FACTOR-BASED INVESTING IN AN OVERVALUED MARKET

By

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Abstract

Tasked with creating a market-neutral, beta-neutral, long / short, unlevered, minimal-cash portfolio for the Chicago Quantitative Alliance Challenge, our team used a factor-based methodology to develop a portfolio of securities that we believed would perform in a period of market correction from November of 2017 through March of 2018. These factors were weighted in the portfolio as size (20%), value (35%), momentum (30%), and beta (15%). We later added quality as a factor and removed size, while also adding a small sector bet on technology and healthcare. We backtested the portfolio seven times by reconstructing the factor-method with a Python algorithm that ran on data and computing power provided by the Quantopian servers. These backtests indicated that the portfolio would succeed in a period of market correction. At the end of the challenge, the portfolio returned -0.07% and had a Sharpe ratio of -0.37. Despite not generating positive returns, we believe that these results were overall positive in teaching us how to construct and manage a portfolio with an array of quantitative skills.

Delineation of Duties

The additional members of the team were Justin Jost, Sebastian Laguna, Joey Leduc, and Ryan Shumway. All members of the team worked in some capacity on every aspect of the project. Whether it was idea generation, portfolio construction, backtesting, analyzing results, or implementing changes, all team members played an equal part in the completion of this project.

Introduction

The pervasive problem in the world of portfolio management is generating high returns with low levels of risk. This was the task presented to us by the Chicago Quantitative Alliance (CQA) Challenge. One of the strategies used to tackle this problem is to push the portfolio risk to almost zero while selecting investments that maintain factors which are understood to be return-generating. This strategy is known as factor-based investing, and it applies a purely quantitative method to selecting investments and completely removes any qualitative analysis from the process. We utilized this strategy while constructing our portfolio, a process which will be further detailed later in this document.

When constructing a portfolio, its important to test the method being used. We tested our portfolio by recreating our factor-based strategy with a Python algorithm that used historical information to test how the strategy would have performed in prior market periods. This allowed us to test our portfolio in a variety of conditions and gave us an expectation for how we would perform over the course of the competition.

Towards the conclusion of this paper, we'll address the results and then reflect on our process of portfolio construction and testing to highlight any successes or failures. Let's start at the beginning though, with the original bounds of the CQA Challenge.

The Competition

The CQA Challenge is a competition to manage a portfolio of investments by applying principles of stock selection and portfolio management in a simulated experience that emulates a process similar to what hedge funds do. A team of undergraduate students are supervised by a member of the CQA and, in our case, a faculty member. The team is expected to complete analysis that encompasses initial stock selection, portfolio management, and risk allocation decisions.

The bounds on the portfolio are somewhat stringent. They are detailed below:

1. The portfolio must be a long / short selection of equities that together are market neutral. This means that the team may buy or short-sell equities, but the overall portfolio must be structured to perform in both increasing and decreasing markets in order to avoid market risk. The team's portfolio must have a portfolio beta between -0.25 and +0.25 on a weekly basis.
2. $1,000,000 of capital must be invested. Because this is a long / short portfolio, that means that each portfolio will have a value of $2,000,000.
3. The equities for the portfolio will be selected from a list provided by the CQA. This list essentially mimics the stocks that are listed in the Russell 1000, although is not exactly the same. There are a few discrepancies which are immaterial.
4. Each position in an equity cannot be larger than 5% of the overall unlevered portfolio value. When the challenge begins, the maximum position size for any individual position cannot be larger than $50,000. However, an existing position (after the challenge begins) may be over 5% of the unlevered portfolio value.
5. Teams cannot lever greater than a 2:1 ratio. This ratio is created by the shorts in the portfolio and therefore teams cannot borrow additionally.
6. The portfolio cannot have more than 5% of the overall unlevered value in cash.

If these constraints were violated for a period of more than a week, a team would have their ranking in the competition decreased by five places. If a team infringed upon the rules again, they were removed from the competition.

Team's rankings were scored on a basis of three elements. The first of which was the absolute return of the portfolio. The portfolio was managed on the StockTrak platform and so the absolute return of the portfolio could be tracked on a day-to-day basis. Additionally, teams were scored by a risk adjusted return as calculated by the Sharpe ratio. The meaning of the Sharpe ratio will be further elucidated upon in the discussion of results section of this document. The final factor was a video presentation that discussed the portfolio strategy. This video was scored by a panel of CQA members. These elements were weighted as follows:

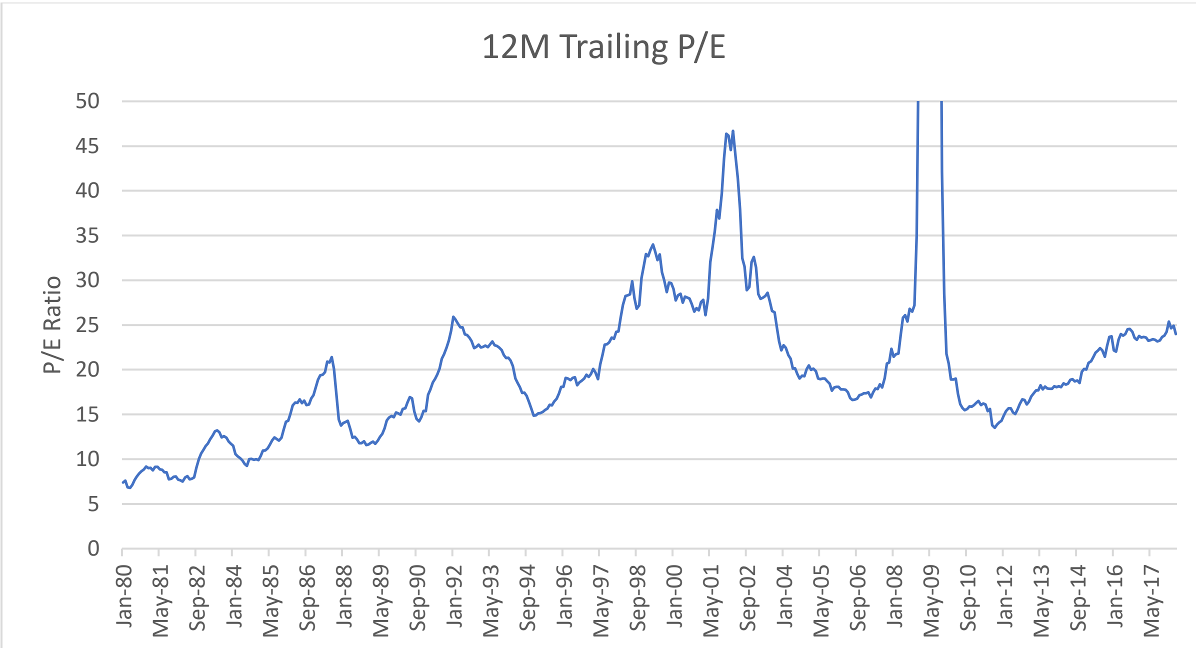
- 45% to risk adjusted return
- 30% absolute return
- 25% video strategy evaluation

The next section of this document will outline how we constructed the portfolio to adhere to the constraints of the competition.

Portfolio Construction

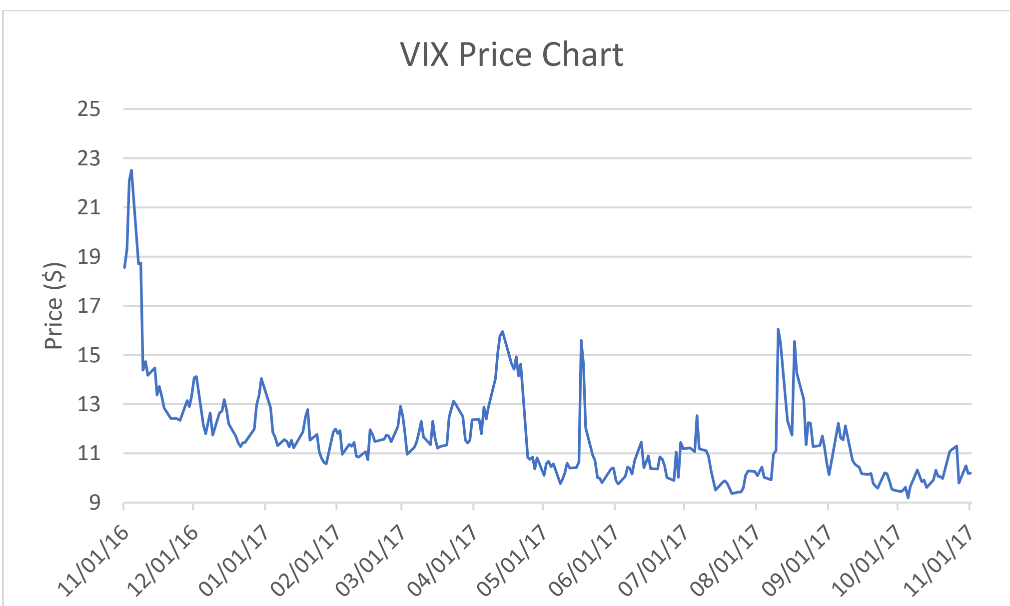
Market Analysis and Geopolitical Risk

When we began considering how we wanted to structure our portfolio, we first turned to the market and geopolitical atmosphere to determine what type of investments we should be making. In the market we saw extremely high valuations and an unusual low-volatility environment. High valuations in the market were indicated by several different factors. Performance across sectors in 2017 saw every sector except Energy and Telecom gain double-digit percentages (Real estate gained just under 10%). The Dow Jones Industrial Average was climbing towards a coveted 25,000 mark. Markets had rallied after the election of pro-business President Donald Trump. Additionally, the S&P was trading at levels that were much greater versus historical values as evidenced by the following graph.



Ignoring the period just prior to the financial crisis, it is notable that the P/E ratio was starting to crawl back up to historically very high levels. All these factors indicated an overvalued market which was ripe for a correction.

Volatility, as best measured by the CBOE Volatility Index, was at an unusually low and stable level when we began constructing our portfolio. The chart below shows the change in the VIX during the year prior to portfolio construction.



This chart indicates that the market we were about to invest in was not as volatile as it had historically been, so we believed that the VIX would experience some reversion to the mean and drive down equity prices. Particularly in conjunction with the geopolitical risk mentioned hereafter, we found these low VIX values to be somewhat concerning for the market's valuation. The combination of this chart and our belief that the market was unnaturally overvalued were the first basis point of the construction of our portfolio.

We also saw high levels of geopolitical tension that could tilt investor sentiment towards a correction or limit the gains that were evident in 2017. Although many of President Trump's new policies could be beneficial to the economy, his policies regarding diplomatic relations with other countries were a cause for concern. Additionally, his desire to drive up investment in US based companies could be a boon for some potential investments, but again would not be beneficial to an international slew of investments. Also in the US, we saw instability with a flare-up of social unrest following multiple shootings and political marches. Furthermore, we saw continued struggles in the Eurozone, particularly with Great Britain's inability to outline trade agreements that would be beneficial to their economy following Brexit. There were also a string of terrorist attacks in England in mid-2017. Across Turkey and the Middle East there were a series of coups and wars that generated additional geopolitical risk, including the war in Syria. Although we saw growth and development in India and China, there was significant corruption that again limited the sustainability of the world economy.

By analyzing these geopolitical risk factors in conjunction with an overvalued market we believed that the US market was due for a correction. With this in mind, we set about deciding how we would build a portfolio that would favor these conditions.

A Factor-Based Strategy

With input from our advisors Scott Cederburg and Chris Campisano, we quickly settled on constructing our portfolio using a factor-based strategy. We learned that using too many factors could have a cannibalization effect, where the benefits of one factor dominated the benefits of another. So, we needed to select a small group of factors that would be beneficial in the event of a market correction. The factors we selected are as follows:

1. Size: as measured by the market capitalization of the company. In times of a market correction we expected that small-cap companies would outperform large-cap ones.
2. Value: as measured by the book-to-market ratio. We expected that companies with low book-to-market metrics would outperform high book-to-market ones. This metric was considered independently of the position of the market because it is specific to each company.
3. Momentum: as measured by week-over-week trading performance, investments that move in one direction (up / down) tend to usually continue trending in that direction.
4. Beta: we preferred stocks with lower (even negative) betas to counteract the movement of a market we had deemed overvalued. Like the value factor, beta was also considered independently of the market position.

In order to create a portfolio based on these factors, we completed the following process.

1. We downloaded data associated with each of these factors from Bloomberg for each stock in the investment universe provided by the CQA.
2. We separated the universe out by sector and then z-scored (or used a logarithmic function) to modify the data so that it could be used in ranking the stocks.

    a. This step is completed to prevent a grouping effect, so that data for each stock in the universe is more equally distributed and one factor does not end up determining a ranking for a stock.
3. We applied a quintile ranking to each security by factor where a fifth quintile ranking was considered the highest and a first quintile ranking was considered the worst.
4. We then multiplied the quintile of the factor by a weight for each factor. Those factor weights are as follows:
    a. Size: 20%
    b. Value: 35%
    c. Momentum: 30%
    d. Beta: 15%

   These values were selected based on personal interpretation by the team. We thought that most returns could be garnered from value, then momentum, then size, then beta.
5. Once each security had a score, we selected the top two stocks in each sector to buy and the bottom two stocks to short-sell. This allowed us to keep our leverage ratio equal to 2:1 and the portfolio would be composed of long / short investments with a beta that we expected to be close to zero.

Its important to note here that once a security had been selected, we did not determine whether we should include that stock in the portfolio on an individual basis. This was done to prevent individual bias from entering the selection process.

Also, its important to note here that there are two ways to develop a factor-based portfolio. The method outlined above is considered a top-down approach because stocks are broken out by sector and then ranked. However, it is also possible to use a bottom-up approach that ranks stocks in the universe and then sorts them by sector. However, this can prevent a portfolio from selecting the best stocks in the portfolio because quintile rankings can be affected by stocks in one industry that tend to score better or worse. Therefore, we deemed the top-down method of selection to be the best for the creation of the portfolio.

In order to meet the constraints of the portfolio we also calculated a portfolio beta based on the cash, longs, and shorts in the portfolio. This calculation is done with the following formula:

$$\beta_P = \sum \beta_s * w_s$$

Where β_s is the beta of an individual stock and w_s is the weight of the stock in the portfolio. Cash is considered to have a beta of zero. There was a small amount of cash in the portfolio, less than 5% (per the competition constraints), and so this did have a small effect on the beta of our portfolio.

Additionally, to get a metric for how our portfolio would perform, we calculated expected volatility using a correlation matrix between all the stocks in the portfolio in order to determine the risk inherent in the portfolio that we had constructed. This value was originally close to 7% which was determined reasonable by the team as well as our advisor.

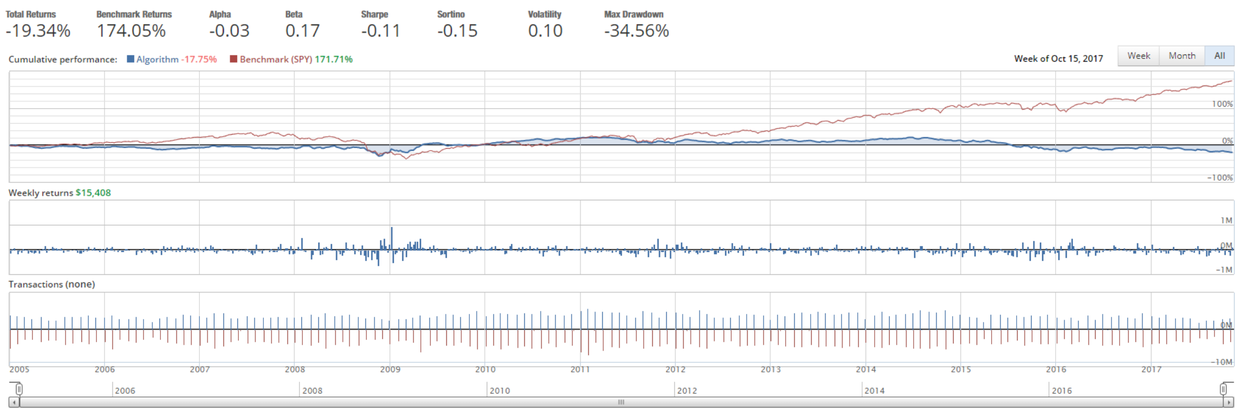
With our selection of stocks that met the constraints of the portfolio and also a comfortable risk metric, we wanted to further test the applications of this portfolio in times of a market correction. In order to do so, we turned to the process of backtesting.

Backtesting

In order to further our understanding of how the portfolio would perform in times of market correction, we backtested the strategy with a Python algorithm that ran on the Quantopian datasets and servers. Python is a basic programming language while Quantopian is a service provider that allows users to manipulate datasets and build algorithms that can test performance in the market over historical periods.

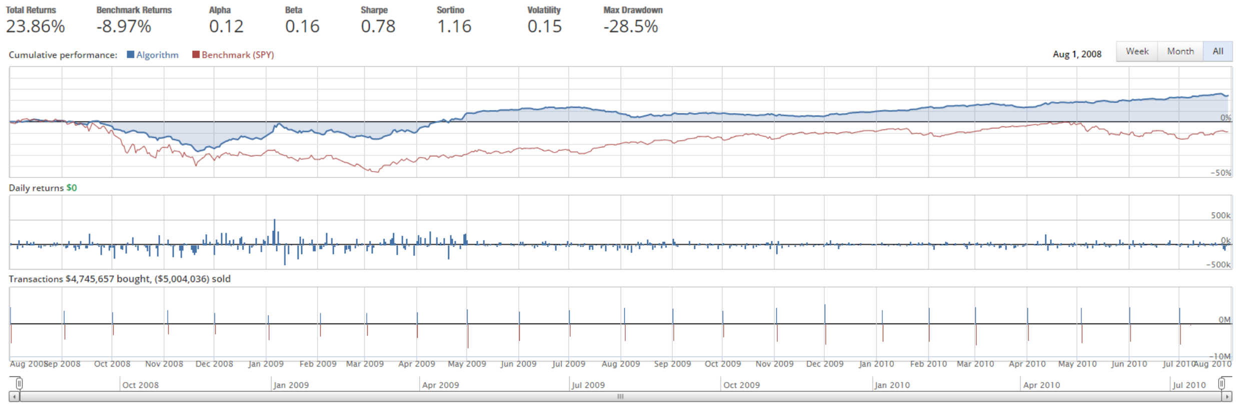
The algorithm that we developed used the same strategy to pick stocks as outlined above, but operated on a slightly different universe. The universe of stocks used in backtesting was the top 1,500 stocks in the US market. This was used because this universe of stocks is built into the Quantopian platform and would provide a good benchmark for portfolio performance because the strategy was the same, only operating on a slightly different universe of stocks.

We initially backtested four different time periods that each showed different types of market performance. The first was from the beginning of 2005 through the current date (November 10th, 2017). This simulated how our portfolio would perform over a long period of time with both a correction and a bull market. The following picture illustrates performance:



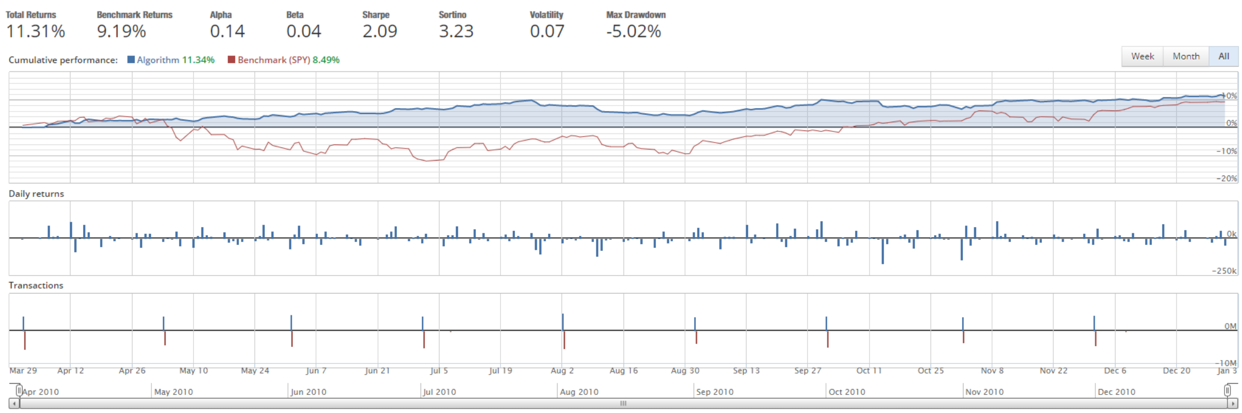
The red line indicated the market performance while the blue line indicates portfolio performance. Our first takeaway was that during the 2008 correction we outperformed the market significantly and so it would be worthwhile to investigate further testing of that period. Additionally, the beta of the portfolio was 0.17 over the course of the test, which indicated that our portfolio was in fact market neutral. These were both positive signals for us.

We next further tested the financial crisis period, beginning in August of 2008 and ending in August of 2010, when the market saw its greatest downturn. Performance is seen below.



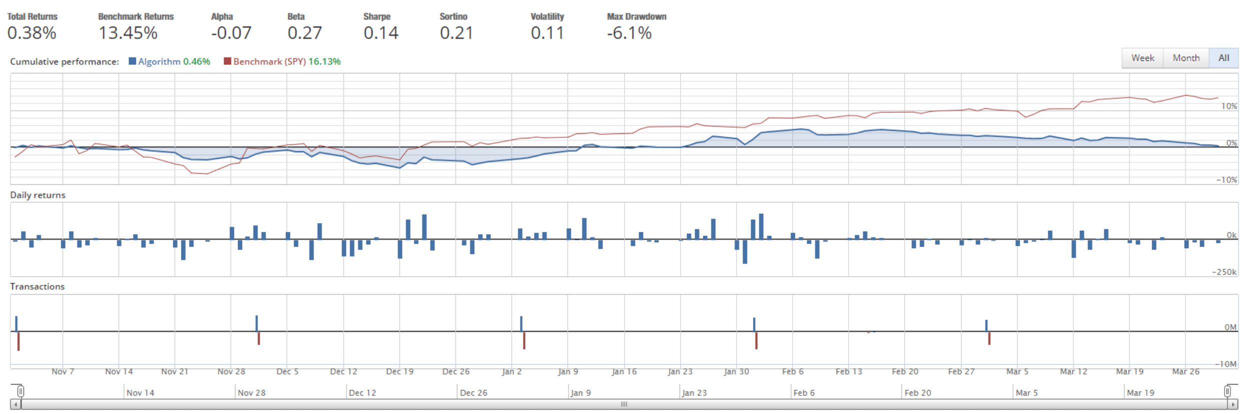
This backtest showed us exactly what we wanted to see. Despite falling during late 2008, the portfolio did not fall as significantly and began to recover much faster than the market over this period. Again, we had a sustainable beta value. Additionally, total return outpaced the market significantly, 23.86% for the portfolio and -8.97% for the market. These were positive signs for the performance of our portfolio.

Our next backtest examined a period of time in 2010 (roughly about eight months from April to December) when the market struggled a bit. Performance is below:



Here, it was interesting to note that our portfolio never dropped into losing territory while the market did. This is slightly different then the last test, but makes sense because in 2008 the economy came to a grinding halt while in 2012 we saw a more minor recession. This is the type of event we were anticipating over the course of our competition, and so we gained more confidence in our strategy from this test.

Our final test was to examine what would happen if the opposite of our prediction occurred and the market continued to rise. To do so, we examined a period of about five months in late 2011 through early 2012 (November to April).



This test, although not good for returns, was still a positive sign for our portfolio. Even when the market was taking off and generating enormous returns, our portfolio was still not losing any money. The market was doing much better, but our portfolio that favored a correction was not trading opposite to the overall market. This was further indicated by a beta of 0.27, which, although slightly outside the bounds of the competition, was manageable.

These four backtests confirmed that our strategy was solid and that we had the potential to perform well in the competition. With this in mind, we executed the trades for the securities based on the output of our model.

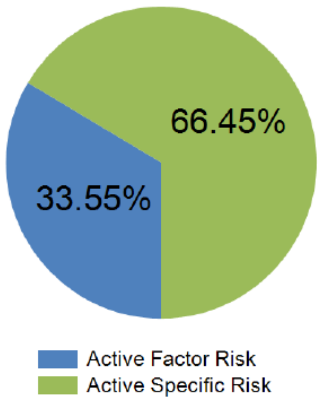
Portfolio Reconstruction

After the portfolio began we watched it on a daily basis with the intent to rebalance the portfolio on a monthly basis. Over the course of the competition, we made two adjustments to the portfolio. One of these adjustments was very minor while the other was an alteration to our initial portfolio strategy and resulted in a much greater change.

When the initial trades were executed, we noticed that we had made a small mistake in our factor-based model and some of the rankings in the portfolio were off. This was less than a month into the competition and so the results of the adjustment to correct for this mistake were negligible in our overall results. However, this was a valuable learning moment for everyone involved in terms of completing due diligence and verifying the results of our output.

Our second adjustment to the portfolio came about halfway through the competition. One tool provided by the CQA was a monthly report from Axioma that explained the performance of our portfolio and the how the risk in the portfolio was divided up. The results of our first report were non-material because the time-period was very short, and the portfolio had been minorly affected by the mistake listed in the prior paragraph. However, the January Axioma report in conjunction with our current middle-of-the-pack ranking for the competition indicated to us that we were should take on significantly more risk in an attempt to generate a higher return.

Active Risk Decomposition

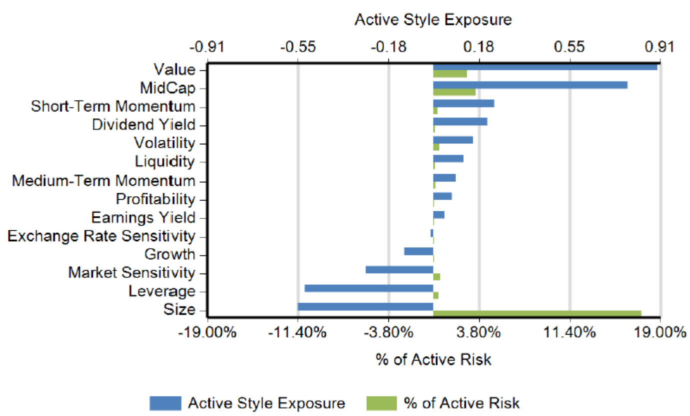


Risk Decomposition	Active Std Dev (%)	Active % of Var	Active % of Var (Cov-Dist)
Active Risk	7.60%	100.00%	100.00%
Specific Active Risk	6.20%	66.45%	66.45%
Factor Active Risk	4.40%	33.55%	33.55%
Style	2.98%	15.39%	18.38%
Industry	2.62%	11.89%	15.18%
Market	0.33%	0.19%	-0.01%

This chart is the best indicator of that shortcoming in our portfolio. At this point in the competition, we had only 7.6% of risk inherent in the portfolio and only 4.40% of that was derived as factor risk. We deemed this to be too low, and so we set about coming up with a better method to generate factor risk.

The second indicative part of this report came from a breakdown of what factors were affecting our portfolio the most.

Style Factors



This breakdown highlighted that the value, volatility, and momentum factors were having some effect on the portfolio's risk, but they were dwarfed by the bet that we were taking in the size factor. We decided that we wanted to trim down the weighting of that factor in the stock-selection criteria.

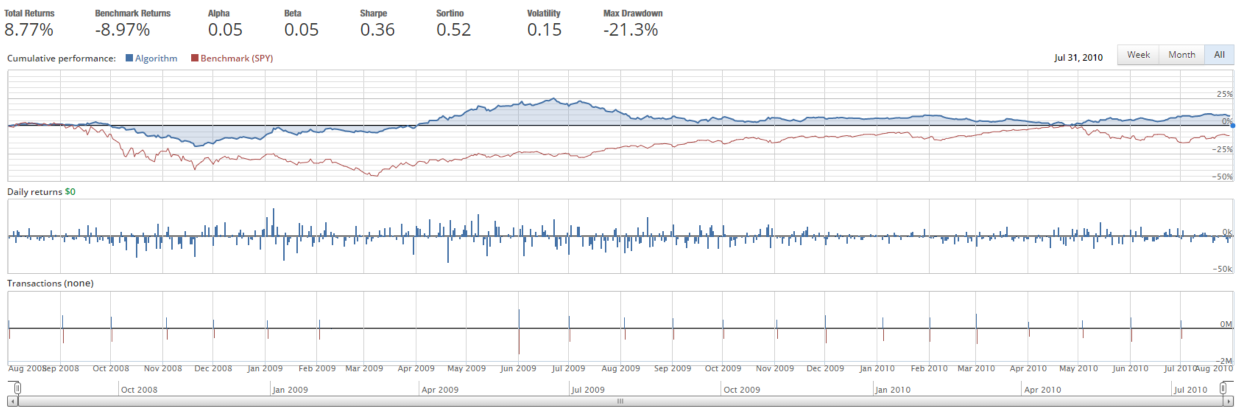
We determined based off these two pieces of the Axioma report that we first needed to increase the risk that we were taking on and second decrease the effect that the size factor was having on the portfolio. We decided to change three things about our selection process:

1. The weighting of the size factor was reduced to zero so that it no longer influenced the rankings in the selection criteria.
2. We added quality as a metric to replace size. This metric was measured by each company's ratio of gross profit / assets. The higher this ratio was, the higher the quality of the security.
3. In order to add risk to the portfolio, we increased the bets in two sectors:

a. We increased the number of long positions in the healthcare sector to four and removed the shorts, with the belief that the healthcare sector performs better in periods of economic downturn.
b. We increased the number of short-sells in the tech sector to four and removed the long positions, with the belief that the tech sector suffers the most during market corrections.

The effects of these changes will be addressed in the next section which discusses the overall results of the portfolio.

We also backtested this new portfolio strategy by altering the Python algorithm that was developed earlier to match our new strategy. This time we ran three backtests, one of which was the same period, one was a new period, and one a slightly different period. The first period tested was again the time from 2008-2010 when the market saw the worst of the financial crisis.

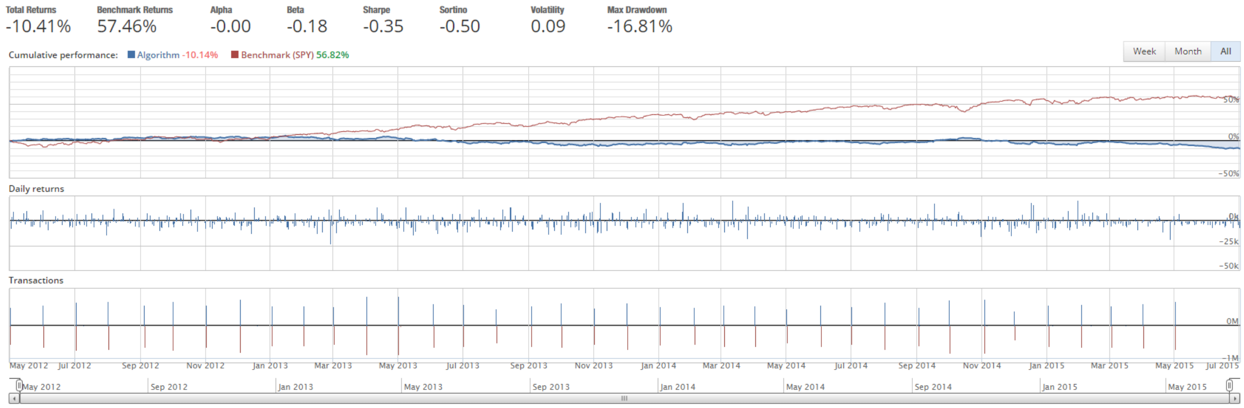


It's interesting to note that this new strategy still beat the market significantly over this period (8.77% vs. -8.97%), but it returned much less than the prior strategy (~24%). This is contrary to our belief that adding more risk would allow us to generate larger returns.

The next backtest was over a new period in 2010 where the market saw a minor dip.

In this backtest, our portfolio barely beats out the market, but its interesting to note that when the market falls heavily towards the beginning of this backtest our portfolio remains in positive territory. This suggested to us that that our portfolio would be robust enough to outperform in times of market correction. This was a trait that we desired in our portfolio.

The final test began around the same time as the prior test from 2012 but this time extended into 2014.



This backtest shows how our portfolio would perform in the extreme bull market that was similar to what we had experienced thus far in the competition. Although our portfolio ended up returning -10.41%, most of this loss was generated in the final months of the backtest. This means that when the market saw most of its gains, our portfolio was holding around a return of zero before it began to dip. This again indicated the robustness of our portfolio.

Discussion of Results

The results of our portfolio construction can be viewed under several lenses: the return of the portfolio in conjunction with its Sharpe ratio, the ability of our portfolio to meet the constraints, our success in building a portfolio with a factor-based methodology, the results of the adjustments we made to the portfolio, and our performance in the video component of the competition. These are all useful tools in examining the success of our portfolio.

Return and Sharpe Ratio

The final results of our portfolio are best quantified by its overall return, which was -0.07%. This is slightly behind the benchmark (cash for a market-neutral portfolio). Money market funds tend to return 2-3% over the course of an investment, and our portfolio fell short of that mark. Against the rest of the competition however, this return value was directly in the middle of the pack at 27 out of 51 participants. The Sharpe ratio of the portfolio, which is calculated using the following formula, yielded similar results for us:

$$Sharpe\ ratio = \frac{r_p - r_f}{\sigma_p}$$

Where r_p is the mean return of the portfolio, r_f is the risk-free rate (usually the return on a 10-year Treasury), and σ_p is the standard deviation of the portfolio. The Sharpe ratio is a measure of how much return a portfolio manager can generate versus how much risk was used in the investment. The Sharpe ratio of our portfolio ended at -0.37, which means that we generated some small level of negative return for the amount of risk that we were using. Versus our peers in the competition, this was right in the middle at 26 out of 51 participants.

Operating within Constraints

Our portfolio never strayed outside the bounds of the competition, which can be considered a success. This means that we maintained a beta between -0.25 and +0.25, we did not over-lever, we did not over-invest in one security, and we never had too much cash on hand. Such a feat can be attributed to the construction method that we used. This allowed us to immediately test for whether our portfolio operated within the beta restraints and could calculate the weight of each investment in our portfolio. Although this is a small victory, it indicates how we were able to apply our knowledge and skillset to meet the constraints of the CQA Challenge.

Construction Methodology

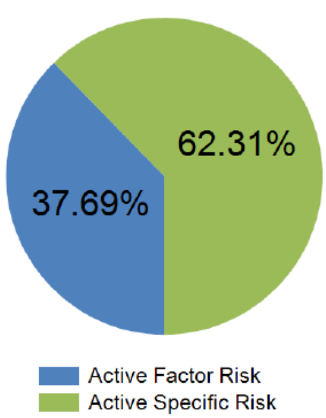
Our success operating within the competition constraints was derived from the successes that we found in the actual construction of our portfolio. Over the course of the competition we learned how to build a factor-based portfolio, what factors are useful and how to combine them in order to not cannibalize their effects, and how to test our methodology to determine its effectiveness. Being able to field such a portfolio that required in-depth analysis and extensive quantitative skills is a success in itself, and creating one that was able to return (almost) non-negative results is further reputable. The learning process that we underwent in this portfolio construction will be applicable in the future for other types of analysis.

Some shortcomings of the construction were apparent however. We should have spent more time analyzing the effect that size as a factor would have on the portfolio. Unfortunately, too much of our risk was derived from this factor and that probably drew away some of our returns. Additionally, as was mentioned prior, the small mistake that we made in the portfolio construction probably also affected our ability to generate some returns even though it was only inherent in the portfolio for a short period of time.

Ability to Adjust

When we determined that we wanted to make some adjustments to the portfolio we were able to achieve the results that we wanted. After the adjustments, the Axioma report showed the following information for risk decomposition:

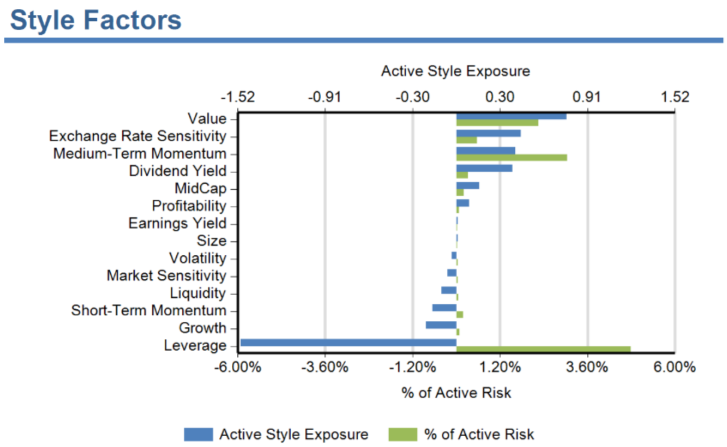
Active Risk Decomposition



Risk Decomposition	Active Std Dev (%)	Active % of Var	Active % of Var (Cov-Dist)
Active Risk	6.98%	100.00%	100.00%
Specific Active Risk	5.51%	62.31%	62.31%
Factor Active Risk	4.29%	37.69%	37.69%
Style	1.98%	8.00%	8.14%
Industry	3.73%	28.47%	29.00%
Market	0.49%	0.49%	0.56%

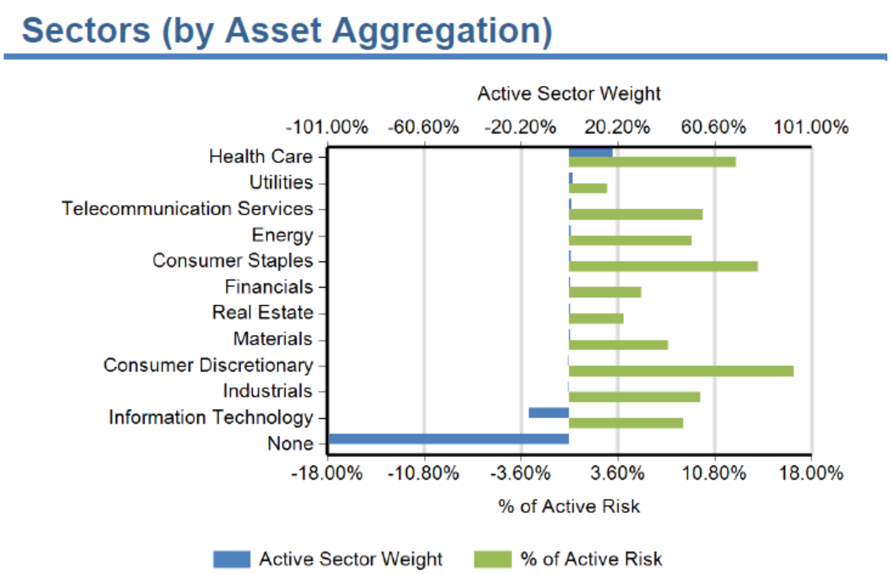
This means that we were able to drive up some of the active factor risk that we wanted to. The change was only of 4.14% however being able to move the needle with the changes that we wanted to make was important.

Additionally, the style factors changed to show the following:



In this chart, it can be seen that size has completely been removed as a factor from the portfolio. This was an effect that we wanted to create. Additionally, the effects of momentum and value became more prevalent, another effect that we wanted to establish in the portfolio. Its interesting to note here that leverage also increased as a factor despite us not changing the leverage of our portfolio. It can be hypothesized that this factor is somehow attached to the quality metric that we tried to inject into the model.

Another chart of interest is the distribution of risk across sectors:



The blue lines in this chart indicate that our bets against information technology and for health care were in fact generating some level of risk in the portfolio. Although all of these sectors were generating some risk, the fact that our weighting was registering on these reports can be considered a win for our team.

However, its important to note that these adjustments to the portfolio still did not generate the additional return that we were hoping for. Therefore, although we were successful in implementing these changes, they did not have the desired effect on the portfolio.

Video Component

As mentioned in the competition section of this document, the final scored component of the competition was the video explanation of our methodology and results. Our team worked to develop a video that was altogether interesting, informative, and creative. The final video can be viewed at the link given in the appendix of this document.

Our video was scored by several judges and we received the highest marks in the competition (1st out of 51 teams). The feedback from the judges noted that our video was the most clear, concise, and understandable video by a large margin. These ratings were provided based on the content of our video and our ability to convey our ideas. These high marks verify the result of our hard work in designing our portfolio, testing it, and then reconstructing it. This affirms that although we did not receive the results we had hoped for in the competition, we had a strong understanding of the process and could convey this to an audience. Due to the short trading window of the competition and the inherent randomness of short-term stock market performance, this is a very meaningful metric and should be the hallmark of our success.

Appendix

Video

https://www.youtube.com/watch?v=s7mNM16W40w

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