2017 CHICAGO QUANTITATIVE ALLIANCE INVESTMENT CHALLENGE: UNIVERSITY OF ARIZONA CQA TEAM – INVESTMENT STRATEGY

By

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With Honors in

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UNIVERSITY OF ARIZONA

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Abstract

In order to complete my honors thesis in finance, I joined a team of five finance students in participating in the 2017 Chicago Quantitative Alliance Investment Challenge. The challenge required teams to create $2,000,000 market-neutral investment portfolios utilizing both long and short equity positions. From November 8th until March 31st, our team actively managed our equity portfolio by selecting stocks from a 1,000 stock investment universe, while 53 other teams from universities around the world competed against our portfolio using measures of absolute return, risk-adjusted return, and a team video explaining our performance and investment strategy. By utilizing a strategy contingent on both industry bets and style exposures to value and momentum, the University of Arizona team has achieved an absolute return of 12.23% and a Sharpe Ratio of 1.43.

Challenge Overview

The Chicago Quantitative Alliance (CQA) Investment Challenge in 2017 took place from November through March, and it involved 54 separate teams from around the world. The competition was to create a $2,000,000 long-short equity portfolio that met requirements set forth by the CQA's guidelines. These included: the portfolio must remain market-neutral by maintaining a portfolio beta between -0.25 and 0.25 over the entirety of the competition; the portfolio must remain fully-invested with no more than 5% of capital allocated to cash; no individual position is greater than 5% of the portfolio's value; and the portfolio must maintain dollar-neutrality by ensuring that total long positions and total short positions are never more than 5% less or greater in market value than one another.

Just past the halfway point in the investment period, each team was required to submit to CQA a video explaining their investment strategy, portfolio construction, risk analysis, and performance attribution. The video, in conjunction with the performance of each team's portfolio as determined by measures of absolute return and risk-adjusted return, forms the bases for the CQA's decision of the competition winner. At the time of this writing, the University of Arizona team's portfolio ranks first in absolute return and in the top 5 in risk-adjusted return.

The competition uses the online trading simulating platform StockTrak, and provides risk reports from Axioma to each team on a monthly basis. Our team was mentored by CQA member Chris Campisano and University of Arizona Professor Dr. Scott Cederburg. Our team of five members divided roles equally amongst the team, with every member contributing to both long and short selection. The team included members Spencer Bateman (Risk Management), Charles Recchion (Portfolio Management), Edward Recchion (Factor Analysis), Kham To (Trading), and Hilla Hascalovici (Long and Short Selection). For the purposes of the competition, I was assigned the role of managing risk in our portfolio and keeping the portfolio within the competition bounds set forth by CQA.

Investment Strategy and Thesis

Overview

Our investment thesis was based on both macroeconomic industry trends we expected to emerge following the 2016 Presidential Election and empirically demonstrated investment strategies based on specific style exposures. First, our team expected that Republican nominee Donald Trump would win the U.S. Presidential Election, and that the Republican Party would maintain control of the U.S. Congress. The challenge required that the portfolio be fully-invested by November 8th, Election Day, which meant that much of the performance in this year's competition would be heavily-related to the election result and the first months of a new presidency. Using this information, we made both long and short industry-specific bets in our portfolio. Second, longstanding evidence of positive portfolio performance related to quantitative investment elements like style exposures led us to tilt our portfolio in a manner consistent with those exposures.

Industry Bets

The central theme of our investment strategy was our industry-specific bets, which we made in anticipation of Republican wins in the 2016 Election. Understanding the perceived near-certainty that Hillary Clinton would win in 2016 and that Democrats had a strong chance at capturing control of the Senate would lead to a pricing-in for those results in the market, we believed that betting on a seemingly less-likely Republican win would yield greater returns. This included long positions in both energy and financials, where we believed deregulation that Republicans had voiced support for would lead to greater profits and outperformance for these two sectors. The bet on financials was particularly attractive, given likely interest rate rises and Clinton's own close ties to Wall Street firms. Even if Clinton won the White House, financials stood to benefit and thus carried less risk.

Our industry shorts were made up of the consumer discretionary sector, which we viewed as being at-risk in a Trump Administration due to greater uncertainty and the looming threat of trade wars with China, Mexico, and other partners. Donald Trump repeatedly insinuated on the campaign trail that current trade deals like the North American Free Trade Agreement (NAFTA) would be restructured and that future trade deals like the Trans-Pacific Partnership (TPP) would be rejected entirely if he were to assume office. Additionally, tensions with the Mexican government revolving around the construction of a border wall and potential high tariffs on Mexico in order to pay for the wall led us to believe that sectors that benefit directly from the import-export relationships that the U.S. engages in would be most negatively impacted by a Trump Administration.

Style Exposures

Studies have repeatedly shown that exposing a portfolio to value and momentum measures both independently and together leads to higher returns (Barroso and Santa-Clara, 2015), (Daniel and Moskowitz, 2016), (Moreira and Muir, 2016), (Cliff Asness, 1997). Understanding this, our group choose to include both tilts in our portfolio. We took long positions in low price-to-book ratio stocks and stocks with high relative share price momentum over the past 6 months, and we took short positions in stocks with high price-to-book ratios and low relative share price momentum over the past 6 months. Therefore, we bet on value-winners and bet against growth-losers. This strategy coincided well with our industry bets, as value-winner stocks include several financials and energy firms, while growth-losers are largely consumer discretionary firms.

Portfolio Construction

We constructed our portfolio by first screening all of the stocks in the competition's universe via Bloomberg terminal. While screening, we separated stocks by price-to-book ratio, relative share price momentum, and price-to-free-cashflow, while also collecting the beta and sector for each stock. We then input the gathered data into our Excel model, which allowed us to assign numerical scores to each stock based on its value and momentum measures relative to the rest of the universe. Scores provided a numerical ranking of the stock relative to the universe in ascending order for the value measures. Price-to-free-cashflow was only used to evaluate stocks for which Bloomberg did not provide a price-to-book ratio. Then numerical rankings were assigned by relative share price momentum in descending order. The two scores were then added to one another, and that number became the score for the stock. Therefore, the stocks with the lowest score were those that were the value-winner stocks, while the highest scores signified growth-loser stocks.

1										
2										
3										
4	Ticker	CQA Beta	Price to Book	Relative P/B Score	P/B Rank	RSPM	Momentum Rank	Beta Bloomberg	P/FCF	Overall Attractiveness Ranking
5	NBR	1.8847	0.935525477	2.989820594	42	28	19	1.984561306	13.2	61
6	CNX	1.6436	0.947693467	2.95143254	44	23.36	28	1.861562192	21.76	72
7	MS	1.5356	0.916282892	3.052608928	38	20.55	46	1.568900306	3.57	84
8	WPX	2.0958	1.188961744	2.352517523	84	37.29	7	1.919744637	--	91
9	WRK	1.1525	1.170253634	2.390125743	76	24.75	24	1.407743946	12.91	100
10	TRN	1.527	0.884444892	3.16249589	29	16.16	72	1.330745756	16.43	101
11	HPE	1.6726	1.185932398	2.358526795	81	27.45	20	1.42955738	--	101
12	ZION	1.369	0.94324851	2.965340847	43	16.65	65	1.44068684	15.87	108
13	ENH	0.6798	1.316561103	2.12451464	105	38.78	5	0.757002621	26.77	110
14	LNC	1.6689	0.72998327	3.831667726	20	12.89	98	1.600056403	8.8	118
15	RF	1.4057	0.828004897	3.378063763	27	12.94	95	1.472762704	--	122
16	HPQ	1.0259	0	2.829142012	48	15.3	81	1.294596731	6.76	129
17	BAC	1.3893	0.703277349	3.97716966	17	11.49	112	1.452227417	--	129
18	CFG	1.3016	0.711020947	3.933855044	18	10.98	119	1.251438255	9.66	137
19	CMA	1.3716	1.157960057	2.415500707	72	16.38	69	1.422925021	18.73	141
20	PTEN	1.7219	1.381046772	2.025313982	116	23.69	25	1.621363451	13.74	141
21	FITB	1.3162	1.071365833	2.610735988	57	13.94	91	1.37756623	9.37	148
22	PWR	1.2108	1.260952473	2.21820679	92	18.68	57	1.096549322	11.31	149
23	RGA	0.9854	0.885242879	3.159645112	31	10.78	122	1.015176972	3.21	153
24	MU	1.7535	1.573530555	1.777565316	153	57.71	3	1.660349728	--	156
25	NOV	1.1337	0.821718633	3.403906428	24	9.99	133	1.29008299	11.2	157
26	SM	2.2087	1.469498754	1.903406403	136	27.17	21	2.252911112	--	157

Exhibit IIA: Long-stock Screening and Sorting

699	GGG	1.1126	5.970794678	0.46845579	598	-11.11	614	1.069296517	20.33
700	TJX	0.8732	10.8173275	0.258571568	685	-6.63	528	0.937311716	22.56
701	KO	0.5768	7.022931576	0.398274326	628	-9.33	588	0.737785708	28.67
702	CELG	1.4394	14.75102901	0.189617506	702	-6.25	520	1.265309044	24.79
703	VFC	0.7114	4.660824299	0.600119884	546	-17.18	682	1.086342953	17.66
704	GWW	0.8781	6.121099472	0.456952766	600	-12.25	632	0.895591879	21.68
705	AMG	1.6871	4.494570255	0.622318304	535	-19.95	698	1.714934922	6.9
706	PPG	1.2596	4.950894833	0.56495915	559	-19.17	696	1.145531045	22.28
707	REGN	1.3911	8.885959625	0.314772231	668	-9.82	595	1.261371406	45.64
708	VRTX	1.5809	20.20561981	0.138429475	711	-7.98	561	1.410770943	981.83
709	ABC	0.7019	8.035817146	0.348073293	653	-11.99	626	0.78180408	5.13
710	EL	0.8714	8.069725037	0.346610736	654	-12.06	627	0.904936482	26.85
711	CRI	0.7026	5.597262859	0.49971806	587	-19.15	695	0.852940271	25.02
712	DLPH	1.3859	7.350645542	0.380518054	636	-13.45	649	1.412750019	16.24
713	SPG	0.6934	12.45745564	0.224528461	693	-9.6	592	0.842750614	28.15
714	PII	1.1255	5.474912167	0.510885518	582	-21.4	705	1.071200025	34.89
715	FAST	1.0339	6.147441864	0.454994679	603	-17.67	684	1.023243359	35.73
716	LOW	0.9146	8.567862511	0.326458709	663	-11.86	624	0.948813417	14.54
717	WYN	1.1148	9.017932892	0.310165685	669	-11.85	623	1.142951853	9.89
718	NKE	0.9972	6.980508327	0.400694793	625	-15.43	668	0.92811442	38.44
719	CMG	0.679	7.692693233	0.36359871	647	-13.71	653	0.682377175	104.33
720	GILD	1.1542	5.635252953	0.496349208	590	-23.57	711	0.965338531	6.1
721	CLX	0.5064	50.89080048	0.054961866	731	-8.34	570	0.592618043	24.76
722	SBUX	0.8956	13.52526379	0.206802128	696	-10.73	610	0.980706554	25.69
723	HBI	1.308	7.739957333	0.361378392	649	-14.43	661	1.098326207	21.58
724	BMY	0.9252	5.604831219	0.499043277	588	-30.1	723	0.883394364	64.81

Exhibit IIB: Short Position Screening and Sorting

After the investment universe had been screened and sorted by relative attractiveness for inclusion in our portfolio, we began selecting stocks with both beta considerations and industry bets in mind. We quickly learned that those stocks that inhabited the value-winner range tended to also have relatively high betas, which complicated the selection process. While we had intended to go down the list of prospective longs and shorts fairly one-after-the-other, we were forced to draw many of our longs from further down the list and many of our shorts from higher up the list in order to maintain market-neutrality. However, the size of the investment universe did ensure that none of our longs were growth-loser stocks and none of our shorts were value-winner stocks.

As soon as we had constructed a portfolio with roughly $1,000,000 long and $1,000,000 short that was within the prescribed beta guidelines and in-line with our investment strategy, we made little changes over the course of the competition. Some early success led us to shave some of the long positions and add that money to short positions, in order to keep the portfolio market- and cash-neutral, but we did not need to rescreen stocks. Entering the last month of the competition, after weeks of stagnant growth, we decided to limit some of the portfolio's risk by readjusting our industry bets to a more balanced level. This meant we sold five financials stocks and covered five consumer discretionary positions, replacing both with either information technology or industrials firms.

Portfolio Risk Attributes

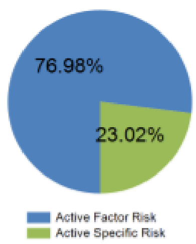
Unsurprising, given our team's investment strategy, our portfolio's active risk was generally confined to industry and style exposure, with minimal market exposure. Midway through the investment period (February 6th), at the peak of our portfolio's risk given the increased share of our portfolio dominated by industry-specific positions, the total portfolio risk was given by a standard deviation of 8.88%. This active risk was divided into four major subcategories: specific active risk, style exposure risk, industry exposure risk, and market risk.

Specific active risk, or risk provided by the individual stocks we selected for our portfolio, made up only 23.02% of total risk in our portfolio. The actual standard deviation risk measure for firm specific risk in our portfolio was 4.26%, the second highest of any individual risk type. Despite this seemingly high level, the relatively small portion of our portfolio's risk attributable to specific risk made it less of a driver for our overall risk and return. This was positive for us, as our team chose not to focus our stock picking effort on a more fundamental approach that would have yielded greater firm specific risk, but instead on industry-wide bets and more quantitative style measures. Additionally, the diversification of our portfolio across roughly 80 positions effectively limited firm specific risk exposures. While specific active risk was quite low, our active risk attributed to factors (industry, style, and market) was 76.98% of our portfolio's risk.

Risk Analytics

Summary	
Portfolio Risk	8.88%
Benchmark Risk	0.00%
Active Risk	8.88%
Historical Beta	0.28
Total Value at Risk ($) (5.00%)	$165,691.40
Active Value at Risk ($) (5.00%)	$165,691.40

Active Risk Decomposition



Risk Decomposition	Active Std Dev (%)	Active % of Var	Active % of Var (Cov-Dist)
Active Risk	8.88%	100.00%	100.00%
Specific Active Risk	4.26%	23.02%	23.02%
Factor Active Risk	7.79%	76.98%	76.98%
Style	3.63%	16.73%	18.97%
Industry	6.59%	55.17%	57.72%
Market	0.15%	0.03%	0.29%

Exhibit IIIA: Risk Decomposition (Axioma)

The factor active risk attributable to style exposure in our portfolio, as of February 6th, was 18.97% of the risk in our portfolio, and it carried a standard deviation of 3.63%. Of the style exposures in our portfolio, exposures to medium-term momentum and value predictably carried the greatest portion of risk, with other style exposures posing relatively minimal risk contributions. Profitability and leverage did contribute some relatively high individual exposures, but their percentage of active risk in the portfolio was negligible. This risk distribution amongst style factors is important in demonstrating that our team effectively screened stocks for style exposures without creating additional unwanted exposures in the process.

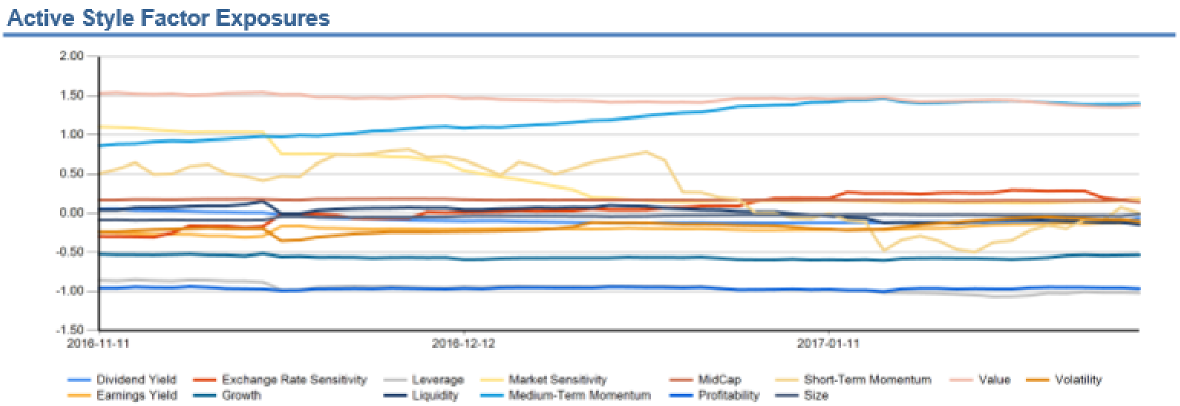


Exhibit IIIB: Active Style Risk Exposures (Axioma)

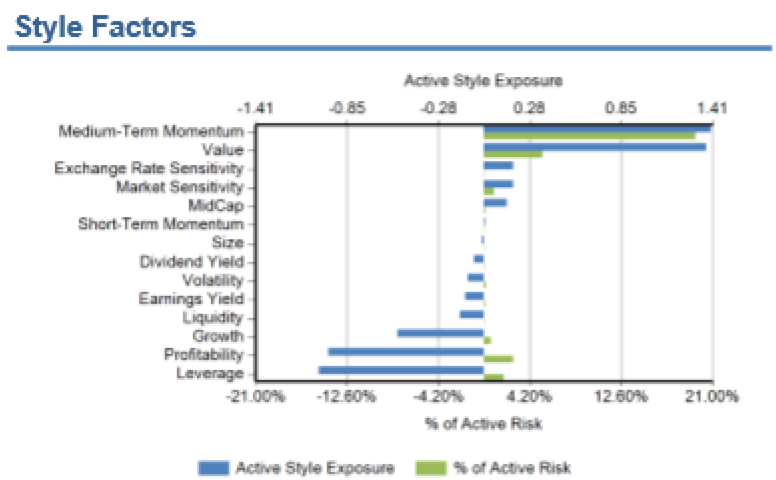


Exhibit IIIC: Style Factor Decomposition (Axioma)

The factor active risk attributable to industry exposure in our portfolio was by far our largest, both in standard deviation and in share of portfolio risk, with 6.59% and 57.72% respectively. Predictably, the greatest portion of our portfolio's industry factor risk was borne by financials, energy, and consumer discretionary, with consumer discretionary yielding the greatest sector weight and financials yielding the greatest percentage of active risk. Other industry contributions to risk were fairly negligible, although information technology carried some active risk in the portfolio. This distribution is also important in demonstrating the effectiveness of our team's ability to effectively screen stocks by industry, particularly when taken in conjunction with the aforementioned style exposure distribution.

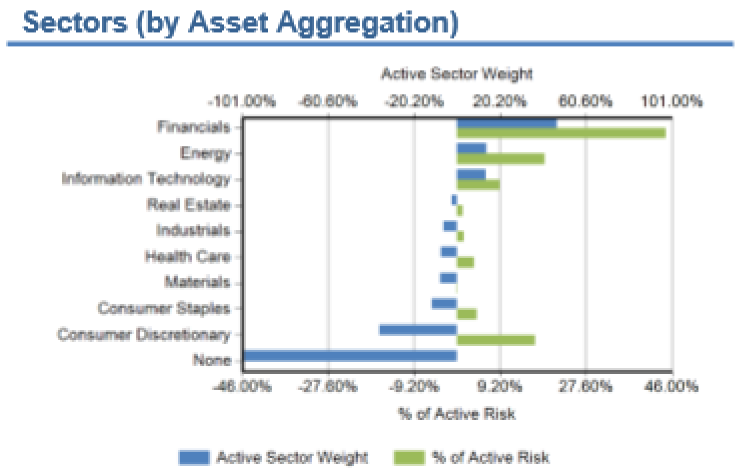


Exhibit IIID: Industry Factor Decomposition (Axioma)

Lastly, market factor risk was the smallest component of our portfolio's risk composition, which is especially important given the market-neutral nature of our portfolio. While we maintained a portfolio beta of close to the 0.25 upper boundary for the entirety of the competition, we were able to avoid over exposure to market risk, keeping the share of market risk in the portfolio to just 0.29% with a standard deviation of 0.15%. Our team was particularly proud of this fact, as it showcased our ability to create a truly market-neutral long-short portfolio.

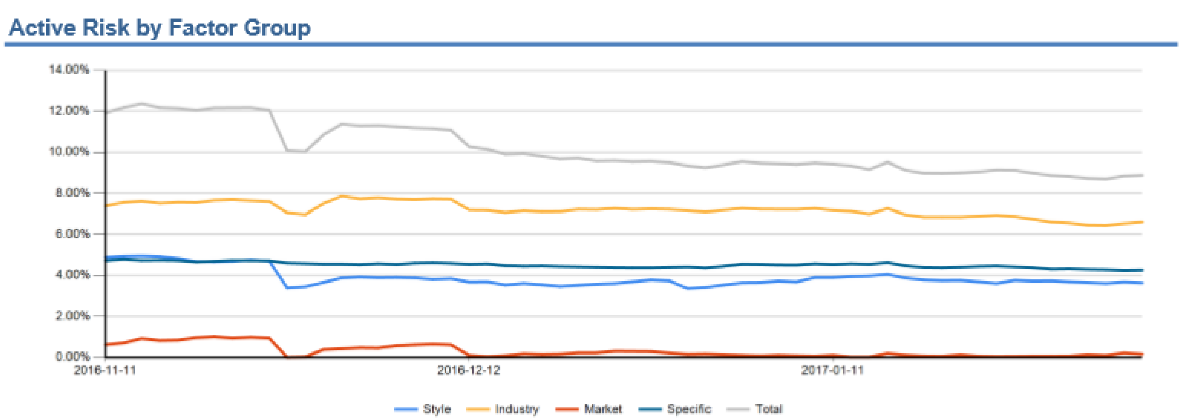


Exhibit IIIE: Active Risk by Factor Group (Axioma)

Portfolio Performance

Over the investment period thus far, our portfolio has achieved exceptional performance, and currently leads the competition in terms of absolute return with 12.23% return, while remaining in the top 5 teams in terms of risk-adjusted return with a Sharpe Ratio of 1.43. Our high return is due to the outperformance of the financials sector over the investment period, as well as underperformance by the consumer discretionary sector. As of February 6th, a total of 6.62% of return was attributable to our industry exposures, more than half of our overall absolute return. Our industry bet on financials contributed just over 2.00% return itself, while our consumer discretionary short contributed just under 3.00% return to our portfolio. Our third main industry exposure to energy contributed just over 1.00% return to the portfolio. No other industry exposure in our portfolio contributed more than 0.50% to our return. Ultimately, this breakdown of industry specific return suggests that our team made quality bets regarding the macroeconomic potential we saw for returns with long positions in financials and energy and a short position in consumer discretionary equities.

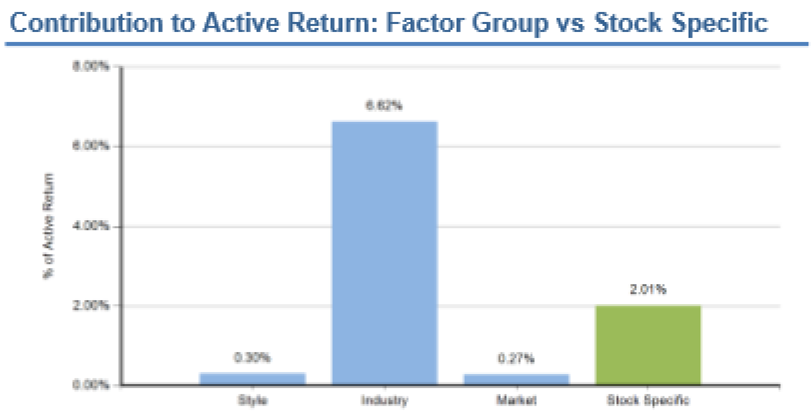


Exhibit IVA: Active Return Contributions (Axioma)

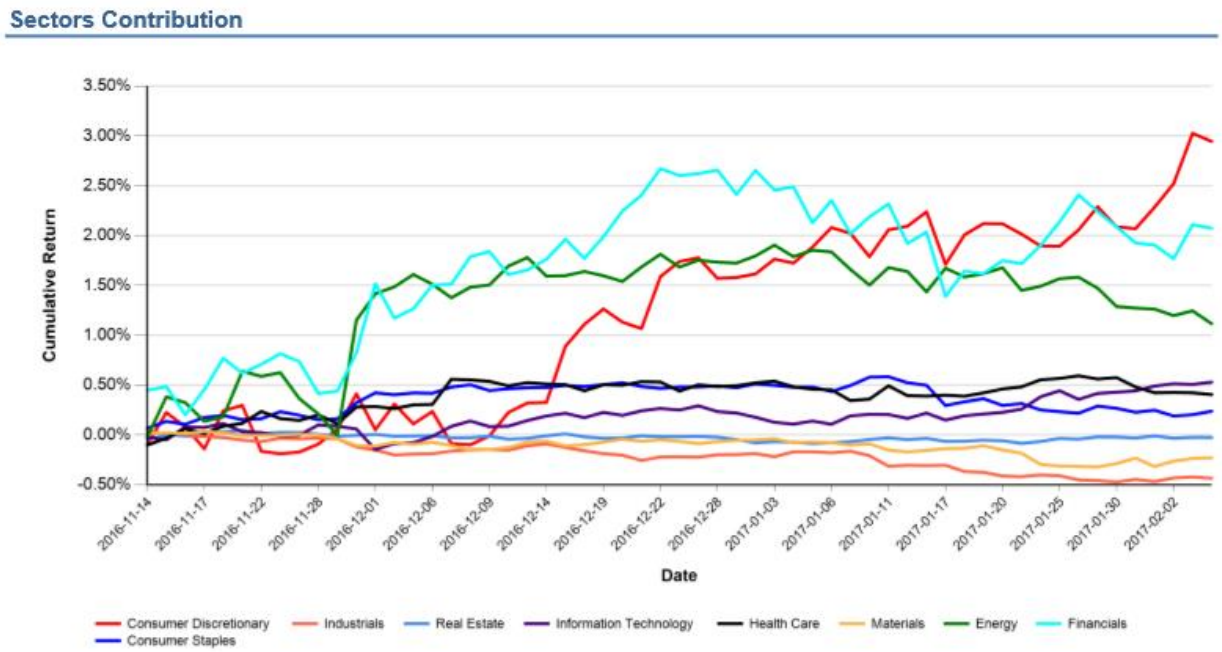


Exhibit IVB: Sectors Contributions (Axioma)

Style exposures, while contributing relatively significant risk to our portfolio, did not yield nearly as positive returns as our industry exposures. The cumulative return contributed by all of our style exposures was only 0.30%. This return was largely attributable to positive returns on exposure to value, but insignificant returns on exposure to momentum witnessed over the investment period. Value contributed roughly 2.00% return to the portfolio, while medium-term momentum only contributed about 0.25% to the portfolio. The limited success of momentum strategies may actually be in-line with our investment thesis. If a Clinton-Democrat victory in the 2016 Election was indeed priced into the market, a Trump-GOP victory would likely lead previously successful stocks to be less successful. Stocks with less momentum could have actually outperformed in such a scenario. The other style exposures that our portfolio included, although relatively small individually in terms of risk exposure, mostly contributed small negative returns to the portfolio. The added effect of these small but negative contributions led to a very small cumulative style exposure return for the portfolio as a whole.

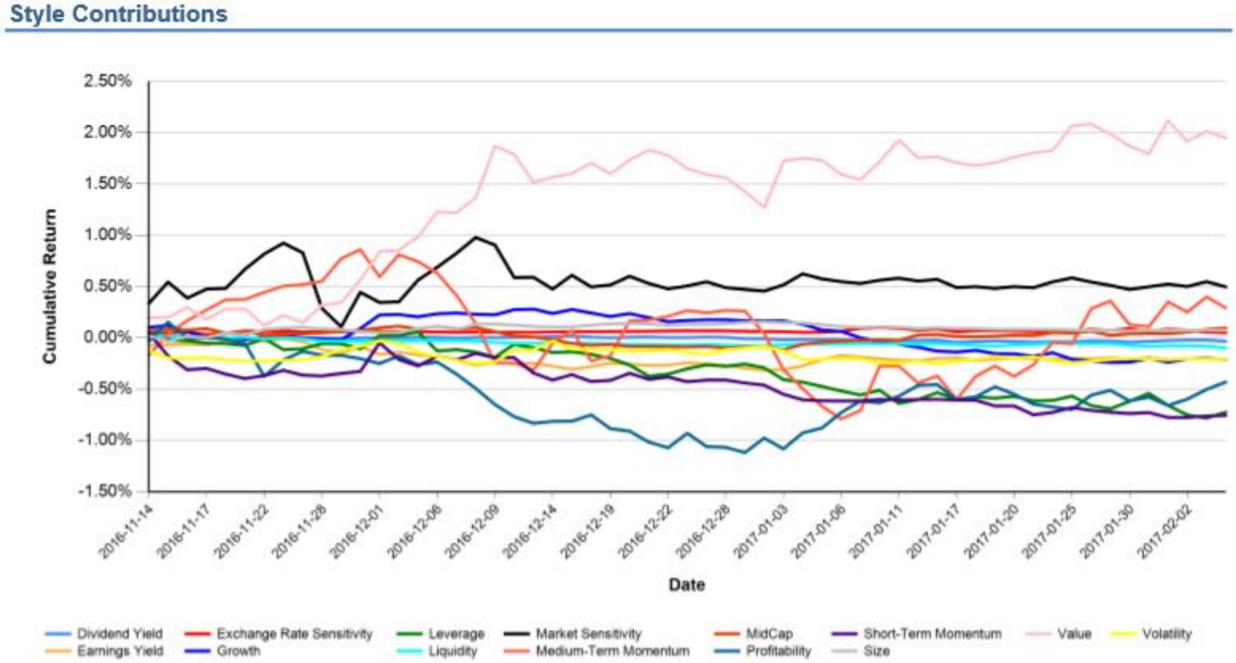


Exhibit IVC: Style Contributions (Axioma)

The remaining portion of our portfolio's active return, roughly 2.01% and 0.27% respectively, can be attributed to stock specific exposures and market exposure. These smaller contributions reflect the diversified and market neutral nature of our portfolio, demonstrating the effectiveness of our teams at following the guidelines set forth by CQA.

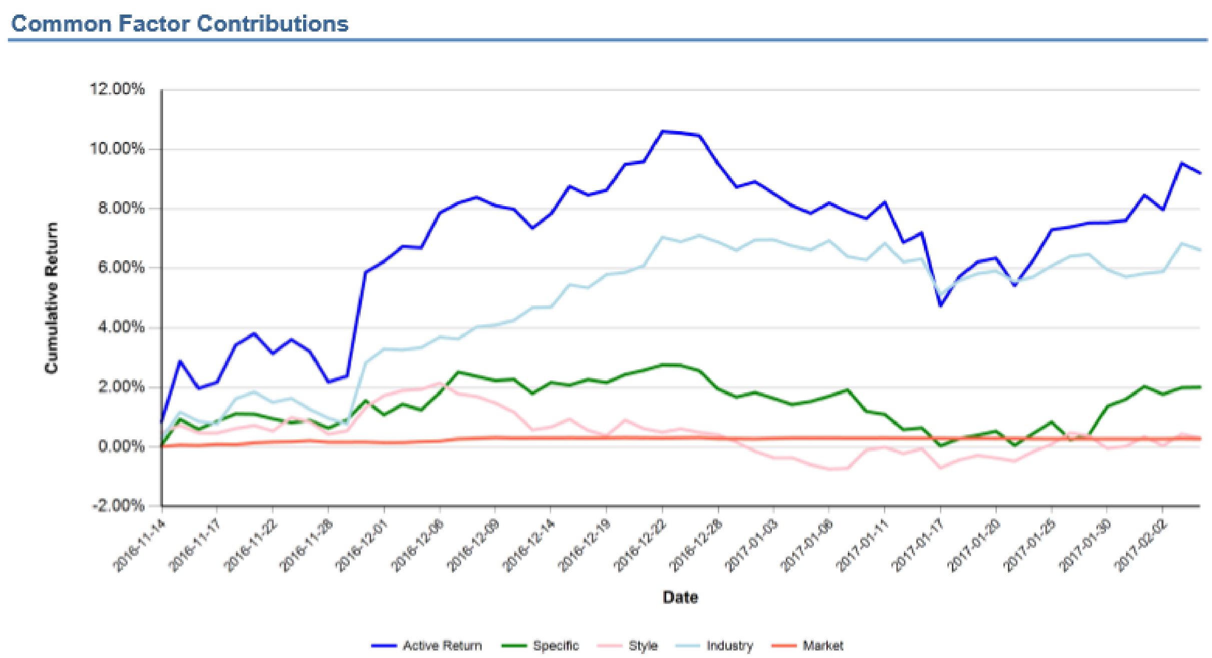


Exhibit IVD: Common Factor Contributions (Axioma)

Reflection

Throughout the CQA Investment Challenge, our team made significant realizations about quantitative investing, portfolio management, and the relationships between macroeconomic trends and quantitative measures of portfolio attribution. First, quantitative investing, although radically different from the fundamental style analysis that is arguably more common, is just as complex. It requires access to screening tools and a knowledge of the academic information that suggests which style exposures will function best in which scenarios and in conjunction with other style exposures. Additionally, it requires special focus to ensuring a portfolio does not gain exposures that are unintended and tied to intended exposures.

Second, management of a long-short market-neutral portfolio requires constant attention to ensure that the portfolio remains within prescribed bounds set forth prior to investing. Just as we were given specific guidelines in the investment competition, a client or firm would give a real-world portfolio manager strict guidelines regarding market-neutrality, dollar-neutrality, and allowable position size that must be maintained. Exposure to such guidelines in this investment challenge was a great opportunity to get experience operating under similar conditions.

Lastly, the results of our portfolio performance confirmed our belief that a Trump win in November of 2016 would result in positive outperformance by the financials and energy sectors, with underperformance by the consumer discretionary sector. As mentioned earlier, part of the challenge of maintaining a portfolio invested with quantitative designs is the possible intersection between various factor exposures. We knew that value and momentum screening would likely result in an intersection with our desired industry bets, but the resulting performance of momentum following the pricing-in of a Clinton-Democrat win was not something we anticipated until after we witnessed it in action. Additionally, we didn’t anticipate the resulting exposures to leverage and profitability that existed as a result of our intended style and industry exposures. Although relatively insignificant, they were unexpected and provided insight into the inherent cross-dimensionality of many style exposures.

Ultimately, our participation in the CQA Investment Challenge was a valued educational and professional experience. Gaining new knowledge regarding quantitative investing, which I had received little outside exposure to, was vital in obtaining a well-rounded finance education. Firsthand experience managing a long-short portfolio could prove important in my future professional efforts, and new understanding of the relationship between style exposures and macroeconomic conditions was an enlightening component of my fresh view of quantitative investing.

Appendices

CQA Investment Challenge Final Video

https://www.youtube.com/watch?v=cPTOF6t8BuQ&feature=youtu.be

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