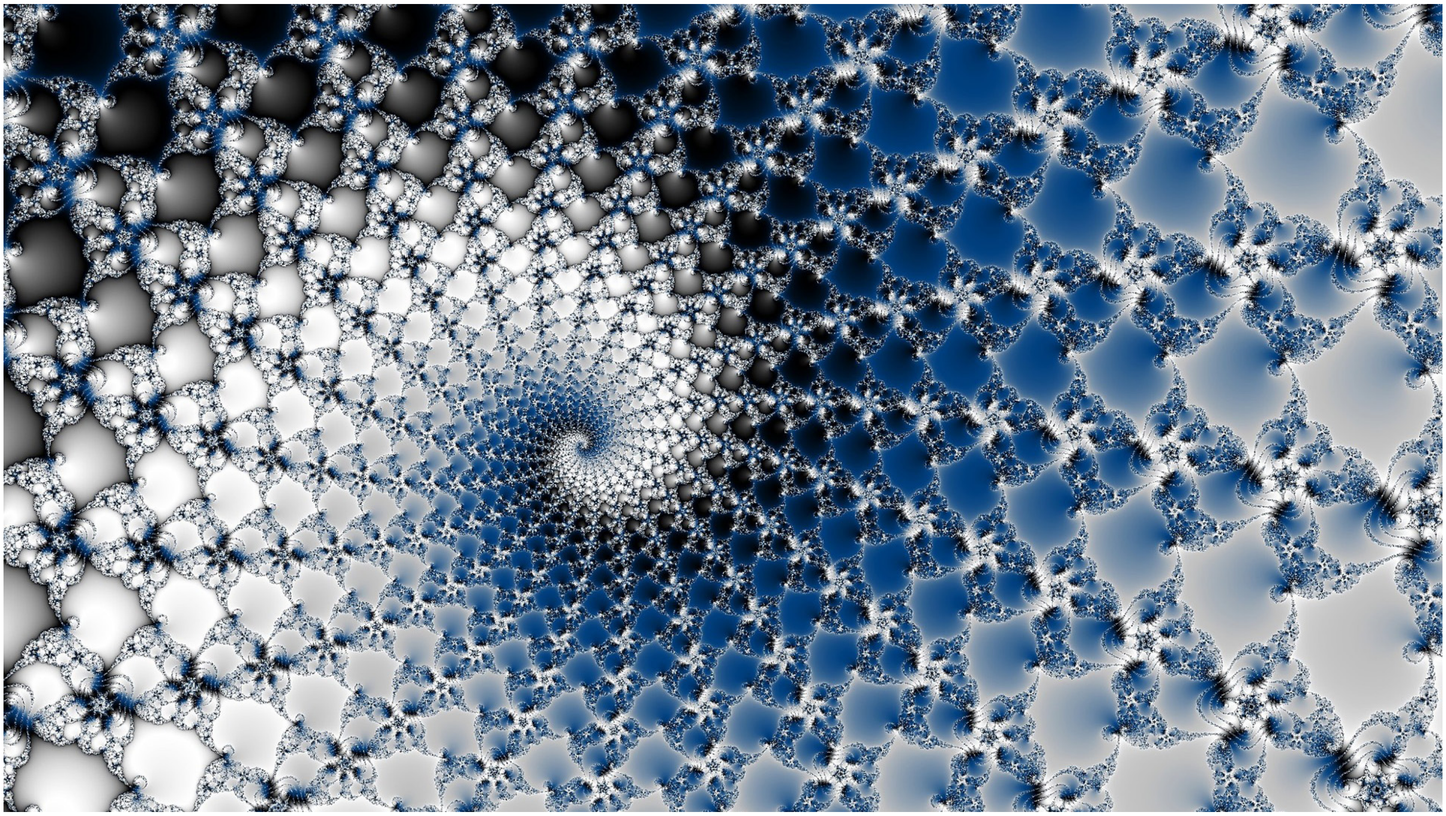

Adding Alpha by Subtracting Beta

A Case Study on How Quantitative Tools Can Improve a Portfolio's Returns

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Executive Summary

Fundamental (discretionary) portfolio managers typically build their portfolios from the bottom up.

That is, they identify stocks they expect to beat the market and combine them to create a portfolio. However, fundamental managers can leverage quantitative tools to help identify and lessen potential issues in their portfolio, while still maintaining their investment views and goals. In this paper, we'll use a "real world" portfolio[1] to illustrate how quantitative tools can improve a portfolio's realized returns.

Introduction

Fundamental investment management is like an iceberg. Although icebergs appear small above water, the majority of their mass is below water and so often unseen. For a fundamental manager, the tip of the exposed iceberg is the portfolio invested in and is the main product they share with the world. Under the water and behind the scenes, analysts pore over balance sheets, analyze industry and country trends, create cash flow models and valuations to help screen the large numbers of potential assets to buy. The fundamental management investment process can add much value by screening out winners, but the challenge still remains on how to translate these extensive "underwater findings" to an "above water" actionable portfolio in line with the manager's investment mandate and convictions on which assets are more attractive investments than others.With all of the work that goes into finding the best companies to invest in, the exact weighting of these various assets is the final hurdle to building a successful portfolio.

A fundamental manager's overall conviction in the stock often drives how much of each name they purchase in the portfolio, outside of simple rules such as making sure their allocations to certain industries, sectors, and/or countries are reasonable. The name they feel the highest conviction for will often have the largest weight in the portfolio, while the name they feel the lowest conviction for may have the smallest weight in the portfolio. Regardless, the final position weighting of fundamental portfolios is often based on heuristics, and the manager's conviction is the main driver of asset weightings in the portfolio.

Because fundamental managers use a bottom-up investment process, we'd expect their fund's positive performance to come from the outperformance of individual stocks in their portfolio. This is in contrast to quantitative investing, where the managers make systematic factor bets – such as on Value, Momentum, or Profitability – that they expected to add positive return performance to the portfolio. Newer, passive "Smart Beta" products – which are an increasingly competitive threat to attracting investment in fundamental managers' actively managed portfolios – similarly embed systematic factor bets in the portfolio. Smart beta products are more similar to quantitative investment products than they are to the stock pickers' actively managed portfolios.

How can fundamental managers ensure their actual value add is in line with what they promise? What happens if the story they are telling doesn't match the story told by the quantitative tools their own clients and outside consultants are using? Is manager conviction the best way to build a portfolio? We will dive into a high-level review of the tools that quantitative investors typically use and see how fundamental investors can adapt them to help them understand what's driving their portfolios' returns, as well as aid them in making better decisions, avoiding undesired risks, and delivering higher alpha.

Quantitative Tools

Factor Risk Models

Factor risk models are tools to help finance professionals understand the sources of predicted (ex-ante) risk and realized (ex-post) risk and return in a portfolio. The factors that comprise factor risk models are characteristics of individual stocks that tend to lead to cross-sectional differences in returns. For example, smaller stocks tend to perform differently from their larger-cap counterparts, and highly levered stocks may outpace unlevered stocks under certain economic conditions. At their most basic, factor risk models provide a predicted standard deviation of active returns given a portfolio and a benchmark and decompose the sources of those risks across both systematic (i.e., factor) components and an idiosyncratic (i.e., specific) component. Typically, a fundamental manager's value proposition is in identifying those idiosyncratic returns. In other words, they believe they select a stock that is likely to perform better than other stocks in the same industry, size category, valuation level, etc.

Axioma's Worldwide factor risk model (WW4) includes several different factor blocks, including style, industry, country and currency factors, and a market factor – along with a specific risk model. Within the factor blocks, the underlying components (such as Value in the style-factor block or euro/USD in the currency block) are used to help a manager understand the risk in each of the portfolio's bets and determine whether that risk is expected to be compensated.

The factors in a fundamental model are typically based on commonly used and well-understood measures. Style factors include factors comprising market-based measures such as Medium-Term Momentum, Size, and Volatility, and balance sheet and income-statement-based measures such as Value, Leverage, and Growth. Assets with a high Value score behave differently than assets with a low Value score, and the risk model accordingly captures this behavior. Industry factors are driven by the GICS (Global Industry Classification Standard) industry mapping, Country factors by the country membership, and Currency factors by the currency denomination of the asset. Assets with a common industry or country will generally behave more similarly than assets in a different industry, and again the risk model accordingly captures this behavior.

How to Select the Right Factors

To date, more than 350 individual factors, or factor premia, have been identified as potential sources of outperformance, and it is a list that is likely to grow as fund managers turn to more esoteric characteristics in order to stand out in an increasingly competitive marketplace.

But at the heart of factor investing there are eight factors that form the cornerstone of any strategy:

	Explanation	Examples
Value	Undervalued relative to corporate fundamentals	Price-to-book, price-to-earnings
Growth	Above-average earnings growth	Price-to-earnings
Momentum	Rate of acceleration of price	3-month, 6-month, 12-month
Volatility	The dispersion of returns	Volatility, VIX
Size	High or low market capitalisation	Market cap
Liquidity	Low trading volume	ADV
Yield	Income return on investment	Dividend per share, buybacks
Quality	Sustainable profitability	Profitability, margins

This chart and text originally appeared in the article, "Multi-factor Investing Practical Considerations for Portfolio Managers" originally published by Ian Webster in June 2016

Every asset has an exposure to every one of these factors, and each factor not only has its own behavior, but also a correlation with other factors. Any returns that are not captured by the factors are considered "idiosyncratic" or "specific risk" – the risks that stem from the unique business model of the company itself and are not common across the broad market. In other words, a stock's return is explained by summing its exposure to each factor times that factor's return. The difference between that sum and its actual return is its idiosyncratic return.

From an ex-post perspective, factor risk models allow finance professionals to understand what drove their portfolios' realized returns. Fundamental managers expect to see most of their return coming from the "specific risk" described above, but may find they have more factor exposure than they thought, those factor exposures added risk to their portfolios, and may have hurt their returns. The portfolio manager can analyze these realized returns and risks using a factor risk model, which helps decompose realized results across the various factor blocks and the specific block. Factor-based performance attribution can also help portfolio managers understand if factors are helping or hurting their realized performance, so they can make better portfolio management decisions on an ongoing basis.

Stock-specific risk and return is also known as “alpha” and delivers value that factor-based smart beta products and quants don’t always deliver. Factor bets, or “beta bets”, are getting harder to justify management fees for, whereas specific bets, or “alpha bets”, still command a premium.

Optimizers

At a high level, optimizers are tools to help make better decisions – which can apply to almost any facet of life, not just finance. At the core of any optimization is a goal one is trying to achieve (such as minimizing undesired risks), while obeying certain rules that cannot be violated (such as the size of sector overweights). Optimizers are best known in the finance world from Markowitz’s Mean-Variance optimization framework, where the goal is to maximize expected return less variance. In this case, the “variance” is quantified by either a factor risk model or a covariance matrix that quantifies asset-asset interactions. The user of an optimizer does not need to understand all the mathematics and mechanics behind the optimizer, just that it can evaluate thousands or millions of combinations of assets and tell the user which combination best meets their objectives.

Axioma’s optimizer does not force you into the mean- variance optimization space, which wouldn’t make sense for a fundamental manager who is not building quantitative expected returns. Unlike quantitative managers, fundamental managers know the assets they want to buy, and they have an idea of an initial portfolio weighting based on their level of conviction. But the ensuing portfolio weights may be heuristic- based and not necessarily be “tuned” to load up on specific risk and minimize undesired factor risks. In this case study, we were faced with the challenge of staying relatively close to the initial portfolio — so we maintained high weights in high- conviction assets – while attempting to remove unwanted factor risks.

An optimizer is frequently needed for these trade-offs because factor risk models are complex tools. Often, making a small change in the portfolio may help address one factor but force another unintended factor to spring up. Furthermore, because all factors are correlated, risks can also be created from reducing certain factor exposures. For example, we could potentially reduce the risk coming from a single factor like Growth but increase net factor risk because Growth may be negatively correlated with another factor like Value. Optimizers can also account for other critical constraints while making trade-offs, such as making sure one does not trade too much, spend too much on transaction costs, or deviate from certain industry, sector, and country bounds. Any mandate-specific rule can be an input to the optimizer to make sure it is not violated.

Portfolio Construction Case Study

We started this case study by using a global portfolio managed by a bottom-up fundamental investment management firm. We pulled the history of quarterly holdings from the start of 2007 to the end of 2015 for a portfolio that was managed relative to the FTSE All-World Index. We started by analyzing the ex-ante predicted risk and ex-post realized return/risk profile of the fund through the lens of Axioma’s WW4 factor risk model.

Current Portfolio Analysis: Ex-Ante Risk

First, we looked at the high-level aggregate active risks across this portfolio:

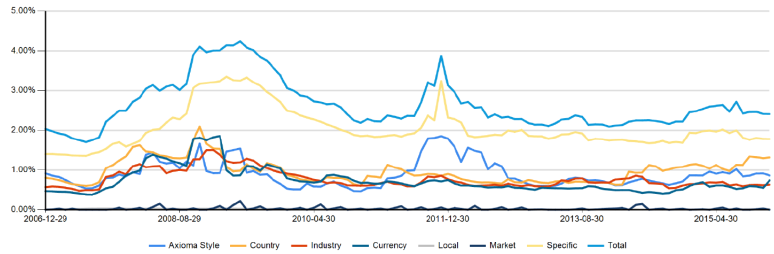

Exhibit 1: Aggregate Active Portfolio Risk

We see that predicted active risk for the portfolio has varied from 1.75% to more than 4% over time, with the largest contribution of active risk coming from active specific risk. Overall, it is good to see that the main driver of the portfolio’s risk is stock-specific, as this is the crux of the manager’s investment process. But we still see that style, country, industry, and currency bets are prevalent in the portfolio: risks that may have been the result of the bottom-up stock selection process, but not necessarily intended by portfolio’s mandate.

Another way to distill the total allocation of the portfolio’s risk to factors versus specific risks is the “% of Active Risk” chart. (See below.)

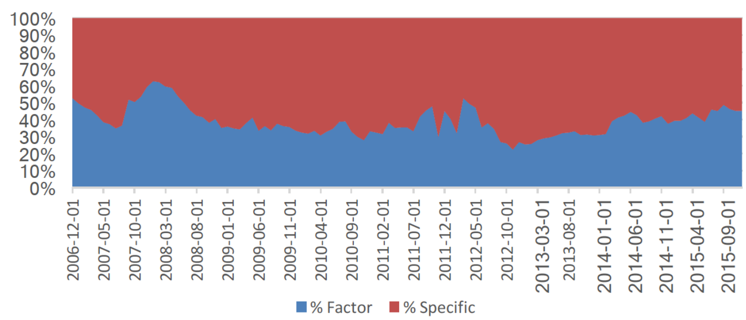

Exhibit 2: Fund: % of Active Risk

Exhibit 2 shows that although the portfolio usually has more specific risk than factor risk, when we add up each of the factor components, we still end up with 40% to 60% of active risk coming from factor bets. This chart verifies that the manager’s fundamentally-constructed portfolio is taking a lot of factor risk that is not in line with his intended investment process.

Current Portfolio Analysis: Ex-Post Factor Attribution

The analysis above provides portfolio managers with a view of predicted active risk and what factors are driving these risks. We can illustrate the impact these risks have on the portfolio’s performance using factor-based performance attribution.

In Exhibit 3 are the high-level realized results of this portfolio, annualized.

	Return	Risk	IR
Portfolio	3.58 %	18.15 %	
Benchmark	3.86 %	17.60 %	
Active	-0.28 %	2.63 %	-0.11

Exhibit 3: Summary of Results from Axioma’s Portfolio Analytics Solutions

Overall, the portfolio has underperformed the benchmark: The portfolio has lower realized returns and more risk than the benchmark, which leads to a negative information ratio (IR). We can then break down the realized active return and risks across specific and factor bets, and then in more detail across the different factor blocks available in the Axioma WW4 factor risk model:

	Return	Risk	IR
Active	-0.28 %	2.63 %	-0.11
Specific	0.31 %	1.92 %	0.16
Factor	-0.59 %	1.69 %	-0.35
Axioma Style	-1.36 %	1.21 %	-1.12
Country	0.11 %	0.88 %	0.12
Industry	0.29 %	0.92 %	0.31
Currency	0.39 %	0.87 %	0.44
Local	-0.01 %	0.02 %	-0.50
Market	0.00 %	0.04 %	0.12

Exhibit 4: Return Decomposition

The first line of this report reiterates what we saw above: The portfolio has a negative active return of -0.28% with a realized active risk of 2.63%, leading to an information ratio of -0.11. The good news is that this manager is adding value through its stock-specific bets (+0.31%) and most of the realized risk is from its stock-specific bets. But the stock-specific gains are more than wiped out by the negative factor returns – especially by the "Axioma Style" block, which also contributes lots of unnecessary risk. The country, industry, and currency bets help add to returns, albeit with relatively low IRs. But generally, given that the overall mandate of this manager is to deliver results via stock-specific bets, many of these factor bets are not necessarily intended – i.e., they are a byproduct of a manual weighting process.

So what is a manager to do? One approach would be to manually re-weight the holdings by trying to reduce exposures to certain factors – especially the Axioma Style factors, given the amount of risk they are contributing to the portfolio and the amount they are detracting from returns. But this manual approach likely requires many iterations, with no guarantee that the changes will actually help improve the risk profile of the portfolio. Furthermore, the various interlinked components of a risk model are nearly impossible for a human to take into consideration when making a decision. We therefore look to an optimizer to help us make trade-offs between maintaining conviction and reducing unwanted factor risks.

Theoretical Portfolio Analysis: Optimal Portfolio Weighting

Trading off reduction in active factor risk and asset-level deviation from the initial portfolio holdings is the challenging part of this exercise. Not allowing too much change in asset holdings relative to the initial portfolio may not make a big enough reduction in the amount of active factor risk of the portfolio, but allowing too much change may dramatically alter the ranking of assets in the portfolio and throw us out of whack with the portfolio manager's convictions.

To better understand how the portfolio would perform under different asset-level weightings, a portfolio manager can run a backtest (i.e., historical simulation) where they make slight changes to the original fundamental portfolio and see how ex-ante and ex-post risk and return change. Four variations of an optimal portfolio were run, weighting where they varied the amount the optimized portfolio can deviate from the original fundamental portfolio. The results are summarized below:

Label	Constraint Description
Fund	Fundamental Portfolio as is
5 bp	Optimized Portfolio weights +/-0.05% relative to Original Fundamental Portfolio
25 bp	Optimized Portfolio weights +/-0.25% relative to Original Fundamental Portfolio
50 bp	Optimized Portfolio weights +/-0.50% relative to Original Fundamental Portfolio
No Limit	Optimized Portfolio is not constrained relative to Original Fundamental Portfolio

Exhibit 5: Backtest Return Variations

In this case, the goal is to find an optimal set of portfolio weights that reduce the potential drag from unwanted factor bets by minimizing active factor risk relative to the FTSE All-World Index. Because the fundamental manager has devoted a great deal of research to the names to be held in this portfolio, we will only allow the optimizer to hold names in the original portfolio. Because there is also conviction information in the holdings as the original portfolio is currently weighted, we probably don't want to dramatically change the asset weights (i.e., an asset with a 0.05% active weight probably should not go to a 4% active weight). The "No Limit" case is an extreme case where the optimizer has the freedom to dramatically change the ranking of assets held and drop the holding of any asset even if it is held at a large weight, purely in pursuit of eliminating factor risk.

We then ran these different optimization strategies on a quarterly basis from the start of 2007 to the end of 2015 and compared how the optimized portfolios performed relative to the original fundamental portfolio.

After looking at some high-level details, we can get a better sense in the differences among some of these portfolios. Exhibit 6 shows the number of names held in the portfolio, which is a portfolio characteristic we did not explicitly constrain.

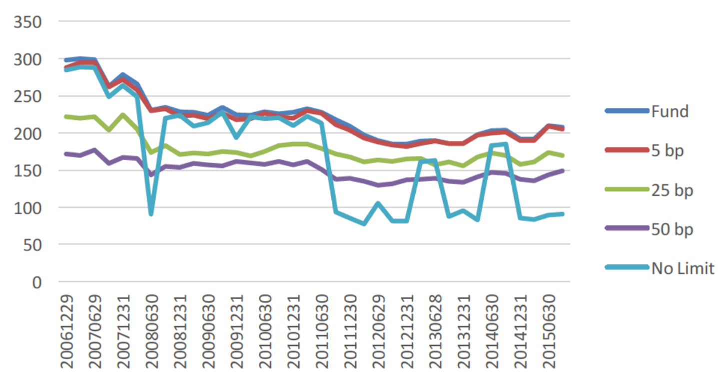

Exhibit 6: Names Held

We see that the number of names held in the "5 bp" portfolio is almost the same as the original fund. As the bounds around the holding of the original fund weights increase, the number of names drops. When a name is dropped, it is only because the holding of that asset in the fund portfolio is less than the specified bounds. For example, when we enforce a limit of +/-25bps change in holdings between the 25bp portfolio and fund portfolio, the only names that are dropped are holdings of 0.25% or less. Such small holdings likely were low-conviction assets whose risks are relatively large, and we see later that the performance doesn't overly suffer with these assets are dropped from the portfolio. In the "No Limit" case, we see the number of names held can drastically fluctuate as even names held at large positions can be dropped from the portfolio.

Exhibit 7 charts the predicted active risk for all of the backtest variants. We see that as we allow larger changes in weights from the original portfolio, we are able to reduce the amount of active risk we are taking. We see that in the "No Limit" case, sometimes the active risk actually increases, likely because of the sharp reduction in names held. The hope is that lower active risk comes from a reduction in active factor risk – those risks that we are accidently picking up when building the fundamental portfolio.

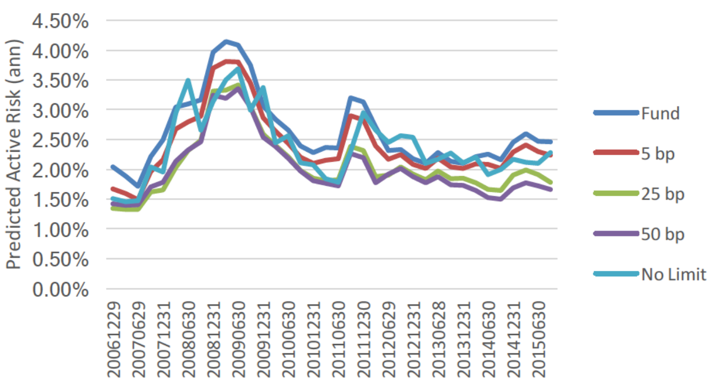

Exhibit 7: Predicted Active Risk

Exhibit 8 summarizes the realized returns and risks of the different backtested strategies, where returns do not include transaction costs or taxes:

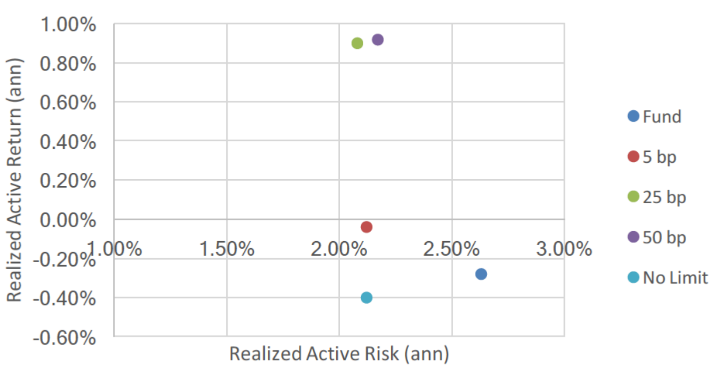

Exhibit 8: Realized Active Frontier: 2007 – 2015

We see that giving the optimizer a mere +/-0.05% room to vary asset weights from the original position size helps us improve active returns and reduce realized active risk. Providing more wiggle room for the optimizer with +/-0.25% and +/-0.50% leads to even more improvements – a large decrease in realized active risk and over 100bp annualized improvement in realized active return! Note that as we open up the bounds too much, as in the "No Limit" case, we drop back down to a negative realized active return, albeit with a smaller amount of realized active risk.

Why do some changes to the portfolio help risk-adjusted performance while other changes hurt it? To answer this question, we can look at the realized factor based performance attribution report. We start by comparing the realized risks and first confirm we are at least reducing the amount of factor risk in the "No Limit" portfolio.

Analytic	Fund	No Limit	Change
Active -	2.63%	2.12%	-0.51%
- Specific -	1.92%	2.03%	0.11%
- Factor -	1.69%	0.39%	-1.30%

Exhibit 9: Annualized Realized Risk Comparison – Performance Attribution Report

We see that the optimizer and risk models are doing their jobs as the realized risk reduction comes almost entirely from the factor block. However, reduced risk at the expense of reduced returns is not acceptable, so we need to identify how the realized returns have changed.

Analytic	Fund	No Limit	Change
Active -	-0.28%	-0.04%	0.24%
- Specific -	0.31%	-0.16%	-0.47%
- Factor -	-0.59%	0.12%	0.71%

Exhibit 10: Annualized Realized Return Comparison – Original Fund Portfolio

In comparing the factor-based performance attribution report of the "No Limit" portfolio to the original fund portfolio, we see that the increase in return comes entirely from harmful factor bets. The portfolio also changes from having a positive specific return contribution to a negative return, which makes sense given how uncorrelated the "No Limit" holdings are relative to the original conviction-weighted fund holdings. Why do we see such a degradation of the realized active specific return?

To dive deeper into this, we look at a period where the fund active return was quite different from the "No Limit" portfolio. On June 29, 2014, in the backtest we see that the "No Limit" portfolio returned -3% less than the fundamental portfolio. In Exhibit 11, Pearson's correlation of the original fund portfolio holdings relative to the holdings of the other strategies, which helps us quantify how similar/dissimilar the fundamental portfolio is to the other portfolio variations.

Fund	5 bp	25 bp	50 bp	No Limit
1.000	0.995	0.894	0.717	0.296

Exhibit 11: Weight Correlation with Fund

Not surprisingly, we see that the less we allow the optimizer to change the holdings from the original portfolio weightings, the more correlated the optimized portfolio is with the original fundamental portfolio. Because the size of the holding is a rough proxy for conviction in a given asset name, keeping the bounds relatively tight to the original portfolio allows us to keep the portfolio manager's conviction in the portfolio. As we allow the optimizer to re-weight all assets in any direction, their holdings become less correlated with the original portfolio. Ultimately, conviction is diluted and the resulting portfolio is very different from that of what they started with. Assuming the manager's conviction is correct, a loss of conviction results in a loss of realized returns. The goal of the final optimization approach should be to strike a balance between these two competing manager goals: minimize factor risk while respecting conviction Clearly, the diminishing returns are allowing the optimized portfolio to move too far away from the original portfolio, as illustrated best by the low correlation between the holdings of the fund portfolio with the "No Limit" portfolio. This should not be surprising, as we already knew that the stock selection portion of return was positive.

Digging deeper into the realized results, Exhibit 12 shows the differences in turnovers across these cases:

Fund	5 bp	25bp	50 bp	No Limit
32.1%	33.1%	40.4%	49.3%	80.1%

Exhibit 12: Average Quarterly Two-Way Turnover

Although the performance increases for all backtested cases, the higher turnover likely means that we actually could not have realized such high returns on an after-transaction cost basis. It also makes it harder to make a direct comparison of the original fund portfolio relative to the backtested cases and perhaps is the sole reason for outperformance of the backtested portfolios. Accordingly, we focused on the "25 bp" case only and re-ran a new backtest where we constrained the turnover of the "25 bp" case to have the same exact turnover as the original fund portfolio, which we'll refer to as the "25 bp – TO" case.

The results are in Exhibit 13, with only the "Fund," "25 bp," and "25 bp – TO" cases included:

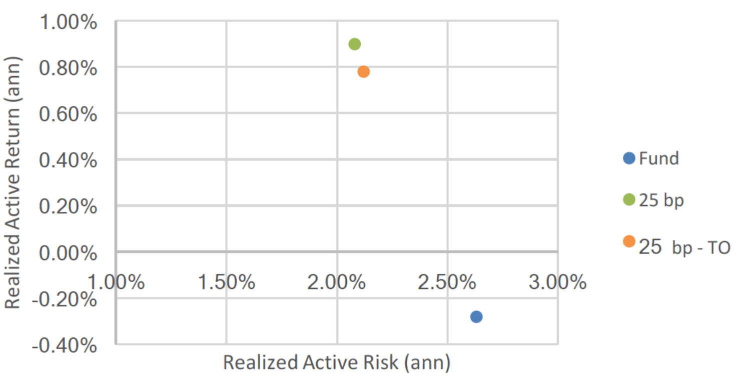

Exhibit 13: Realized Active Frontier: 2007-2015

We see that restricting the turnover of the 25 bp case indeed hurts performance, but not enough to undo the value added by the slight changes to the portfolio.

Now that we've built a portfolio with the same exact amount of quarterly turnover as the fundamental portfolio, we can remove this as a possible source of (unrealizable) outperformance from the backtested results. We will now dig deeper into the reasons behind the increase in performance of the "25 bp – TO" portfolio, relative to the original fund portfolio. To answer this, let's dive into the "25 bp – TO" case in more detail on a predicted risk and perspective on the realized risk and return.

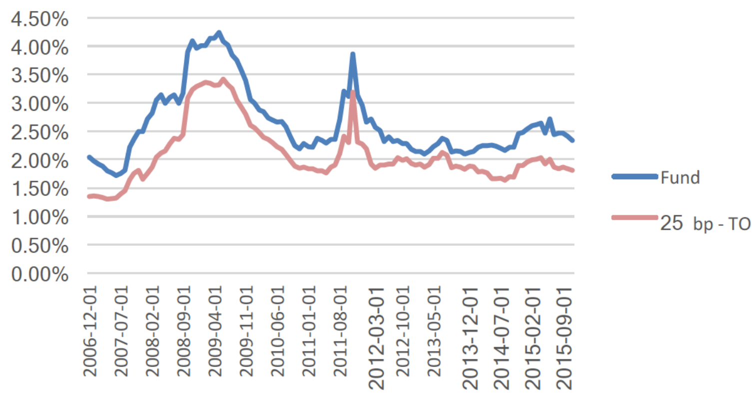

Exhibit 14: Predicted Active Risk

We see that pushing the fundamental portfolio away from unintended factor risks decreases the predicted active risk of the portfolio. The decrease in active risk is potentially a mixed blessing; many times managers are paid to take large amounts of active risk so the reduction in active risk may not be ideal. But on the other hand, taking on extra risk that is unintended simply to increase predicted tracking error is a superfluous activity that will likely only decrease IR.

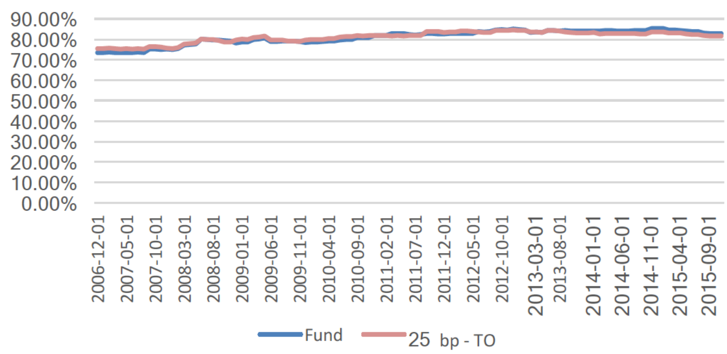

Exhibit 15: Active Share

Active share is the sum of the absolute values of the active bets in the portfolio. When the portfolio holdings are exactly equal to the benchmark holdings, the active share is equal to zero. Because we limit the investible universe to only the assets held by the original portfolio, we see that the active share of the 25bp portfolio is similar on average to the original portfolio. So although the manager's predicted active risk has decreased, they are still taking quite large active positions – just in a more risk-efficient manner.

We've seen that the predicted active risk of the "25 bp – TO" portfolio has decreased, but where is that decrease coming from? In the next Exhibits are charts that decompose the amount of predicted active risk across factor and specific risks for the fund portfolio and "25 bp – TO" portfolio, respectively.

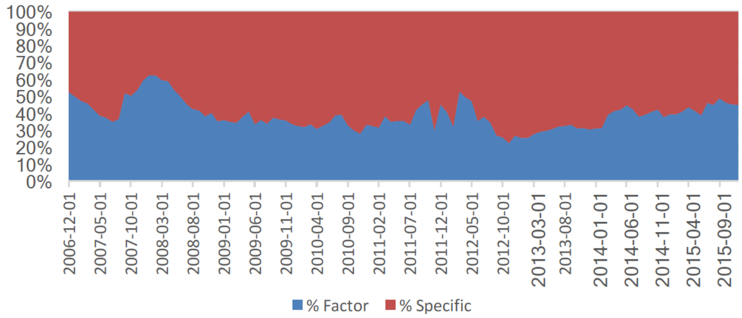

Exhibit 16: Fund: % of Active Risk

We see that the portfolio manager's original fundamental portfolio has 40% - 60% of its active risk coming from factors. We compare this to the amount of predicted active risk across factor and specific risks for the "25 bp – TO" optimized portfolio:

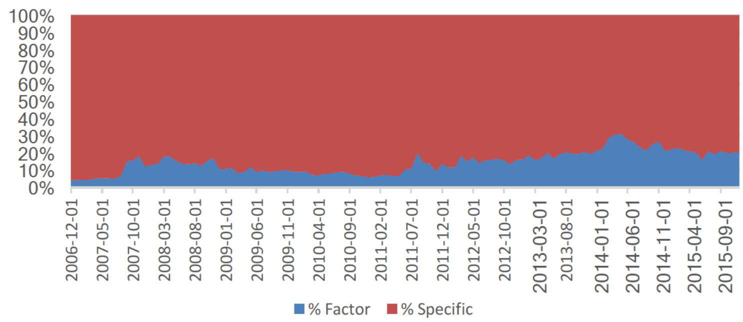

Exhibit 17: 25 bp – TO: % of Active Risk

By reducing the portfolio's unwanted factor bets, we were able to load up more on specific risk – the type of risk that should lead to the returns a stock picker would expect to deliver. Although it reduces factor risks, the +/- 25 bp constraint doesn't completely remove these risks because we still want to maintain the conviction in the assets held in the original portfolio.

We see in Exhibit 17 that the "25 bp – TO" portfolio has much less predicted factor risk than the original fund portfolio, and we've already seen that this portfolio has improved return and risk characteristics. In Exhibit 18 are the factor-based performance attribution results through the lens of Axioma's WW4 factor risk model, which helps us understand where the differences in returns and risks are coming from, starting with the returns:

Analytic	Fund	25 bp - TO	Change
Active -	-0.28%	0.76%	1.04%
- Specific -	0.31%	0.62%	0.31%
- Factor	-0.59%	0.14%	0.73%
- Style	-1.36%	-0.43%	0.93%
- Country	0.11%	0.09%	-0.02%
- Industry	0.29%	0.33%	0.04%
- Currency	0.39%	0.17%	-0.22%

Exhibit 18: Annualized Realized Returns Comparison: Performance Attribution Results

The color scaling helps us quickly identify the sources of the biggest changes in realized returns. We first verify that the "25 bp – TO" portfolio has a much higher realized annualized return – more than 100 basis points higher — with most of the improvement coming from the Style factors. We also see double the amount of stock-specific return from the "25 bp – TO" portfolio as compared with the original fund portfolio. This helps the manager realize more valuable stock-specific "alpha" and better justify the management fees charged. *Overall, the main drivers of improvement in the realized return of the backtested portfolio is an increase in returns from sources consistent with the investment process and a decrease in the drag associated with unwanted factor bets.*

We now look to compare the realized risks of the fund versus the "25 bp – TO" portfolios through the lens of a factor-based performance attribution report using Axioma's WW4 factor risk model:

Analytic	Fund	25 bp - TO	Change
Active -	2.63%	2.12%	-0.51%
- Specific -	1.92%	1.87%	-0.05%
- Factor -	1.69%	0.94%	-0.75%
- Axioma Style	1.21%	0.51%	-0.70%
- Country	0.88%	0.50%	-0.38%
- Industry	0.92%	0.55%	-0.37%
- Currency	0.87%	0.57%	-0.30%

Exhibit 19: Annualized Realized Risk Comparison: 25 bp – TO

In this case, we see the optimization was able to reduce the portfolio's realized active risk by 51 bps annually, with the biggest reduction coming from the factor blocks. We see that the amount of realized specific risk decreased the least of all line items – which is good given these stock-specific risks are the ones the manager wants to take. Overall, all the components of realized risk decrease when they allow the optimizer to make minor suggestions to the original portfolio. This helps managers implement a more efficient portfolio that takes risks in the areas consistent with their investment process.

The increase in realized returns and decrease in realized risks leads to higher IRs across the high-level portfolio, the specific bets, and the factor bets. The higher IR means higher rewards on a risk-adjusted basis from the optimized portfolio, as compared with the fundamentally constructed portfolio.

Analytic	Fund	25 bp - TO	Change
Active	-0.11	0.37	0.48
Specific	0.16	0.36	0.20
Factor	-0.35	0.12	0.47
Axioma Style	-1.12	-1.06	0.06
Country	0.12	0.18	0.06
Industry	0.31	0.76	0.45
Currency	0.39	0.25	-0.14

Exhibit 20: Annualized Information Ratio (IR) Comparison: 25 bp - TO

Conclusion

All investment managers are under pressure to both outperform their benchmarks and prove they are worth the management fees they charge their clients. Axioma's risk models and optimizer are valuable tools that can help fundamental investment managers understand their portfolio risks from a different perspective, make better decisions when sizing assets in a portfolio, while still implementing portfolios consistent with their stated investment process.

Risk models can help managers better understand the ex-ante risks that are embedded in their portfolios, confirm that the risks being taken are in line with their mandate and avoid taking risk where they have no expectation of return. An ex-post factor-based performance attribution report can help managers quantify the risks that led to realized returns to help prove to their clients, prospects, consultants, and internal research teams the value they added during the investment process. When the portfolio risks don't match up with the manager's investment mandate, an optimizer can be used in conjunction with a factor risk model to make slight changes to the fundamentally constructed portfolio to help simultaneously maintain the manager's high conviction in the portfolio, while also minimizing undesired risks.

In the case study, we took a simple real-world portfolio and made some basic assumptions without knowing anything about the fundamental managers besides the fact that they are bottom-up stock-pickers. In real life, fundamental managers can add even more value by adding additional proprietary information into the optimization to help keep their portfolios even more in line with their investment processes. For example, they can force the optimizer to buy a minimum number of all assets on the "buy list," incorporate conviction ratings to make sure the optimizer does not downweight their high- conviction assets, and/or make sure they use the turnover/transaction cost budget as efficiently as possible. Overall, using quantitative tools to incorporate this relatively simple analysis can help a manager focus on generating alpha.

Endnotes

1. Holdings were gathered from the eVestment database.

Author Bio

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Chris Martin has worked at Axioma for more than 10 years in a variety of positions. Internally, he works closely with all members of the Axioma team, including: Product, Research, Content, Sales, and Support. This range of experience allows Chris to support the needs of Axioma's clients, whether it be training new users or helping existing users get the most out of Axioma's Risk Models, Optimizer, and Analytics software. Chris received his Masters in Financial Engineering, a joint degree from the Drucker School of Management and Mathematical Sciences at Claremont Graduate University. He received his bachelor's degree in General Engineering with a concentration in Aeronautical and Mechanical Engineering and a Minor in Physics from California Polytechnic State University, San Luis Obispo. Chris is a certified Engineer-in-Training in California and is a CAIA and CIPM charterholder.