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Smart Beta: Even Smarter with an Optimizer and a Custom Risk Model

Axioma and CS HOLT have collaborated to create a smart beta index — the Credit Suisse HOLT ® Equity Factor Global Multi-Factor Portfolio — that unites the stock selection prowess of CS HOLT with Axioma's portfolio construction and risk model expertise. In this paper, we highlight three key principles that drove the process to create this portfolio:

1. Using an optimizer for portfolio construction (rather than, for example constructing a market-cap weighted portfolio off the highest rated stocks) leads to a portfolio that avoids unintended and uncompensated bets and generates a higher information ratio.

2. By using a custom risk model the process can better assess the trade-off between risk and return of the *systematic portfolio bets*, thereby better capturing ex-ante risk targets and producing a higher information ratio than using a standard model.

3. The combination of optimization and a custom risk model leads to more intuitive, and therefore useful, ex-post attribution of the portfolio, where the active return of the portfolio is primarily explained by all the components of the alpha signal.

Smart Beta: Even Smarter with an Optimizer and a Custom Risk Model

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1 Introduction

Axioma has written a series of papers about risk characteristics and potential pitfalls for Smart Beta ETFs (see, for example, Ceria et al. (2016) and Brown and Ceria (2018)). These papers highlighted the fact that many ETFs bet on style and sector factors that may be incidental to the expected source of alpha. These bets typically arise from the portfolio or the underlying index-construction process. For example, a high dividend yield fund may choose to invest in the highest yielding stocks within a broad universe of stocks, and equal weight them. Another fund may select from a smaller investment universe and weight stocks by their capitalization. While both purport to target high dividend yield, the resulting portfolios can be substantially different, and therefore have many drivers of return that are *not* dividend yield. What they may gain in transparency for the investor (the rules mean the process can be easily replicated), they may very well lose by a drag on returns from unintended bets. In other words, while the inputs may be transparent, the outputs may not be.

We believe there is a better way to build portfolios, one that allows a manager to maximize exposure to the desired factor and minimize bets on other possibly harmful factors: *use an optimizer with a reliable risk model.* To take this one step further, if the manager has a "secret sauce" proprietary factor or set of factors, customizing the risk model to incorporate them allows for a better trade-off between risk and return, which should in turn lead to better risk-adjusted performance and more accurate performance attribution.

Lee and Stefek (2008), Ceria et al. (2012), and Saxena and Stubbs (2013) provide a theoretical framework for misalignment that occurs between the alpha vector, the factor risk model, and constraints in a portfolio construction model. They show that misalignment leads to optimal portfolios that suffer from risk underestimation, undesired exposures to factors with hidden systematic risk, and a consistent failure of the smart-beta manager to adhere to ex-ante performance targets. Canova et al. (2013) and Sivaramakrishnan and Stubbs (2013) consider a CRM that includes all the alpha factors that are used to construct the portfolio. This is done with a view to alleviate the misalignment issues and also to ensure that the portfolio return is primarily explained by the alpha factors rather than the factors in a standard off-the-shelf model.

In this paper we will focus on the benefits of using a custom risk model with a proprietary investment process to create optimized portfolios that target a set of factors and avoid making bets on other risk factors that could move the portfolio away from the desired factor and potentially produce a drag on returns. We will highlight three key points:

1. Using an optimizer for portfolio construction (rather than, for example constructing a market-cap weighted portfolio off the highest rated stocks) leads to a portfolio that avoids unintended and uncompensated bets and generates a higher information ratio,

2. By using a custom risk model the process can better assess the trade-off between risk and return of the *systematic portfolio bets*, thereby better capturing ex-ante risk targets and producing a higher information ratio than using a standard model, and

3. The combination of optimization and a custom risk model leads to more intuitive, and therefore useful, ex-post attribution of the portfolio, where the active return of the portfolio is primarily explained by all the components of the alpha signal with a negligible stock-specific return contribution.

To make our case, we will use alpha signals from CS HOLT. CS HOLT is a well-known provider of effective, proprietary analytics across a global equity universe, and Axioma has collaborated with them to create a series of smart-beta indexes.

The paper is organized as follows: Section 2 briefly describes the CS HOLT and Axioma smart-beta factors that are used in the construction of the Multi-factor composite alpha. Section 3 discusses the use of an optimizer and a CRM in portfolio construction, and compares the realized performance of the optimized portfolio with a portfolio constructed from simple rules. Section 4 compares the intuitive attribution of the multi-factor portfolio using a CRM with that obtained from an "off-the-shelf" risk model. Section 5 concludes with a brief summary of the key contributions of the paper.

2 Multi-factor composite alpha

We consider a Global Multi-factor composite alpha that is constructed from the Credit Suisse HOLT and Axioma factors, and provides exposure to the Value, Momentum, Quality, Low Beta, and Small Size risk premia that are well documented in the equity smart-beta literature (see Ang (2014)).

The main Credit Suisse HOLT Equity factors include their Value, Momentum, and Quality alpha offerings. The Value factor measures the relative valuation of a given equity. The

Momentum factor captures the effects of relative stock price changes and the relative earnings revisions that a stock receives from analysts. The Quality factor is designed to measure the relative operational performance of the stock and uses HOLT's proprietary "Cash Flow Return on Investment" (CFROI) metric. CFROI is defined as the last fiscal year measure of cash return on a firm's capital. We refer to CS-HOLT (2018) for a detailed description of the CS HOLT Value, Momentum, and Quality factors.

We also use the Axioma Leverage, Market Sensitivity, and Size factors in the construction of the composite alpha. The Axioma Leverage factor provides a measure of a company's exposure to debt levels. It is constructed as an equal weighted average of the Debt-to-assets (DTA) and Debt-to-equity (DTE) descriptors. The Axioma Size factor differentiates large and small assets and is defined as the natural logarithm of the total issuer market capitalization averaged over the past month. The Axioma Market Sensitivity factor is a historical measure of the asset's performance relative to that of the overall market. More details on the Axioma style factors can be found in Axioma (2018).

We first construct a composite Quality factor (henceforth Quality) that is an equal-weighted average of CS HOLT Quality (50% weight) and the Negative of Axioma Leverage (50% weight). Our multi-factor alpha is then constructed as an equal-weighted average of the CS HOLT Value, CS Holt Momentum, Quality, Axioma Market Sensitivity, and Axioma Size factors as follows:

1. **CS HOLT Value** - 20% weight
2. **CS HOLT Momentum** - 20% weight
3. **Quality** - 20% weight
4. **Negative of Axioma Market Sensitivity (Low Beta)** - 20% weight
5. **Negative of Axioma Size (Small Size)** - 20% weight.

Figure 1 shows how $100 invested in the different components in the Global Multi-factor alpha grows over time. Each of the factor returns can be interpreted as the return of a Factor Mimicking Portfolio (FMP) that is a minimum variance portfolio with a unit exposure to the factor and neutral to all the other factors in the model. Table 1 gives the realized statistics for the different FMPs over this period.

	AnnualRet	AnnualRisk	Max DD	IR
Value	3.73%	2.57%	-4.21%	1.45
Momentum	3.55%	2.44%	-10.33%	1.45
Quality	0.44%	1.01%	-5.16%	0.43
Low Beta	0.31%	6.49%	-21.94%	0.05
Small Size	2.84%	4.69%	-13.58%	0.60

Table 1: Realized stats for factor FMPs

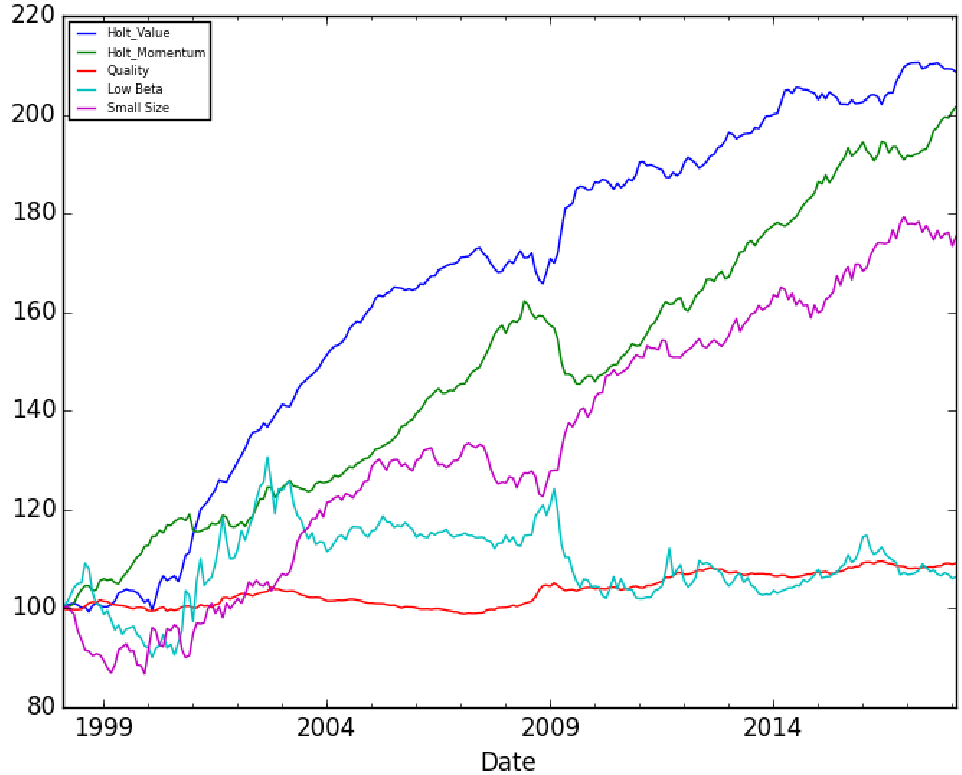


Figure 1: Risk premia for the multi-factor alpha components

Note that CS HOLT Value, CS HOLT Momentum, and Axioma Small Size FMPs have significant risk premia. The CS HOLT Value and Momentum factors have the best IR. The Quality FMP has the lowest annualized risk. Table 2 shows the average rank correlation between the returns of the different components of the Multi-factor signal. The long-term

	Value	Momentum	Quality	Low Leverage	Low Beta	Small Size
Value	1					
Momentum	-0.484	1				
Quality	-0.183	0.16	1			
Low Leverage	-0.328	0.253	0.139	1		
Low Beta	0.195	0.164	0.23	0.05	1	
Small Size	-0.066	0.02	-0.044	-0.029	0.225	1

Table 2: Correlations between Multi-factor components

average correlation between composite Quality and Value returns is negative. Furthermore, the Low Beta return is fairly uncorrelated with the returns of the other components of the multi-factor signal. Including Quality and Low Beta provides a diversification benefit in the composite alpha, and this is the reason to include them despite the muted performance of the associated FMPs.

It is important to emphasize that the CS HOLT factors are based on different valuation data than their counterparts in the Axioma WW4 model. For instance the CS HOLT Momentum factor is calculated as the weighted sum of the following scores

1. **CFROI ® Revisions** - 60% weight
   The CFROI Revisions metric aims to capture the net impact of the CFROI forecast based on the changes in the consensus earnings per share (EPS) estimate by aggregating the week to week changes over the past 3 months.

2. **Price Momentum** - 40% weight
   Measures the cumulative return of the asset over the past one year excluding the most recent month. This matches the definition of the Axioma Medium-Term Momentum (MTM) factor.

Consequently, we have

$$\text{CS HOLT Momentum} \;=\; 0.4 \times \text{Axioma MTM} + 0.6 \times \text{CS HOLT CFROI Revisions}$$

where a portion of the CS HOLT CFROI Revisions factor can, in turn, be explained by some of the other Axioma styles.

We run an end-of-month cross-sectional square-root of market-cap weighted regression between 1999-2018, where we regress the CS HOLT factors against all the style factors in the Axioma WW4MH model along with an intercept term. The CS HOLT Value factor has large betas on the Axioma Value and EY factors, the CS HOLT Momentum factor mostly loads on the Axioma MTM factor, and the CS HOLT Quality factor has a large intercept term and some loading on the Axioma Profitability factor. Table 3 summarizes the overall relationship between the CS HOLT Value, Momentum, and Quality and the Axioma style factors from our cross-sectional regression study.

Factor	Axioma Style	Beta (t-stat)
CS HOLT Value	Axioma Value	0.18 (24.06)
	Axioma EY	0.18 (23.31)
CS HOLT Momentum	Axioma MTM	0.38 (52.86)
	intercept	0.16 (11.55)
CS HOLT Quality	intercept	0.56 (40.59)
	Axioma Profitability	0.2 (24.17)
	Axioma Value	-0.18 (23.49)

Table 3: Axioma Betas for CS HOLT factors

We construct a custom risk model using Axioma's proprietary Risk Model Machine (RMM). The model is constructed daily from the Axioma WW4AxiomaMH model by adding the CS HOLT Value, Momentum, and Quality custom factor scores to the WW4AxiomaMH model. Our factor beta analysis indicates that the Axioma Value, EY, MTM, and Profitability factors should be dropped from this model to avoid any dependence between the factors.

3 Portfolio construction with a CRM and an optimizer

This section investigates the use of a CRM and an optimizer to construct the weights of the Multi-factor portfolio. We run a quarterly backtest from January 2002 to February 2018 where our investment universe and benchmark is the Axioma Developed Markets Select Core Model portfolio that contains all the large and medium-cap assets from the developed world.

We first consider a simple rules based approach to constructing the Global Multi-factor portfolio. We divide the investment universe into quintiles based on the composite alpha score and construct a market-cap weighted portfolio off the top quintile. Figure 2 compares the performance of this portfolio with the benchmark. The high-level statistics for the portfolio are given in Table 4. Although, the portfolio has a good Sharpe ratio of 0.88, it does not track the benchmark closely and the realized active risk is 6.38%. In addition, the portfolio has a low beta of 0.8 to the benchmark, and a large annualized round-trip turnover of 280.5%.

Table 5 shows that the portfolio takes unbalanced active exposures to some of the non-alpha styles, sectors, and countries, and currency factors in the risk model. Some of these unintended exposures result in a drag in performance, notice the -0.4% drag that comes from the unintended exposure to the high idiosyncratic volatility factor in the risk model.

We now employ an optimizer to construct a portfolio that avoids the unintended exposures in the quintile portfolio. We experiment with both the CRM and the Axioma WW4

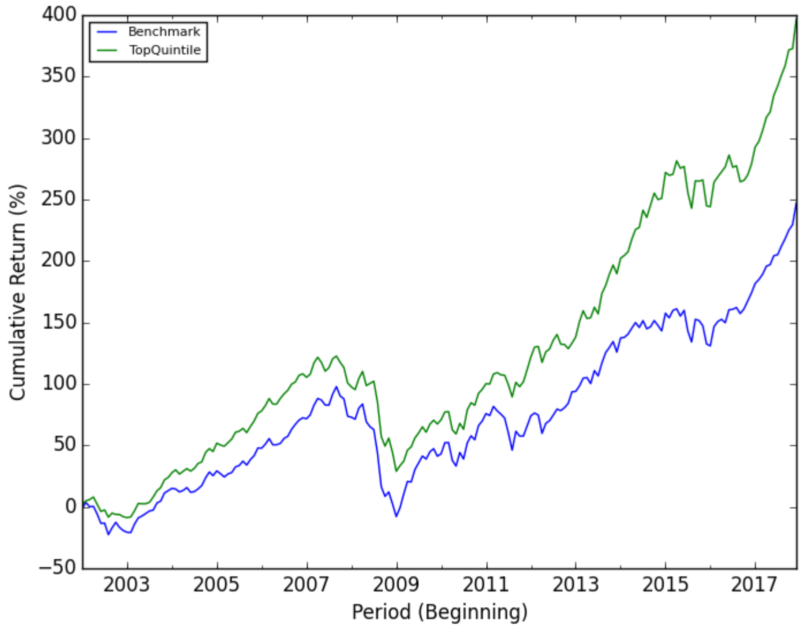


Figure 2: Realized performance of top quintile portfolio

Statistic	Value
Realized Return	10.47%
Realized Risk	11.78%
Sharpe Ratio	0.88
Realized Active Return	2.42%
Realized Active Risk	6.38%
IR	0.38
Average Annualized Round-Trip Turnover	280.5%
Ex-ante Beta	0.8

Table 4: Statistics for quintile portfolio

Factor	Contribution	Active Exposure
Health Care	0.28%	17.83%
Growth	0.07%	20.64%
Volatility	-0.40%	14.16%
Dividend Yield	-0.14%	-12.00%
EUR	0.00%	-7.93%
Japan	0.00%	5.86%

Table 5: Unbalanced active exposures for quintile portfolio

models to trade-off alpha and ex-ante TE in the strategy. Our strategy is to construct a long-only, fully-invested portfolio that maximizes the exposure to the multi-factor alpha. Other optimization parameters, designed to ensure we stayed within tracking error targets and only used risk bets where we had an expectation of return, include

1. Limit active weights to $[-2.5\%, 2.5\%]$.
2. Three annual round-trip turnover limits of 80%, 120%, and 200%.
3. Limit non-alpha style active exposures to $[-10\%, 10\%]$.
4. Limit sector and country active exposures to $[-5\%, 5\%]$.

An annual round-trip turnover of 80% is the usual choice for an index provider or an asset owner. Investment banks, that control the execution of their trades, can handle larger annual round-trip turnovers of 120% going as much as 200%. We show that our CRM improves the portfolio construction for all these annual round-trip turnover limits.

The top, middle, and bottom exhibits in Figure 3 show the realized frontiers for annual round-trip turnovers of 80%, 120%, and 200%, respectively. Each frontier plots the realized active return against the realized TE for varying ex-ante TE targets. We choose all points on the frontier where the ex-ante TE constraint is binding in order to ensure that the risk model is playing a role in portfolio construction. The realized frontiers for the CRM lie above those for the WW4 model indicating that the CRM is better able to trade-off risk and return delivering portfolios with better IR.

We report the realized stats for the frontier backtest with 80% turnover in Table 6. The last row in this table gives the "Bias Statistic" that is the ratio of the realized TE to the ex-ante TE target. One can see that the bias-statistic for the CRM is slightly lower than that for the WW4 model indicating that the CRM better manages ex-ante TE targets.

	Model	Ex-Ante TE						
		1.25%	1.50%	1.75%	2.00%	2.25%	2.50%	2.75%
Active Return	CRM	1.92%	2.24%	2.58%	2.94%	3.40%	3.74%	4.09%
	WW4	1.85%	2.07%	2.38%	2.78%	3.26%	3.44%	3.78%
Realized TE	CRM	1.62%	1.90%	2.12%	2.39%	2.65%	2.93%	3.17%
	WW4	1.64%	1.91%	2.15%	2.41%	2.68%	3.00%	3.18%
IR	CRM	1.19	1.18	1.22	1.23	1.28	1.28	1.29
	WW4	1.13	1.08	1.10	1.15	1.22	1.15	1.19
BiasStat	CRM	1.30	1.27	1.21	1.20	1.18	1.17	1.15
	WW4	1.31	1.27	1.23	1.21	1.19	1.20	1.16

Table 6: Realized Stats for TO=80%: CRM Vs WW4

The top exhibit in Figure 4 compares the realized cumulative IR of the optimized portfolio constructed with a CRM with that of the optimized portfolio constructed with the WW4

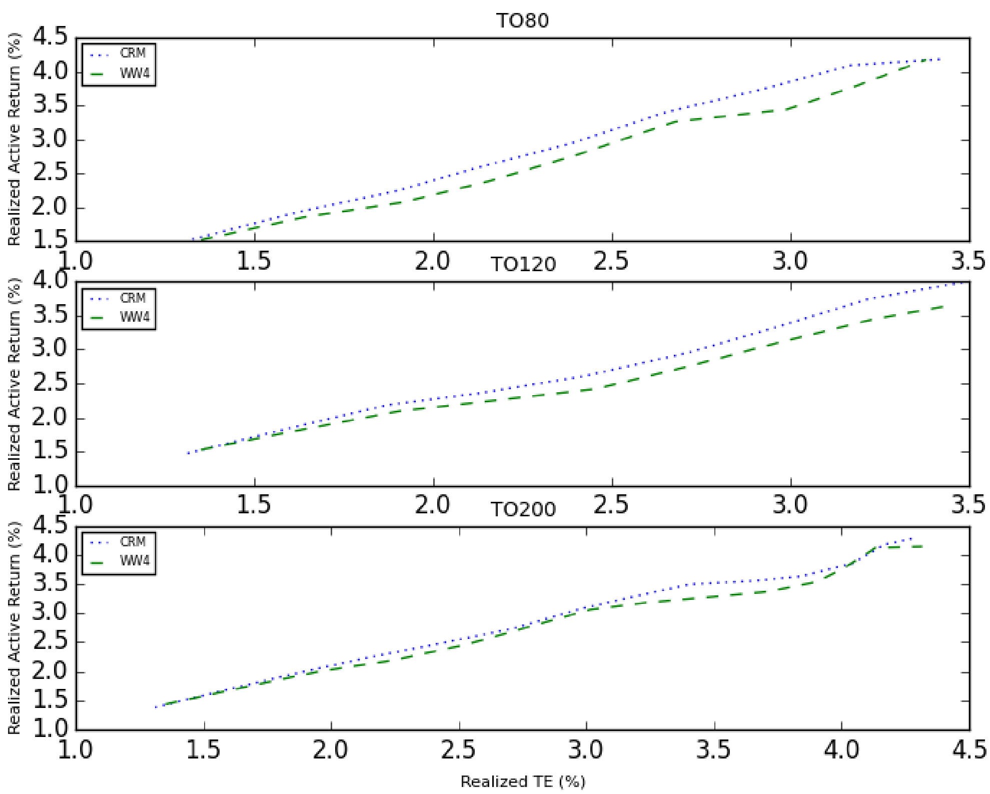


Figure 3: Realized Frontier Plots

model and the top quintile portfolio. The two optimized portfolios use an ex-ante TE of 2.5% and an annual round-trip turnover limit of 80%. Table 7 compares the key statistics for the three portfolios.

Statistic	OptAndCRM	OptAndWW4	Top Quintile	Benchmark
Active Return	3.74%	3.42%	2.45%	-
Active Risk	2.96%	3.02%	6.41%	-
IR	1.26	1.13	0.38	-
Avg Annual Turnover	80.23%	80.0%	280.5%	-
Ex-Ante Beta	0.94	0.94	0.8	1.0
Total Return	11.50%	11.18%	10.22%	7.76%
Total Risk	14.36%	14.59%	11.78%	14.84%
Sharpe	0.8	0.77	0.86	0.52
Max Drawdown	-51.57%	-52.09%	-42.07%	-53.45%

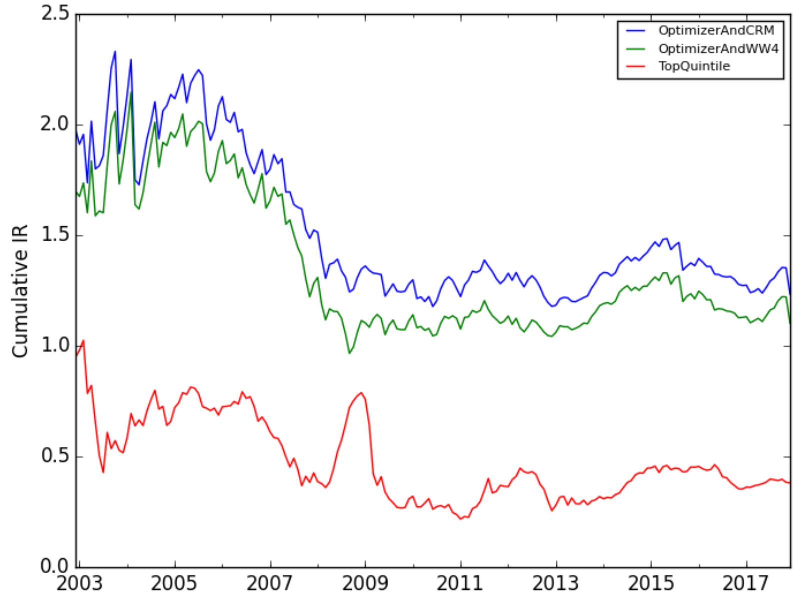
Table 7: Comparing the optimized and top quintile portfolios

We want to highlight that the two optimized portfolios outperform the top quintile portfolio in realized IR, and also that the optimized portfolio constructed with a CRM slightly outperforms the optimized portfolio that is constructed with the standard WW4 model on this metric. The high IR for the optimized portfolios indicates that they outperform the benchmark with balanced risk-premia tilts while staying close to it in a TE sense.

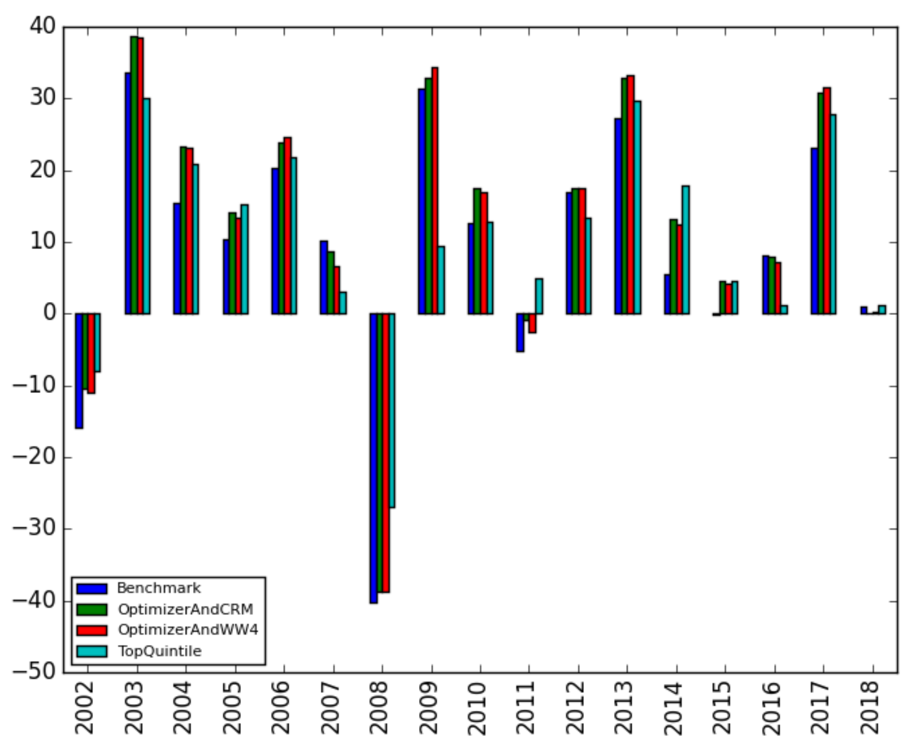
Table 8 shows the contributions from the alpha factors and the stock-specific return for the optimized portfolio constructed with a CRM and the quintile portfolios as seen through the CRM. The quintile portfolio has a large negative specific return that exaggerates the contributions from the alpha factors. The optimized portfolio, on the other hand, gets all its return exclusively by bets on the alpha factors.

Style	OptimizerAndCRM		Top Quintile	
	Contribution	Active Exposure	Contribution	Active Exposure
HOLT Value	1.38%	51.84%	0.91%	33.98%
HOLT Momentum	1.07%	25.38%	1.30%	37.42%
HOLT Quality	0.16%	36.52%	0.11%	36.36%
Size	0.87%	-28.08%	0.63%	-10.90%
Leverage	0.18%	-35.15%	0.31%	-29.33%
Market Sensitivity	0.14%	-18.63%	0.08%	-55.6%
Specific Return	-0.24%		-1.38%	

Table 8: Contributions from the alpha factors



(a) Cumulative IR



(b) Annualized Returns (%)

Figure 4: Optimized portfolio with CRM versus quintile portfolio

4 Use of a CRM in intuitive ex-post attribution

Another advantage of using a custom risk model is in attribution, where we ideally can determine that our intended bets drove the bulk of portfolio returns. We would expect that the use of the custom risk model would drive higher exposure to all the factors that we want to bet on, properly trading off expected return with the appropriate risk, as well as avoiding the bets for which we do not want exposure.

The attribution of returns over the course of our backtest demonstrates this handily. Table 9 details factor attribution for four scenarios

1. Attribution using the standard (WW4) model on the portfolio optimized with that model.
2. Attribution using WW4 on the portfolio optimized with the custom risk model (CRM).
3. Attribution using the CRM on the CRM optimized portfolio.
4. Attribution of the top quintile portfolio using the CRM.

The figures are annualized and the optimized portfolios all targeted 2.5% active risk.

Ideally, we would see most of the portfolio return driven by the factors in the alpha model with relatively little stock-specific return or country, sector, and non-alpha style bets (that are constrained in the optimization).

For the WW4/WW4 combination we can see that the Axioma styles including Medium-Term Momentum, Profitability, Value, and Earnings Yield contributed positively to return, as expected, but we can't see the impact of the various CS HOLT factors. Instead, some of that positive return seems to get pushed into specific return, which is not particularly descriptive.

We see similar results for the portfolio created with the CRM but analyzed with WW4 — and since the return was even higher than for the portfolio created with WW4 even more return was pushed into specific return.

When we use the CRM to attribute the returns, however, we get a more accurate picture of what drove returns. The return contribution from both HOLT Value and HOLT Momentum are much higher than what was obtained from their WW4 counterparts, and even the Size factor contributed more. By attributing returns to the sources of portfolio alpha, we are able to verify their value and reduce the magnitude of the specific return. As we noted earlier, the HOLT Quality had a low return but provided a diversification benefit, and attribution shows a small but positive contribution.

Finally, we ran the attribution of the top quintile portfolio with the CRM. As we would expect, the HOLT Value, Momentum, and Axioma Size were major return drivers for this portfolio as well, but that return was offset to a large extent by a high negative specific return.

For the astute reader who wonders about the other sources of return typically shown in attribution, Country, Currency, Non-alpha Styles, and Industry, we note that those factors were constrained in all of the optimized portfolios, and we would therefore not expect much return from them, and our expectations were met. The top quintile portfolio was not similarly constrained, and we did see a higher overall return from each of those categories than in the optimized portfolios. However, those were active bets for which we did not have a view, and could very well have had the opposite effect.

Optimization/Attribution Model	WW4/WW4	CRM/WW4	CRM/CRM	Top Quintile/CRM
Active Return	3.42%	3.74%	3.74%	2.45%
Factor Contribution	2.48%	2.63%	3.98%	3.84%
Axioma Style	2.08 %	2.08 %	0.82%	0.56%
Earnings Yield	0.17%	0.17%	NA	NA
Leverage	0.10%	0.09%	0.18%	0.31%
Market Sensitivity	0.13%	0.13%	0.14%	0.08%
Medium-Term Momentum	0.61%	0.68%	NA	NA
Profitability	0.40%	0.45%	NA	NA
Size	0.76%	0.73%	0.87%	0.63%
Value	0.37%	0.32%	NA	NA
Volatility	-0.36%	-0.37%	-0.30%	-0.40%
Custom Style	NA	NA	2.61%	2.33%
HOLT Momentum	NA	NA	1.07%	1.30%
HOLT Quality	NA	NA	0.16%	0.11%
HOLT Value	NA	NA	1.38%	0.91%
Specific Return	0.94%	1.11%	-0.24%	-1.38%

Table 9: Attribution of optimized and top quintile portfolios

Overall, this comparison demonstrates our third major point that the combination of the optimizer and a custom risk model leads to more intuitive, and therefore useful attribution, where the active return of the portfolio is primarily explained by all the components of the alpha signal with a negligible stock-specific return. This can be further seen in Figures 5 and 6 that give the time-series of factor and style contributions to the active return as seen through the lens of the CRM.

5 Conclusions

We started our study by showing the results of a series of tests meant to demonstrate the effectiveness of the CS HOLT models, and we confirmed their value. The challenge, however, was to show how those signals could best be used in a portfolio to produce positive active returns to benefit ETF investors. Our study was guided by three main principles:

1. Using an optimizer for portfolio construction leads to a portfolio that avoids unintended and uncompensated bets and generates a higher information ratio than the heuristic approach followed by many ETF providers.

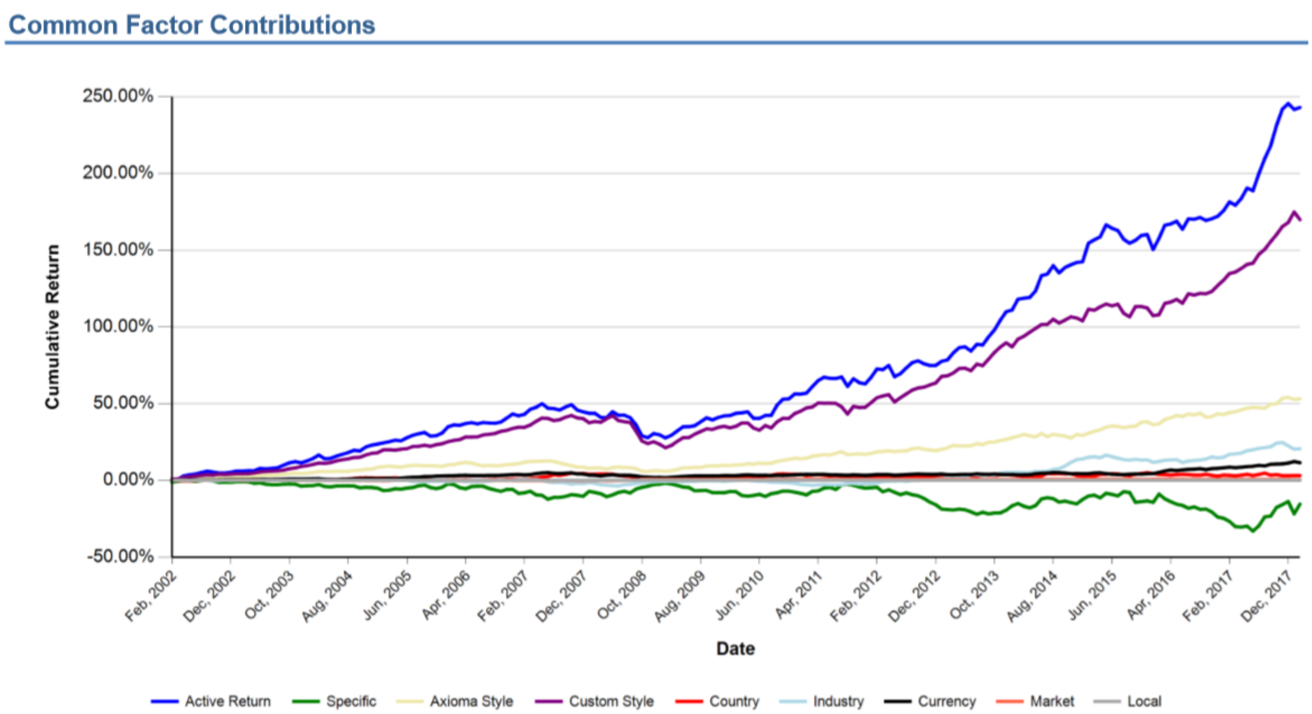


Figure 5: Factor Contributions of active return with CRM

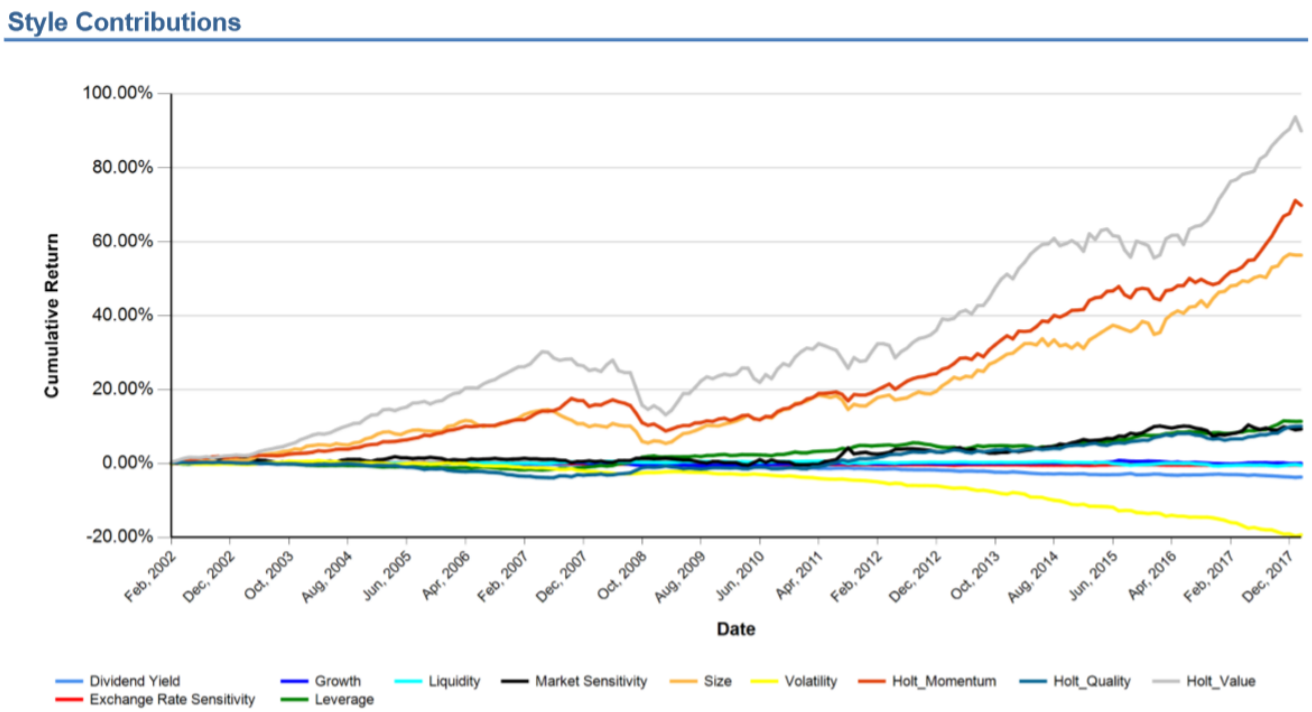


Figure 6: Style Contributions

2. By employing a custom risk model for portfolio construction, the process can better assess the tradeoff between risk and return of the systematic portfolio bets. This should, in turn, lead to a closer match between ex-ante and ex-post risk, and lead to a higher information ratio than we could get from a standard model.

3. An additional advantage of using a custom risk model with an optimizer is that attribution is more intuitive, ties expected to actual results and is therefore more useful in helping us understand portfolio returns.

We found that, indeed, as compared with a common heuristic approach, the optimizer gave us a portfolio that had lower active risk, used the risk budget where there was an expectation of return and avoided taking uncompensated bets. These benefits were enhanced when we added a custom risk model, which led to better risk forecasts and higher information ratios as compared with using a standard risk model. Finally, an additional benefit of the custom risk model was that it allowed for more accurate and intuitive performance attribution.

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