Commodities Market Neutral Investment Strategy

MF703 Fall 2023 Final Project

Group 3: Jack Bartoluzzi, Jim Burrill, Tim Lee, Sagar Mirchandani, Kevin Yang, Hanbo Yu, Hamza Zbiri

GitHub Link: [MF703-Final-Project /Final Project Package]

Project Objective

Inspired by the J.P. Morgan Optimax Market-Neutral Index, we set out with the goal of developing an investment strategy that seeks to generate consistent returns through a selection of commodity-linked component sub-indices. This required the identification of a L/S strategy to generate trading signals based on commodity price movements, and a portfolio optimization technique to minimize portfolio beta and variance for the generated trading signals. To validate the identified investment strategy an extensive back test was required.

Data Collection and Validation

One reason we wanted to focus on commodities was due to their easily accessible data and lack of corporate factors such as stock splits, dividends, mergers and acquisitions, etc. when compared to stocks and bonds.

We proceeded to obtain data on 16 chosen commodity indexes from the S&P GSCI through the Bloomberg terminal. The S&P GSCI is the most widely recognized commodity index benchmark, which was launched in April 1991. It is an index which is considered to be a pure beta (i.e. their risks and returns can be represented by nearly entirely the movement of the market that they track) of the commodities asset class. Similar to the S&P 500 being market capitalization weighted for equities, representing the stock market space, the S&P GSCI is production weighted for the commodities. For example, it is expected to see heavier energy indices versus agriculture indices on the S&P GSCI as this is how the world looks.

The S&P GSCI uses a systematic approach to manage rolling in its commodity index. During a monthly five-day roll period, the index gradually shifts its portfolio from expiring futures contracts to new ones, utilizing a fixed daily adjustment rate of 20%. This systematic process ensures a smooth transition, reducing the potential for market disruptions. The percentage allocation between the old and new contracts is based on the number of contracts, not their value, providing transparency in the rolling methodology. By systematically spreading the transition over a defined period, the S&P GSCI aims to minimize the impact of rolling on the overall performance of the index, offering investors a structured and predictable approach to managing commodity futures contracts within the Portfolio.

In our opinion, futures are the most practical and direct way to facilitate exposure to commodities. Futures, as the name implies, are directly related to the future expected spot prices in the market. These future spot prices are driven by supply and demand, which is ultimately what drives the commodities market. Hence, by utilizing historical data of futures, we can model the liquidity and direct exposure that investors would experience when adding commodities to their portfolios.

The 14 commodity indices chosen were divided among the 4 main types of commodities, to help spread risk and reduce overall portfolio volatility. The commodities chosen, the code checking for outliers, and a sample data graph are shown below:

Table 1: Bloomberg Commodities Indexes

Energy	
S&P GSCI	**Bloomberg Ticker**

Natural Gas	SPGCNGP Index
Gasoline	SPGCHUP Index
Heating Oil	SPGCHOP Index
WTI Crude Oil	SPGCCLP Index
Gas Oil	SPGCGOP Index
Industrial Metals	
S&P GSCI	**Bloomberg Ticker**
Nickel	SPGCIKP Index
Lead	SPGCILP Index
Copper	SPGCICP Index
Aluminium	SPGCIAP Index
Zinc	SPGCIZP Index
Agricultural	
S&P GSCI	**Bloomberg Ticker**
Wheat	SPGCWHP Index
Corn	SPGCCNP Index
Coffee	SPGCKCP Index
Sugar	SPGCSBP Index
Precious Metals	
S&P GSCI	**Bloomberg Ticker**
Silver	SPGCSIP Index
Gold	SPGCGCP Index
Benchmark Index	
Bloomberg	**Bloomberg Ticker**
Bloomberg Commodities	BCOM Index

Trading Strategies

During the development of our investment strategy two potential trading strategies were identified to be paired with our covariance optimizer to achieve a market neutral trading strategy. The first trading strategy is based off the AQR momentum trading strategy. This approach involves calculating the trailing 12 month return of all the commodities in our universe for the past year and ranking these trailing returns at every point in time. A short position is taken in the bottom 25% of commodities (based on returns rank) and a long position is taken in the top 20% of commodities (based on returns rank). These percentages were chosen so that our portfolio always had the same number of L/S positions, resulting in 3-4 long and 3-4 short positions at all times based on the available commodities to trade at that point in time. The underlying calculations are provided below:

- r_t = 1 Year trailing return at time t
- p_t = Price at time t
- N_t = Number of commodities in investible universe at time t
- $R_{k,t}$ = Rank of r_t of security K in investible universe at time t

$$r_t = p_t - p_{t-252}$$

$$Position = \begin{cases} 1 & if\ R_{k,t} > .8N_t \\ -1 & if\ R_{k,t} < .25N_t \\ 0 & otherwise \end{cases}$$

The second trading strategy we explored was a technical analysis-based breakout strategy. This approach involves calculating the average true range (ATR) via absolute price changes over a 14-day period. The upper channel is then defined by adding a 7 ATR to the 1 year moving average (MA), and the lower channel is defined by subtracting a 3 ATR from the year MA. A buy signal is generated when the price of the commodity rises above the upper channel, and a sell signal is generated when the commodity price falls below the lower channel at a point in time. The underlying calculations are provided below:

- ATR = Absolute price changes over a 14-day period
- A_n = Average price in period n
- p_n = Price at time n
- UB = Upper band
- LB = Lower band

$$\text{Upper Band} = \frac{1}{n}\sum_{n=1}^{n} A_n + (7 \cdot ATR)$$

$$\text{Lower Band} = \frac{1}{n}\sum_{n=1}^{n} A_n - (3 \cdot ATR)$$

$$Position = \begin{cases} 1 & if\ P_n > UB \\ -1 & if\ P_n < LB \\ 0 & otherwise \end{cases}$$

Preference was given to the AQR momentum strategy due to its widespread acceptance, and the flaws of technical analysis-based trading strategies such as the breakout strategy.

<u>Optimization</u>

Given the long and short signals provided by the trading strategy, we then aimed to allocate our portfolio's funds in the safest possible manner. There are two fundamental ways a portfolio can be made safe: the portfolio returns can be made to be market neutral, i.e. have a low beta (in absolute value) to market returns, or it can be made to have low variance. Achieving one does not imply in any way that the other is achieved; in fact, we anticipated a tradeoff between the two.

Wanting to minimize both undesirable quantities, we designed our objective function to be a linear sum of the square of the portfolio beta to market and the portfolio variance. Because the two quantities are in different units, we multiplied the first by a scalar parameter α, which can be thought of as capturing an investor's preference between what she would rather minimize. This yields the objective function below:

$$\alpha\, \beta_{portfolio}^2 + \sigma_{portfolio}^2$$

$$= \alpha\, (w^T\beta)^2 + w^T\, Cw$$

Where:
α is the Neutrality Preference Coefficient
$w = \{w_1, \ldots, w_n\}$ are our weights
$\beta = \{\beta_1, \ldots, \beta_n\}$ are the betas of the individual commodities: $\beta_i = \frac{cov(r_i, r_{mkt})}{\sigma_{mkt}^2}$
C is the covariance matrix of returns.

Without constraints, the solution to the optimization problem would be $w = 0$. We applied constraints to the optimization problem to ensure that the resulting portfolio would be fully leveraged, would not be overinvested in any one position, and would adhere to the strategy. These constraints can be quantified as follows:

1. $\sum_{i=1}^{n} |w_i| = 1$
2. $|w_i| < 0.5$ for $i = 1, \ldots, n$
3. $sign(w_i)$ is as dictated by the strategy

The w vector satisfying the above constraints that minimizes the objective function would be the optimal portfolio allocation for that given day.

Methodology

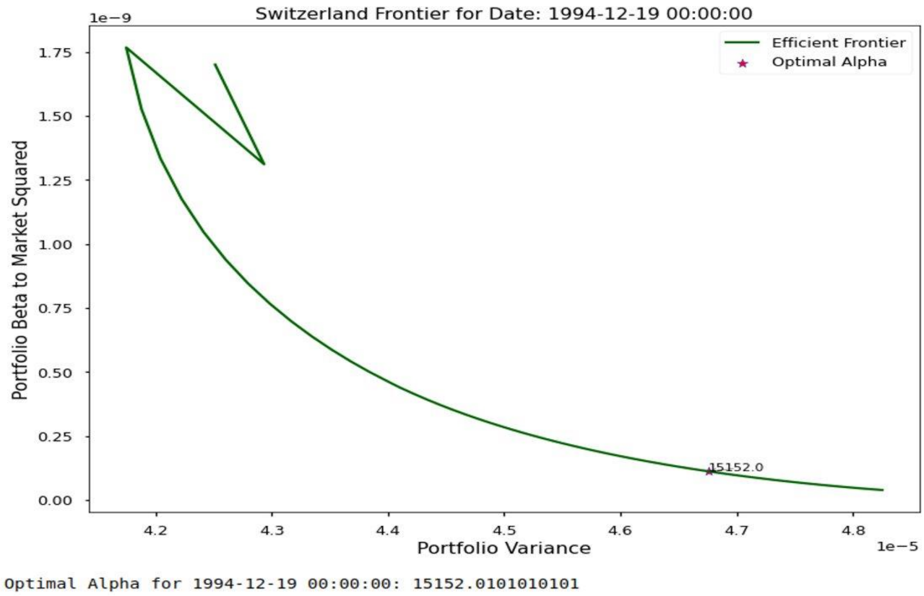
While it is possible that the solution to our optimization problem can be found analytically with skillful application of Lagrangian multipliers to represent the numerous inequality constraints, we opted to use the minimize function from the Scipy.optimize library instead.

For the calculation of the covariance matrix C and the β vector, we opted to utilize a function that re-calculated the variables at every date to capture the variables' propensity to change over time. Because historical trends become less meaningful the further in the past they are, we calculated both C and β using only returns data from the past year. For the calculations of C and β , we used additional Python libraries including Numpy and Sklearn.linearmodel.

The Switzerland Frontier

Allowing α to vary yields a range of optimal portfolios, each one having the minimum possible $\beta_{portfolio}^2$ for a given level of variance.

Figure 1: Switzerland Frontier Example



We coined this range of portfolios the Switzerland Frontier, reflecting the model's goal of balancing neutrality and safety.

<u>α Deep Dive</u>

While our initial results provided potential evidence of a relationship between $b^2_{portfolio}$ and $s^2_{portfolio}$, further examination was performed on a to shine light on underlying mechanics behind the vague relationship. We confronted the challenge of balancing market neutrality (low beta) and portfolio safety (low variance) when presented with long and short signals from our trading strategy. Our objective was to find the optimal alpha for a tradeoff between these two measures.

Given the difference in scale between $b^2_{portfolio}$ and $s^2_{portfolio}$, we chose the Mahalabonis distance to determine the alpha that strikes a balance been both variables. This statistical measure calculates the dissimilarity between two data points, factoring in not only their separation in space but also accounting for variations in scale. We observe that the optimal alpha corresponds to a point with low squared beta to the market. This implies that our portfolio exhibits minimal correlation with market movements, which aligns with our strategy.

<u>Back Testing</u>

To test and validate the performance of our market neutral investment strategy an extensive back test was carried out. Increased attention was given to potential points of bias and ensuring that all assumptions within our model had sound economic reasoning. Our back test methodology can be broken down into 5 main steps:

1. Data ingestion
2. Trading signal generation
3. Portfolio rebalancing identification
4. Portfolio optimization
5. Performance analysis

Data ingestion began with the intake of clean commodity data from Bloomberg. Further cleaning and validation of the data was performed in accordance with the techniques discussed in the data collection and validation portion of this report. The relevant commodities data is then compiled into a data frame and passed to the respective trading strategy function being tested. The trading signal generation function then parses through the data frame according to the strategies discussed earlier to determine which commodities to take a position in, and what commodities not to take a position in. The trading strategy function returns a data frame with a column for each commodity in the investible universe containing a 1 to recommend a long position, a 0 to recommend no position, and a –1 to recommend a short position for each date.

After determining the recommended positions for each date of the respective trading strategy being tested, the back testing engine moves onto calculating the scaled daily returns of each of the recommended positions. The daily return's calculation function accepts two data frames as inputs, one containing daily commodity price data and one containing the recommended daily positions in each commodity generated by the trading strategy. Daily returns for each commodity are first calculated before being scaled according to the recommended position in each commodity of the trading strategy for that date. The underlying calculations are provided below:

- r_t = Daily return for a commodity at time t
- p_t = Price of a commodity at time t
- k_t = Recommended position for a commodity at time t
- sr_t = Scaled daily return for a commodity at time t

$$r_t = \frac{(p_{t+2} - p_{t+1})}{p_{t+1}}$$

$$sr_t = 1 + (r_t \cdot k_t)$$

Note that daily returns were calculated based on the change in price between tomorrow (t+1) and the day after (t+2) to avoid any potential look ahead bias in our back test. Given the use of daily close data we worked under the assumption that our trading strategy would recommend a position in a commodity at the market close on the current day (t), and therefore this position cannot be executed until the following day (t+1), and thus its daily return cannot be calculated until two days from now (t+2). The scaled daily returns function returns a data frame containing the scaled daily returns for each commodity in their respective columns.

The next calculation the back testing engine moves onto is determining the correct days to rebalance the portfolio on. This is completed by passing a data frame containing the recommended positions (i.e. -1, 0, 1) in each commodity for every date to the rebalancing dates identification function. This function iterates over the data frame containing all of the recommended positions and identifies portfolio rebalancing dates whenever a recommended position changes (i.e. –1 to 0, 0 to 1, etc.) or whenever the portfolio has not been rebalanced in the past five days. This function returns a series with the dates as the index and a column of 1's and 0's where a 1 represents a date that rebalancing occurs on and a 0 represents a date when rebalancing does not occur.

After determining which dates to rebalance the portfolio on, the back testing engine moves onto calculating the weights for each position recommended by the trading strategy. Two different sets of weights are calculated for the recommended positions, equal weights and optimized weights. Calculating both sets of weights allows for a meaningful evaluation of the effectiveness of the portfolio optimization technique discussed in previously.

The equal weights calculation function takes in two data frames, one containing scaled daily returns and another containing the recommended daily positions for each commodity. For each day, the function determines the number of commodities for which a non-zero position is taken, and then divides the non-zero scaled daily returns minus 1 (i.e. a return of 4% is transformed from 1.04, to 0.04) by this value. The function then returns a data frame containing the appropriate weights for each commodity in their respective columns on all relevant dates.

To calculate the optimized weights the back testing engine passes three data frames to the previously mentioned weight optimization function, one containing BCOM index prices, one containing commodity prices, and one containing the recommended positions in each commodity for a given day. The function than calculates the optimal weights for each rebalancing date by calling the weight optimizer function for each date respectively and calculating the corresponding position weights as previously discussed. These position weights are then saved in a data frame.

Finally, the portfolio returns for each set of weights is calculated by the rebalancing returns function. This function takes three data frames as inputs, scaled daily returns, rebalancing dates, and position weights. Portfolio returns are calculated by taking the dot product of position weights and the scaled cumulative returns for each commodity between the current rebalancing date and the prior rebalancing date. Note that this function accounts for the fact that the return captured by the rebalancing is based on the return for the day following the date for which the need for rebalancing is identified, as this is when the rebalancing can be executed. Additionally, the portfolio returns can be calculated with a 5-bps transaction cost to account for fees paid in a live trading scenario. This function returns a data frame containing the returns of the portfolio at each rebalancing date.

After the portfolio returns have been calculated the back testing engine generates a graphical comparison of the equal weight's portfolio, optimized weights portfolio, and the BCOM index returns over time. Additionally, the optionality exists to return all back test engine function outputs as csv files for further analysis.

Performance Analysis

After reviewing the results of the back test of the AQR momentum trading strategy we were able to conclude that our market neutral commodities investment strategy outperforms the BCOM index, and that our portfolio optimization techniques reduce variance and improve the Sharpe ratio of our strategy when compared to an equal weight portfolio. Detailed strategy performance results and statistics can be found below:

- Cumulative Returns = $\Pi_{t=0}^{T}(1 + r_t)$, (r_t: portfolio return at time t, T: Total Time Period)

- Volatility $= \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(r_t - \overline{r})^2}$ ($\overline{r}$ average portfolio return, N: Total Number Return)
- Sharpe Ratio: $\frac{\overline{r}-r_f}{Volatility}$ (r_f : risk-free rate)
- Annualized Turnovers $= \frac{1}{N}\sum_{t=1}^{N}\sum_{i=1}^{N}\left|w_{i,t} - w_{i,t-1}\right| \cdot 252$, ($w_{i,t}$: weight of asset i at time t, N: total number of time periods)

Figure 2: AQR Momentum Strategy Performance

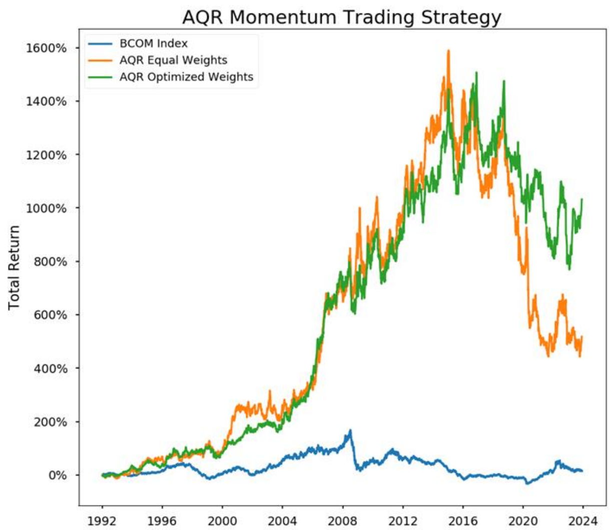


Figure 3: AQR Momentum Strategy Analysis

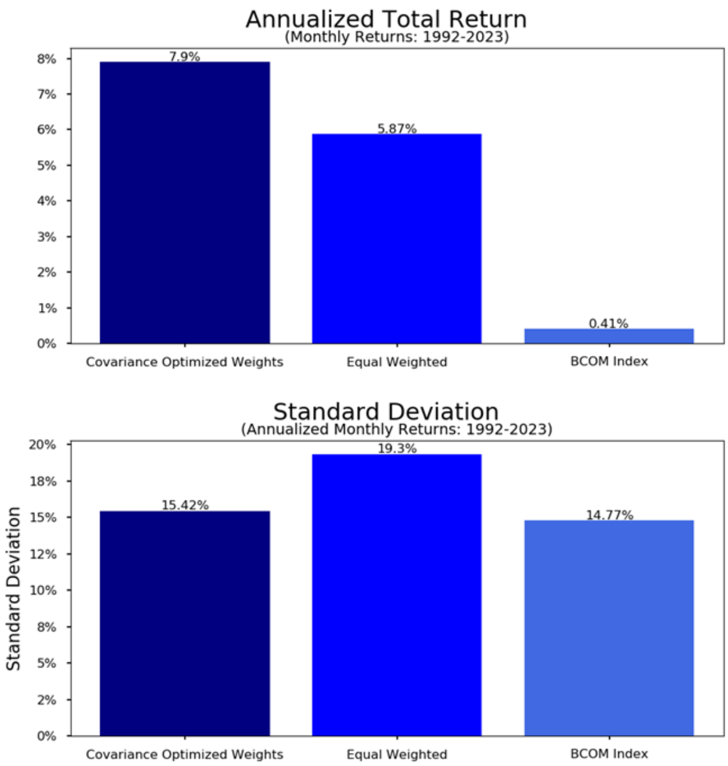


Figure 4: AQR Momentum Strategy Max Drawdown Analysis

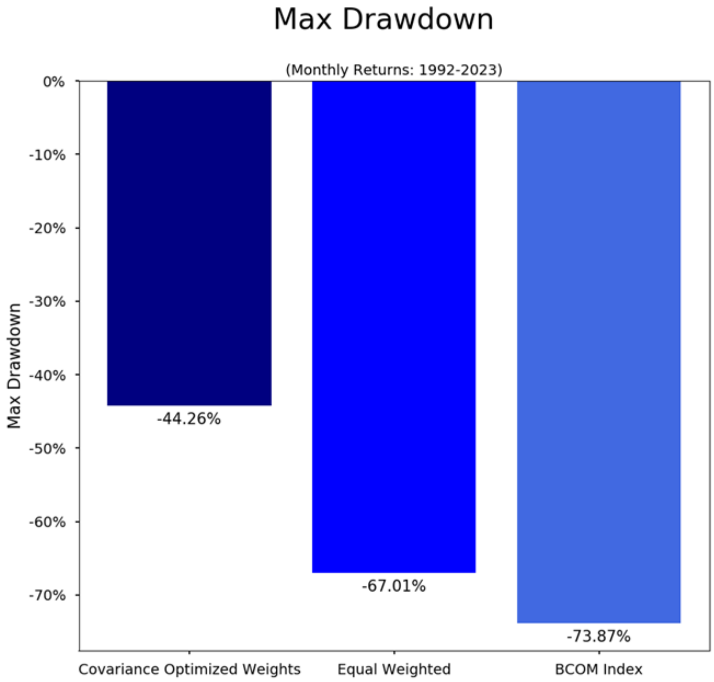


Figure 5: AQR Momentum Strategy VaR Analysis

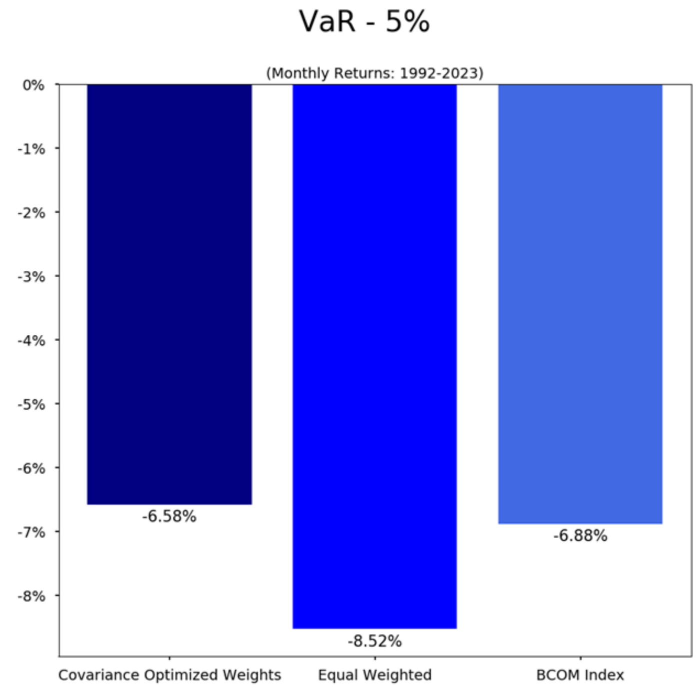


Figure 6: AQR Momentum Strategy Beta Analysis

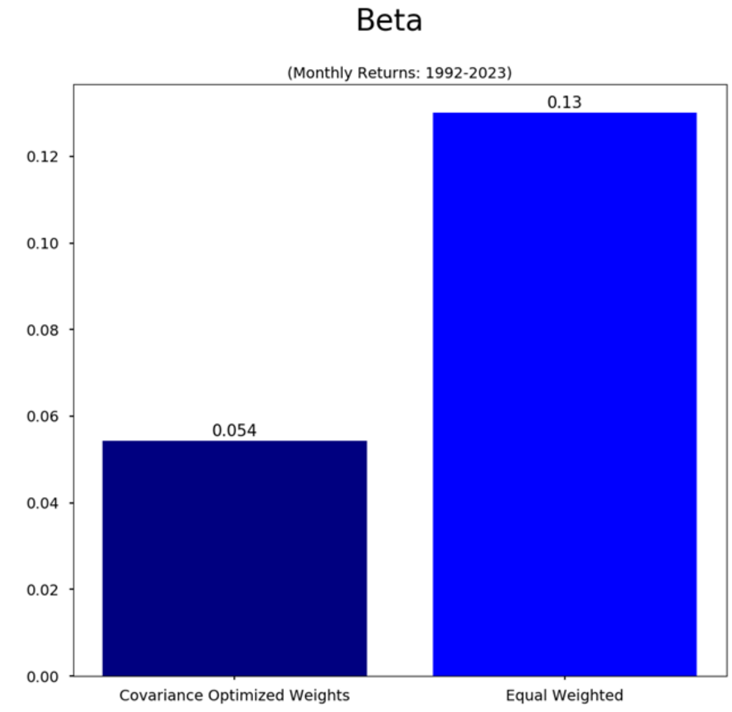


Figure 7: AQR Momentum Strategy Alpha Analysis

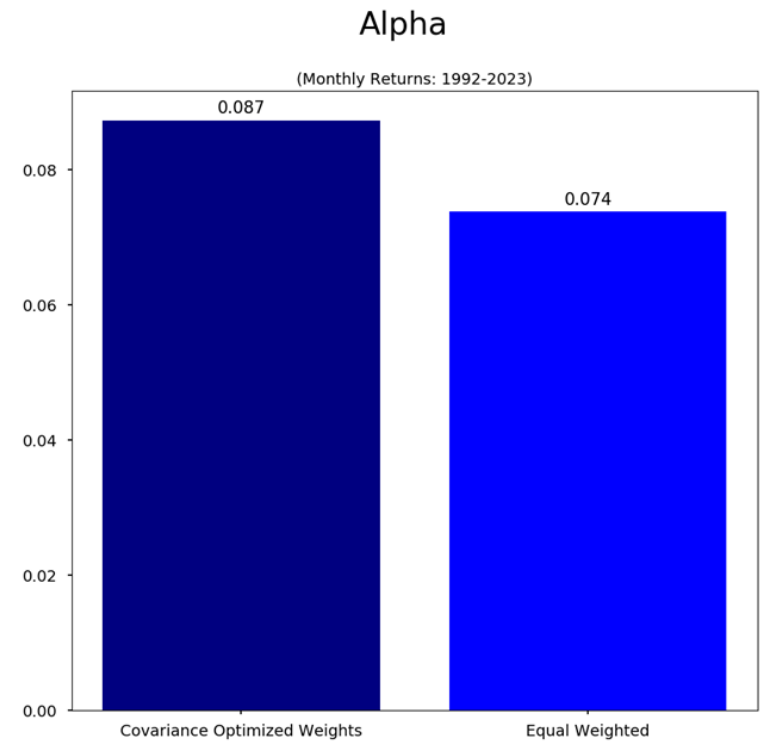


Figure 8: AQR Momentum Strategy Sharpe Ratio Analysis

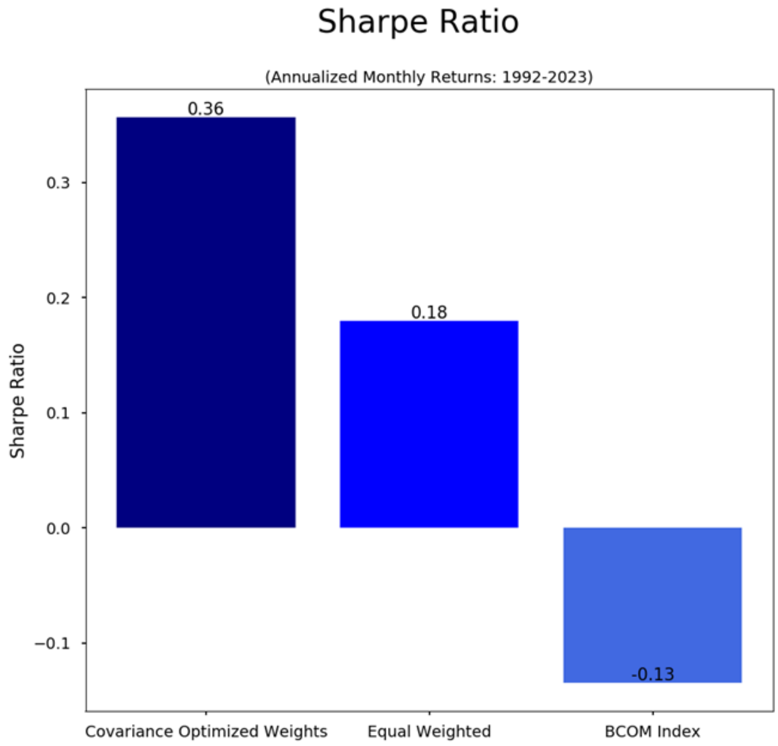
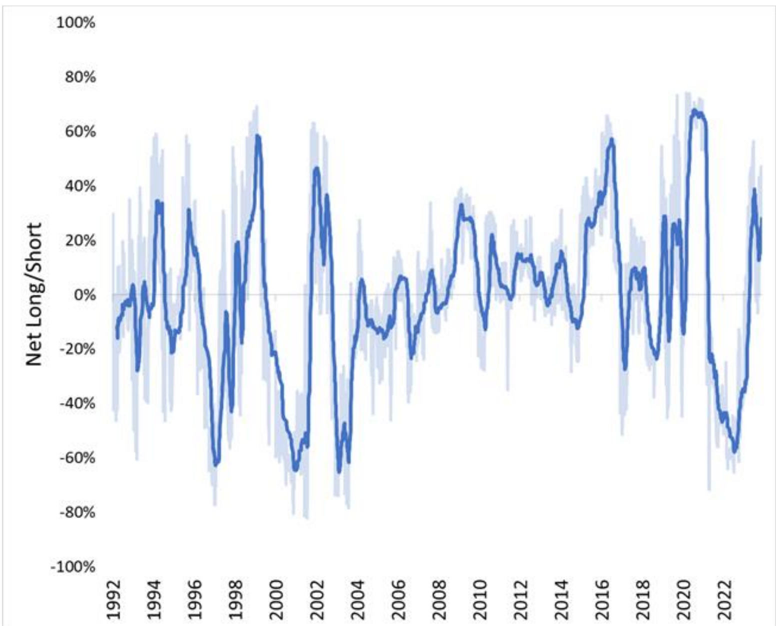


Figure 9: AQR Momentum Strategy Net L/S Position Analysis



Additional strategy analysis was performed to see how transaction costs affect the overall performance of the investment strategy. As can be seen in the following images and statistics, transaction costs significantly reduce the performance of our investment strategy:

Figure 10: AQR Momentum Strategy Performance with Transaction Costs

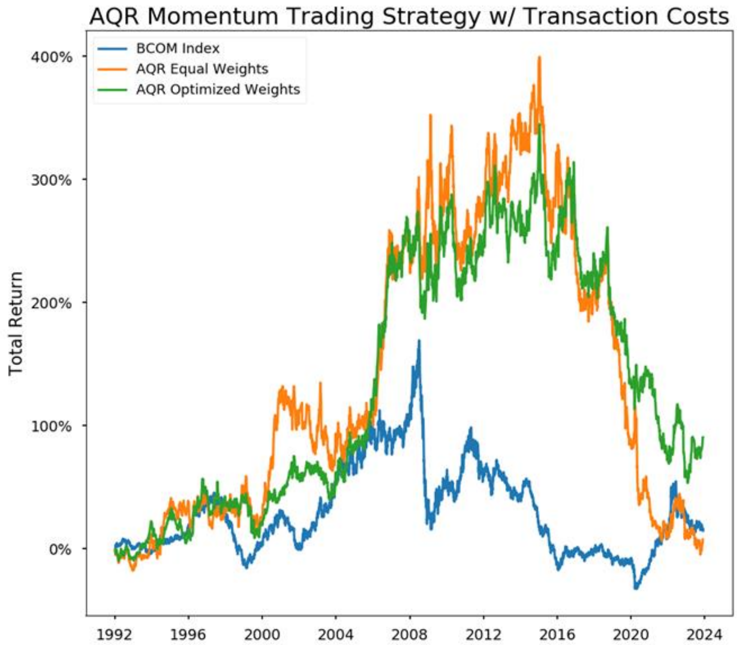
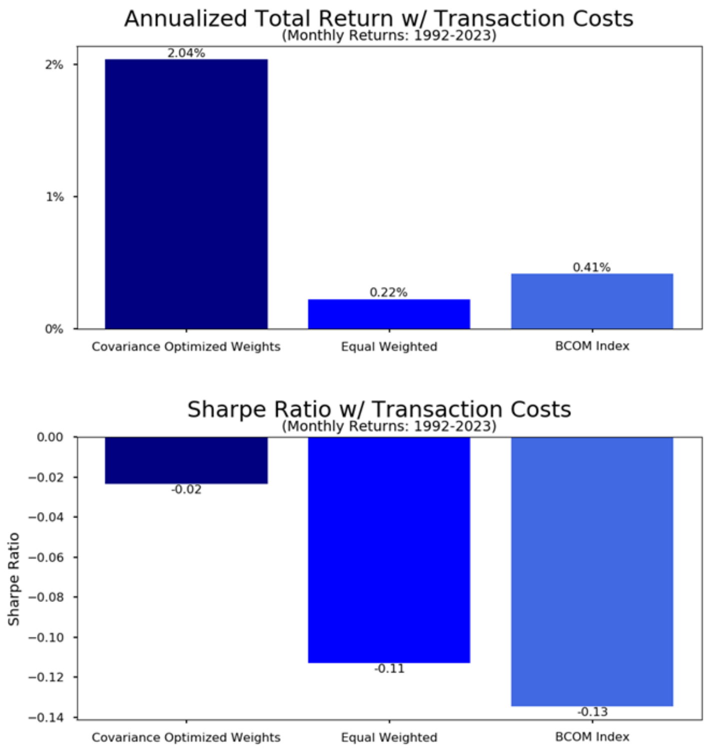


Figure 11:AQR Momentum Strategy with Transaction Costs Analysis



Back test results for the breakout trading strategy, while not as promising as the AQR results, can be found below:

Figure 12: Breakout Strategy Performance

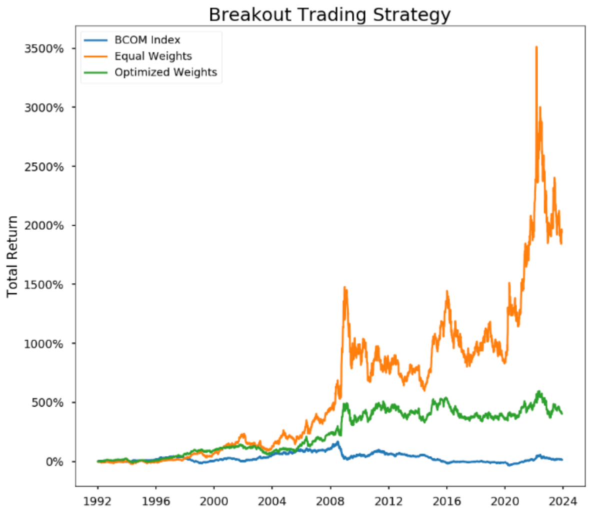


Figure 13: Breakout Strategy Standard Deviation

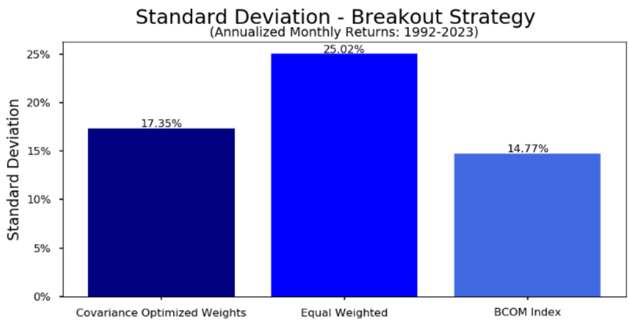


Figure 14: Breakout Strategy VaR

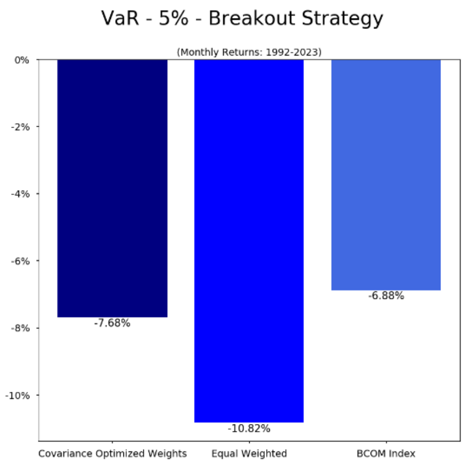


Figure 15: Breakout Strategy Beta

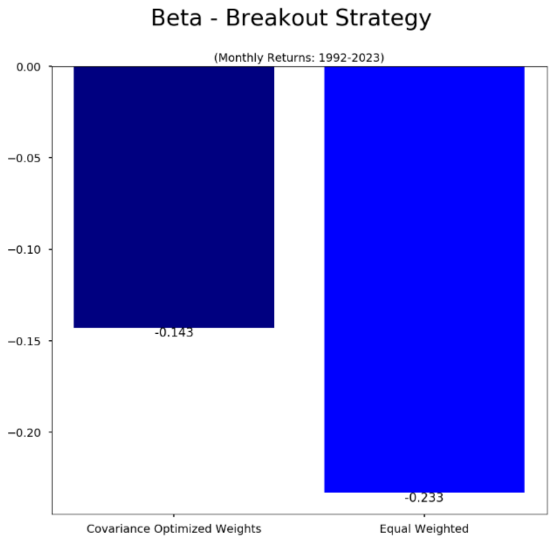


Figure 16: Breakout Strategy Alpha

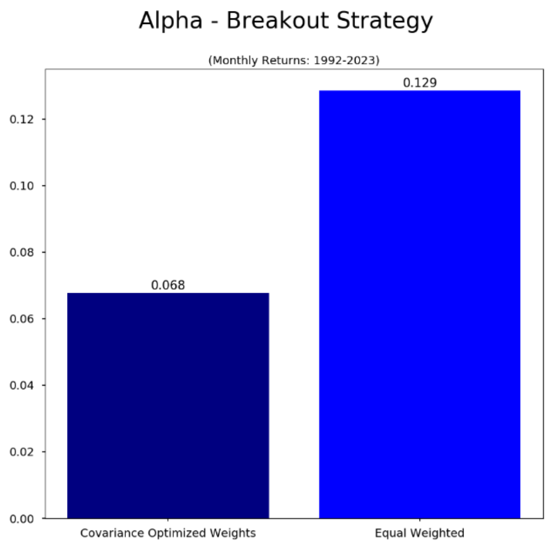


Figure 17: Breakout Strategy Sharpe Ratio

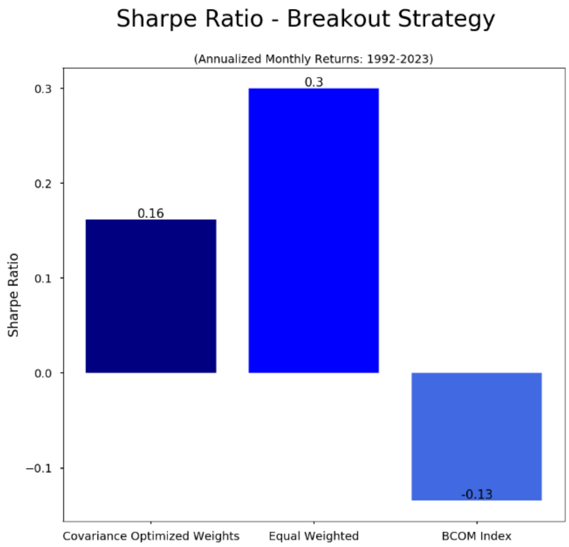


Figure 18: Breakout Strategy Annualized Total Return

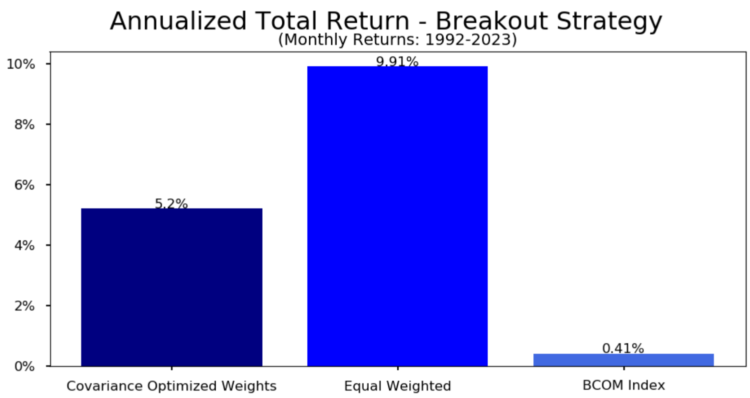
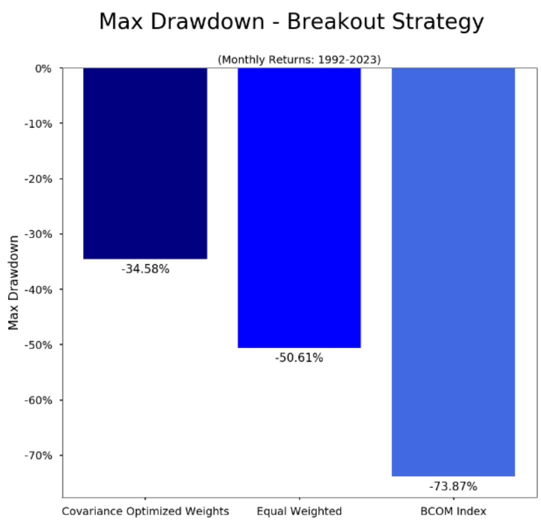


Figure 19: Breakout Strategy Max Drawdown



The results for the breakout strategy with transaction costs back test can be found below:

Figure 20: Breakout Strategy Performance with Transaction Costs

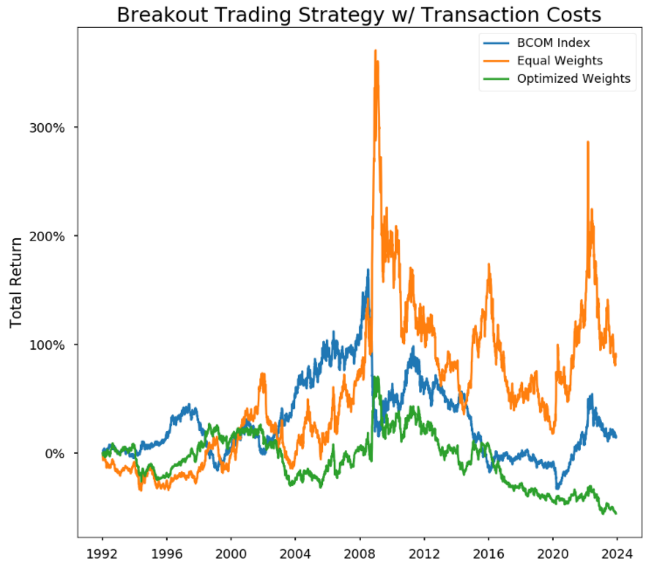


Figure 21: Breakout Strategy with Transaction Costs Sharpe Ratio

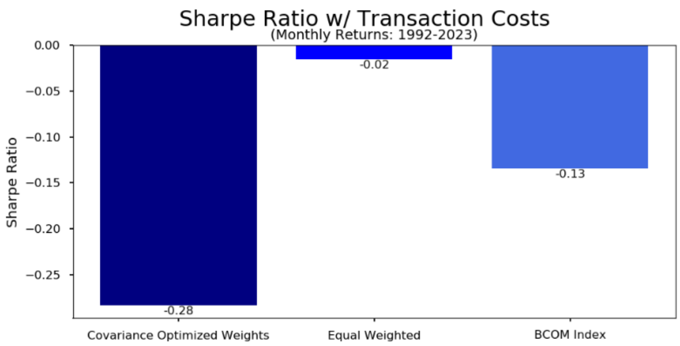
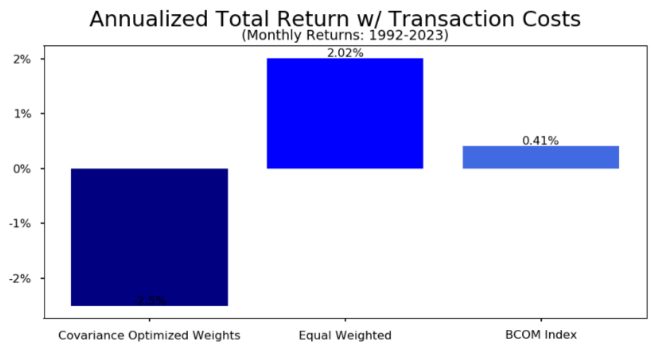


Figure 22: Breakout Strategy with Transaction Costs Annualized Returns



Conclusions, Limitations, and Future Research

Based on the results of our back test, the theoretical performance of our investment strategy reduces portfolio variance and improves performance in comparison to the benchmark and equal weights portfolio. Despite this success, the following areas are model limitations and potential areas of future research:

1. Despite attempting to capture both volatility and neutrality in a model, future research and investigation should be done to isolate the effects of market return on the variance term. This would allow for a cleaner model that looks specifically at the idiosyncratic properties of a portfolio.
2. Develop methods to manage the effects of transaction costs on strategy performance.
3. Explore the effects of leverage on performance and include futures specific trading considerations into the strategy

Works Cited

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