Portfolio of stocks with sensitivity to oil prices

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Oil investment has been very profitable at some specific points in time. It also exhibits interesting diversification, contracyclical as well as seasonality purposes. Therefore, it aims to find seat in some well diversified strategies such as all-weather strategies.
However, oil market has been particularly bearish and volatile over the last decade. Today, we believe that there are rooms for the oil prices to be substantially higher. In this context, a portfolio of stocks with sensitivity to oil prices could be the good investment vehicle to profit from a potential upward trend on the oil market. Stocks, which are fundamentally different from commodities, also exhibit interesting hedging properties against strong adverse movement that have characterized oil market over time. Hence, we designed and criticised several equity based strategies which could potentially be used to benefit from the oil market.

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1 Introduction

Gordon and Rouwenhorst (2006), found that during the 2nd half of the 20th century, commodities as an asset class experienced the same returns and Sharpe ratio as equity. However, commodities tend to exhibit low correlation with other major asset classes which makes it a great diversification instrument. Another research also discovered that commodities could also serve to hedge against inflation. All these findings suggest that it is interesting for institutions as well as individual investors to have commodities in their portfolio.

Energy commodities have recently gone through very tumultuous time. Since the Great Recession of 2008-2009, they have experienced very high volatility and low returns. During the last decades, the WTI crude oil fell from a high level of 140 in 2009 to a 40 level with valley beyond zero because of supply and demand imbalances. All this, makes it dangerous for investors to invest in this market and potentially profit from the low actual level of prices.

A study by Brown & al (2007), suggests that "oil prices and energy public equity typically exhibit large, positive correlation with each other". In addition, they also found a convex relationship between rolling 3 years returns of energy equity and rolling 3 years returns of WTI. This suggest that equities better capture upside potential while better edging downside risk. Hence, a portfolio of stocks seems to be a good way to profit from a rise of the oil prices while hedging downside risk.

In our research to design an optimal portfolio, we have faced two challenges. First, we had to find an appropriate way to capture the stock' sensitivity to oil prices. Relying on Patterson & al (2017), we have used an OLS regression to find the coefficient of regression of the oil (in % changes) on stock (in % changes) in order to sort stocks from the most sensitive to the "most" inversely sensitive. Beside, in order to avoid over-fitting and "Survival bias". Then, we had to think of an ideal weighting scheme. We have believed that oil strategies were risky and volatile enough to consider the problem from a risk manager point of view. Hence, our solutions mainly focus on risk adjusted returns solutions.

2 Data

First, we selected the 1'000 most liquid stocks (according to the exchanged volume in USD) among the Nasdaq, the NYSE and the AmEx.

These stocks are initially classified in six categories:

- N: Normal (manufacturing)
- M: Mining
- U: Utility
- T: Transportation
- B: Bank
- I: Insurance

Gogineni (2009) has highlighted the sensitivity of each sector to oil market. According to his findings, we preselect up to 500 stocks in the aforementioned categories:

- In "Normal" (which includes manufacture products),
- in "Mining" (which includes all the activities for mining),
- in "Transportation" (which includes the transportation sector).

Then, our strategies are designed to pick 50 stocks (depending on the strategies) in the long list of preselected stocks.

Our benchmark was the SPY, which is an etf that tracks the S&P500 index. This is a stock market index which includes the performances of the 500 largest US equities.

The explanatory variables we used consist of the WTI Crude Oil Barrel, because we are picking US stocks. Instead we used the WTI Oil Barrel to measure its non linear relation with our strategy. As we want to only profit from the upside movements.

The GDP (Gross Domestic Product) of the USA and the CPI (Consumer Price Index) will both be used as explanatory variables.

We have been particularly careful to always be out-of-sample when computing different coefficients of regressions. In order not to have a stale universe, we used a rolling window which takes into account delistings and new listings. We have been able to do these operations on QuantConnect.com, which is an algorithmic trading platform that allows to code (on Python or C++) your trading algorithm and realize your backtests in the most realistic way.

Here the principal difficulties were to set the moment of the recomputation of the universe, based on the sensibility coefficient of the stocks to the WTI crude oil. As we were dealing with almost 500 assets each time we changed the universe. The operations were very computationally expensive, even though we used a server with 12 GB Ram and 4 CPU cores. This is why we decided to update the stock universe we are using on a yearly basis (by taking into account delistings though).

We are using monthly data, except for the GDP which consists of quarterly data. Finally, the data sample ranges from the first of January 2000 to the 17th of December 2020

3 Methodology

In this section, we will explain some important methods used in order to perform our strategies. However, as we have considered four different strategies (two long only and two long-short) we will only go through key concepts used in order to design our strategies:
- Sensitivity to oil prices: the linear regression used to find the coefficient β of the oil (as a % changes)
- Weighting schemes: Equally weighted, risk parity and minimum variance
- Long and short signals

For the long strategies, we have applied a constraint so that the model is not able to short. The allocated weights must be at least 1% and at most 10%. In addition for the Long Short Strategy we have set a maximum in absolute value of position from 0% to 10%,an objective of 0 exposure (1 for the Long strategy) and a short exposure of -1 along with a long exposure of 1.

Additionally, in order to rebalance monthly the positions for the minimum variance and risk parity weighting schemes, we use the previous 60 months of monthly data.

3.1 Linear regression - OLS approach

In order to filter stocks as a function of oil, we have measured the impact of oil prices on the latter. For this purpose, we have used the regression inspired by Patterson & al (2017), however we have slightly modified it.

The regression they used in their paper is the following:

$$ln(ETF_{i,j}) = \beta_0 + \beta_1 ln(Oil_{i,j}) + \beta_2 GDP_j + \beta_3 CPI_j + \epsilon$$

The regression that we used for our strategy is the following:

$$R_i = \beta_0 + \beta_1 Oil + \beta_2 GDP + \beta_3 CPI + \epsilon$$

Where R_i is the log stock return , Oil is the log return in oil prices, GDP is the log return in GDP (Growth Domestic Product) and finally CPI (Consumer Price Index) is the log return of the CPI in the United States with i being the index for stocks and j the index for time.
We have performed a linear regression with stock returns as the explained variables and we have used the percent change in oil prices , GDP as well as CPI as explanatory variables.
This regression allowed us to filter the stocks and sort them by sensitivity to the change in oil prices. We took an approach where the universe of 50 stocks is rebalanced one time per year.However weights are rebalanced each month following the weighting scheme.

3.2 Equal weighting

The equal weighting is a natural and very intuitive choice which consists to allocate the same amount to each assets.

$$\omega_i = \omega_j = \frac{1}{N}$$

Where ω_i and ω_j are respectively the weight allocated to asset i and asset j and N is the total number of assets.
It is a well-known heuristic approach. It can generate value even if the simple intuition behind is not very developed.

3.3 Minimum variance

Minimum variance is one of the most famous investment solution of the last decade. This method manages risk and volatility portfolio efficiently. It aims to solve the following equation which consists to minimize the resulting variance of the portfolio:

$$\omega^* = arg\, min\, \frac{1}{2}\omega' \Sigma \omega$$

$$u.c.\ 1'\omega = 1$$

Analytical solution for the long-only portfolio is:

$$\omega^*_{i,LO} = \frac{\sigma^2_{MV}}{\tilde{\sigma}^2_i}(1 - \frac{\beta_i}{\beta^*_{LO}})$$

for $\beta_i < \beta^*_{LO}$, else $\omega^*_i = 0$. And,

$$\beta^*_{LO} = \frac{\frac{1}{\sigma^2_M} + \Sigma_{\beta_i < \beta^*_{LO}} \frac{\beta^2_i}{\tilde{\sigma}^2_i}}{\Sigma_{\beta_i < \beta^*_{LO}} \frac{\beta^2_i}{\tilde{\sigma}^2_i}}$$

Analytical solution for the long-short portfolio with unconstrained weights:

$$\omega^*_i = \frac{\sigma^2_{MV}}{\tilde{\sigma}^2_i} (1 - \frac{\beta_i}{\beta^*})$$

And,

$$\beta^* = \frac{\frac{1}{\sigma^2_M} + \Sigma \frac{\beta^2_i}{\tilde{\sigma}^2_i}}{\Sigma \frac{\beta_i}{\tilde{\sigma}^2_i}}$$

3.4 Risk parity

We defined the risk of each asset (and each asset class) in the strategy by the marginal contribution of risk (MCR). Indeed, we want to know how each asset class contributes to the overall risk of the portfolio. Given this, we can show the following identity for the sum of the risk for an asset class:

$$\sum_j \frac{w^j_t MCR^j_t}{\sigma^p_t}$$

Where, the MCR for each asset is $MCR^i_t = \frac{\partial \sigma^p_t}{\partial w^i_t} = \frac{\sum_{\nu=1}^{N_t} w^i_t \sigma^{\nu i}_t}{\sigma^p_t}$.

In order to distribute equally the risk, we need to meet the following equation:

$$w^{i,Net,RP}_t \cdot MCR^i_t = constant, \forall i$$

The $w^{i,Net,RP}_t$ are derived from the risk-parity strategy. Indeed, we can obtain these weights by the following optimization, which is a long-only risk-parity strategy:

$$Maximize : \sum_{i=1}^{N_t} log(w^i_t)$$

$$Subject\, to : \sqrt{w'_t \cdot \sum_t \cdot w_t} \leqslant \sigma_{TGT}$$

We can see that this optimization is subject to a constraint that will allow us to meet the equation that we wanted to meet above. As we also want to be allowed to short positions in our strategy we will consider an approach taken by Baltas (2015). In fact, we cannot take the log of the negative weights. We need to transform the optimization as follow:

$$Maximize : \sum_{i=1}^{N_t} log(\mid w_t^i \mid)$$

$$Subject\, to : \sqrt{w_t' \cdot \sum_t \cdot w_t} \leqslant \sigma_{TGT}$$

Finally, this leads us to the risk-parity trend-following strategy:

$$r_{t,t+1} = \frac{\sigma_{TGT}}{\sigma_t^{TF}} \cdot \sum_{i=1}^{N_t} w_t^{i,Net,RP} \cdot r_{t,t+1}^i$$

Through, this process, we know that the risk will be fairly distributed with each asset contributing to $\frac{1}{N}$ of the total contribution.

3.5 Spearman's Correlation Coefficient

Spearman's correlation coefficient is a measure of the strength of a monotonic relationship between 2 variables (returns in our case). This includes non linear relationships. The Spearman's correlation coefficient is more robust against outliers rather than the Pearson correlation.

A simple formula to compute the spearman's correlation coefficient is :

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

With the difference between the two ranks of each observation, n is the number of observations:

$$d_i = \mathrm{rg}(X_i) - \mathrm{rg}(Y_i)$$

where rg is a ranking function in our case.

We wanted to use this coefficient in order to evaluate the Information Coefficient (IC) of our portfolios as we aim to inherit from the upward movement of the WTI crude oil.

3.6 Generalized Pareto distribution and VaR

The standard cumulative distribution function (cdf) of the GPD is defined by

$$F_{(\mu,\sigma,\xi)}(x) = \begin{cases} 1 - \left(1 + \frac{\xi(x-\mu)}{\sigma}\right)^{-1/\xi} & \text{for } \xi \neq 0, \\ 1 - \exp\left(-\frac{x-\mu}{\sigma}\right) & \text{for } \xi = 0, \end{cases}$$

with location μ, the scale σ and ξ the shape parameter.

Using the Standardized input, we retrieve our original data from :

$$X_t = \mu_t + \sigma_t Z_t$$

And finally, using a Garch model in order to find (the same approach is used with the Conditional Normal VaR and Conditional t-student VaR) :

$$\begin{aligned} F_{X_{t+1|G_t}}(x) &= P(\sigma_{t+1} Z_{t+1} + \mu_{t+1} \leq x | G_t) \\ &= F_Z(\frac{x - \mu_{t+1}}{\sigma_{t+1}}) \end{aligned}$$

in which we develop in order to get the respectively Conditional VaR and CVaR :

$$x_q^t = \mu_{t+1} + \sigma_{t+1} z_q$$

$$S_q^t = \mu_{t+1} + \sigma_{t+1} E[Z|Z > z_q]$$

3.7 Normal Distribution and VaR

In order to calculate the VaR for the normal distribution, we suppose $L \sim N(\mu, \sigma^2)$. Then the VaR is computed as the following:

$$VaR_\alpha = \mu_{t+1} + \sigma_{t+1} \Phi^{-1}(\alpha)$$

where $\phi(.)$ is the standard normal CDF. This allows us then to calculate the expected shortfall with a normal distribution:

$$ES_\alpha = \mu_{t+1} + \sigma_{t+1} \frac{\phi(\Phi^{-1}(\alpha))}{1 - \alpha}$$

with $\phi(.)$ being the PDF of the standard normal distribution.

3.8 Student Distribution and VaR

As for the VaR using a Normal distribution, we assume $L \sim t(v, \mu, \sigma^2)$. $\frac{L-\mu}{\sigma}$ would have a standard t distribution with v>2 degrees of freedom. The VaR is calculated in the following manner:

$$VaR_\alpha = \mu_{t+1} + \sigma_{t+1} t_v^{-1}(\alpha)$$

where t_v is the CDF for the t distribution with v degrees of freedom. If we let $L \sim t(v, \mu, \sigma^2)$ such that $\tilde{L} := \frac{L-\mu}{\sigma}$ has a standard t distribution with v>2 degrees of freedom. We can then see that $ES_\alpha(L) = \mu + \sigma ES_\alpha(\tilde{L})$. This allows us to obtain the following:

$$ES_\alpha(\tilde{L}) = \frac{g_v(t_v^{-1}(\alpha))}{1-\alpha}(\frac{v + (t_v^{-1}(\alpha))^2}{v-1})$$

with $t_v(.)$ and $g_v(.)$ being the CDF and PDF of a standard t distribution with v degrees of freedom

3.9 Introducing fees

Frequently rebalancing the portfolio's weights leads to severe transaction costs that will negatively impact the overall performance of the strategies. Therefore, to obtain a more realistic approach, we set a real-world framework by implementing some fees that differ from long positions to short ones. Therefore, we have considered the fees charged to institutional investors by "Interactive Broker". We have implemented these costs in the following way:

- **Institutional & long position** : 0.005 USD / Share
- **Institutional & short position** : 0.005 USD/ Share + 0.75%(Close to 0.624 %,which is the average Risk Free Rate since 2000 in the United States)

4 Empirical Analysis

We chose to test and compare three main strategies which are :

1. Long Only / High Beta
2. Long Only / High Beta & Low Beta
3. Long Short / High & Low Beta

Additionally, we have chosen to compare three different ways of attributing weights. They are the following:

1. Equally Weighted (EW)
2. Risk Parity (RP)
3. Minimum Variance (MV)

4.1 Long Only / High Beta

Our first strategy is designed to take long positions on high beta stocks. In other words, it consists to buy stocks with the highest sensitivity to oil prices.

While looking at the annualized return we notice that the Minimum Variance strategy falls short of the two others strategies with respect to returns. With annual returns of, respectively, 8.9% and 9.0% for the EW and the RP against 7.1% for the MV. Of course, certain allocation scheme also exhibit better risk management features. For instance, the MV allocation has a lower maximum drawdown at -54.8%, while the EW and the RP were respectively at a drawdown of -58.7% and -60.1%. When we look at the Sharpe Ratios of the three strategies (EW: 0.44, RP: 0.45, MV: 0.41) there is no doubt that the Risk Parity better fits investor's needs. From a risk management point of view as well as an overall performance point of view, it achieves better performances in both. All the strategies have 100% PSR ratios, which means that they all tend to outperform the SPY index by far when we take into consideration the skewness and the kurtosis of the returns.

We could also notice that the RP portfolio exhibits a tail ratio higher than 1.0 (1.1), which indicates that there are more extreme positive returns than extreme negative returns at a threshold of 5% for each tails, a near zero skewness (-0.27), and one of the highest omega ratio with the EW portfolio (1.09). This last metric is computed by dividing the probability of positive returns by the probability of negative ones. The strategy also exhibits the fastest recovery rate from all the strategy with a maximum drawdown duration of 668 days (EW : 818 days, MV : 848 days). In addition, the Sortino ratio of the RP portfolio is the highest. It implies that the standard deviation of the strategy during drawdowns are more mitigated when adjusted to returns.

However, the RP portfolio took almost two years to recover from the 2008 global Financial Crisis and has a small Information ratio (EW: 0.169, RP: 0.165, MV: -0.0749), which denotes low returns beyond the returns of a benchmark. The RP portfolio also has a high volatility compare to the MV portfolio even if it exhibits the highest stability coefficient (R^2). This latter indicates that the cumulative log return tends to be linear rather than flattening across time. What we can extrapolate from the stability coefficient is that between all the strategies, the RP portfolio has the most exponential growth.

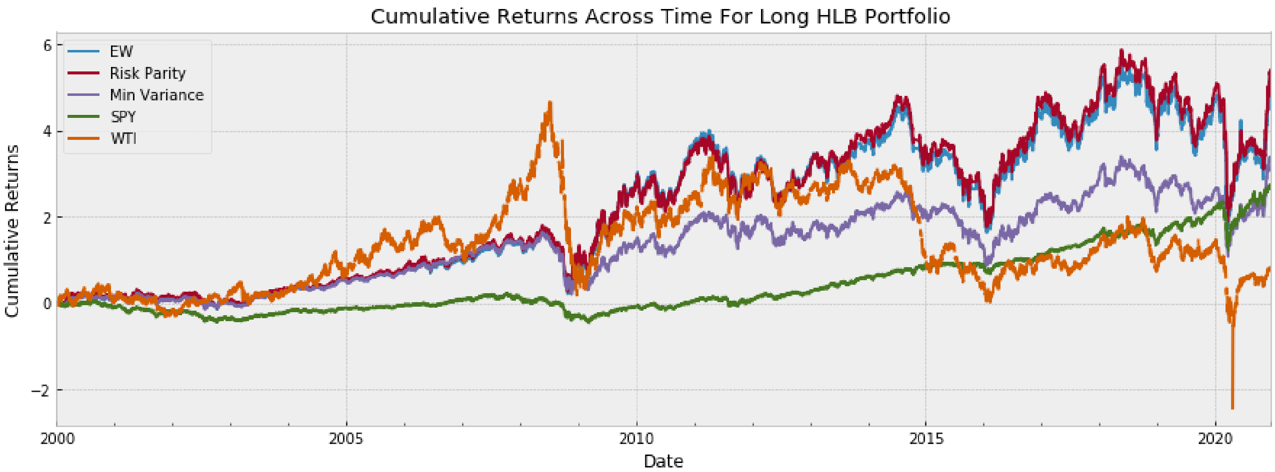

Figure 4.1: Cumulative returns of the Long Only / High Beta strategies

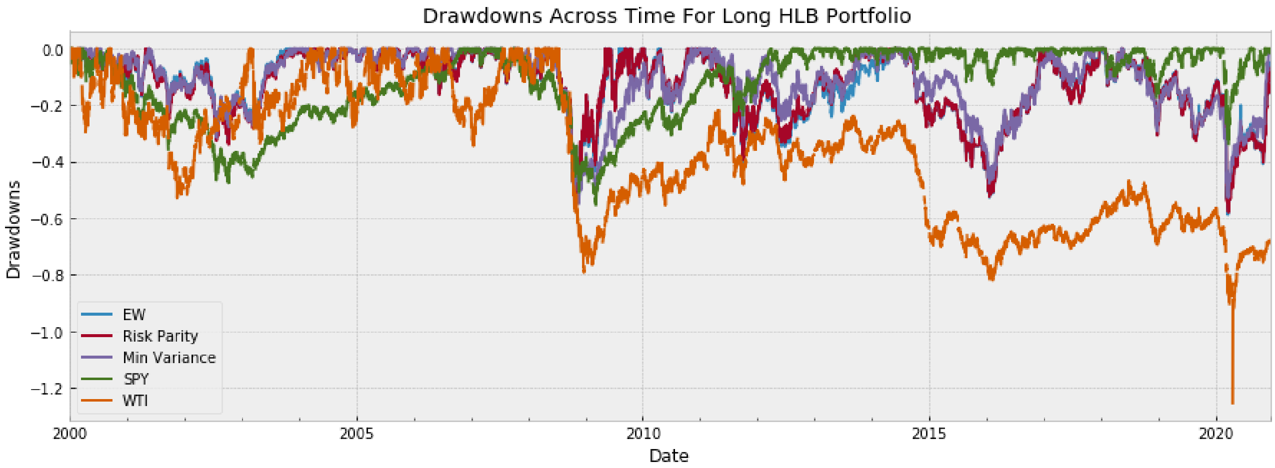

Figure 4.2: Drawdowns of the Long Only / High Beta strategies

4.2 Long Only / High Beta & Low Beta

For our second long only strategy, our will was to edge long positions in stocks with sensitivity to oil prices. Hence, this strategy is designed to also take long positions in stocks which are inversely sensitive to oil prices (for instance air transportation related stocks, etc).

Minimum Volatility weighting scheme exhibits superior overall performances. Indeed, among the three different ways to allocate weights, it is the one which experience the best Sharpe ratio (RP: 0.55, MV: 0.61, EW: 0.54) even if it does not have the lowest maximum drawdown (RP: -54.0%, MV: -55.9%, EW: -53.6%). Meanwhile, the MV scheme has the highest annual return (RP: 10.7%, MV: 11.1%, EW: 10.5%) and a lower volatility (of 20.0%) than its peers (RP: 23.3% and EW: 24.1%). When we look at the PSR, the three portfolios beat the market Sharpe ratio in probabilistic measure.
However, the MV has a tail ratio lower than 1 (0.98), even if the other strategies do not substantially beat it (RP: 0.96, EW: 0.99). Besides, all three strategies have almost similar Omega ratio with MV having the largest at 1.13 against 1.11 for the RP and the EW. RP has the lowest skewness of -0.50 (MV: -0.44 and EW: -0.39). We can deduce from the previous metrics that and the associated kurtosis (RP:12.19,EW:12.21,MV:13.76) that the EW is less likely to have extreme negative returns than others.
Finally, by looking at the information ratio we notice that MV has the best ratio (MV: 0.2938, EW: 0.1962, RP: 0.199). Therefore, we notice a better ability to have excess risk adjusted return using a minimum variance scheme. This means that the MV strategy beats the benchmark more consistently than the other two.

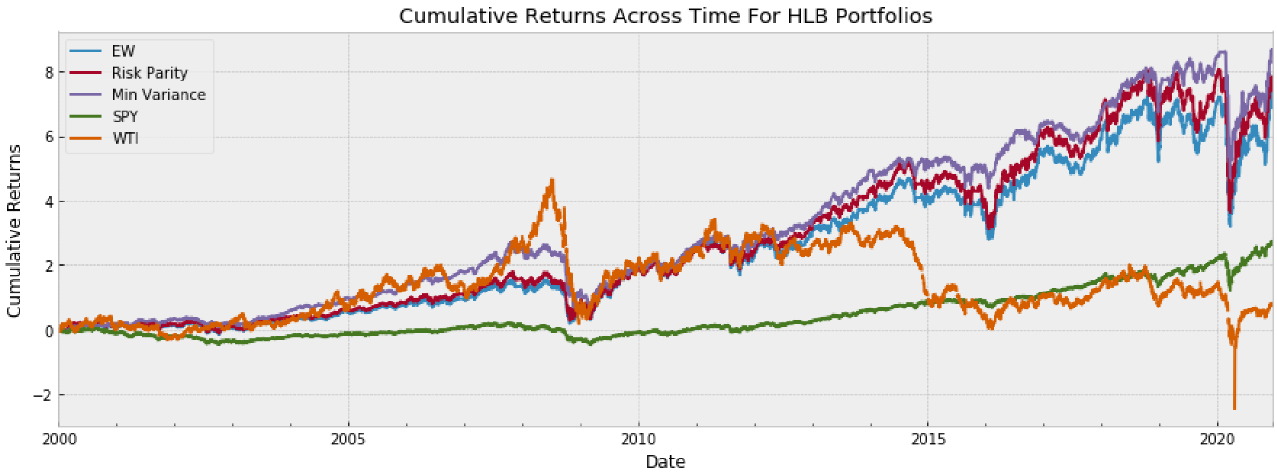

Figure 4.3: Cumulated returns of the Long only High & Low Beta strategies

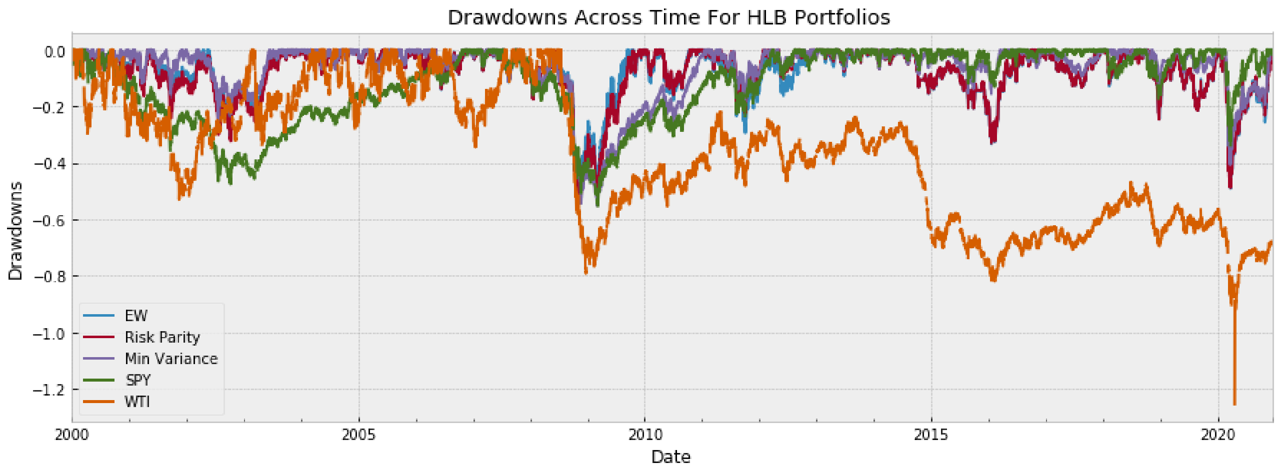

Figure 4.4: Drawdowns of the Long only High & Low Beta strategies

4.3 Long Short / High & Low Beta

Our last strategy consists of taking long and short positions on stocks that have an extreme positive or negative sensitivity to the oil. At least, this is the case for the EW portfolio. The other two strategies doesn't always behave this way, as the optimiser selects the stocks. This long/short strategy created a hedged portfolio as we are about to see with the results.

With this strategy we notice that when we attributed the weights equally (EW) the performances were poor as we obtained an annualized return of -3.1% with a large maximum drawdown of -83.2%. If we compare it to the two other weighting schemes, they obtained better but unsatisfactory results over the whole sample period. The highest CAGR was reached with the RP portfolio at -0.1%. The MV strategy from its side has a CAGR of -0.6%. The Sharpe Ratios are all practically very low(MV: -0.45, RP: -0.12, EW: 0). However, there is no difference at all when we observe the PSR. They all have a PSR of 0.0% as they performed very badly compared to the market across time.
When we look at the kurtosis and skeweness, the MV strategy (kurt: 117.50, skew.: -2.68) is

the most highly leptokurtic and negatively skewed strategy. This means that the distribution has a flatter shape and fatter tails than a normal distribution. The strategy is more likely to experience extreme negative returns. Another issue with these 3 strategies is that none of them has ever recovered from their maximum drawdown. The EW had a maximum drawdown of 83.24% in 2011 and it still has not recovered. The maximum drawdown of the RP was in 2020, there is not much to comment on this one as the pandemic is not over yet. However, the second maximum drawdown was in 2001 and it recovered only in 2019. For the MV strategy, the maximum drawdown was of 12.16% which is not much in comparison to other strategies. Nevertheless, it still has not recovered to this day. Therefore, we concluded that these strategies have no interest to the investor as he would lose money and there would not be hope for recovery.

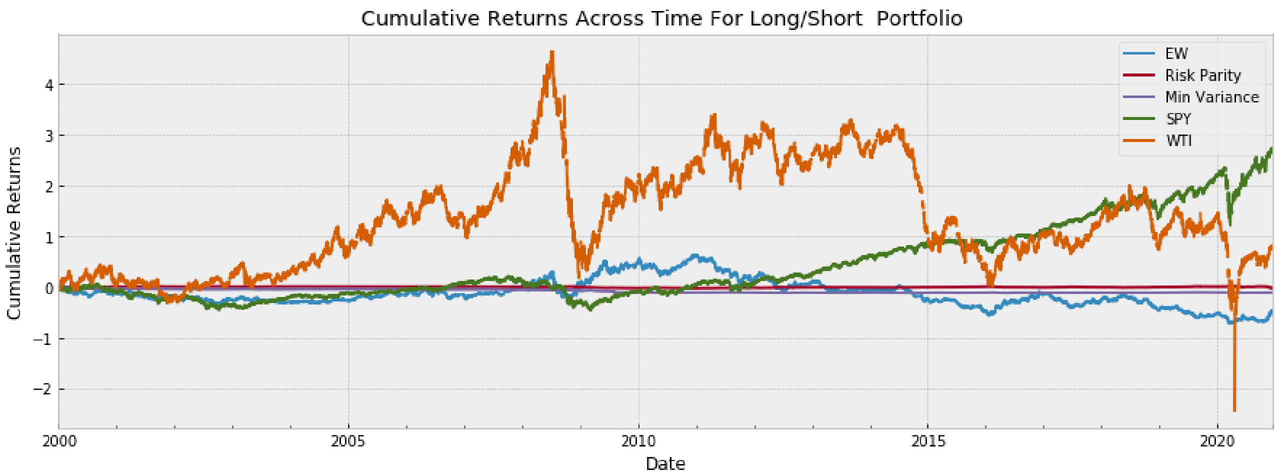

Figure 4.5: Cumulated returns of the Long Short strategies

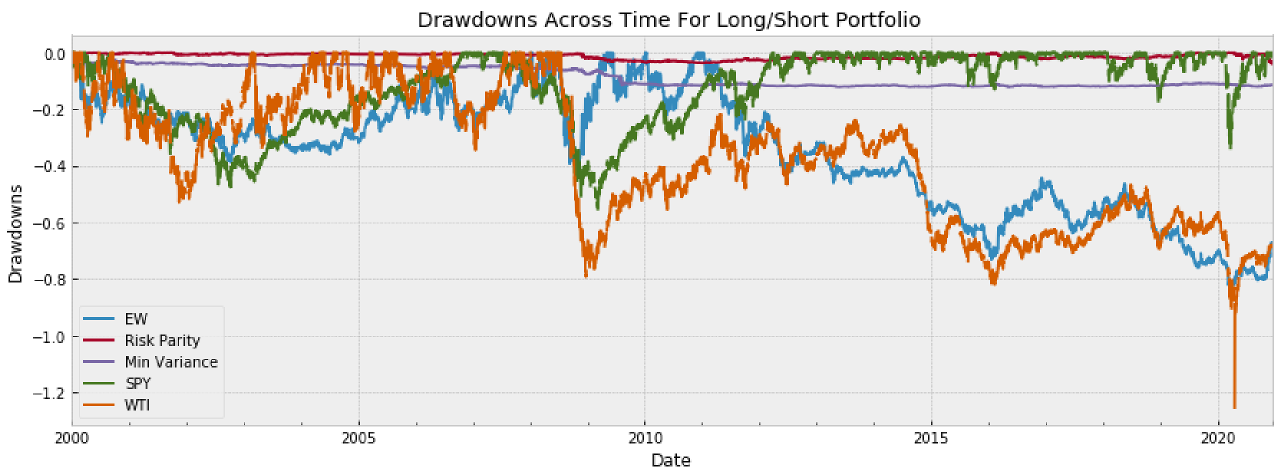

Figure 4.6: Drawdowns of the Long Short strategies

4.4 The appropriate strategy and weighting scheme

Thanks to the empirical analysis, we will try to retain some strategies with their specific weighting scheme and their specific characteristics.

In term of Sharpe ratio and strict performance measures, one should consider the Long Only High / Low Beta minimum variance or the Long Only High Low beta risk parity strategies. Both have the most attractive ratios between all the weighted schemed strategies. They offer the minimum annualized volatility for investors (LHLBMV = 20.0% and LHLBRP = 23.3%) and the best adjusted returns ratios. As mentioned in the empirical analysis, the quoted strategies have the lowest maximum drawdown, which is the best fit for risk averse investors, and exhibit the lowest daily Value at Risk at 5% (LHLBMV = 2.5% and LHLBRP = 2.9%). Therefore, over the whole period, we can see a clear outperformance of the two last Long Only High / Low Beta strategies as they exhibit the highest risk adjusted ratios so far (see Appendix). Lastly, our Long on high Betas strategies tend to generate returns even if the WTI is in a constant decline since 2015. In order to explain that, a lot of invisible factors by our model contribute to that trend as many company we invest in are not solely dependent on the oil price. For instance, the booming demand we have seen for the last 10 years can help to explain the Long on High Betas portfolios upward movements. In addition,stocks tend to exhibit an upward drift in general.

5 Robustness check and sensitivity analysis

The "Market-Rf" factor and every other factors based on the Fama & French Theory are non significant at 95% for the majority of the portfolios which we built. This is important as it suggests that the strategies has a limited exposure to the market. However, for long allocations the alphas are considerable (annualized Jensen Alpha in percent LHBRP = 10.08%, LHBEW = 12.6%, LHBMV = 7.56%) and all significant at a threshold of 90% for RP and EW unlike the MV which is not significant at the threshold. It means that our strategy generates strong abnormal returns with respect to the US stock market in which we pick the stocks.

We selected the stocks on the basis of a robust sensitivity to the WTI Crude oil. To be selected, the OLS coefficient of the sensibility must had a p-value lower than, or equal to 0.10. Otherwise, the stock is not selected into the universe. Then, we cannot differentiate any of these two strategies based on the robustness of the sensitivity coefficients as all strategies use significant one.

As the first main goal of our strategy was to track the upward movement of the WTI crude oil barrel, we decided to implement a special Information Coefficient (IC). Our coefficient was the Spearman's yearly rolling correlation between the monthly WTI returns and our returns. In this case, one would rather go for the long only strategy with high beta stocks along with a minimum variance weighting scheme (average IC for the whole period : LHLBMV = 27.13% and LHLBRP = 34.49%). In fact, we have a better tracking of oil movements from the 1st January of 2000 up to December 2020. We prefer to be exposed to the risk parity as it satisfies more the problematic of our customers who want to profit from upward WTI movements.

As we tend to profit from the WTI crude oil upward movements, you may notice that our strategies experience particularly large drawdowns along with a large annualized volatility. Thus, we may only recommend those strategies as a part of a wider, more diversified investment plan.

We could also better manage risks as we evaluate the conditional Daily VaR at 95% for the Long High Low Beta Risk Parity Portfolio (using the Normal, Student-t and Generalized Pareto Distribution). The results show that the VaRs computed once each 10 days at a threshold of 95% are all rejected by the christophersen Test. However, the independence hypothesis is not rejected for the Conditional EVT 95% VaR under the binomial test.

Concerning long-short strategies, they all seem to be sub-optimal and unrelated to the oil movements as their IC coefficients are the smallest (apart for the EW which is long only on the Highest Beta, therefore explains the highest IC coefficient between all the strategies). In order to design a better long-short strategies we may take into consideration more dynamic and more sophisticated solution such as trend following or momentum strategies. However, we may lose control over the positive sensitivity of stocks to oil prices. (The topic is not discussed on this paper but the insight is available in the methodology).

6 Conclusion

Through this project, we have established several strategies that allow us to benefit from the upside of the WTI crude oil barrel while mitigating the risk on its downside. To do so, we have isolated the sensitivity coefficients (β_1) using the regressions developed in the Methodology. Then, we established three strategies, each evolving differently around the sensitivity coefficient. These strategies were a long position only on high betas, a long positions on both high and low betas in order to hedge, and finally a long/short position high/Low Beta depending the weighting scheme. Additionally, we have implemented three different weighting schemes for these strategies (equally weighted, risk parity and minimum variance)
As discussed previously, our goal was to profit from the upward movements of the oil price. The most appropriate strategy is the long only on high and low betas with risk parity weighting scheme. It is the strategy that most consistently tracks the performance of the WTI crude oil, along with having the most solid risk adjusted metrics on the Long term and short term. However, this strategy should be implemented in a more global one, therefore we would have the opportunity to have a less volatile and better diversified portfolio.

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Appendix

Github of the project: https://github.com/EM51641/Crude-Oil-and-Equity

.1 Long-Only High Beta

	All	2000-2015	2015-2020
Annual return	8.9%	8.6%	9.8%
Cumulative returns	510.6%	274.9%	62.8%
Annual volatility	28.6%	27.2%	32.8%
Sharpe ratio	0.44	0.44	0.45
Calmar ratio	0.15	0.15	0.17
Stability	0.87	0.91	0.07
Max drawdown	-58.7%	-56.0%	-58.7%
Omega ratio	1.09	1.09	1.09
Sortino ratio	0.63	0.62	0.64
Skew	-0.23	-0.11	-0.45
Kurtosis	9.81	8.24	11.16
Tail ratio	1.03	1.04	0.92
Daily VaR 95%	-3.6%	-3.4%	-4.1%

Table .1: Results of the Long only Equally Weighted High Beta strategy

Probabilistic Sharpe Ratio	99.997%
Modigliani Ratio	0.0729
Information Ratio	0.169
Tracking Error	34.773%
CAGR	8.997%

Table .2: Additional ratios for the Long only Equally Weighted High Beta strategy

	Net DD in %	Peak date	Valley date	Recovery date	Duration
0	58.71	2018-05-22	2020-03-19	NaT	NaN
1	56.01	2008-05-21	2008-10-28	2009-05-05	250
2	52.77	2014-07-07	2016-01-21	2017-01-25	668
3	40.32	2011-04-06	2011-10-04	2014-05-24	818
4	32.70	2001-05-22	2002-10-10	2003-10-14	626

Table .3: Worst Drawdown (DD) periods for the Long only Equally Weighted High Beta strategy

Figure .1: Long only EW HB IC rolling 1 year

	All	2000-2015	2015-2020
Annual return	9.0%	8.9%	9.5%
Cumulative returns	531.7%	294.2%	60.2%
Annual volatility	28.1%	26.6%	32.3%
Sharpe ratio	0.45	0.45	0.44
Calmar ratio	0.15	0.16	0.16
Stability	0.89	0.92	0.06
Max drawdown	-60.1%	-55.0%	-60.1%
Omega ratio	1.09	1.09	1.09
Sortino ratio	0.64	0.65	0.62
Skew	-0.27	-0.08	-0.60
Kurtosis	10.17	8.12	12.04
Tail ratio	1.01	1.03	0.94
Daily VaR 95%	-3.5%	-3.3%	-4.0%

Table .4: Results of the Long only Risk Parity High Beta strategy

Probabilistic Sharpe Ratio	99.990%
Modigliani Ratio	0.0743
Information Ratio	0.165
Tracking Error	34.298%
CAGR	9.173%

Table .5: Additional ratios for the Long only Risk Parity High Beta strategy

	Net DD in %	Peak date	Valley date	Recovery date	Duration
0	60.08	2018-05-22	2020-03-19	NaT	NaN
1	54.98	2008-05-21	2008-10-28	2009-05-07	252
2	52.49	2014-07-07	2016-01-21	2017-01-25	668
3	39.30	2011-04-06	2011-10-04	2013-10-19	663
4	33.94	2001-05-22	2002-10-10	2003-11-29	659

Table .6: Worst Drawdown (DD) periods for the Long only Risk Parity High Beta strategy

Figure .2: Long only RP HB IC rolling 1 year

	All	2000-2015	2015-2020
Annual return	7.1%	5.9%	10.9%
Cumulative returns	336.1%	155.4%	70.8%
Annual volatility	23.8%	22.7%	27.2%
Sharpe ratio	0.41	0.37	0.52
Calmar ratio	0.13	0.11	0.20
Stability	0.85	0.87	0.14
Max drawdown	-54.8%	-54.8%	-53.7%
Omega ratio	1.08	1.07	1.10
Sortino ratio	0.57	0.52	0.74
Skew	-0.13	-0.06	-0.27
Kurtosis	8.98	8.88	8.30
Tail ratio	1.01	1.01	0.97
Daily VaR 95%	-3.0%	-2.8%	-3.4%

Table .7: Results of the Long only Min Variance High Beta strategy

Probabilistic Sharpe Ratio	99.999%
Modigliani Ratio	0.185
Information Ratio	-0.0749
Tracking Error	54.059%
CAGR	7.264%

Table .8: Additional ratios for the Long only Min Variance High Beta strategy

	Net DD in %	Peak date	Valley date	Recovery date	Duration
0	54.85	2008-05-21	2008-11-21	2010-11-05	643
1	53.66	2018-05-22	2020-03-24	NaT	NaN
2	47.74	2014-07-07	2016-01-21	2017-10-04	848
3	31.41	2001-05-22	2002-07-24	2003-11-26	657
4	27.58	2011-04-06	2011-10-04	2013-10-19	66

Table .9: Worst Drawdown (DD) periods for the Long only Min Variance High Beta strategy

Figure .3: Long only MV HB IC rolling 1 year

.2 Long Only High-Low Beta

	All	2000-2015	2015-2020
Annual return	10.5%	10.5%	10.6%
Cumulative returns	742.7%	397.9%	69.2%
Annual volatility	24.1%	22.9%	27.5%
Sharpe ratio	0.54	0.55	0.50
Calmar ratio	0.20	0.20	0.22
Stability	0.96	0.94	0.41
Max drawdown	-53.6%	-53.6%	-49.0%
Omega ratio	1.11	1.11	1.11
Sortino ratio	0.76	0.78	0.70
Skew	-0.39	-0.21	-0.69
Kurtosis	12.21	9.43	15.23
Tail ratio	0.99	0.98	0.92
Daily VaR 95%	-3.0%	-2.8%	-3.4%

Table .10: Results of the Long only Equally Weighted High-Low Beta strategy

Probabilistic Sharpe Ratio	99.999%
Modigliani Ratio	0.0892
Information Ratio	0.1962
Tracking Error	31.095%
CAGR	10.682%

Table .11: Additional ratios for the Long only Equally Weighted High-Low Beta strategy

	Net DD in %	Peak date	Valley date	Recovery date	Duration
0	53.63	2007-11-07	2008-10-28	2009-09-11	483
1	48.99	2018-10-17	2020-03-24	2020-11-25	551
2	33.27	2014-09-03	2016-01-21	2016-08-19	513
3	30.89	2002-05-18	2002-10-10	2003-08-22	330
4	29.33	2011-02-18	2011-10-04	2012-12-08	471

Table .12: Worst Drawdown (DD) periods for Long only Equally Weighted High-Low Beta strategy

Figure .4: Long only EW HLB IC rolling 1 year

	All	2000-2015	2015-2020
Annual return	11.1%	11.6%	9.5%
Cumulative returns	862.4%	508.7%	58.1%
Annual volatility	20.0%	19.6%	21.1%
Sharpe ratio	0.63	0.66	0.54
Calmar ratio	0.20	0.21	0.22
Stability	0.96	0.93	0.52
Max drawdown	-55.9%	-55.9%	-42.8%
Omega ratio	1.13	1.13	1.12
Sortino ratio	0.88	0.93	0.73
Skew	-0.44	-0.25	-0.96
Kurtosis	13.76	9.78	23.31
Tail ratio	0.98	0.98	1.00
Daily VaR 95%	-2.5%	-2.4%	-2.6%

Table .13: Results of the Long only Min Variance High-Low Beta strategy

Probabilistic Sharpe Ratio	100.0%
Modigliani Ratio	0.1053
Information Ratio	0.2938
Tracking Error	27.912%
CAGR	11.384%

Table .14: Additional ratios for the Long only Min Variance High-Low Beta strategy

	Net DD in %	Peak date	Valley date	Recovery date	Duration
0	55.93	2007-11-01	2009-03-10	2011-02-02	850
1	42.78	2020-02-20	2020-03-24	2020-12-05	207
2	24.89	2002-03-20	2002-07-24	2003-08-16	368
3	18.60	2011-05-02	2011-10-04	2012-02-04	200
4	15.76	2015-04-16	2016-01-21	2016-03-18	242

Table .15: Worst Drawdown (DD) periods for Long only Min Variance High-Low Beta strategy

Figure .5: Long only MV HLB IC rolling 1 year

	All	2000-2015	2015-2020
Annual return	10.7%	11.1%	9.6%
Cumulative returns	773.8%	442.0%	61.2%
Annual volatility	23.3%	22.3%	26.4%
Sharpe ratio	0.55	0.58	0.48
Calmar ratio	0.20	0.21	0.20
Stability	0.96	0.94	0.43
Max drawdown	-54.0%	-54.0%	-48.8%
Omega ratio	1.11	1.12	1.10
Sortino ratio	0.78	0.83	0.66
Skew	-0.50	-0.27	-0.91
Kurtosis	12.19	8.48	16.98
Tail ratio	0.96	0.95	0.95
Daily VaR 95%	-2.9%	-2.8%	-3.3%

Table .16: Results of the Long only Risk Parity High-Low Beta strategy

Probabilistic Sharpe Ratio	100.0%
Modigliani Ratio	0.0921
Information Ratio	0.199
Tracking Error	30.431%
CAGR	10.873%

Table .17: Additional ratios for the Long only Risk Parity High-Low Beta strategy

	Net DD in %	Peak date	Valley date	Recovery date	Duration
0	54.00	2007-11-07	2008-10-28	2009-11-26	537
1	48.79	2018-10-17	2020-03-24	NaT	NaN
2	33.01	2014-09-03	2016-01-21	2016-08-19	513
3	32.27	2001-05-22	2002-10-10	2003-09-03	597
4	22.42	2011-04-29	2011-10-04	2012-02-02	200

Table .18: Worst Drawdown (DD) periods for Long only Risk Parity High-Low Beta strategy

Figure .6: Long only RP HLB IC rolling 1 year

.3 Long-Short

	All	2000-2015	2015-2020
Annual return	-3.1%	-3.0%	-3.4%
Cumulative returns	-48.6%	-38.5%	-16.5%
Annual volatility	25.3%	22.1%	33.2%
Sharpe ratio	0.00	-0.03	0.06
Calmar ratio	-0.04	-0.05	-0.05
Stability	0.12	0.14	0.50
Max drawdown	-83.2%	-65.0%	-69.9%
Omega ratio	1.00	1.00	1.01
Sortino ratio	0.00	-0.04	0.09
Skew	0.33	0.06	0.53
Kurtosis	8.75	4.33	8.62
Tail ratio	1.01	1.04	1.00
Daily VaR 95%	-3.2%	-2.8%	-4.2%

Table .19: Results of the Long-short Equally Weighted strategy

Probabilistic Sharpe Ratio	0.0%
Modigliani Ratio	-0.004
Information Ratio	-0.211
Tracking Error	31.459%
CAGR	-3.123%

Table .20: Additional ratios for the Long-short Equally Weighted strategy

	Net DD in %	Peak date	Valley date	Recovery date	Duration
0	83.24	2011-01-04	2020-03-19	NaT	NaN
1	42.34	2008-07-15	2008-10-28	2009-05-02	209
2	38.64	2000-01-22	2002-10-09	2008-01-03	2074
3	22.08	2010-01-09	2010-05-21	2010-12-03	235
4	17.13	2009-06-02	2009-07-09	2010-01-06	157

Table .21: Worst Drawdown (DD) periods for the Long-short Equally Weighted strategy

Figure .7: Long short EW IC rolling 1 year

	All	2000-2015	2015-2020
Annual return	-0.1%	-0.0%	-0.4%
Cumulative returns	-2.4%	-0.1%	-2.3%
Annual volatility	0.9%	0.7%	1.4%
Sharpe ratio	-0.12	-0.00	-0.31
Calmar ratio	-0.03	-0.00	-0.11
Stability	0.10	0.41	0.15
Max drawdown	-4.0%	-3.7%	-4.0%
Omega ratio	0.98	1.00	0.94
Sortino ratio	-0.15	-0.00	-0.39
Skew	-1.89	-0.50	-2.06
Kurtosis	28.77	15.05	18.89
Tail ratio	1.02	1.00	0.98
Daily VaR 95%	-0.1%	-0.1%	-0.2%

Table .22: Results of the Long-short Risk Parity strategy

Probabilistic Sharpe Ratio	0%
Modigliani Ratio	-0.142
Information Ratio	-0.384
Tracking Error	17.506%
CAGR	-0.113%

Table .23: Additional ratios for the Long-short Risk Parity strategy

	Net DD in %	Peak date	Valley date	Recovery date	Duration
0	3.96	2020-04-17	2020-12-11	NaT	NaN
1	3.75	2001-10-02	2011-01-06	2019-08-27	4671
2	0.87	2019-09-04	2019-09-17	2020-03-10	135
3	0.76	2000-01-13	2000-03-14	2000-05-23	94
4	0.67	2000-05-27	2000-09-20	2000-12-01	135

Table .24: Worst Drawdown (DD) periods for the Long-short Risk Parity strategy

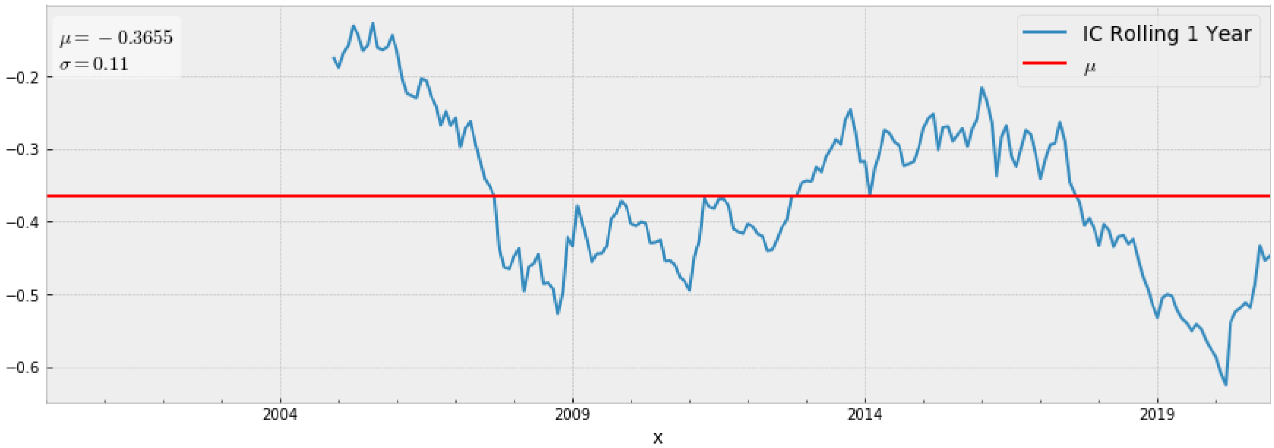

Figure .8: Long short RP IC rolling 1 year

	All	2000-2015	2015-2020
Annual return	-0.6%	-0.8%	0.1%
Cumulative returns	-11.4%	-11.9%	0.6%
Annual volatility	1.3%	1.4%	0.7%
Sharpe ratio	-0.45	-0.56	0.16
Calmar ratio	-0.05	-0.06	0.07
Stability	0.81	0.86	0.20
Max drawdown	-12.2%	-12.2%	-1.5%
Omega ratio	0.89	0.86	1.03
Sortino ratio	-0.58	-0.72	0.22
Skew	-2.68	-2.58	-0.15
Kurtosis	117.50	102.33	2.84
Tail ratio	0.93	0.92	0.99
Daily VaR 95%	-0.2%	-0.2%	-0.1%

Table .25: Results of the Long-short Min Variance strategy

Probabilistic Sharpe Ratio	0%
Modigliani Ratio	-0.168
Information Ratio	-0.413
Tracking Error	17.569%
CAGR	-0.573%

Table .26: Additional ratios for the Long-short Min Variance strategy

	Net DD in %	Peak date	Valley date	Recovery date	Duration
0	12.16	2000-01-04	2016-05-19	NaT	NaN
1	0.00	2000-01-04	2000-01-04	2000-01-04	1
2	0.00	2000-01-04	2000-01-04	2000-01-04	1
3	0.00	2000-01-04	2000-01-04	2000-01-04	1
4	0.00	2000-01-04	2000-01-04	2000-01-04	1

Table .27: Worst Drawdown (DD) periods for the Long-short Min Variance strategy

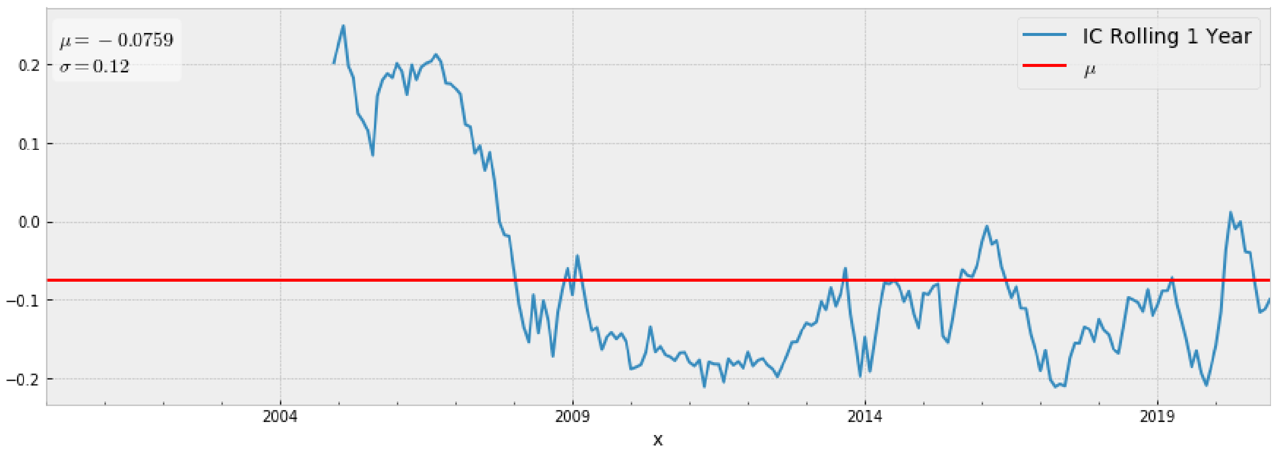

Figure .9: Long short MV IC rolling 1 year

Tests or Distributions	Christoffersen Log Ratio	Binomial p-val
Student-t 95	24.096***	0.0004***
Normal 95	23.064	*** 0.0013***
Cond.EVT 95	13.237***	0.181
Uncond.EVT 95	32.844***	0***

Table .28: VaR study for the Long Only Risk Parity on High Beta strategy

Tests or Distributions	Christoffersen Log Ratio	Binomial p-val
Student-t 95	29.192***	0.0007***
Normal 95	29.673***	0.0005***
Cond.EVT 95	12.212***	0.422
Uncond.EVT 95	32.767***	0.005***

Table .29: VaR study for the Long Only Risk Parity on High/Low Beta strategy

	Equally weighted	Risk parity	Minimum variance
Long High Beta	36.81% **	36.40%**	36.48%**
Long High Low Beta	33.93%**	34.49%**	27.13%
Long/Short High Beta	41.65%***	-36.55%***	-7.59%

Table .30: Spearman correlation for each strategy

	alpha	MRK-Rf	SMB	HML	RMW	CMA
LHBRP	0.0004*	-0.0900***	0.0238	-0.0392	0.0147	-0.0442
LHBEW	0.0005*	-0.0400*	-0.0683*	0.0951**	-0.1275**	-0.0568
LHBMV	0.0003	-0.0094	-0.0605**	-0.0207	-0.0623	0.1190**
LHLBEW	0.0005**	-0.0414**	0.0474	0.0758**	-0.0365	-0.0007
LHLBRP	0.0005**	0.0180	-0.0606*	-0.0564*	-0.0324	0.1354**
LHLBMV	0.0004***	0.00892	0.0453	-0.0371	0.0132	0.0521
LSHBEW	0	-0.0141	0.0101	-0.0417	0.0006	-0.0047
LSHBRP	0	-0.0002	-0.0157	-0.0147*	-0.0108	0
LSHBMV	0**	0.0026***	0.0009	-0.0030*	0.0035	0.0093***

Table .31: Fama french factors coefficients