanatory variables (e.g. macroeconomic data, firm's characteristics, etc.). The problem is then equivalent to solving a mean-variance optimization with respect to unconditional weights. Then, conditional weights can easily be recovered from unconditional weights. The set of explanatory variables can be of any type, but typically consist of macroeconomic variables in our paper.

3 Data

To construct our portfolio of factors in the Swiss market, we collected the list of all companies which have been a constituent of the Swiss Performance Index (SPI) from 01-01-2009 to 01-10-2021. Afterwards, we collected the stock price and all fundamental values as listed in table 8.1 to construct our factors from these aforementioned companies from 01-01-2000 to 01-10-2021. We decided to collect monthly data as we are aiming to perform a portfolio re-balancing at the beginning of each month. Consequently, we were able to collect the values for a total of 262 Swiss companies for 298 periods. Additionally, we collected the value of the SPI for the same time horizon to conduct a Fama-French Analysis. All these data were retrieved from Thomson Reuters Datastream.

In terms of general industry classification, the companies are being registered to the following categories: industrial, utility, transportation, banking/savings and loans, insurance and other financial. Due to the composition of the Swiss market, we have a significant concentration in the industrial sector, as shown on figure 8.1, reflecting some possibility of over-exposure to idiosyncratic risks.

From our raw monthly prices, we decided to compute the monthly simple returns as in equation (A.1). Although the data are indicated to be at the beginning of each month, it is in fact available the day prior. Consequently, all strategies are being implemented from data of the previous day, implying that no lag was necessary.

To perform a factor timing using the parametric model, we collected various macroeconomic data of the US market as listed in table 8.2, which we believed would be important drivers of our portfolio. The rationale of disregarding the Swiss market for the parametric optimization is due to the prominence of the US market globally. Nevertheless, to perform a Fama-French analysis, we collected the short-term London Interbank Offered Rate (LIBOR), based on Swiss Franc. All these data were retrieved from the Federal Reserve Economic Data (FRED). To be in line with our portfolio construction, we collected monthly data, when feasible, otherwise we computed a monthly average when the latter was provided daily only. For best practice, we introduced a lag of 3 months in our macroeconomic data to reflect the difficulty of collecting live data of this sort.

4 Methodology

Factor investing allows investors to use their creativity to reproduce popular risk premia in order to potentially provide results out-performing the market. In this study, we developed 8 long-only factors applied to the Swiss market. Those factors were constructed as follows:

- ***Momentum***: Take a long position in companies with 12-month average simple returns above a certain percentile.
- ***Value***: Take a long position in companies with a E/P above a certain percentile.
- ***Size (Small vs. Big)***: Take a long position in companies with a market-cap below a certain percentile.
- ***Profitability***: Take a long position in companies with a gross-margin above a certain percentile. Values such as ROE or ROA could have also been considered.
- ***Low-Beta***: Take a long position in companies with a beta below a certain percentile.
- ***Low-Volatility***: Take a long position in companies with a 12-month rolling variance below a certain percentile.
- ***Dividend***: Take a long position in companies with a dividend yield above a certain percentile.
- ***Quality-Earnings***: Take a long position in companies with an EPS above a certain percentile.

For simplicity, the allocation among each factors is based on an equal weight. By default, we selected the 50^{th} percentile for all factors. Such variable will be subject to our sensitivity analysis. To incorporate the liquidity constraint some small Swiss companies may have on the market, we decided to invest only in the companies with a monthly traded volume above the 25^{th} percentile. This variable will also be subject to our sensitivity analysis.

We then created portfolios of these factors using 4 different approaches. In the first approach, we allocate our capital in a way that Equalizes the Risk Contribution (ERC) of each factors, as described in Appendix B. This method is the only non-tilting strategy as we are aiming to determining whether factor timing can indeed improve the performances of our portfolio. The second model aims to develop an allocation using a Ridge regression, as described in Appendix C, which is an approach that promotes stability and sparsity in the exposures. This can be interesting for an investor with no leverage constraint. The third approach was a momentum of our developed factors, where we take a long position in factors with 12-month average simple returns above the same aforementioned percentile. Equal weights were also attributed among all selected factors each month. The final approach determines parametric weights, as described in the paper of Brandt and Santa-Clara (2006) and summarized in Appendix D. The idea is to parametrize the portfolio weights as linear functions of observable quantities (i.e. macroeconomic variables, firm's characteristics, etc.). We decided to consider exclusively macro data, listed in section 3.

To evaluate the performances of our allocations relative to a benchmark, we created one using a cap-weighted (CW) portfolio of all constituents. Throughout the construction of the portfolios, we aimed to have a relatively low tracking-error (TE), as required by many pension funds. To do so, we proceeded in two different approaches. The first one aims to reach a target ex-ante TE (see Appendix A.5) when optimizing each month for the models requiring an optimization (i.e. ERC and Ridge regression). Alternatively, we can also make a combination of our portfolio and the CW benchmark in order to reduce the ex-post TE (see Appendix A.6). This combination will also be subject to a sensitivity analysis. Finally, we performed a Fama-French analysis of our portfolios, as described in Appendix E, to determine whether an alpha can be generated and to understand which factors the portfolio is the most exposed to. We decided to use the Swiss Performance Index as our market premium instead of the cap-weighted benchmark, as we are aiming to be close to the public market quotation and we would like to make a clear distinction between the dependent and independent variables.

Finally, we conducted a sensitivity analysis on the (i) liquidity constraint, (ii) the quantile in the factor construction and (iii) the combination of the portfolio with the CW benchmark to reduce the TE.

5 Results

We now analyze the performances of the different strategies. Before going through the details of each strategy, note that all portfolios start at the same date, that is, on the 1^{st} of January 2009. This is due to the fact that it is the first date after which we know the exact composition of the SPI from Thomson Datastream, and thus the first date of our created cap-weighted benchmark.

5.1 Equal-Risk Contribution Portfolio

The first strategy is the ERC portfolio. As expected, because of its more defensive profile, the ERC portfolio shows lower annualized return than the benchmark. However, due to the lower risk of the strategy, it depicts a similar or higher Sharpe ratio than the benchmark, depending on if we impose constraints for the tracking error. However, overall, it appears to be a disappointing strategy as it has negative information ratio and similar maximum drawdown than the benchmark.

In terms of weights evolution, it is very stable over time when imposing no constraint for the tracking error, with a significant exposure to the low volatility factor, and the smallest share in the size factor. There is also a positive exposure to momentum, around 10%, across the whole sample. When imposing a 6% ex-ante tracking error constraint in the optimizer (that fails to be achieved over the period), the weights are varying much more importantly, as can be seen on the chart 8.5. Turnover might thus be an issue in terms of cost, especially due to the no leverage constraint and the low returns of the strategy. A Fama-French analysis shows a negative exposure to size and low volatility in all cases, as well as a positive exposure to value. There is also a statistically significant alpha of 0.007.

5.2 Ridge Regression Portfolio

Let's now consider the portfolio using Ridge regression as in Ulloa et al. (2012). This strategy outperforms the benchmark when we impose no constraint on the tracking error, or when we control it by investing 20% in the benchmark and 80% to the portfolio. The latter appears to be interesting as it implies an ex-post tracking error below 6%, and a 0.2 higher Sharpe ratio than the benchmark. The information ratio is also positive and the maximum drawdown in the same order of magnitude as the one of the benchmark.

Regarding the weights evolution over the period, it is also quite stable for the case without any constraint for the tracking error. It invests mostly in quality, momentum and low beta, and almost zero in value. The case where we impose a 6% tracking error constraint, as for the ERC portfolio, is much less stable over time, as can be seen on the chart 8.7.

A Fama-French analysis reveals positive statistically significant exposures to value, momentum (without controlling for the tracking error), and investment. There are also negative exposures to size, quality, and volatility. Note that, for the Fama-French analysis, the factors are long short and calculated as on the Kenneth French's website. This might explain why we have negative exposures to some factors, while we have positive weights in our factors.

5.3 Momentum of Factors Portfolio

We now consider the momentum of factors portfolio. Despite the Covid-19 and the subsequent market crash in March 2020, the portfolio consistently beats the benchmark, no matter if we impose restrictions for the tracking error or not. Indeed, in the two cases, it shows a Sharpe ratio around 1.15 whereas the benchmark is below at 0.87. It also shows a positive information ratio of 0.412. However, this comes at a cost since the portfolio has a higher maximum drawdown as well as a relatively high tracking error. Based on table 8.12, we notice that the portfolio has on average a significant allocation in the momentum, profitability and quality earnings (EPS) factors, suggesting that these risk premia performed relatively well from 2009. Nevertheless, the value factor is almost never allocated, due to its poor performances in the recent years[2]

When performing a Fama-French analysis for the factor exposures, we get statistically significant negative exposures to size, quality and volatility, while it has positive exposures to

[2] Factors behind value's underperformance. https://www.msci.com/www/blog-posts/factors-behind-value-s/01647315543. Accessed: 20 December 2021

momentum and investment.

5.4 Parametric Model Portfolio

The case of the parametric portfolio, as described by Brandt and Santa-Clara (2006), requires more attention. Indeed, if we try to inject all the macro variables in one matrix and then compute the optimal weights, we introduce too much noise and the estimates result in a disappointing portfolio. This is why we first model the optimal weights depending on each individual macro variable separately, in order to detect which one times the best the factors. We concluded that the best predictor for the timing of factors is the VIX.

The parametric portfolio with respect to the VIX shows the best performance across the sample and ends its path far above the benchmark (see chart 8.8), with Sharpe ratio of 1.17 without restrictions for the tracking error, and 1.16 otherwise. This comes from both an increase in return and a decline in volatility. Also, it has a positive information ratio, and a maximum drawdown slightly above the one of the benchmark for the case where we invest 20% in the benchmark, and 80% in the portfolio.

In terms of weights, there is mostly exposure to momentum, quality and profitability, as can be seen on chart 8.11, and the allocation is quite stable over time when we do not have any constraint for the tracking error. A Fama-French analysis reveals a positive and statistically significant alpha of 0.01. Moreover, we have positive and statistically significant exposure to value, and negative exposures to size, quality, and volatility.

5.5 Conclusion of the Results

When comparing the aforementioned strategies, we notice that they all have strengths and weaknesses. The key point to understand is that our non-tilting factor strategy (i.e. ERC portfolio) is the laggard of all strategies, in term of raw and risk-adjusted performances, indicating that factor timing can indeed improve the performances of portfolios. Based on our results, we believe that the portfolio built with a Ridge regression is more defensive as it has one of the lowest volatility and TE. The portfolio built with parametric weights using VIX as the only explanatory variable is more balanced as it provides a decent trade-off between risk-adjusted performances and TE. Finally, the momentum of factors portfolio is more dynamic due to its high raw returns while carrying a significant amount of risk and a high tracking-error.

6 Sensitivity Analysis

In this section, we quantify the impact on portfolios of variations of the liquidity constraint, quantile for the construction of factors, and share invested in the benchmark when controlling for the tracking error.

6.1 Liquidity Constraint Sensitivity

Concerned about the liquidity issue that may arise in the Swiss market, we decided to test our strategies under restrictions of the investment universe to the most liquid companies. We used the trading volume of the stocks as a proxy of liquidity and we invest only in stocks whose trading volume is above a certain quantile (25% quantile in the default case). The results for each portfolio are explained below.

6.1.1 Equal-Risk Contribution Portfolio

For the ERC portfolio, it seems to be the case that the performance is monotonically increasing in the restriction for liquidity, and without any difference whether controlling the tracking error or not. When reducing the universe, we observe higher returns as well as higher volatility, leading to relatively small increase in the Sharpe ratio. The information ratio also becomes positive when restricting the universe to the 50% most liquid companies, while it is always negative otherwise. The interesting feature here is that this restriction of the stock selection does not increase the tracking error as compared to the unrestricted case. The maximum drawdown is slightly higher (around 4%). All figures can be seen in table 8.21.

6.1.2 Ridge Regression Portfolio

The Ridge regression portfolio depicts the same trend as the previous one when considering different quantiles of liquidity, that is, an increasing performance when restricting the universe. Moreover, we end up above the benchmark in all cases except the one without liquidity restriction, as can be seen on chart 8.24. Reducing the investment universe based on liquidity allows to increase the annualized return, but it also amplifies the volatility. The net effect on the Sharpe ratio remains positive though, and the information ratio is always above zero, except for the case without restrictions on liquidity. Finally, the tracking error is also augmenting when we limit the stocks to be invested in.

6.1.3 Momentum of Factors Portfolio

When considering the momentum of factors portfolio, it can be seen on chart 8.26 that the performance is, as for the other portfolios, monotonically increasing with the constraint for liquidity. That is, the more we restrict the universe based on liquidity, the better the performance is (more than the double when we compare the case without constraint and the one with 50% constraint). This is also reflected by the numbers. Indeed, when inspecting the Sharpe and information ratios, they monotonically rise when imposing constraints on liquidity. However, this comes at the expense of a higher maximum drawdown, as well as a higher ex-post TE.

6.1.4 Parametric Portfolio

The last portfolio to consider for the liquidity sensitivity is the parametric one, with a focus on VIX for tilting, as in the base case. The return rises dramatically the more we restrict the universe (more than 6% increase with 50% of the universe relative to no liquidity constraint). The volatility also increases, but the net effect on Sharpe ratio and information ratio is positive. The increase in performance comes at a cost of a higher tracking error and a higher maximum drawdown though. Therefore, it might be a good strategy to allocate more of the budget to the benchmark and less to the portfolio, in order to mitigate the tracking error while still benefiting from the outstanding returns of the strategy. All figures can be seen in table 8.27.

6.2 Quantile Sensitivity in Factor Construction

In this section, we analyze how the performance of the different strategies is affected when we change the factor's quantile, that is the quantile above or below which we go long in the securities to construct each factor. Notice that we investigate the change in quantile for the eight factors that we have constructed, but we do not change the quantile that we use to construct our momentum of factors strategy, where we always keep the same quantile at 50%.

6.2.1 Equal-Risk Contribution Portfolio

Concerning the ERC portfolio, we can remark in table 8.29 that the volatility decreases as the quantile increases. However, the expected return is also decreasing as we increase the quantile. Consequently, Sharpe ratio remains quite stable, ranging from 0.88 to 0.94. One can also notice that the TE is decreasing when quantile increases as well as the information ratio, which even becomes negative. This means that we are not able to beat the benchmark anymore with the ERC portfolio when we are choosing a high quantile.

6.2.2 Ridge Regression Portfolio

As we can see in table 8.31, the expected return remains remarkably stable as the quantile increases (it varies within a band of 0.5%). However, the volatility is decreasing as the quantile is increasing. Consequently, Sharpe ratio increases from 0.9 to 1.17. Concerning the other risk metrics, we can also see that the maximum drawdown is decreasing quite significantly. Moreover, we can observe that tracking error decreases as the quantile increases and the information ratio remains quite stable, although it decreases slightly.

6.2.3 Momentum of Factors Portfolio

As we increase the quantile of the factor construction, the return of the momentum of factors strategy tends to increase as we can see in table 8.33. This is intuitive since by increasing the quantile, we increase the exposure to the given factor and hence the strategy tends to become more profitable as we are long-only. However, it is interesting to notice that when the quantile goes from 40% to 60%, the performance decreases. It shows that it is better not to take too extreme quantile to build the strategy. Nevertheless, we can see that the performance is quite robust to the chosen quantile since the variation of performance is roughly 1.3% between the best and the worst. Concerning the risk, volatility is monotonically decreasing as quantile increases. Hence, the Sharpe ratio is larger for high quantiles, and is maximized for 40% quantile. Moreover, we can see that the Sharpe ratio is also quite stable, varying between 0.95 and 1.15 when quantile is changing.

6.2.4 Parametric Portfolio

Concerning the parametric weights portfolio, we can see in table 8.35 that the expected return as well as the volatility are decreasing when the quantile is higher. Sharpe ratio is increasing, because volatility decreases more than the expected return. Regarding the drawdown, we can notice that the portfolio is becoming clearly less risky as quantile increases, since maximum drawdown and the expected shortfall are decreasing. As for the other portfolios, the tracking error is decreasing substantially as quantile increases, as well as the information ratio.

6.3 Combination with CW Benchmark Sensitivity

The idea of combining our portfolios with the CW benchmark is to decrease the tracking-error (TE), which may be a concern for some institutional investors. Indeed, as we are aiming to outperform the benchmark, but still being relatively indexed to it, we target a TE of 3% to 7%, common for traditional active managers[3]. Hence performing a sensitivity analysis on the combination between our portfolios and the CW benchmark allows us to understand the trade-off between returns if out-performance is observable, and the tracking-error.

6.3.1 Equal-Risk Contribution Portfolio

The ERC portfolio is the worst performing portfolio since it is taking few bets due to its objective of equal-risk contribution among all assets. Nevertheless, it is also the portfolio with the lowest risk and tracking-error. When allocating 50% to this portfolio and 50% in the benchmark, we obtain a TE of approximately 3.5%, as shown in table 8.37, which is very favorable for conservative and risk-averse investors.

6.3.2 Ridge Regression Portfolio

Compared to the ERC portfolio, the Ridge portfolio is taking more bets, thus obtaining sightly better returns and risk-adjusted performance, while still maintaining a relatively low TE and risk. At the highest in our sensitivity analysis, it can reach a TE of approximately 6.5%, and at the lowest a TE of approximately 3.5% as shown in table 8.38, also very favorable for conservative and risk-averse investors

6.3.3 Momentum of Factors Portfolio

The momentum of factors is one of the portfolios that outperforms significantly our benchmark with respect to almost all metrics. However, it implies relatively high TE, as shown in table 8.39. We notice however that when allocating more into the benchmark, the TE decreases significantly, reaching approximately 4.5% at lowest, by sacrificing some of its out-performance. The information ratio remains the same as we have a one-to-one decrease in excess returns and volatility of excess returns between the portfolio and benchmark.

6.3.4 Parametric Portfolio

The parametric portfolio, when tilted exclusively with the VIX, can provide a great trade-off between performance and TE. Indeed, as shown in table 8.40, the highest tracking-error is approximately 7%, while providing one of the highest Sharpe ratios among all our portfolios. When combining it with the CW benchmark, we are able to decrease significantly the TE while maintaining great performances, reaching at lowest a TE of 4%. This portfolio can be suitable for investors moderately concerned about the tracking-error, but still interested to outperform the benchmark.

[3]Tracking Error. https://financialintelligence.informa.com/~/media/Informa-Shop-Window/Financial/StatFACTs/statfacts-trackingerror.pdf. Accessed on 16 December 2021.

7 Conclusion

In this paper, we constructed eight long-only factors in Swiss equities and we provided a comprehensive set of strategies that aim to combine those factors in one single portfolio. We then built four different strategies aiming to construct portfolios of factors.

Firstly, we built an ERC portfolio on the set of factors. This approach is a risk-based approach, incorporating no tilt on the different risk premia. This ERC portfolio provides less absolute return than the benchmark but is also less risky, providing a better risk-adjusted performance.

Then, we built three other strategies aiming to tilt the factors. The first one is the Ridge regression, which aims at maximizing the information ratio of the portfolio at each date, while adding a penalty to portfolios that deviate from the equally-weighted. This approach provides solid performance, improving both in terms of return and volatility compared to the benchmark, with a tracking error of about 7%.

We also constructed a momentum of factors, which provides impressive performance in terms of return, with an expected return of more than 13% over the period compared to about 10% for the benchmark. This portfolio gives the best absolute return among our portfolios, with similar volatility as the benchmark. However, in the base case, the TE is quite high (about 9%), which could be a concern for an institutional investor.

Finally, we implemented a parametric weights portfolio using the VIX as tilt variable. This portfolio provides good performance in terms of absolute return as well as in terms of risk-adjusted return, with an information ratio of about 0.3 and a Sharpe ratio of 1.17 over the period, compared to a Sharpe ratio of 0.86 from our benchmark. This strategy also has a tracking error of 7.6%, close to the one of the Ridge regression portfolio.

Using a multi-factor Fama and French analysis revealed that all portfolios provide positive and statistically significant alpha, at 1% significance level.

We have also seen that we can efficiently reduce the tracking error by constructing a portfolio that mixes the benchmark and the active portfolio, or by controlling it explicitly using the optimizer (for the ERC or the Ridge regression). However, we can see that when we aim to reduce the tracking error, the performances of our portfolios are decreasing (nevertheless marginal), showing that there exists a trade-off between risk-adjusted returns and tracking error.

Therefore, we can notice that both in terms of return and risk-adjusted return the best strategies are the momentum of factors and the parametric weights based on the VIX. The momentum of factors delivers a slightly higher expected return and also a higher information ratio compared to the parametric weights, but also a higher tracking error and a slightly lower Sharpe ratio. Moreover, we can say that the parametric weights based on the VIX is therefore a strong portfolio with great balance between returns and tracking error, that we can also combine with the benchmark depending on our preferences regarding tracking error and return. A limitation in our research is the lack of consideration of the transaction cost, which can however be minimized with the liquidity constraint set. Nevertheless, we can still conclude that tilting factors can indeed improve the performance compared to a simple ERC of factors that incorporates no tilt, while preserving a decent tracking error.

8 Figures & Tables

8.1 Data

Table 8.1: Firms' Characteristics

Firms' Characteristics
Stock Price
Market Capitalization
Price-to-Earnings Ratio
Dividend Yield
Beta
ROE
ROA
Gross Margin
EPS
Volume Traded
Market-to-Book Ratio
Investments
Operating Profit Margin

Table 8.2: Summary of Macro Data

	10y Bond Yield US	VIX	CPI US	TED Spread	3M Libor US	12M Libor US
count	258.00	258.00	258.00	258.00	258.00	258.00
mean	3.27	19.99	218.56	0.42	1.97	2.33
std	1.34	8.48	27.23	0.38	1.90	1.79
min	0.62	10.13	169.30	0.12	0.15	0.26
25%	2.19	14.08	193.70	0.21	0.31	0.90
50%	3.06	17.77	219.03	0.29	1.28	1.73
75%	4.29	23.69	238.03	0.47	2.79	3.11
max	6.66	62.67	270.98	3.35	6.79	7.38

8.2 Cap-Weighted Benchmark

Table 8.3: Performances of CW Benchmark

	CW
Ann. Return (%)	10.086
Ann. STD (%)	12.051
SR	0.869
Max DD (%)	-18.161
Hit Ratio (%)	66.234
TE Ex-Post (%)	0.000
Info. Ratio	0.000
VaR (%)	3.671
ES (%)	4.885

Figure 8.1: General Industry Classification

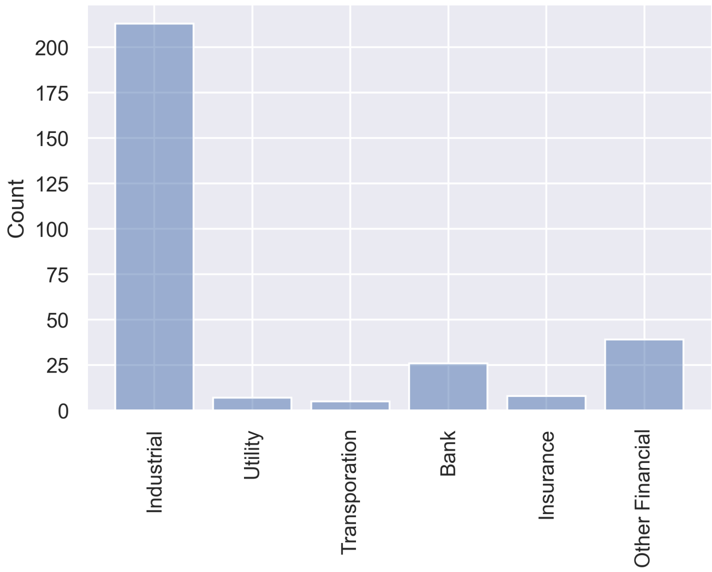
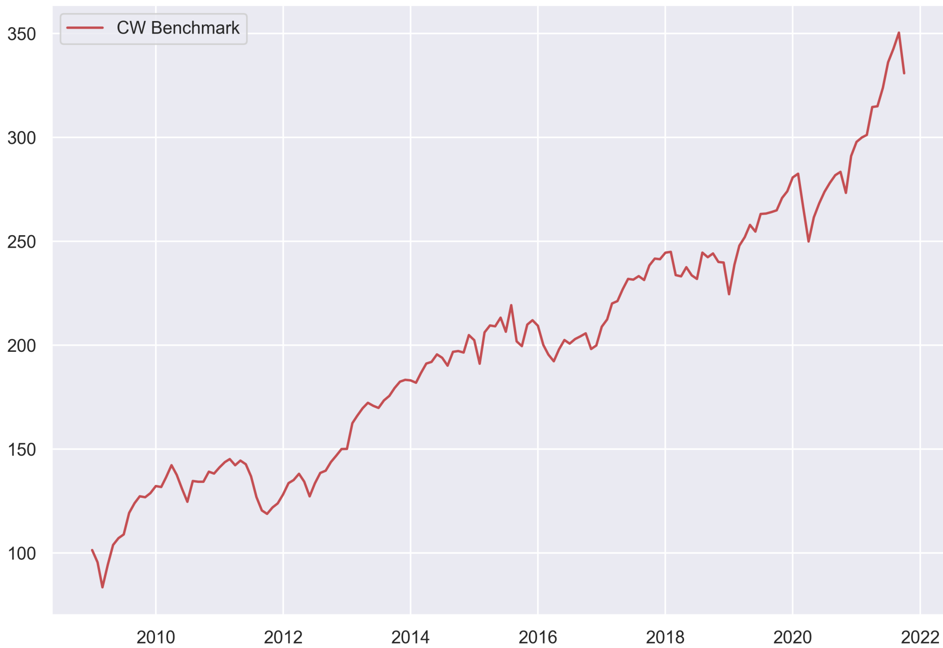
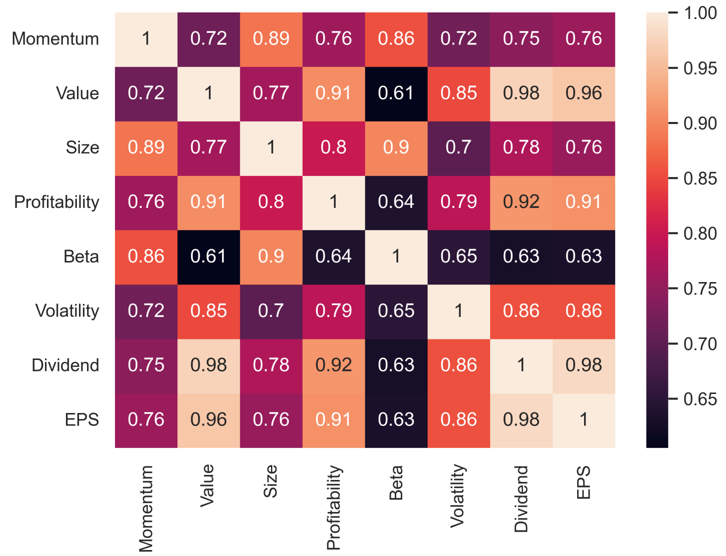


Figure 8.2: CW Benchmark Cumulative Return



8.3 Factors Portfolio

Figure 8.3: Correlation Matrix of Factors



8.4 Portfolios Results with Default Parameters

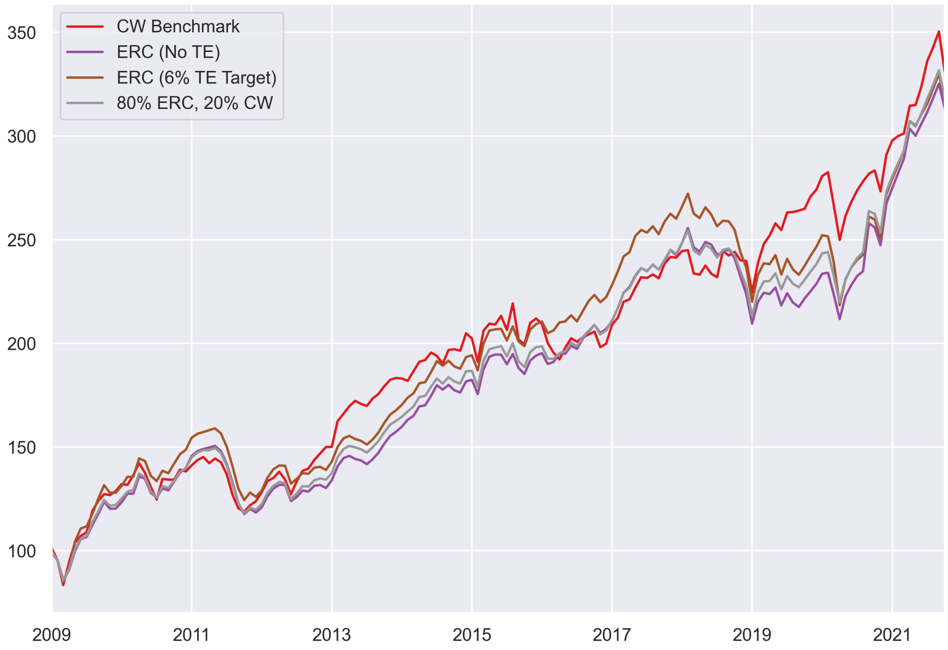
8.4.1 Equal-Risk Contribution Portfolio

Table 8.4: Performances of ERC Porfolio

	CW	ERC (No TE)	ERC (6% TE Target)	80% ERC, 20% CW
Ann. Return (%)	10.086	9.500	9.698	9.617
Ann. STD (%)	12.051	10.653	11.466	10.577
SR	0.869	0.928	0.879	0.945
Max DD (%)	-18.161	-21.859	-21.743	-21.043
Hit Ratio (%)	66.234	65.584	64.935	65.584
TE Ex-Post (%)	0.000	7.077	6.766	5.662
Info. Ratio	0.000	-0.083	-0.057	-0.083
VaR (%)	3.671	3.216	3.449	3.228
ES (%)	4.885	4.146	4.525	4.232

Table 8.5: Evolution of Factor Weights in ERC Portfolio

Figure 8.4: ERC Portfolio Cumulative Return (Default Settings)

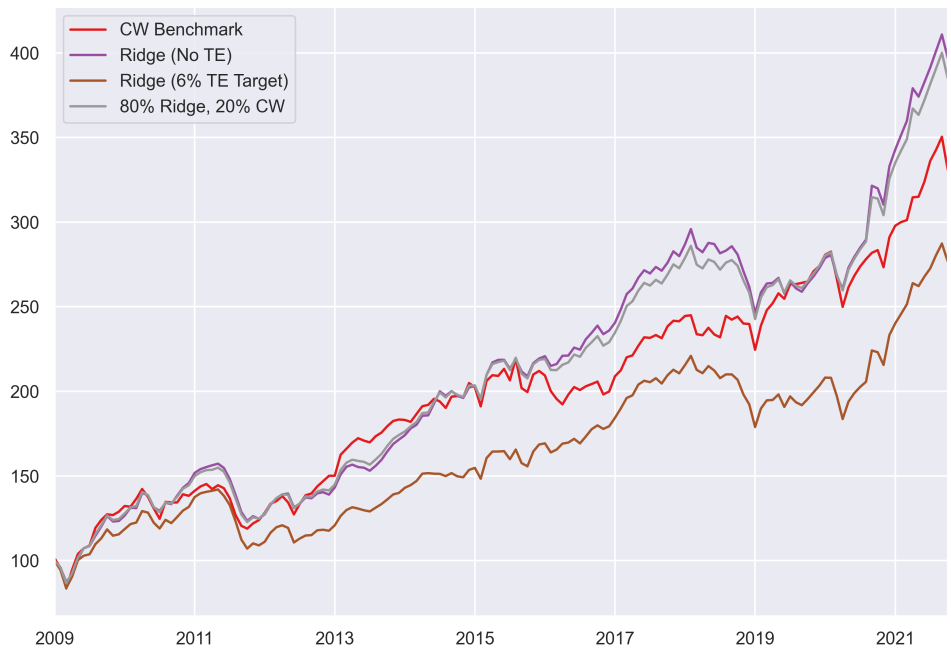


8.4.2 Ridge Regression Portfolio

Table 8.6: Performances of Ridge Portfolio

	CW	Ridge (No TE)	Ridge (6% TE Target)	80% Ridge, 20% CW
Ann. Return (%)	10.086	11.352	8.614	11.099
Ann. STD (%)	12.051	10.602	11.438	10.511
SR	0.869	1.107	0.787	1.092
Max DD (%)	-18.161	-21.496	-24.616	-20.751
Hit Ratio (%)	66.234	66.883	64.935	66.234
TE Ex-Post (%)	0.000	7.308	6.194	5.846
Info. Ratio	0.000	0.173	-0.238	0.173
VaR (%)	3.671	3.041	3.606	3.076
ES (%)	4.885	3.997	4.660	4.107

Figure 8.5: Ridge Portfolio Cumulative Return (Default Settings)



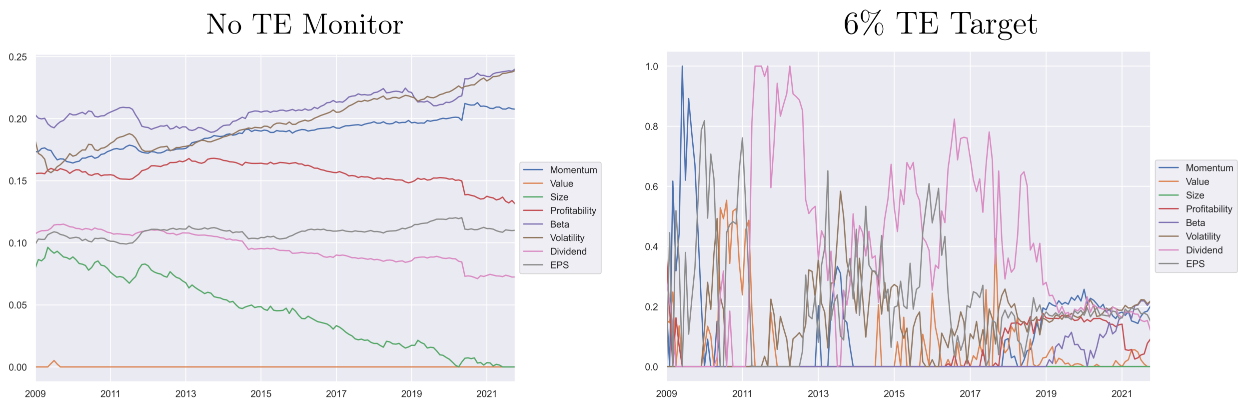


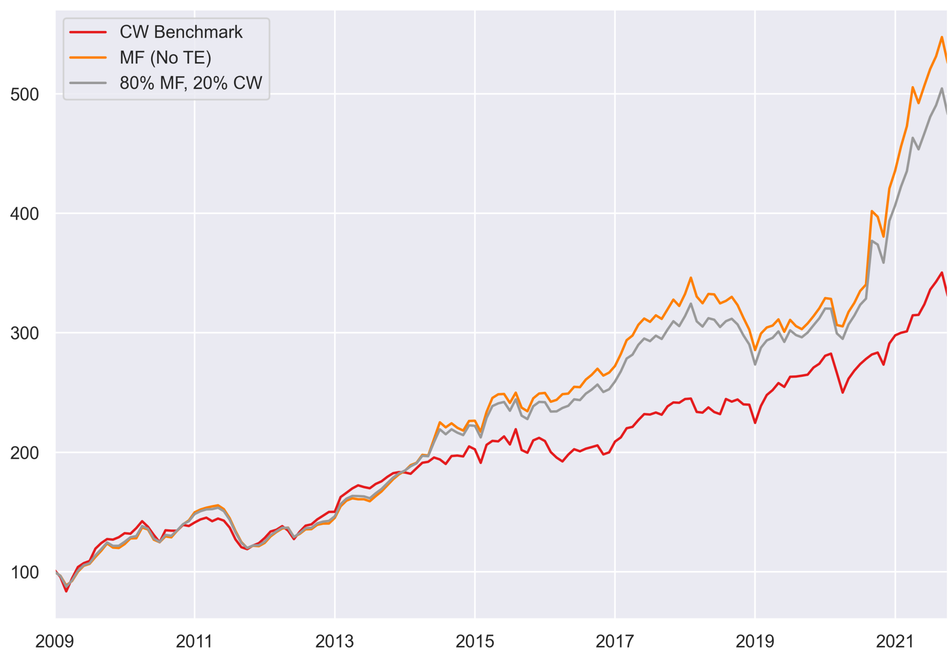
Table 8.7: Evolution of Factor Weights in Ridge Portfolio

8.4.3 Momentum of Factors

Table 8.8: Performances of Momentum of Factor

	CW	MF (No TE)	80% MF, 20% CW
Ann. Return (%)	10.086	13.738	13.007
Ann. STD (%)	12.051	12.219	11.662
SR	0.869	1.156	1.148
Max DD (%)	-18.161	-23.006	-21.974
Hit Ratio (%)	66.234	67.532	66.883
TE Ex-Post (%)	0.000	8.860	7.088
Info. Ratio	0.000	0.412	0.412
VaR (%)	3.671	3.331	3.297
ES (%)	4.885	4.550	4.587

Figure 8.6: Momentum Factor Cumulative Return (Default Settings)



8.4.4 Parametric Weights Portfolio

Table 8.9: Performances of Parametric Portfolio (All Macro Data)

	CW	Parametrics (No TE)	80% Parametrics, 20% CW
Ann. Return (%)	10.086	10.240	10.310
Ann. STD (%)	12.051	11.532	11.315
SR	0.869	0.921	0.945
Max DD (%)	-18.161	-22.467	-21.533
Hit Ratio (%)	66.234	66.667	65.584
TE Ex-Post (%)	0.000	6.612	5.290
Info. Ratio	0.000	-0.053	-0.053
VaR (%)	3.671	3.595	3.519
ES (%)	4.885	4.809	4.751

Figure 8.7: Parametric Portfolio Cumulative Return (All Macro Data, Default Settings)

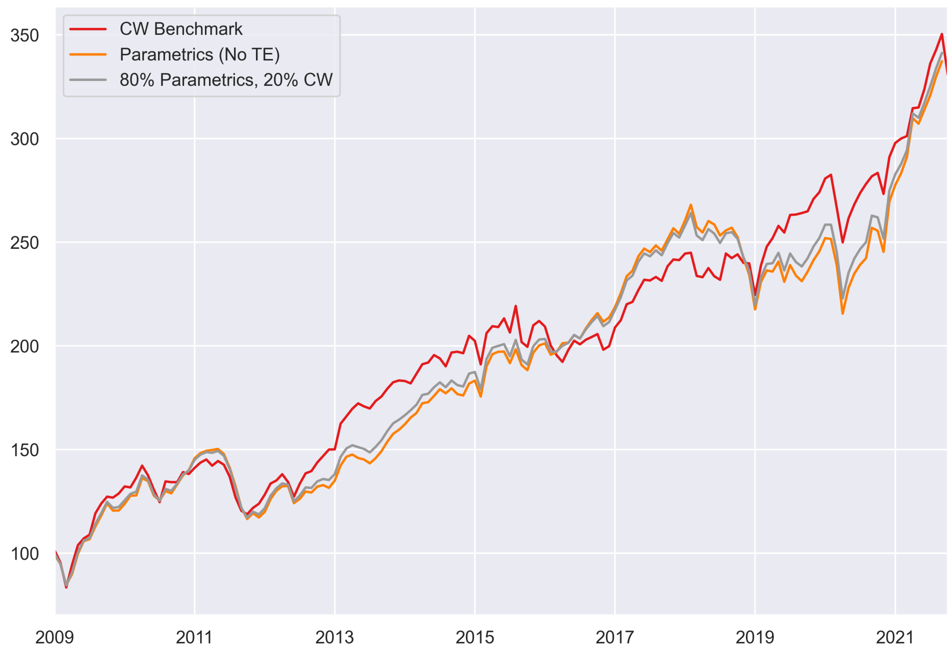
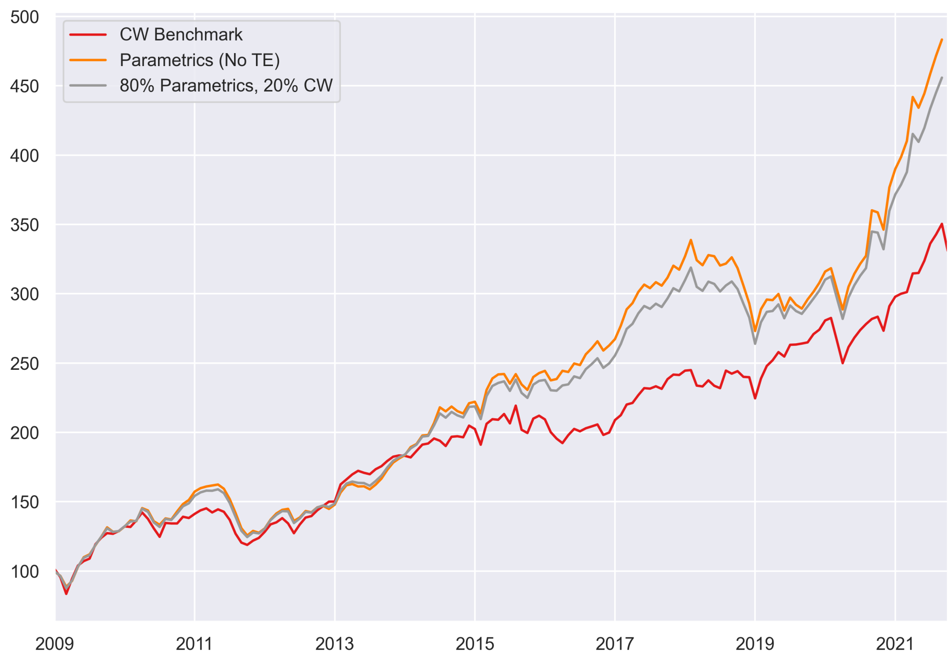


Table 8.10: Performances of Parametric Portfolio (VIX)

	CW	Parametrics (No TE)	80% Parametrics, 20% CW
Ann. Return (%)	10.086	13.075	12.578
Ann. STD (%)	12.051	11.462	11.148
SR	0.869	1.174	1.163
Max DD (%)	-18.161	-22.644	-21.678
Hit Ratio (%)	66.234	66.667	65.584
TE Ex-Post (%)	0.000	7.698	6.158
Info. Ratio	0.000	0.323	0.323
VaR (%)	3.671	3.353	3.318
ES (%)	4.885	4.291	4.330

Figure 8.8: Parametric Portfolio Cumulative Return (VIX, Default Settings)



All Macro Data (No TE Monitor) VIX (No TE Monitor)

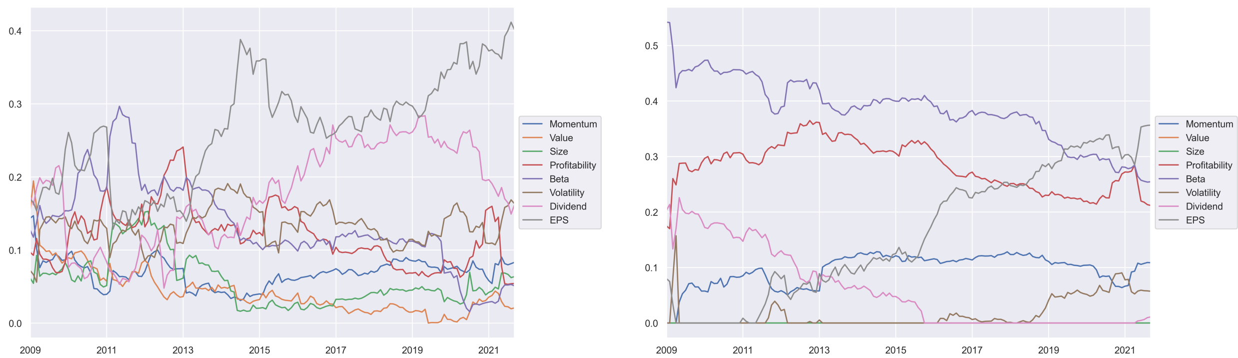


Table 8.11: Evolution of Factor Weights in Parametric Portfolio

8.4.5 Portfolio Weights

Table 8.12: Average Portfolio Weights

	Mom Factor	ERC	Ridge	Parametrics
Momentum	23.38	11.61	18.79	9.57
Value	0.97	9.52	0.01	0.00
Size	10.06	8.91	4.51	0.00
Profitability	19.16	9.74	15.56	28.27
Beta	12.99	15.35	20.91	38.35
Volatility	7.47	22.60	19.75	1.71
Dividend	7.31	11.31	9.59	6.07
EPS	18.67	10.96	10.88	16.03

8.5 Fama-French Analysis

Table 8.13: Fama-French: ERC Portfolio (No TE Monitor)

	Intercept	MktRf	SMB	HML	WML	RMW	CMA	VOL	R2
Coeff.	0.007	0.391	-	-	-	-	-	-	0.185
Pval	0.004	0.000	-	-	-	-	-	-	-
Coeff.	0.005	0.371	0.021	-0.118	-	-	-	-	0.209
Pval	0.085	0.000	0.819	0.045	-	-	-	-	-
Coeff.	0.008	0.097	-0.19	0.156	0.041	-0.187	0.144	-0.519	0.801
Pval	0.000	0.021	0.007	0.0	0.221	0.022	0.013	0.0	-

Table 8.14: Fama-French: ERC Portfolio (20% CW)

	Intercept	MktRf	SMB	HML	WML	RMW	CMA	VOL	R2
Coeff.	0.007	0.431	-	-	-	-	-	-	0.228
Pval	0.005	0.000	-	-	-	-	-	-	-
Coeff.	0.004	0.399	-0.044	-0.103	-	-	-	-	0.239
Pval	0.111	0.000	0.624	0.07	-	-	-	-	-
Coeff.	0.008	0.125	-0.281	0.154	0.023	-0.235	0.119	-0.484	0.81
Pval	0.000	0.002	0.0	0.0	0.479	0.003	0.034	0.0	-

Table 8.15: Fama-French: Ridge Portfolio (No TE Monitor)

	Intercept	MktRf	SMB	HML	WML	RMW	CMA	VOL	R2
Coeff.	0.008	0.396	-	-	-	-	-	-	0.191
Pval	0.001	0.000	-	-	-	-	-	-	-
Coeff.	0.006	0.370	0.019	-0.149	-	-	-	-	0.232
Pval	0.035	0.000	0.834	0.01	-	-	-	-	-
Coeff.	0.009	0.101	-0.183	0.153	0.087	-0.177	0.158	-0.539	0.81
Pval	0.000	0.013	0.007	0.0	0.009	0.025	0.005	0.0	-

Table 8.16: Fama-French: Ridge Portfolio (20% CW)

	Intercept	MktRf	SMB	HML	WML	RMW	CMA	VOL	R2
Coeff.	0.008	0.434	-	-	-	-	-	-	0.234
Pval	0.001	0.000	-	-	-	-	-	-	-
Coeff.	0.005	0.399	-0.046	-0.128	-	-	-	-	0.255
Pval	0.055	0.000	0.604	0.023	-	-	-	-	-
Coeff.	0.008	0.128	-0.276	0.152	0.059	-0.227	0.13	-0.5	0.816
Pval	0.000	0.001	0.0	0.0	0.063	0.003	0.018	0.0	-

Table 8.17: Fama-French: Momentum of Factor (No TE Monitor)

	Intercept	MktRf	SMB	HML	WML	RMW	CMA	VOL	R2
Coeff.	0.010	0.446	-	-	-	-	-	-	0.182
Pval	0.001	0.000	-	-	-	-	-	-	-
Coeff.	0.005	0.402	0.035	-0.291	-	-	-	-	0.322
Pval	0.095	0.000	0.718	0.0	-	-	-	-	-
Coeff.	0.008	0.112	-0.203	0.083	0.17	-0.233	0.172	-0.603	0.815
Pval	0.000	0.015	0.008	0.084	0.0	0.009	0.007	0.0	-

Table 8.18: Fama-French: Momentum of Factor (20% CW)

	Intercept	MktRf	SMB	HML	WML	RMW	CMA	VOL	R2
Coeff.	0.009	0.474	-	-	-	-	-	-	0.227
Pval	0.001	0.000	-	-	-	-	-	-	-
Coeff.	0.004	0.424	-0.033	-0.242	-	-	-	-	0.316
Pval	0.118	0.000	0.726	0.0	-	-	-	-	-
Coeff.	0.008	0.136	-0.292	0.095	0.126	-0.272	0.141	-0.551	0.817
Pval	0.000	0.002	0.0	0.038	0.0	0.002	0.019	0.0	-

Table 8.19: Fama-French: Parametric Portfolio (No TE Monitor)

	Intercept	MktRf	SMB	HML	WML	RMW	CMA	VOL	R2
Coeff.	0.010	0.401	-	-	-	-	-	-	0.169
Pval	0.000	0.000	-	-	-	-	-	-	-
Coeff.	0.007	0.375	0.031	-0.152	-	-	-	-	0.208
Pval	0.025	0.000	0.758	0.016	-	-	-	-	-
Coeff.	0.010	0.076	-0.199	0.129	0.05	-0.216	0.106	-0.562	0.798
Pval	0.000	0.091	0.009	0.007	0.166	0.014	0.089	0.0	-

Table 8.20: Fama-French:Parametric Portfolio (20% CW)

	Intercept	MktRf	SMB	HML	WML	RMW	CMA	VOL	R2
Coeff.	0.009	0.437	-	-	-	-	-	-	0.212
Pval	0.000	0.000	-	-	-	-	-	-	-
Coeff.	0.006	0.403	-0.037	-0.131	-	-	-	-	0.233
Pval	0.041	0.000	0.699	0.03	-	-	-	-	-
Coeff.	0.010	0.108	-0.289	0.132	0.03	-0.258	0.088	-0.518	0.81
Pval	0.000	0.011	0.0	0.003	0.376	0.002	0.133	0.0	-

8.6 Sensitivity Analysis

8.6.1 Liquidity Constraint Sensitivity Analysis

8.6.1.1 Equal-Risk Contribution Portfolio

Table 8.21: Performances of ERC Portfolio (Liquidity Constraint Sensitivity)

	0% Qtl		10% Qtl		30% Qtl		50% Qtl	
	No TE	20% CW	No TE	20% CW	No TE	20% CW	No TE	20% CW
Ann. Return (%)	7.255	7.821	8.474	8.797	10.026	10.038	11.529	11.240
Ann. STD (%)	9.035	9.251	9.824	9.896	10.936	10.806	12.079	11.734
SR	0.845	0.887	0.902	0.928	0.952	0.964	0.986	0.991
Max DD (%)	-19.053	-18.499	-20.441	-19.822	-21.868	-21.050	-23.921	-22.691
Hit Ratio (%)	66.234	64.935	65.584	65.584	66.883	66.883	62.987	64.286
TE Ex-Post (%)	7.428	5.942	7.238	5.791	7.075	5.660	7.130	5.704
Info. Ratio	-0.381	-0.381	-0.223	-0.223	-0.009	-0.009	0.202	0.202
VaR (%)	2.796	2.893	3.011	3.061	3.269	3.268	3.537	3.479
ES (%)	3.682	3.855	3.953	4.066	4.203	4.280	4.577	4.564

No TE Monitor

80% Portfolio, 20% CW

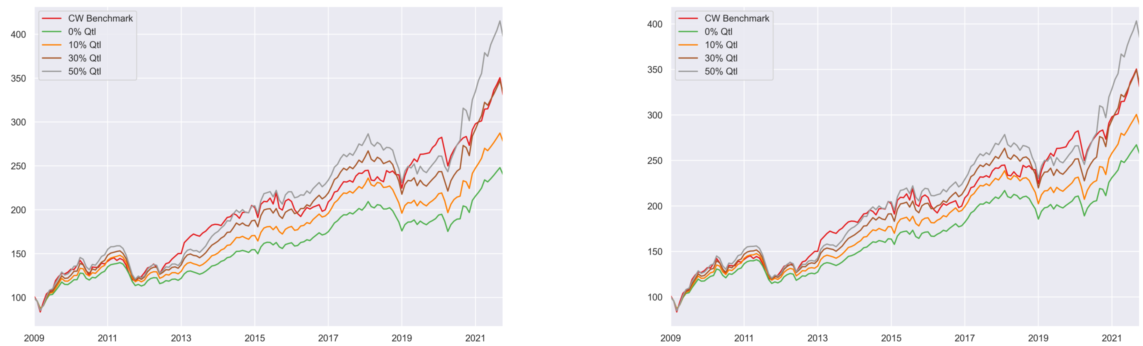


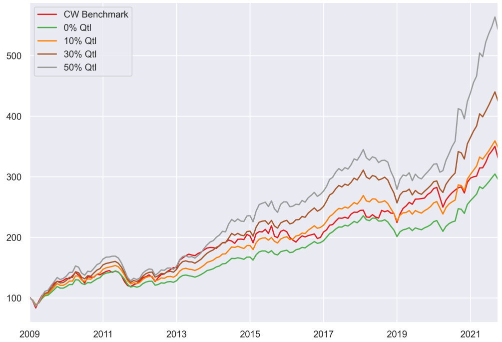
Table 8.22: Cumulative Returns of ERC Portfolio (Liquidity Constraint Sensitivity)

8.6.1.2 Ridge Regression Portfolio

Table 8.23: Performances of Ridge Portfolio (Liquidity Constraint Sensitivity)

	0% Qtl		10% Qtl		30% Qtl		50% Qtl	
	No TE	20% CW	No TE	20% CW	No TE	20% CW	No TE	20% CW
Ann. Return (%)	8.868	9.112	10.231	10.202	11.918	11.552	14.037	13.247
Ann. STD (%)	8.808	9.057	9.670	9.756	10.894	10.748	12.584	12.076
SR	1.050	1.048	1.098	1.085	1.129	1.110	1.146	1.129
Max DD (%)	-18.233	-18.000	-19.740	-19.337	-21.587	-20.824	-24.098	-22.855
Hit Ratio (%)	66.234	66.234	67.532	66.234	66.883	67.532	66.234	64.286
TE Ex-Post (%)	7.560	6.048	7.393	5.915	7.298	5.839	7.888	6.310
Info. Ratio	-0.161	-0.161	0.020	0.020	0.251	0.251	0.501	0.501
VaR (%)	2.596	2.734	2.815	2.898	3.111	3.124	3.530	3.441
ES (%)	3.383	3.622	3.659	3.830	4.109	4.198	4.604	4.587

No TE Monitor



80% Portfolio, 20% CW

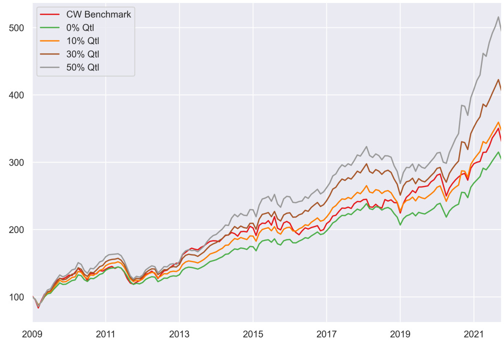


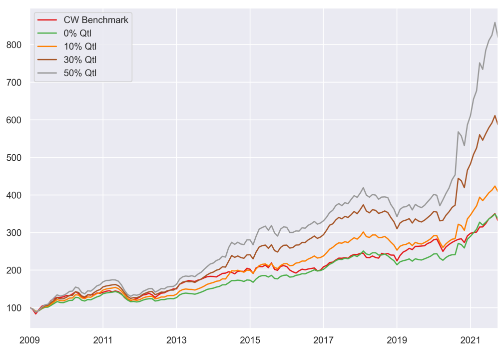
Table 8.24: Cumulative Returns of Ridge Portfolio (Liquidity Constraint Sensitivity)

8.6.1.3 Momentum of Factors

Table 8.25: Performances of Momentum of Factor (Liquidity Constraint Sensitivity)

	0% Qtl		10% Qtl		30% Qtl		50% Qtl	
	No TE	20% CW	No TE	20% CW	No TE	20% CW	No TE	20% CW
Ann. Return (%)	9.957	9.983	11.607	11.303	14.644	13.732	17.558	16.064
Ann. STD (%)	9.606	9.608	10.934	10.674	12.644	12.000	14.825	13.684
SR	1.076	1.079	1.096	1.095	1.188	1.176	1.210	1.202
Max DD (%)	-19.360	-18.621	-22.355	-21.245	-22.825	-21.828	-25.094	-23.545
Hit Ratio (%)	66.883	67.532	65.584	66.883	68.182	66.234	65.584	65.584
TE Ex-Post (%)	8.150	6.520	8.228	6.582	9.024	7.220	10.533	8.427
Info. Ratio	-0.016	-0.016	0.185	0.185	0.505	0.505	0.709	0.709
VaR (%)	2.753	2.870	3.195	3.219	3.441	3.368	3.812	3.672
ES (%)	3.686	3.856	4.167	4.250	4.684	4.695	5.099	5.029

No TE Monitor



80% Portfolio, 20% CW

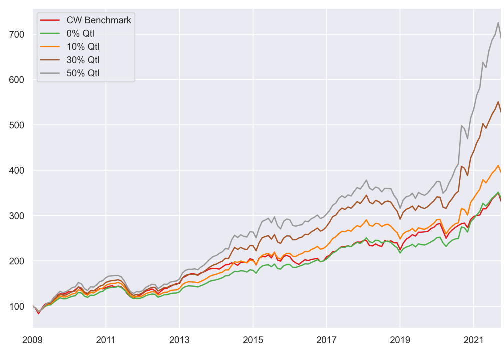


Table 8.26: Cumulative Returns of Momentum of Factor (Liquidity Constraint Sensitivity)

8.6.1.4 Parametric Weights Portfolio

Table 8.27: Performances of Parametric Portfolio (Liquidity Constraint Sensitivity)

	0% Qtl		10% Qtl		30% Qtl		50% Qtl	
	No TE	20% CW	No TE	20% CW	No TE	20% CW	No TE	20% CW
Ann. Return (%)	9.842	9.992	11.702	11.479	13.809	13.165	17.067	15.772
Ann. STD (%)	9.534	9.621	10.550	10.467	11.890	11.501	13.992	13.152
SR	1.072	1.078	1.145	1.133	1.194	1.178	1.247	1.228
Max DD (%)	-17.987	-17.930	-20.028	-19.569	-22.594	-21.637	-24.766	-23.299
Hit Ratio (%)	68.627	66.883	69.281	68.182	66.667	66.883	64.706	63.636
TE Ex-Post (%)	7.415	5.932	7.122	5.698	7.699	6.159	8.767	7.013
Info. Ratio	-0.101	-0.101	0.156	0.156	0.418	0.418	0.739	0.739
VaR (%)	2.846	2.938	3.152	3.184	3.486	3.429	3.908	3.743
ES (%)	3.833	3.967	4.249	4.293	4.461	4.480	5.049	4.930

No TE Monitor | 80% Portfolio, 20% CW

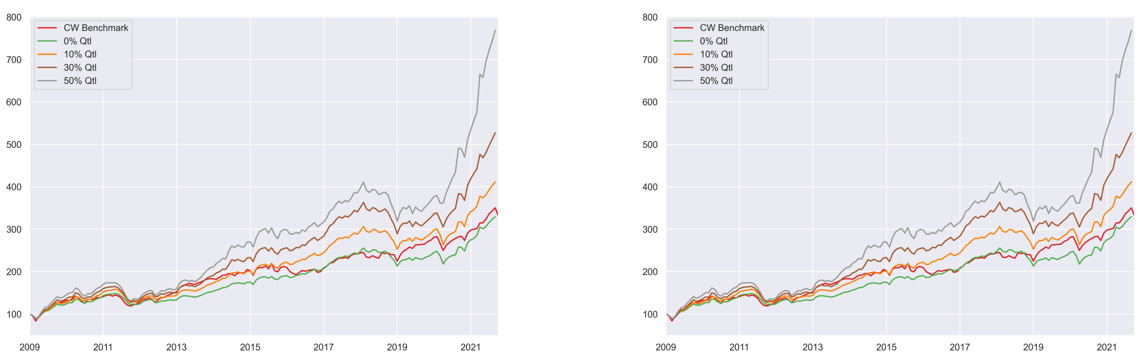


Table 8.28: Cumulative Returns of Parametric Portfolio (Liquidity Constraint Sensitivity)

8.6.2 Factor Construction Sensitivity

8.6.2.1 Equal-Risk Contribution Portfolio

Table 8.29: Performances of ERC Portfolio (Factor Construction Sensitivity)

	20% Qtl		30% Qtl		40% Qtl		60% Qtl	
	No TE	20% CW	No TE	20% CW	No TE	20% CW	No TE	20% CW
Ann. Return (%)	11.020	10.833	10.814	10.669	10.261	10.226	8.668	8.952
Ann. STD (%)	12.915	12.387	12.254	11.874	11.402	11.193	9.867	9.924
SR	0.883	0.905	0.914	0.931	0.933	0.948	0.917	0.941
Max DD (%)	-24.649	-23.299	-23.968	-22.747	-22.655	-21.686	-20.325	-19.807
Hit Ratio (%)	64.935	66.234	64.286	67.532	65.584	66.234	65.584	66.234
TE Ex-Post (%)	7.540	6.032	7.177	5.742	6.989	5.591	7.286	5.829
Info. Ratio	0.124	0.124	0.101	0.101	0.025	0.025	-0.195	-0.195
VaR (%)	3.914	3.777	3.739	3.640	3.467	3.429	2.903	2.974
ES (%)	5.029	4.907	4.904	4.816	4.510	4.514	3.743	3.907

No TE Monitor | 80% Portfolio, 20% CW

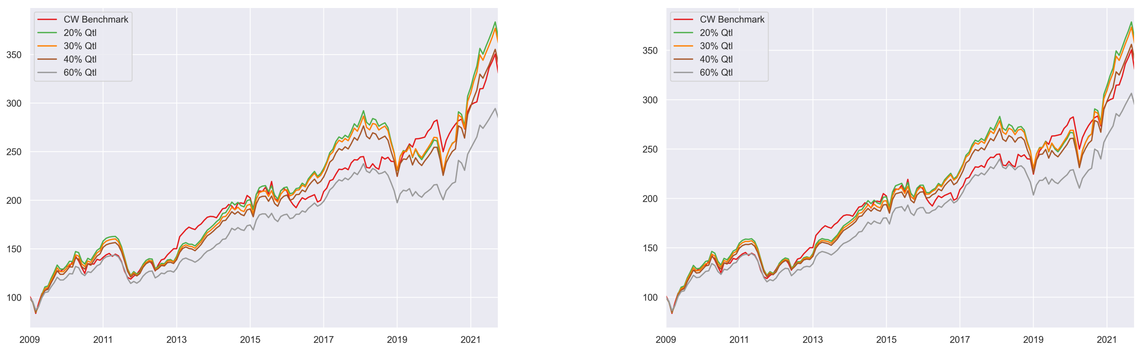


Table 8.30: Cumulative Returns of ERC Portfolio (Factor Construction Sensitivity)

8.6.2.2 Ridge Regression Portfolio

Table 8.31: Performances of Ridge Portfolio (Factor Construction Sensitivity)

	20% Qtl		30% Qtl		40% Qtl		60% Qtl	
	No TE	20% CW	No TE	20% CW	No TE	20% CW	No TE	20% CW
Ann. Return (%)	11.513	11.228	11.583	11.283	11.553	11.260	11.241	11.010
Ann. STD (%)	13.190	12.601	12.515	12.076	11.509	11.268	9.753	9.743
SR	0.902	0.921	0.956	0.966	1.037	1.033	1.192	1.169
Max DD (%)	-24.972	-23.561	-24.271	-22.993	-22.639	-21.673	-19.317	-18.997
Hit Ratio (%)	64.935	66.234	64.286	67.532	66.234	66.883	68.182	66.883
TE Ex-Post (%)	7.711	6.169	7.320	5.856	7.111	5.689	8.014	6.411
Info. Ratio	0.185	0.185	0.204	0.204	0.206	0.206	0.144	0.144
VaR (%)	3.976	3.826	3.777	3.668	3.411	3.380	2.607	2.703
ES (%)	5.092	4.958	4.930	4.838	4.380	4.416	3.488	3.705

No TE Monitor | 80% Portfolio, 20% CW

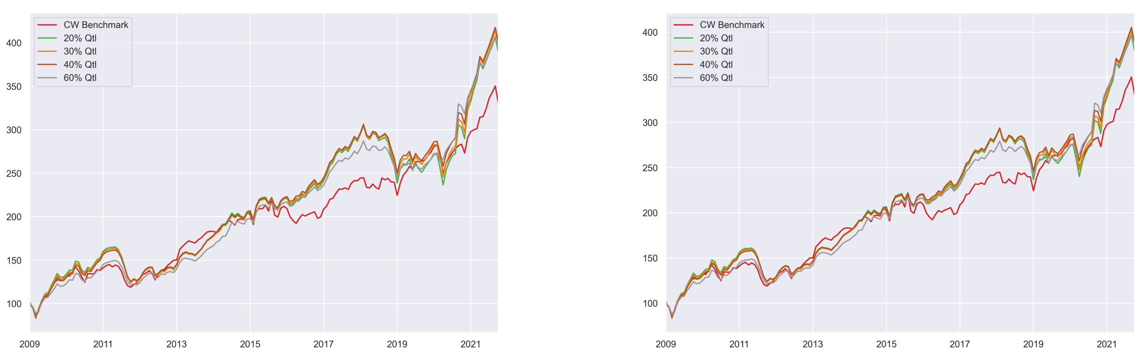


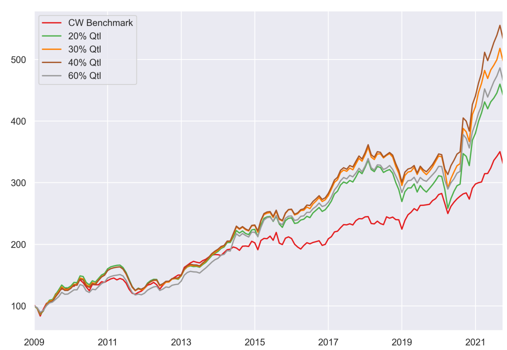
Table 8.32: Cumulative Returns of Ridge Portfolio (Factor Construction Sensitivity)

8.6.2.3 Momentum of Factors

Table 8.33: Performances of Momentum of Factor (Factor Construction Sensitivity)

	20% Qtl		30% Qtl		40% Qtl		60% Qtl	
	No TE	20% CW	No TE	20% CW	No TE	20% CW	No TE	20% CW
Ann. Return (%)	12.574	12.077	13.424	12.757	13.884	13.124	12.750	12.218
Ann. STD (%)	13.726	12.968	13.151	12.493	12.405	11.889	11.943	11.435
SR	0.944	0.961	1.050	1.052	1.150	1.136	1.100	1.102
Max DD (%)	-24.728	-23.366	-23.750	-22.575	-23.317	-22.224	-21.999	-21.161
Hit Ratio (%)	66.883	66.883	67.532	67.532	67.532	67.532	67.532	65.584
TE Ex-Post (%)	8.536	6.829	8.444	6.755	8.241	6.593	8.833	7.066
Info. Ratio	0.291	0.291	0.395	0.395	0.461	0.461	0.302	0.302
VaR (%)	4.110	3.946	3.822	3.734	3.483	3.444	3.371	3.357
ES (%)	5.288	5.158	4.940	4.896	4.663	4.679	4.445	4.510

No TE Monitor



80% Portfolio, 20% CW

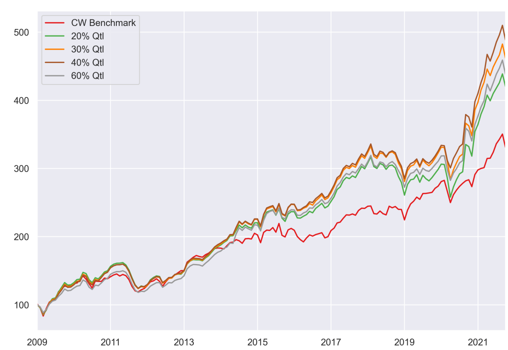


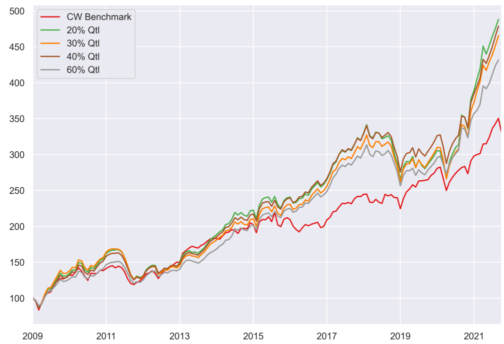
Table 8.34: Cumulative Returns of Momentum of Factor (Factor Construction Sensitivity)

8.6.2.4 Parametric Weights Portfolio

Table 8.35: Performances of Parametric Portfolio (Factor Construction Sensitivity)

	20% Qtl		30% Qtl		40% Qtl		60% Qtl	
	No TE	20% CW	No TE	20% CW	No TE	20% CW	No TE	20% CW
Ann. Return (%)	13.385	12.826	12.969	12.493	13.050	12.558	12.079	11.781
Ann. STD (%)	13.362	12.690	13.056	12.478	11.929	11.601	10.554	10.431
SR	1.030	1.041	1.023	1.032	1.126	1.115	1.181	1.166
Max DD (%)	-24.594	-23.255	-25.207	-23.825	-23.088	-22.037	-20.360	-19.836
Hit Ratio (%)	66.667	65.584	64.706	66.883	66.667	66.234	67.320	66.883
TE Ex-Post (%)	8.081	6.465	7.632	6.106	7.027	5.621	7.474	5.979
Info. Ratio	0.346	0.346	0.312	0.312	0.350	0.350	0.199	0.199
VaR (%)	3.984	3.826	3.980	3.824	3.627	3.550	3.068	3.112
ES (%)	5.069	4.924	5.237	5.073	4.755	4.697	3.976	4.081

No TE Monitor



80% Portfolio, 20% CW

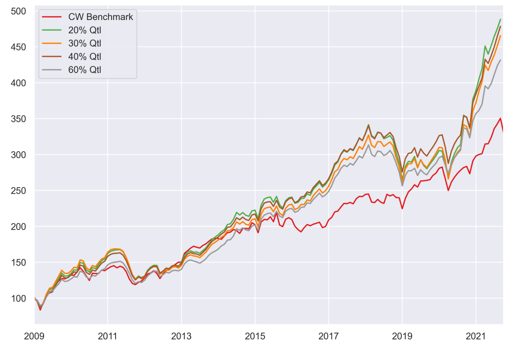


Table 8.36: Cumulative Returns of Parametric Portfolio (Factor Construction Sensitivity)

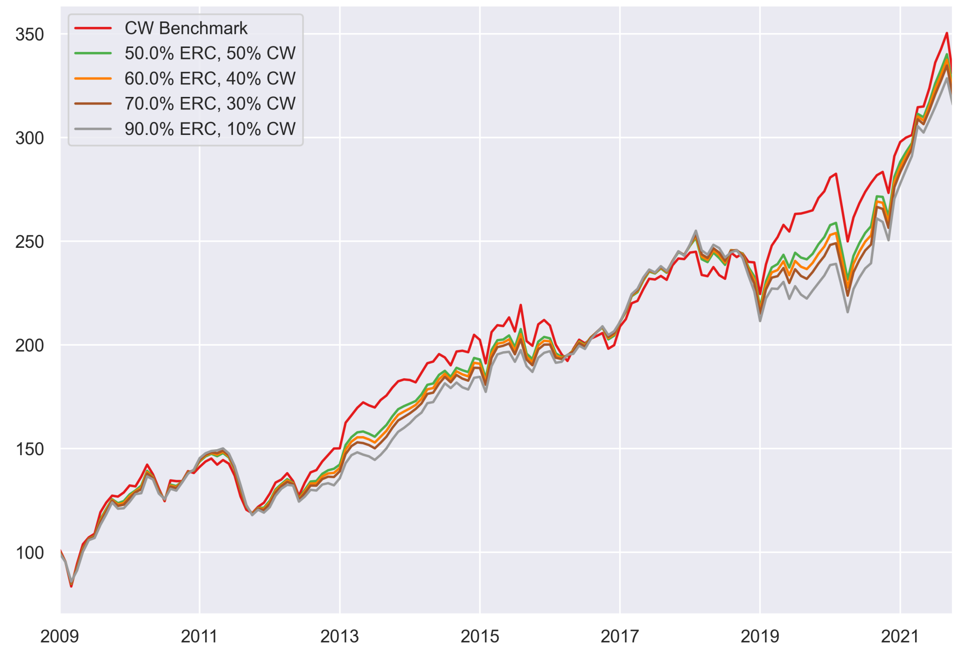
8.6.3 CW Benchmark Combination Sensitivity

8.6.3.1 Equal-Risk Contribution Portfolio

Table 8.37: Performances of ERC Portfolio (CW Combination Sensitivity)

	50% Ptf, 50% CW	60% Ptf, 40% CW	70% Ptf, 30% CW	90% Ptf, 10% CW
Ann. Return (%)	9.793	9.734	9.676	9.558
Ann. STD (%)	10.813	10.688	10.609	10.592
SR	0.941	0.947	0.948	0.939
Max DD (%)	-19.813	-20.224	-20.634	-21.451
Hit Ratio (%)	66.883	66.234	64.935	66.234
TE Ex-Post (%)	3.539	4.246	4.954	6.369
Info. Ratio	-0.083	-0.083	-0.083	-0.083
VaR (%)	3.352	3.309	3.267	3.215
ES (%)	4.438	4.354	4.286	4.181

Figure 8.9: ERC Portfolio (CW Combination Sensitivity)

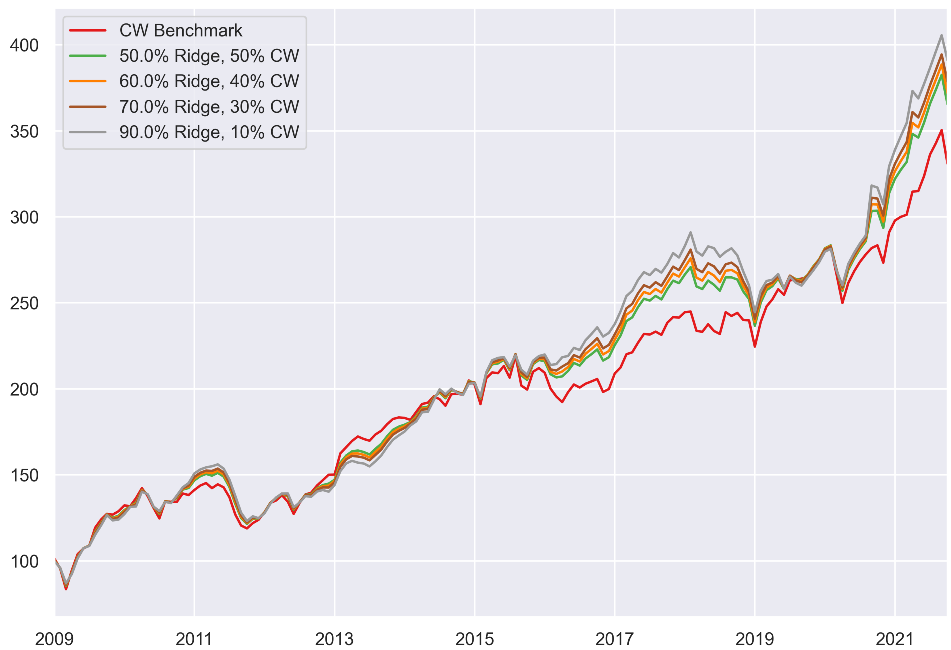


8.6.3.2 Ridge Regression Portfolio

Table 8.38: Performances of Ridge Portfolio (CW Combination Sensitivity)

	50% Ptf, 50% CW	60% Ptf, 40% CW	70% Ptf, 30% CW	90% Ptf, 10% CW
Ann. Return (%)	10.719	10.846	10.973	11.226
Ann. STD (%)	10.750	10.621	10.541	10.531
SR	1.033	1.057	1.077	1.102
Max DD (%)	-19.629	-20.004	-20.378	-21.124
Hit Ratio (%)	68.182	66.883	65.584	67.532
TE Ex-Post (%)	3.654	4.385	5.115	6.577
Info. Ratio	0.173	0.173	0.173	0.173
VaR (%)	3.256	3.192	3.131	3.053
ES (%)	4.350	4.256	4.170	4.046

Figure 8.10: Ridge Portfolio (CW Combination Sensitivity)

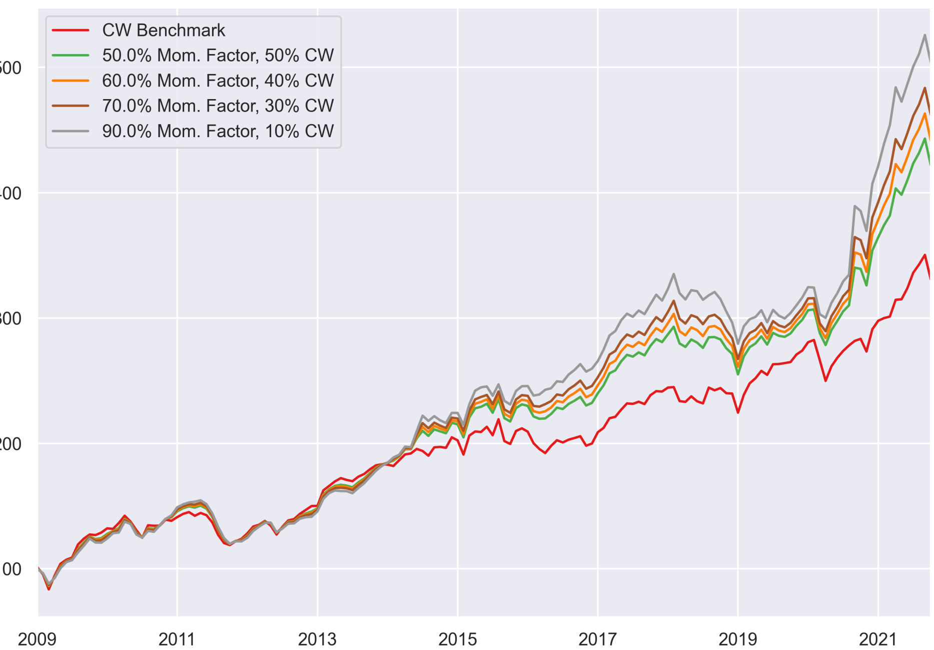


8.6.3.3 Momentum of Factors

Table 8.39: Performances of Momentum of Factor (CW Combination Sensitivity)

	50% Ptf, 50% CW	60% Ptf, 40% CW	70% Ptf, 30% CW	90% Ptf, 10% CW
Ann. Return (%)	11.912	12.277	12.642	13.372
Ann. STD (%)	11.303	11.356	11.476	11.911
SR	1.088	1.115	1.135	1.155
Max DD (%)	-20.408	-20.932	-21.455	-22.491
Hit Ratio (%)	67.532	66.883	66.883	66.234
TE Ex-Post (%)	4.430	5.316	6.202	7.974
Info. Ratio	0.412	0.412	0.412	0.412
VaR (%)	3.374	3.342	3.318	3.302
ES (%)	4.658	4.633	4.609	4.567

Figure 8.11: Momentum Factor Cumulative Return (CW Combination Sensitivity)

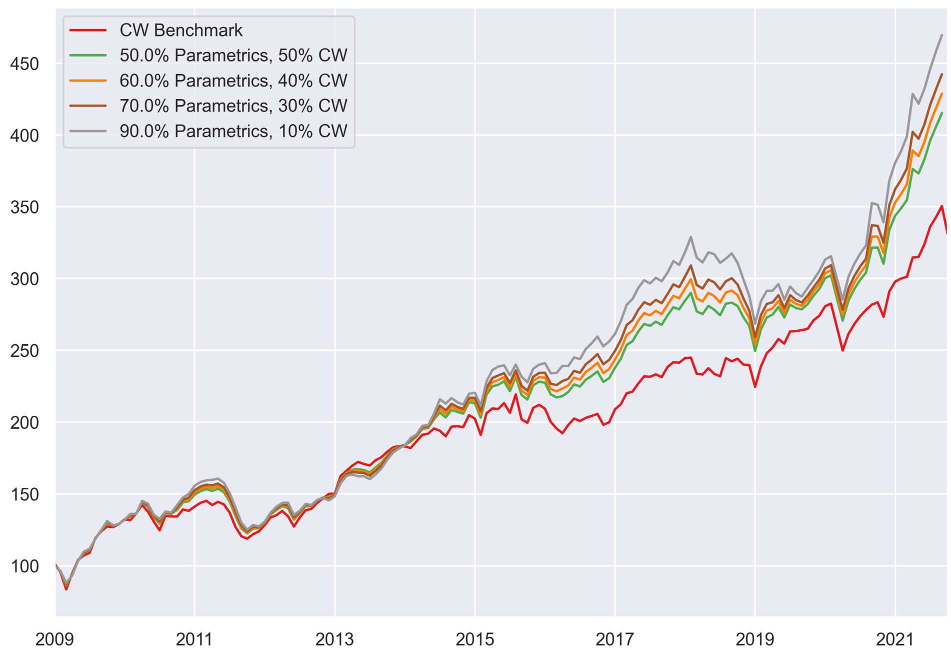


8.6.3.4 Parametric Weights Portfolio

Table 8.40: Performances of Parametric Portfolio (CW Combination Sensitivity)

	50% Ptf, 50% CW	60% Ptf, 40% CW	70% Ptf, 30% CW	90% Ptf, 10% CW
Ann. Return (%)	11.832	12.081	12.329	12.826
Ann. STD (%)	11.065	11.040	11.067	11.280
SR	1.104	1.129	1.149	1.171
Max DD (%)	-20.216	-20.705	-21.192	-22.161
Hit Ratio (%)	68.182	65.584	65.584	66.234
TE Ex-Post (%)	3.849	4.619	5.388	6.928
Info. Ratio	0.323	0.323	0.323	0.323
VaR (%)	3.388	3.350	3.320	3.326
ES (%)	4.495	4.423	4.365	4.302

Figure 8.12: Parametric Portfolio (CW Combination Sensitivity)



Bibliography

M. W. Brandt and P. Santa-Clara. Dynamic portfolio selection by augmenting the asset space. *The journal of Finance*, 61(5):2187–2217, 2006.

M. W. Brandt, P. Santa-Clara, and R. Valkanov. Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. *The Review of Financial Studies*, 22(9): 3411–3447, 2009.

F. Chincoli and M. Guidolin. Linear and nonlinear predictability in investment style factors: Multivariate evidence. *Journal of Asset Management*, 18(6):476–509, 2017.

E. F. Fama and K. R. French. *Common risk factors in the returns on stocks and bonds*. University of Chicago Press, 2021a.

E. F. Fama and K. R. French. *The cross-section of expected stock returns*. University of Chicago Press, 2021b.

P. Hodges, K. Hogan, J. R. Peterson, and A. Ang. Factor timing with cross-sectional and time-series predictors. *The Journal of Portfolio Management*, 44(1):30–43, 2017.

M. R. D. Ulloa, D. Giamouridis, and C. Montagu. Risk reduction in style rotation. *The Journal of Portfolio Management*, 38(2):44–55, 2012.

Appendix

A General Formulas

Simple return formula:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{A.1}$$

Maximum Drawdown is defined as the minimum of all drawdowns:

$$\begin{aligned} Drawdown_t &= \frac{P_t - P_t^*}{P_t^*} \\ P_t^* &= \max_{s \leq t} P_s \\ MaxDrawdown &= \min Drawdown_t \end{aligned} \tag{A.2}$$

- With $s \leq t$.

Hit Ratio is defined as:

$$HitRatio = \frac{n_{pos}}{N} \tag{A.3}$$

- Where n_{pos} is the number of times the portfolio witnessed a positive return and N is the total number of observations.

Sharpe Ratio (SR) is defined as:

$$SharpeRatio = \frac{r_p - r_f}{\sigma_p} \tag{A.4}$$

The ex-ante tracking-error is defined as:

$$TE_{ex-ante} = \sqrt{w^T \Sigma w} = \sqrt{(w_p - w_b)^T \Sigma (w_p - w_b)} \tag{A.5}$$

The ex-post tracking-error is defined as:

$$TE_{ex-post} = std(r_p - r_b) \tag{A.6}$$

Information ratio is defined as:

$$IR = \frac{r_p - r_b}{std(r_p - r_b)} = \frac{r_p - r_b}{TE_{ex-post}} \tag{A.7}$$

B Equal-Risk Contribution

In the ERC portfolio, we allocate our capital between the assets/factors in a way that *Equalizes the Risk Contribution* of each asset. In mathematical terms, this is expressed by:

$$\alpha_i MCR_i = \alpha_j MCR_j \tag{B.1}$$

With the vector of Marginal Contributions to Risk (MCR) defined in the following manner:

$$MCR = \frac{\Sigma\alpha}{\sigma_p} \tag{B.2}$$

Where:

- Σ is the covariance matrix of asset returns;
- α is the vector containing the portfolio weights;
- σ_p is the portfolio volatility.

We also define the risk contribution:

$$RC = \sigma_i(\alpha) = \alpha' MCR \tag{B.3}$$

Which is vector composed of the seven $\sigma_i(\alpha)$, the risk contributions of each asset.

C Ridge Regression

The methodology for the Ridge regression portfolio is the same as the one in Ulloa et al. (2012). It consists in timing factor exposure by maximizing the factor portfolio information ratio, without deviating too much from the equally-weighted portfolio of factors. Therefore, the optimization problem to solve at each period is:

$$\max_{w} \left(\frac{\bar{R}_{factors}}{\sigma^2_{factors}} - \lambda \sum_{i=1}^{K} w_i^2 \right) \tag{C.1}$$

subject to:

$$\begin{cases} w_{min} \leq w_i \leq w_{max} \\ \sum_{i=1}^{K} w_i = 1 \end{cases} \tag{C.2}$$

where:

- w is the weight in each factor
- $\bar{R}_{factors} = w\bar{R}$ and $\bar{R}$ is the expected return vector of the factors
- $\sigma^2_{factors} = w\Sigma_{factors}w'$ is the variance of the portfolio composed of factors, $\Sigma_{factors}$ is the variance-covariance matrix of the factors
- λ is a non-negative constant that penalizes departures from the equally-weighted portfolio of factors.

D Parametric Weights

The idea of the parametric weights developed in the paper of Brandt and Santa-Clara (2006) is to parametrize the portfolio weights as functions of observable quantities (i.e. macroeconomic variables, firm's characteristics, etc.), which in our case are the major macro variables of the US market. Then we solve for the parameters that maximize the expected utility. Let z_t be the set of explanatory variables. Then, the parameterized portfolio weights can be determined as follows:

$$\alpha_t = \theta z_t \tag{D.1}$$

Let's consider a single-period mean-variance problem. Assume that the optimal portfolio weights are a linear function of K state variables z_t. Then, the investor's conditional optimization problem, with a risk aversion parameter λ is:

$$\max_{\{\theta\}} E_t[(\theta z_t)' r_{t+q}] - \frac{\lambda}{2} V_t[(\theta z_t)' r_{t+q}] \tag{D.2}$$

Let's define $\tilde{\alpha}_t = vec(\theta)$ and $\tilde{r}_{t+1} = z_t \otimes r_{t+1}$. Thus, we obtain:

$$\max_{\{\tilde{\alpha}\}} \mathbb{E}[\tilde{\alpha}' \tilde{r}_{t+1}] - \frac{\lambda}{2} \mathbb{V}[\tilde{\alpha}' \tilde{r}_{t+1}] \tag{D.3}$$

Since the same $\tilde{\alpha}$ maximizes the conditional expected utility at all dates t, it also maximizes the unconditional expected utility, which corresponds to the problem of finding the unconditional portfolio weights. Thus, the optimal solution is:

$$\tilde{\alpha} = \frac{1}{\lambda} \mathbb{E}[\tilde{r}_{t+1} \tilde{r}'_{t+1}]^{-1} \mathbb{E}[\tilde{r}_{t+1}] = \frac{1}{\lambda} \mathbb{E}[z_t z'_t \otimes r_{t+1} r'_{t+1}]' \, \mathbb{E}[z_t \otimes r_{t+1}] \tag{D.4}$$

The optimal solution can also be computed using sample averages (as we did in our strategy):

$$\tilde{\alpha} = \frac{1}{\lambda} \left[\sum_{t=1}^{T} z_t z'_t \otimes r_{t+1} r'_{t+1} \right]^{-1} \left[\sum_{t=1}^{T} z_t \otimes r_{t+1} \right] \tag{D.5}$$

E Fama-French Analysis

To provide a risk-adjusted performance analysis of our portfolios, we decided to regress the traditional CAPM, 3-factor regression and a multiple factors regression developed by Fama and French (2021b).

- ***CAPM Regression***

$$R_{p,t} - R_{f,t} = \alpha + \beta_1 * MktRf_t + \varepsilon \tag{E.1}$$

- ***3 Factors Fama-French Regression***

$$R_{p,t} - R_{f,t} = \alpha + \beta_1 * MktRf_t + \beta_2 * SMB_t + \beta_3 * HML_t + \varepsilon \tag{E.2}$$

- ***Multiple Factors Fama-French Regression***

$$\begin{aligned} R_{p,t} - R_{f,t} = \alpha + \beta_1 * MktRf_t + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * WML_t \\ + \beta_5 * RMW_t + \beta_6 * CMA_t + \beta_7 * VOL_t + \varepsilon \end{aligned} \tag{E.3}$$

To construct the factors of the above equations, we decided similarly as indicated in Kenneth R. French's website[4]. The details of their construction is as follow:

[4]Kenneth R. French - Data Library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/da

- ***MktRf:*** It it the excess return of the Swiss market, as a difference between the Swiss Performance Index (SPI) and the 1-Month London Interbank Offered Rate (LIBOR), based on Swiss Franc.
$$MktRf_t = R_{M,t} - R_{f,t} \tag{E.4}$$

- ***SMB (Small minus Big):*** It is the average return on the nine small stocks portfolios minus the average on the nine big stocks portfolios. The portfolios are constructed using the book-to-market ratio (B/M), operating profitability (OP) and investment (INV) of all assets available. The distinction between the small and big companies is made via their market share.

$$SMB_{B/M} = 0.5*(SmallValue+SmallGrowth)-0.5*(BigValue+BigGrowth) \tag{E.5}$$

$$SMB_{OP} = 0.5*(SmallRobust+SmallWeak)-0.5*(BigRobust+BigWeak) \tag{E.6}$$

$$\begin{aligned} SMB_{INV} = 0.5 * (&SmallConservative + SmallAggressive) \\ &-0.5 * (BigConservative + BigAggressive) \end{aligned} \tag{E.7}$$

Thus, the average return is:

$$SMB = \frac{SMB_{B/M} + SMB_{OP} + SMB_{INV}}{3} \tag{E.8}$$

- ***HML (High minus Low):*** It is the average return on the two value portfolios minus the average return on the two growth portfolios, based on the book-to-market ratio (B/M).

$$HML = 0.5*(SmallValue+BigValue)-0.5*(SmallGrowth+BigGrowth) \tag{E.9}$$

- ***RMW (Robust minus Weak):*** It is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, based on the operating profitability of the company (OP).

$$RMW = 0.5*(SmallRobust+BigRobust)-0.5*(SmallWeak+BigWeak) \tag{E.10}$$

- ***CMA (Conservative minus Aggressive):*** It is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, based on the investments of the company (INV).

$$\begin{aligned} CMA = 0.5 * (&SmallConservative + BigConservative) \\ &-0.5 * (SmallAggressive + BigAggressive) \end{aligned} \tag{E.11}$$

- ***WML (Winners minus Losers):*** It is the average return on the two winner portfolios minus the average return on the two loser portfolios, based on the past 12 months average returns.

$$WML = 0.5*(SmallHigh+BigHigh)-0.5*(SmallLow+BigLow) \tag{E.12}$$

- ***VOL (Low Vol minus High Vol):*** It is the average return on the two portfolios

`ta_library.html`. Accessed on 16 December 2021.

with the lowest volatility minus the average return on the two portfolios with the highest volatility, based on the past 12 months volatility.

$$VOL = 0.5 * (SmallLow + BigLow) - 0.5 * (SmallHigh + BigHigh) \tag{E.13}$$

F Value-at-Risk & Expected Shortfall

To compute the VaR and ES based on historical simulation. we computed historical loss and then ranked them in descending order (i.e. from the greatest loss to the smallest). Finally, quantile at 95 % of VaR and ES have been computed as follows (i.e. $\theta = 5\%$) :

$$VaR_{\theta}(L) = \tilde{L}_{[N(1-\theta)],N} \tag{F.1}$$

$$ES_{\theta}(L) = \frac{1}{[N(1-\theta)]} \cdot \sum_{i=1}^{[N(1-\theta)]} \tilde{L}_{i,N} \tag{F.2}$$

Therefore, VaR is the sample of loss above $N(1-\theta)$. Additionally, observing equation (F.2) one can notice that ES is the average amount of loss for the given percentage of cases (i.e. 5%).