Long/Short Global Macro Strategy with a Factor-based Model Allocation

FE-630 Final Project

Fangchi Wu

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Substract

This project aims 1) to build a factor-based model allocation namely a Long/Short Global Macro Strategy with a Target Beta and 2) to evaluate its sensitivity to variations of Beta and its sensitivity to the length of the estimators for covariance matrix and the expected returns under different market scenarios.

The whole project is divided into the following phases:

1. Establish the CAPM model to calculate the beta for each ETF in specific time, and the French-Fama three factor model to calculate the $beta^3$, size factor and value factor for each ETF in specific time.

2. Establish the trend estimator model based on French-Fama model and use trend following estimators for the expected returns. Get the covariance matrix based on French-Fama model.

3. Use the optimal solution of the quadratic optimization problem to allocate portfolio every week.

4. Establish the simulation tool to plot a cumulative return curve for a certain time.

5. Evaluate the portfolio's performance for different target beta during several historical periods : before the subprime (2008) crisis, during that crisis and after the crisis.

Key Words: French-Fama, Trend Estimator, Quadratic Optimization

1 Data Universe

ETFs

1. CurrencyShares Euro Trust (FXE)
2. iShares MSCI Japan Index (EWJ)
3. SPDR GOLD Trust (GLD)
4. Powershares NASDAQ-100 Trust (QQQ)
5. SPDR SP 500 (SPY)
6. iShares Lehman Short Treasury Bond (SHV)
7. PowerShares DB Agriculture Fund (DBA)
8. United States Oil Fund LP (USO)
9. SPDR SP Biotech (XBI)
10. iShares SP Latin America 40 Index (ILF)
11. iShares MSCI Pacific ex-Japan Index Fund (EPP)
12. SPDR DJ Euro Stoxx 50 (FEZ)

We will assume that our universe of investment is a set of ETFs large enough to represent the World global economy.

French-Fama History Data

Freely available for download from Ken French's website for the factors historical values (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french)

Data Combine

Original data of HML, SMB, Mkt-RF, RF in FF history data is percentage, so need to divided by 100.

from 2007-03-01 to 2020-06-20

Date	DBA	EPP	EWJ	FEZ	FXE	GLD	ILF	QQQ	SHV	SPY	USO	XBI	Mkt-RF	SMB	HML	RF
2007-01-12	0.079681	0.015441	0.012978	0.007280	0.001936	0.025400	0.015682	0.005102	0.000552	0.007597	0.006540	0.015164	0.0050	0.0021	-0.0028	0.00022
2007-01-16	-0.040590	0.004667	0.003558	-0.002594	0.000155	-0.003217	-0.005685	-0.000663	-0.000184	-0.001955	-0.028904	0.000409	0.0000	-0.0026	0.0006	0.00022
2007-01-17	-0.005000	0.002642	0.000000	-0.005946	0.000850	0.010812	0.003431	-0.008171	0.000551	0.000419	0.020305	0.001841	-0.0014	-0.0021	-0.0005	0.00022
2007-01-18	0.005025	0.001917	-0.000709	-0.003177	0.002626	-0.006066	-0.011516	-0.018481	-0.000091	-0.003356	-0.022388	-0.010617	-0.0048	-0.0107	0.0053	0.00022
2007-01-19	-0.005769	0.016820	0.007097	0.012376	0.000308	0.011886	0.019114	0.002042	-0.000184	0.001964	0.027759	0.000825	0.0033	0.0042	0.0007	0.00022

Figure 1: Data Universe

2 CAPM Model

The goal of establishing the CAPM Model is to get the beta of each ETF in specific time period, which will be required in later portfolio allocation to get the target beta.

$$\rho_i = r_f + \beta_i^M(\rho_M - r_f) + \alpha_i$$

where,

- ρ_i is the expected return of the stock,

- r_f is the risk-free return,

- ρ_M is market return,

- α_i is Excess returns.

In specific time period, it's easy to use linear regression to calculate the beta of each ETF or by formula directly:

$$\beta_i^m = \frac{cov(r_i, r_M)}{\sigma^2(r_M)}$$

The implementation code recorded in the appendix.

3 French-Fama Factor Model

$$\rho_i = r_f + \beta_i^3(\rho_M - r_f) + b_i^s\rho_{SMB} + b_i^v\rho_{HML} + \alpha_i$$

where,

- ρ_i is the expected return of the stock,

- r_f is the risk-free return,

- ρ_{SMB} is Size Factor,

- ρ_{HML} is Value Factor.

And estimate β_i^3, b_i^s and b_i^v by linear regression.

So we need to change the function to:

$(\rho_i - r_f) = \beta_i^3(\rho_M - r_f) + b_i^s\rho_{SMB} + b_i^v\rho_{HML} + \alpha_i$

Same to the CAPM model, the coefficients of FF model are directly estimated by the linear regression based on the time series data in specific time period.

4 Trend Following Estimator

The goal of trend following estimators is to get the expected ETFs' returns.

This model is established on FF-model, relying on the change trend of factors(SMB, HML, Mkt-RF). (Using Quadratic function regression)

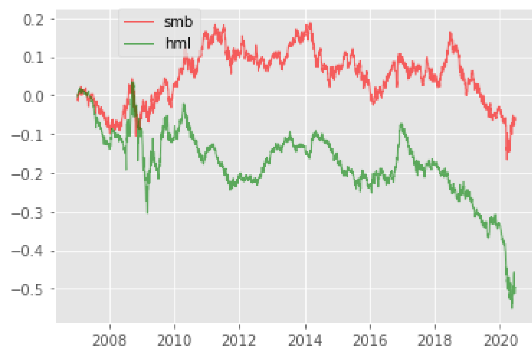


Figure 2: Cumulative change of SMB, HML

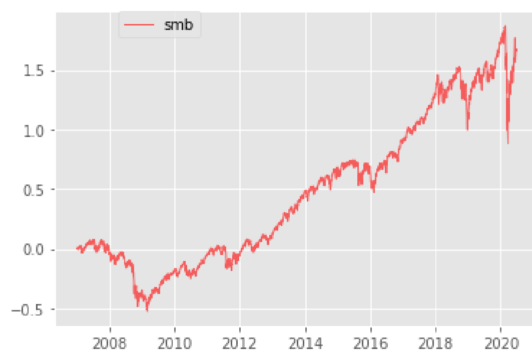


Figure 3: Cumulative change of Mkt-RF

According to the curves of SMB and HML, we can infer that the change of factor is trending over a period of time, so the method is estimating the next week mkt value, hml value and smb value based on the lookback period data, and using these factors to predict the next week ETF expected return according to established FF model:

$$\rho_i = r_f + \beta_i^3(\rho_M - r_f) + b_i^s \rho_{SMB} + b_i^v \rho_{HML} + \alpha_i$$

There are several steps to get the expected return of each ETF:

1. Establish the FF model for specific return lookback period (eg. 40 days), using the time series data as the input get the value of β_i^3, b_i^s, b_i^v, α_i.

2. Use Polynomial Regression to fit the 40 days cumulated SMB (or HML, Mkt) time series data, predict the next cumulated SMB (HML, Mkt) value (41 days), and then take the root 41 times get the predicted SMB (HML, Mkt) value (41th day).

3. Use the predicted SMB, predicted HML and predicted Mkt to predict the expected return based on the established FF model:

$$\rho_i = r_f + \beta_i^3(\rho_{Mpre} - r_f) + b_i^s \rho_{SMBpre} + b_i^v \rho_{HMLpre} + \alpha_i$$

which is the important input as one component of target function in later portfolio allocation.

Reason to use Polynomial regression to fit trend:

1. Linear Regression is too slow to reflect the value or trend change.

2. The daily and weekly time series data of SMB, HML and Mkt does not have significant auto-correlation to build time series model.

3. Polynomial regression is not bad to reflect the change in the overall trend of the value during not too long time horizon.

5 Theoretical Derivation of Σ

According to FF-model: $\rho_i = r_f + \beta_i^3(\rho_M - r_f) + b_i^s \rho_{SMB} + b_i^v \rho_{HML} + \alpha_i$

Thus, $cov(\rho_i, \rho_j)$

$= \beta_i^3 \beta_j^3 Var(\rho_M - r_f) + b_i^s b_j^s Var(\rho_{SMB}) + b_i^v b_j^v Var(\rho_{HML})$

$+(\beta_i^3 b_j^s + \beta_j^3 b_i^s) cov(\rho_M - r_f, \rho_{SMB}) + (\beta_i^3 b_j^v + \beta_j^3 b_i^v) cov(\rho_M - r_f, \rho_{HML})$

$+(b_i^s b_j^v + b_j^s b_i^v) cov(\rho_{SMB}, \rho_{HML})$

Based on the this formula, we can calculate the covariance between each pair of ETFs, and get the matrix.

The implementation code recorded in the appendix.

6 Portfolio Allocation

The allocation of portfolio satisfy following conditions:

$$\begin{cases} \begin{array}{rc} max & \rho^T\omega - \lambda(\omega-\omega_p)^T\Sigma(\omega-\omega_p), \\ subject\ \ to & \sum_{i=1}^n \beta_i^m\omega_i = \beta_T^m, \\ & \sum_{i=1}^n \omega_i = 1, \\ & -2 \le \omega_i \le 2 \end{array} \end{cases}$$

Define $S_{60}^{90}(0.5)$ - say using 60 days for estimation of covariance, 90 days for estimation of Expected Returns and a target $\beta = 0.5$

- The portfolios will be rebalanced once a week.

- Divide the overall analysis period into 3 sub-periods: before, during and after the subprime crisis.

The formula showed before is not easily implemented. It needs to be transformed to another expression form:

let $\omega_c = \omega - \omega_p$

Then, the optimization problem will be transformed to:

$$\begin{cases} \begin{array}{rc} max & \rho^T\omega_p + \rho^T\omega_c - \lambda\omega_c^T\Sigma\omega_c, \\ subject\ \ to & \sum_{i=1}^n \beta_i^m(\omega_{ci}+\omega_{pci}) = \beta_T^m, \\ & \sum_{i=1}^n \omega_{ci}, \\ & -2-\omega_{pci} \le \omega_{ci} \le 2-\omega_{pci} \end{array} \end{cases}$$

Because the $\rho^T\omega_p$ is a constant value, so the target function is same to

$$min\ \ \frac{1}{2}\omega_c^T(2\lambda\Sigma)\omega_c - \rho^T\omega_c$$

The implementation code recorded in the appendix.

7 Simulation and Performance

7.1 Before the Crisis (2007-04-01 to 2007-12-31)

7.1.1 Influence of return lookback period

RLP	SPY	10	20	40	60	80	120	180
CumulatedR	4.5%	69.6%	30.7%	52.8%	67.2%	75.8%	57.7%	46.7%
MeanR(Anual)	7.2%	74.1%	40.6%	61.1%	72.8%	79.0%	65.0%	54.3%
Max10DD	7.6%	13.6%	15.3%	16.4%	15.6%	14.6%	18.7%	15.0%
Volatility	16.7%	29.9%	32.7%	32.4%	31.8%	30.3%	31.4%	27.3%
SharpeRatio	0.166	2.33	1.11	1.75	2.15	2.46	1.93	1.83
skewness	-0.30	-0.18	-0.194	-0.25	-0.38	-0.56	-0.76	-0.89
kurtosis	0.796	1.00	1.61	1.93	2.28	2.38	4.56	7.48
VaR	-2.3%	-2.0%	-2.8%	-3.2%	-2.5%	-2.8%	-3.3%	-1.8%

- Assume that covariance lookback period is 90, $\beta^T = 1$.

7.1.2 Influence of co-variance lookback period

Cov Lookback Period	SPY	30	60	90	120	180
CumulatedR	4.5%	67.3%	72.3%	67.2%	72.9%	79.7%
MeanR(Anual)	7.2%	73.0%	76.7%	72.8%	77.3%	82.3%
Max10DD	7.6%	15.7%	15.8%	15.6%	15.6%	17.4%
Volatility	16.7%	32.1%	31.6%	31.8%	31.8%	31.7%
SharpeRatio	0.166	2.14	2.29	2.15	2.29	2.46
skewness	-0.30	-0.38	-0.40	-0.38	-0.38	-0.39
kurtosis	0.796	1.77	2.10	2.28	2.40	2.38
VaR	-2.3%	-3.4%	-3.2%	-2.5%	-2.2%	-2.2%

- Assume that return lookback period is 60, $\beta^T = 1$.

7.1.3 Influence of target-beta

Target beta	SPY	-1	-0.5	0	0.5	1	1.5	2
CumulatedR	4.5%	24.4%	38.1%	41.9%	58.5%	72.3%	66.8%	63.3%
MeanR(Anual)	7.2%	33.3%	46.5%	50.0%	64.9%	76.7%	73.9%	73.2%
Max10DD	7.6%	19.7%	18.3%	15.8%	15.4%	15.8%	16.8%	20.9%
Volatility	16.7%	30.2%	28.0%	28.0%	28.8%	31.6%	36.0%	41.4%
SharpeRatio	0.166	0.96	1.50	1.63	2.10	2.29	1.93	1.66
skewness	-0.30	-0.46	-0.35	-0.43	-0.39	-0.40	-0.29	-0.30
kurtosis	0.796	0.571	0.563	1.57	2.36	2.10	1.20	0.735
VaR	-2.3%	-2.6%	-3.3%	-2.7%	-2.8%	-3.2%	-3.9%	-4.3%

-Assume that return lookback period is 60, covariance lookback period is 60.

7.2 During the Crisis (2008-01-01 to 2008-12-31)

7.2.1 Influence of return lookback period

RLP	SPY	10	20	40	60	80	120	180
CumulatedR	-36.8%	-11.3%	-8.00%	2.90%	2.2%	30.4%	19.7%	-30.1%
MeanR(Anual)	-36.9%	7.94%	9.50%	22.7%	19.5%	41.1%	32.3%	-17.4%
Max10DD	33.3%	40.7%	57.2%	48.9%	45.1%	45.3%	45.4%	46.0%
Volatility	41.0%	63.0%	59.4%	63.2%	58.8%	54.5%	54.0%	60.2%
SharpeRatio	-0.93	0.10	0.13	0.34	0.30	0.72	0.57	-0.31
skewness	0.57	0.42	-0.02	0.19	0.19	0.14	0.17	-0.31
kurtosis	6.36	6.14	5.31	5.23	3.09	1.30	0.90	1.36
VaR	-3.2%	-6.0%	-5.0%	-5.8%	-6.4%	-5.0%	-5.2%	-6.2%

- Assume that covariance lookback period is 90, $\beta^T = 1$.

7.2.2 Influence of co-variance lookback period

Cov Lookback Period	SPY	30	60	90	120	180
CumulatedR	-36.8%	-10.6%	-8.9%	2.2%	17.3%	0.8%
MeanR(Anual)	-36.9%	5.7%	8.4%	19.5%	32.7%	18.6%
Max10DD	33.3%	44.4%	44.7%	45.1%	45.5%	46.0%
Volatility	41.0%	57.9%	59.4%	58.8%	58.3%	59.8%
SharpeRatio	-0.93	0.07	0.11	0.30	0.53	0.29
skewness	0.57	0.07	0.20	0.19	0.28	0.16
kurtosis	6.36	2.17	2.57	3.09	3.48	3.09
VaR	-3.2%	-5.9%	-5.1%	-6.4%	-6.3%	-5.9%

- Assume that

7.2.3 Influence of target-beta

Target beta	SPY	-1	-0.5	0	0.5	1	1.5	2
CumulatedR	-36.8%	41.9%	88.7%	75.4%	40.6%	2.2%	-22.6%	-38.9%
MeanR(Anual)	-36.9%	66.8%	76.3%	67.7%	46.8%	19.5%	-5.6%	-13.8%
Max10DD	33.3%	30.6%	28.1%	35.6%	40.1%	45.1%	43.1%	51.4%
Volatility	41.0%	60.7%	51.9%	49.4%	51.3%	58.8%	70.7%	83.6%
SharpeRatio	-0.93	1.08	1.44	1.34	0.88	0.30	-0.10	-0.18
skewness	0.57	-0.41	-0.17	0.10	0.16	0.19	0.27	0.37
kurtosis	6.36	1.78	1.29	0.983	1.35	3.09	4.18	5.42
VaR	-3.2%	-6.9%	-4.0%	-5.9%	-6.0%	-6.4%	-7.6%	-9.2%

7.3 After the Crisis (2009-01-01 to 2020-06-19)

7.3.1 Influence of return lookback period

RLP	SPY	10	20	40	60	80	120	180
CumulatedR	331.8%	165.7%	265.4%	724.8%	980.5%	302.5%	150.9%	429.9%
MeanR(Anual)	14.3%	13.4%	16.3%	23.5%	25.9%	17.7%	13.3%	21.0%
Max10DD	30.5%	54.3%	64.2%	69.1%	69.1%	69.1%	68.8%	69.3%
Volatility	18.2%	31.5%	31.9%	32.5%	32.5	33.5%	32.8%	33.6%
SharpeRatio	0.76	0.41	0.50	0.71	0.78	0.51	0.39	0.61
skewness	-0.43	0.06	0.27	0.33	0.25	0.16	0.28	0.46
kurtosis	11.3	3.43	5.40	4.85	5.28	4.43	4.39	5.06
VaR	-1.8%	-3.1%	-3.2%	-3.2%	-3.0%	-3.2%	-3.2%	-3.2%

- Assume that covariance lookback period is 90, $\beta^T = 1$.

7.3.2 Influence of co-variance lookback period

Cov Lookback Period	SPY	30	60	90	120	180
CumulatedR	331.8 %	990.4%	1369.4%	980.5%	988.3%	733.1%
MeanR(Anual)	14.3%	26.0%	28.7%	25.9%	25.9%	23.5%
Max10DD	30.5%	69.0%	69.1%	69.1%	69.1%	67.4%
Volatility	18.2%	32.6%	32.8%	32.5%	32.3%	32.2%
SharpeRatio	0.76	0.78	0.86	0.78	0.79	0.72
skewness	-0.43	0.32	0.26	0.25	0.26	0.22
kurtosis	11.3	4.73	4.82	5.28	5.34	4.56
VaR	-1.8%	-3.1%	-3.3%	-3.0%	-3.0%	-3.2%

- Assume that return lookback period is 60, $\beta^T = 1$.

7.3.3 Influence of target-beta

Target beta	SPY	-1	-0.5	0	0.5	1	1.5	2
CumulatedR	331.8%	-64.5%	51.4%	233.0%	649.3%	1369.4%	1927.5%	1531.3%
MeanR(Anual)	14.3%	-3.4%	8.0%	14.3%	21.8%	28.7%	33.3%	34.0%
Max10DD	30.5%	66.6%	51.6%	51.3%	64.0%	69.1%	68.6%	89.5%
Volatility	18.2%	33.2%	29.7%	28.0%	29.5%	32.8%	37.9%	44.1%
SharpeRatio	0.76	-0.12	0.25	0.49	0.72	0.86	0.87	0.76
skewness	-0.43	0.66	0.44	0.26	0.23	0.26	0.13	-0.14
kurtosis	11.3	9.88	7.62	4.13	3.73	4.82	6.41	8.24
VaR	-1.8%	-3.0%	-2.7%	-2.7%	-2.8%	-3.3%	-3.6%	-4.0%

-Assume that return lookback period is 60, covariance lookback period is 60

7.4 Whole Period (2007-04-01 to 2020-06-19)

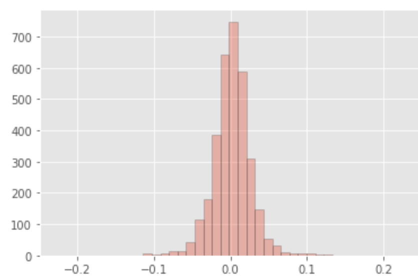
I will choose 5 strategies (different beta) over the whole period and do comparison. In addition, I added distribution of daily returns and cumulated profit.

1. $S_{60}^{60}(-1)$ 2. $S_{60}^{60}(0)$ 3. $S_{60}^{60}(0.5)$ 4. $S_{60}^{60}(1)$ 5. $S_{60}^{60}(1.5)$

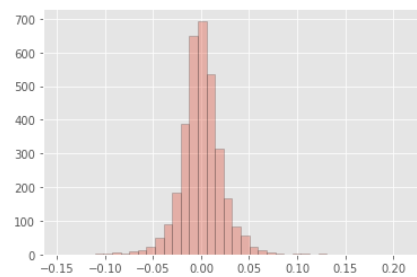
7.4.1 Indicators

Structure	SPY	$S_{60}^{60}(-1)$	$S_{60}^{60}(0)$	$S_{60}^{60}(0.5)$	$S_{60}^{60}(1)$	$S_{60}^{60}(1.5)$
PnL	185.1$	-39.2$	902.1$	3581.1$	4549.4$	6184.6$
CumulatedR	185.1%	-39.2%	902.1%	3581.1%	4549.4%	6184.6%
MeanR(Anual)	10.0%	2.4%	21.8%	32.1%	35.2%	39.7%
Max10DD	33.3%	53.2%	52.8%	64.7%	68.9%	73.8%
Volatility	20.8%	35.3%	30.0%	31.6%	35.7%	41.3%
SharpeRatio	0.44	0.05	0.70	0.99	0.97	0.94
skewness	-0.03	0.31	0.28	0.21	0.08	0.06
kurtosis	15.1	6.86	4.05	5.11	6.77	8.98
VaR	-1.9%	-3.5%	-2.7%	-2.9%	-3.4%	-3.9%

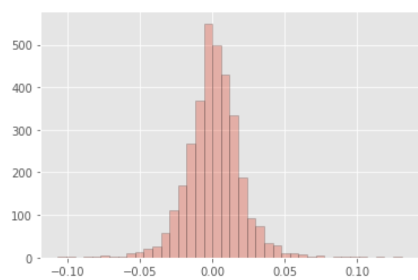
7.4.2 Return Distribution (daily)



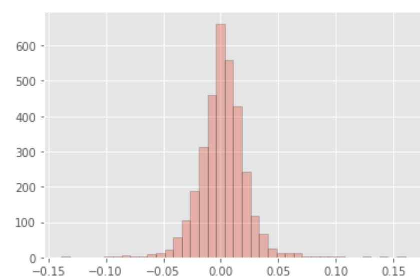
(a) SPY Daily Return Distribution



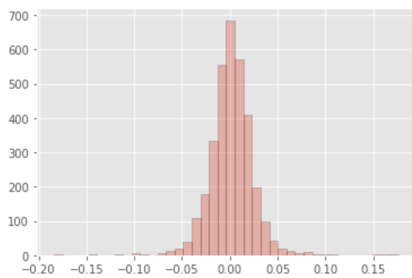
(b) $S_{60}^{60}(-1)$ Daily Return Distribution



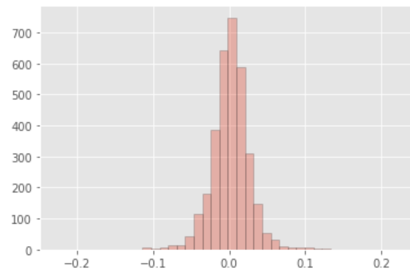
(c) $S_{60}^{60}(0)$ Daily Return Distribution



(d) $S_{60}^{60}(0.5)$ Daily Return Distribution

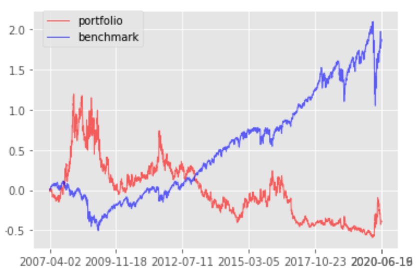


(e) $S_{60}^{60}(1)$ Daily Return Distribution

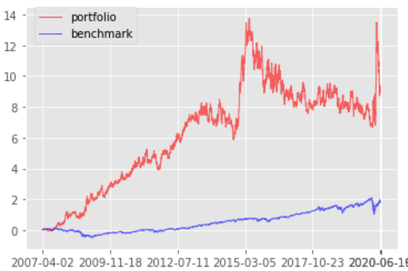


(f) $S_{60}^{60}(1.5)$ Daily Return Distribution

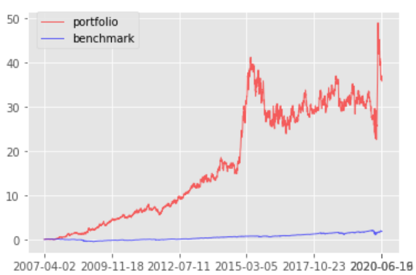
7.4.3 Cumulated Return



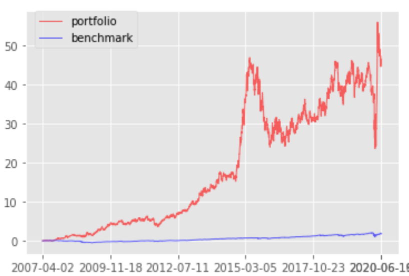
(g) $S_{60}^{60}(-1)$ Daily Return Distribution



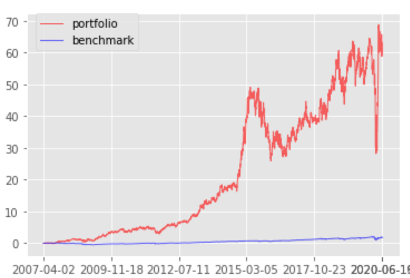
(h) $S_{60}^{60}(0)$ Daily Return Distribution



(i) $S_{60}^{60}(0.5)$ Daily Return Distribution



(j) $S_{60}^{60}(1)$ Daily Return Distribution



(k) $S_{60}^{60}(1.5)$ Daily Return Distribution

8 Conclusion

1. For return lookback period, the interval from 40 days to 80 days is best time horizon for estimator. Too short or too long time horizon result in under-fitting or over-fitting. This conclusion holds true in different times of crisis.

2. For co-variance lookback period, the interval from 60 days to 120 days is best time horizon for the cummulated return. However, the change of CLP doesn't result in significant change in Volatility.

3. With the change of Target-beta, the performance of portfolio has the significant difference. During Crisis, low or negative beta is likely to have better performance, but when the period is before crisis or after crisis, positive and high beta is likely to have better performance, which make sense in real world market.

4. The volatility of portfolio varies with the absolute size of target beta. When I set the target beta 0, the portfolio is likely to have the smallest volatility (except the SPY).

5. In conclusion, the best strategy is using 60 days return lookback period, 60 days covariance lookback period, keeping the target beta = 1.5 or 1 in a non-financial-crisis period and keeping target beta = -0.5 or 0 in a financial-crisis period.

9 Future Work

1. Consider the monthly mean value of HML, SMB and Mkt, and explore the possibility of establishing time series model to predict the expected return.

2. Expand the universe of assets, including single stocks, options and T-bills because the universe of this project is not good enough to reduce the portfolio volatility.

3. Add a detector to the strategy to help identify the arrival of large or small financial crises and change the portfolio structure automatically.

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