Evolution of Russell Investments' equity active positioning strategies

Evgenia Gvozdeva, Ph.D., Director, Strategy and Research
Nick Zylkowski, CFA, Senior Portfolio Manager

This two-part paper describes the evolution of Russell Investments' equity factor investing. The first part will focus on utilizing a Custom Risk Model (CRM) with Russell Investments' (RI) factor scores for portfolio construction and will examine the robustness of concentrating factor portfolios. The second part will focus on the evolved active positioning strategies (APS)[1], providing a fully integrated approach that embeds overall preferred positioning into a custom-built strategy designed to meet the unique needs of each fund.

The main goals of this research are to:

1. Develop a technique to build more concentrated single factor portfolios, multi-factor portfolios and positioning strategies without materially increasing idiosyncratic risk and active drawdowns.
2. Align APS portfolio construction with our investment process and define portfolio construction specifications for APS 2.0. This includes developing methods to incorporate sector/country/region tilts with factor exposures based on the Dynamic Preferred Positioning (DPP) framework and using Russell Investments CRM.
3. Build more robust portfolios that are defined by a) higher levels of returns explained by targeted factors, ex-post, b) simpler optimizations with fewer constraints and c) smaller estimation errors and corner solutions. We expect that better distribution of scores in the CRM model and alignment of risk model factor definitions with our investment process will help us achieve this goal.

The main empirical conclusions are:

1. We find evidence that we can concentrate our factor portfolios (especially multi-factor portfolios) to some extent, but overconcentrating can be detrimental to the performance due to concentrated portfolios being exposed to higher levels of unrewarded stock specific and other risks.
2. We find an approach to incorporate the Dynamic Preferred Positioning (DPP) model output (factor/sector/country/region views) using APS strategies, which can work in both broad and concentrated universes.
3. We improve the robustness of portfolio construction when using CRM in comparison to the Axioma Risk Model (ARM), which is observed by achieving high factor exposures in a diversified way without imposing any additional constraints in the optimization problem.
4. We observe initial evidence that CRM typically improves the accuracy of portfolio-risk forecasts for factor-based strategies.

Part one: Using Russell Investments' factor scores and Custom Risk Model, and building concentrated factor portfolios

Comparison of Axioma and Russell Investments' factor scores

Factor score distributions in Axioma's and Russell Investments' (RI) risk models have notable differences, which are important to highlight. We expect these differences to have meaningful impacts on portfolio construction, and the thoughtful design of score distributions should promote more robust portfolios.

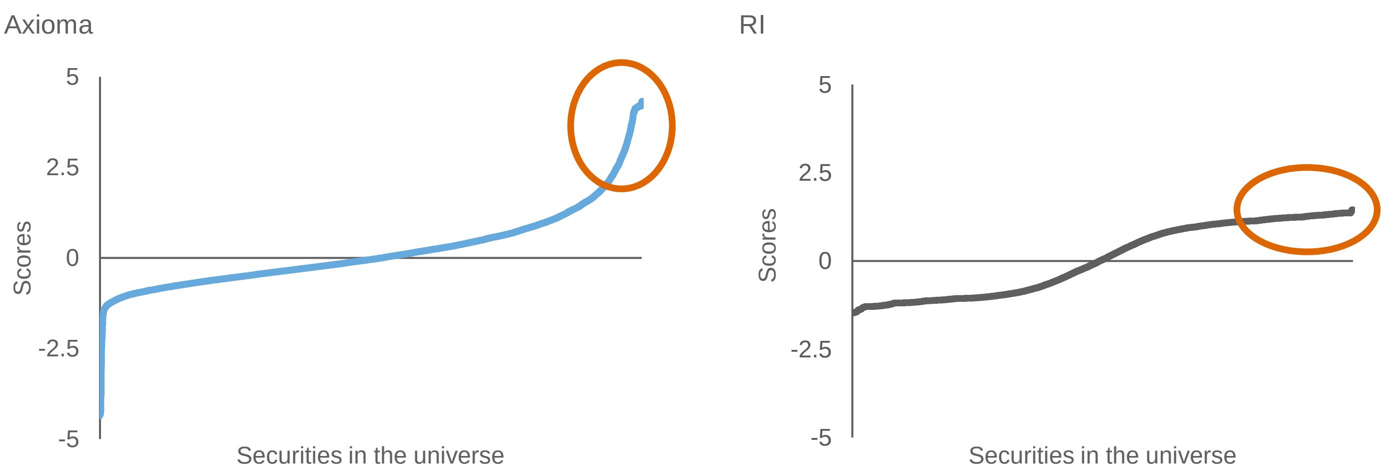
To compare these distributions, Axioma uses a normal-like distribution when constructing their factors. This leads to a majority of Axioma's universe having scores close to the mean, with fewer securities in the tails. In addition, the tails of these factor distributions are long with larger score magnitudes for the highest/lowest ranked securities; scores typically range from -4 to 4. In contrast to this approach, Russell Investments uses a non-linear probability (NLP) transformation, which leads to a more bi-modal type of distribution. The construction of our factors bound the ranges of scores to roughly -1.3 to 1.3.

Exhibit 1: Comparison of distribution characteristics

	AXIOMA FACTORS	RI FACTORS
Type of distribution	Normal-like	Bi-modal
Range	-4 to 4	-1.3 to 1.3
Tails	thin, long	short, fat

Our belief and understanding of factors suggest that a security having high or low exposure to a factor is a meaningful signal. Distinguishing between the highest of the high and the lowest of the low is less important.[2] With the RI score distributions, securities in the universe are distinguished on whether they have high or low exposure to the factor, as opposed to Axioma's distribution, which distinguishes mostly between the highest of the high and lowest of the low. Exhibit 2 shows an example of the Value factor in both Axioma and RI's models.

Exhibit 2: Value factor scores[3] for Global LC universe as of Dec 2016



The RI Value factor follows this belief with a meaningful amount of the universe reflected near the high and low ends of the distribution. If we contrast this to Axioma's factor, we see the most meaningful differences in scores only at the very end of the distribution. The percentile breakpoints shown in Exhibit 3 are telling; our belief is that the first percentile and 10th percentile of Value stocks are both high Value exposures, and there should be little differentiation between these two stocks along the Value dimensions. The Russell Investments' factor distribution reflects this view, whereas Axioma's distribution would suggest the first percentile name has three times as much Value exposure as does the 10th percentile. This score relationship exists across all factors.

Exhibit 3: Differences in the tails of distributions

	VALUE FACTOR SCORE	
PERCENTILE	AXIOMA FACTORS	RI FACTORS
1st	4.1	1.3
10th	1.4	1.2

When constructing factor portfolios using an optimized approach[4], our hypothesis is that RI scores will foster more robust results in portfolios seeking to increase factor exposure without imposing any additional diversification constraints. Due to the distribution of Axioma's scores, unconstrained optimization tends to select a handful of securities with the highest factor exposures. The large portfolio concentration on just a few securities ultimately leads to too much idiosyncratic risk. Since there are more similar (high) exposure securities in RI distribution than in Axioma's distribution, these portfolios are expected to achieve desired factor exposures in a diversified way. We expect to see fewer corner solutions than what we'd typically see when tilting a portfolio using Axioma's distribution.

Data limitations

Russell Investments' scores are only available starting from 2008. Our results should therefore be treated with care.

Single factor portfolios

First, we construct single factor portfolios ranging from concentrated to diversified in terms of the number of stocks using both Axioma's and Russell Investments' (RI) scores and corresponding risk models. In Exhibit 4 and 5 below, we provide the results for Value portfolios within the Russell Investments Global Large Capitalization universe. We compare optimized portfolios with different concentration levels (from 200 to 1000 securities) with our standard rules-based RGI LC Value Russell Investments Factor Portfolio (RFP). Russell Investments Factor Portfolios are built using a set of rules with NLP weighting methodology at the core of the portfolio construction rather than using an optimizer. The full methodology is documented in Bennett at el. (2014). For optimized portfolios, we maximize the exposure to Value factor under a number of names constraint as well as a model deviation constraint relative to the benchmark. The optimization problem is the same regardless of whether we use the ARM or the CRM.

Exhibit 4: Performance characteristics for Global LC Value portfolios (ARM, 2008-2017)[5]

	AV 200 STOCKS	AV 300 STOCKS	AV 400 STOCKS	AV 500 STOCKS	AV 600 STOCKS	AV 700 STOCKS	AV 800 STOCKS	AV 900 STOCKS	AV 1000 STOCKS	BENCH-MARK[6]
Return (CAGR)	2.5%	3.7%	4.4%	4.8%	5.2%	5.4%	5.0%	5.0%	5.1%	3.4%
Volatility	22.7%	25.2%	26.4%	26.6%	24.9%	24.9%	22.6%	22.5%	22.4%	19.7%
Excess return (CAGR)	-0.9%	0.3%	1.0%	1.3%	1.8%	1.9%	1.6%	1.6%	1.6%	
Tracking error	6.4%	9.3%	10.6%	11.1%	9.6%	9.6%	6.9%	6.7%	6.6%	
Ex-ante tracking error	4.6%	6.0%	6.5%	6.5%	5.4%	5.3%	3.6%	3.5%	3.5%	
Ex-ante specific risk	1.5%	1.6%	1.6%	1.5%	1.2%	1.2%	0.9%	0.9%	0.8%	
Active share	72.2%	79.2%	82.7%	82.0%	65.0%	63.9%	43.1%	41.5%	40.2%	
Information ratio	-0.04	0.16	0.23	0.25	0.29	0.31	0.31	0.31	0.32	
Max active drawdown	-31.5%	-27.9%	-22.7%	-22.7%	-9.4%	-9.3%	-6.2%	-6.1%	-5.9%	
Average number of names	200	300	400	500	600	700	800	900	1000	
Average factor exposure	1.1	1.5	1.6	1.7	1.5	1.4	1.0	1.0	1.0	

Exhibit 5: Performance characteristics for Global LC Value portfolios (CRM, 2008-2017)[5]

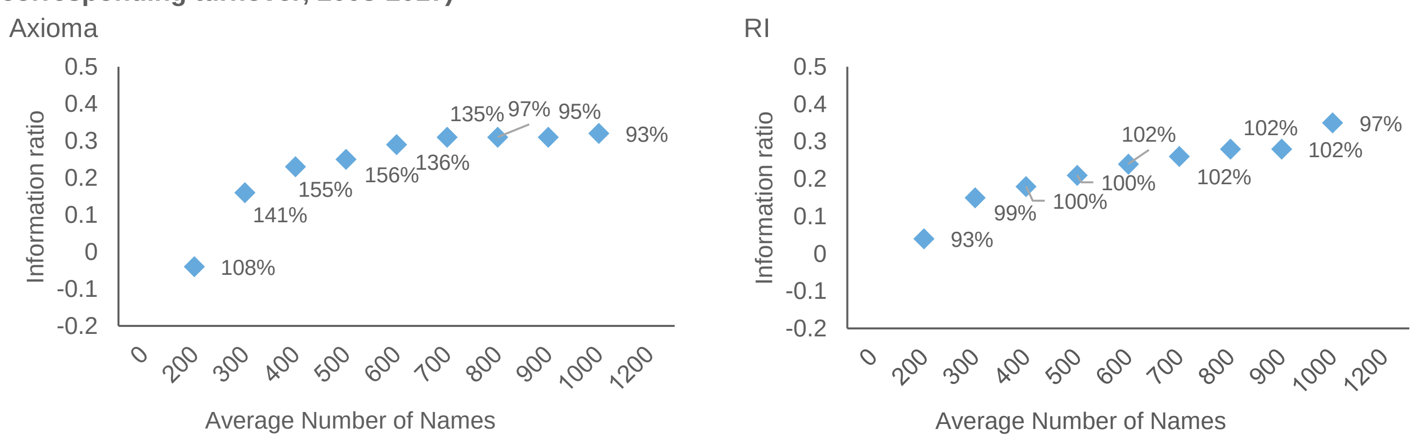
	RV 200 STOCKS	RV 300 STOCKS	RV 400 STOCKS	RV 500 STOCKS	RV 600 STOCKS	RV 700 STOCKS	RV 800 STOCKS	RV 900 STOCKS	RV 1000 STOCKS	RV RULES-BASED	BENCH-MARK[6]
Return (CAGR)	3.2%	3.8%	4.0%	4.2%	4.4%	4.6%	4.6%	4.7%	5.1%	4.8%	3.4%
Volatility	21.8%	22.4%	22.4%	22.5%	22.5%	22.6%	22.6%	22.6%	22.5%	22.5%	19.7%
Excess return (CAGR)	-0.2%	0.4%	0.5%	0.8%	0.9%	1.1%	1.2%	1.2%	1.7%	1.3%	
Tracking error	4.7%	6.1%	5.9%	6.1%	6.1%	6.2%	6.2%	6.2%	6.2%	6.0%	
Ex-ante tracking error	4.7%	4.8%	4.7%	4.7%	4.7%	4.7%	4.7%	4.7%	4.5%	4.4%	
Ex-ante specific risk	1.3%	1.2%	1.1%	1.0%	1.0%	1.0%	1.0%	0.9%	0.8%	0.8%	
Active share	72.0%	70.5%	68.8%	67.6%	66.9%	66.4%	65.8%	65.4%	60.9%	82.9%	
Information ratio	0.04	0.15	0.18	0.21	0.24	0.26	0.28	0.28	0.35	0.3	
Max active drawdown	-17.7%	-15.9%	-8.2%	-8.0%	-7.9%	-7.9%	-7.8%	-7.8%	-7.0%	-6.3%	
Average number of names	200	300	400	500	600	700	800	900	1000	1105	
Average factor exposure	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	0.9	

When we use Axioma's scores, achieving higher exposures generally requires more concentration in terms of the number of stocks. This, however, is not the case when we use Russell Investments' scores. Even though, for RI Value portfolios, average Value exposure doesn't change as the number of names is increased from 200 to 1000, the returns of those portfolios increase and active drawdowns decrease quite significantly. As expected, because of the RI scores distribution, the specific risk is generally lower for RI portfolios than that for Axioma's portfolios. We see similar results for Momentum portfolios but not for Quality portfolios for which tracking errors and active drawdowns are considerably lower from the start.

Consistent with our previous findings, we observe that diversified factor portfolios usually produced better Information ratios (IRs) than concentrated factor portfolios (Exhibit 6). This is due to concentrated portfolios being exposed to a higher level of unrewarded stock specific and other risks. Similar studies were conducted by Amenc et al. (2016) where they found that narrow stock selections may improve returns compared with broad selections, but these increases are accompanied by higher volatility and higher tracking error, which kept performance ratios – the Sharpe Ratio and Information ratio – virtually unchanged. In addition, they find that narrow stock selections present real drawbacks, such as high idiosyncratic risk, higher turnover and longer times to trade portfolios.

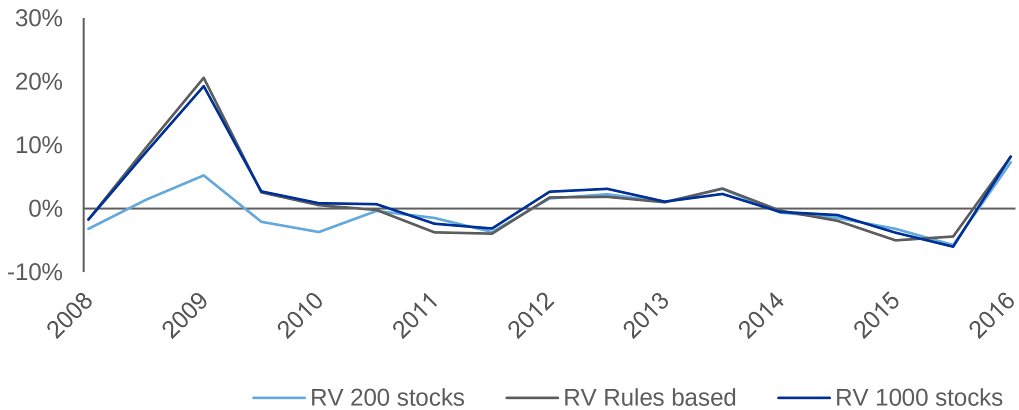
Utilizing the Axioma factor scores typically has led to higher turnover (Exhibit 6) for similar number of names and Information ratios. This is likely a result of greater instability in the factor scores and sensitivity to a wider distribution of scores that are used as inputs to the optimization.

Exhibit 6: Information ratios for Global LC Value portfolios (Axioma versus RI, dots labeled with corresponding turnover, 2008-2017)[5]



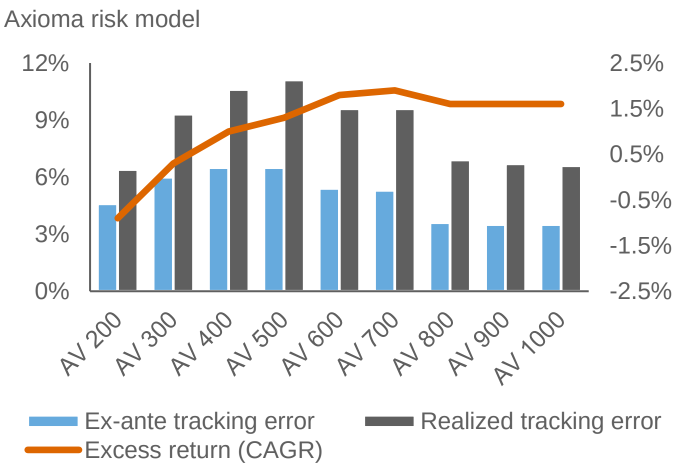
We provide rolling excess returns for three Value portfolios (RV 1000, RV Rules-based and RV 200) in Exhibit 7. We show the most concentrated portfolio for comparison. We observe that during 2009, unintended bets overwhelmed the intended exposure and more concentrated portfolios underperformed. Also, the return patterns of rules-based RFPs are generally similar to those of optimized factor portfolios with similar diversification levels. This holds true for Momentum and Quality portfolios as well.

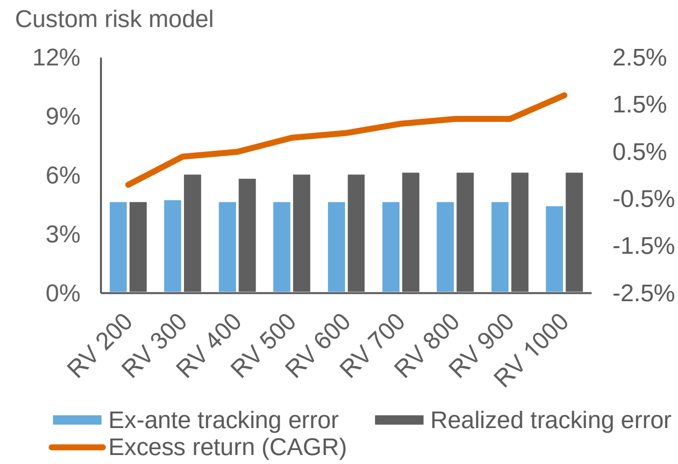
Exhibit 7: One year rolling excess returns vs. RGI LC Index for a subset of Global LC Value portfolios[5]



A custom risk model is supposed to improve the accuracy of portfolio risk forecasts (e.g., see Canova et al., 2013). And this is exactly what we observe: Ex-ante tracking error is much closer to realized tracking error when we use CRM rather than ARM (Exhibit 8). We also notice that the tracking errors are very consistent under the CRM. This holds true for Momentum and Quality factor portfolios.

Exhibit 8: Ex-ante versus realized tracking errors for Global LC Value portfolios (Axioma versus RI, 2008-2017, tracking errors on LHS, excess return on RHS)[5]





Multi-factor portfolios

Next, we construct multi-factor (VMQ) portfolios ranging from concentrated to diversified in terms of the number of stocks using both Axioma's and Russell Investments' (RI) scores and their corresponding risk models. The optimization problem here is to maximize the exposure to the composite score (Value + Momentum + Quality) under the number of names constraint as well as model deviation constraint relative to the benchmark. We call this a composite score approach. The optimization problem is the same regardless of whether we use Axioma risk model (ARM) or CRM.

Exhibit 9: Performance characteristics for Global LC VMQ portfolios (ARM, 2008-2017)[5]

	AVMQ 200 STOCKS	AVMQ 300 STOCKS	AVMQ 400 STOCKS	AVMQ 500 STOCKS	AVMQ 600 STOCKS	AVMQ 700 STOCKS	AVMQ 800 STOCKS	AVMQ 900 STOCKS	AVMQ 1000 STOCKS	BENCH-MARK[6]
Return (CAGR)	2.0%	2.6%	3.2%	3.5%	3.5%	3.6%	3.7%	3.7%	3.7%	3.4%
Volatility	21.0%	22.2%	22.3%	22.3%	22.2%	22.0%	22.0%	22.0%	22.0%	19.7%
Excess return (CAGR)	-1.4%	-0.9%	-0.2%	0.1%	0.1%	0.2%	0.2%	0.3%	0.3%	
Tracking error	3.6%	4.0%	3.8%	3.5%	3.3%	3.2%	3.1%	3.1%	3.0%	
Ex-ante tracking error	2.4%	2.5%	2.4%	2.3%	2.2%	2.1%	2.0%	2.0%	2.0%	
Ex-ante specific risk	1.2%	1.2%	1.1%	1.0%	0.9%	0.9%	0.8%	0.8%	0.8%	
Active share	65.1%	63.9%	60.7%	57.9%	55.2%	52.8%	51.9%	51.0%	50.0%	
Information ratio	-0.28	-0.05	0.11	0.2	0.21	0.23	0.25	0.27	0.28	
Max active drawdown	-23.4%	-19.1%	-12.5%	-9.5%	-8.4%	-7.2%	-6.7%	-6.4%	-5.8%	
Average number of names	200	300	400	500	600	700	800	900	1000	
Average factor exposure[7]	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	

Exhibit 10: Performance characteristics for Global LC VMQ portfolios (CRM, 200-1000 stocks, 2008-2017) [5]

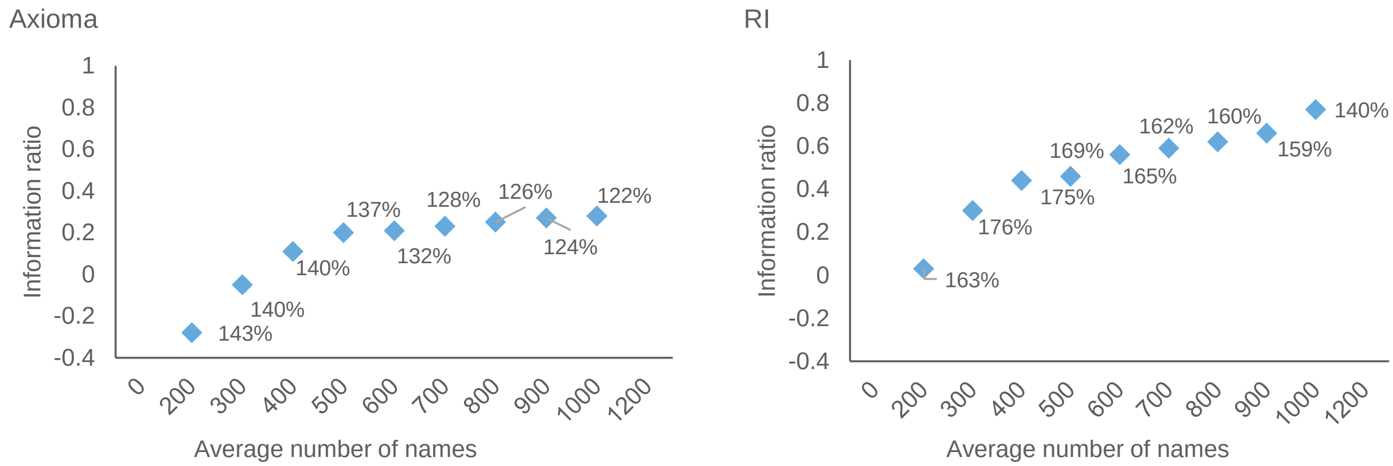
	RVMQ 200 STOCKS	RVMQ 300 STOCKS	RVMQ 400 STOCKS	RVMQ 500 STOCKS	RVMQ 600 STOCKS	RVMQ 700 STOCKS	RVMQ 800 STOCKS	RVMQ 900 STOCKS	RVMQ 1000 STOCKS	RVMQ RULES-BASED	BENCH-MARK[6]
Return (CAGR)	3.4%	4.1%	4.4%	4.3%	4.6%	4.6%	4.7%	4.7%	4.7%	4.5%	3.4%
Volatility	20.2%	20.6%	21.0%	21.1%	21.1%	21.1%	21.1%	21.1%	21.0%	20.6%	19.7%
Excess return (CAGR)	0.0%	0.6%	0.9%	0.9%	1.1%	1.1%	1.2%	1.3%	1.2%	1.1%	
Tracking error	2.9%	2.7%	2.7%	2.6%	2.5%	2.4%	2.4%	2.4%	1.9%	1.8%	
Ex-ante tracking error	3.0%	3.0%	2.9%	2.8%	2.7%	2.7%	2.6%	2.6%	2.3%	1.4%	
Ex-ante specific risk	1.2%	1.1%	1.0%	0.9%	0.9%	0.8%	0.8%	0.8%	0.7%	0.5%	
Active share	69.4%	68.6%	65.2%	61.4%	59.6%	58.2%	57.4%	56.4%	51.6%	35.0%	
Information ratio	0.03	0.3	0.44	0.46	0.56	0.59	0.62	0.66	0.77	0.66	
Max active drawdown	-6.6%	-4.7%	-4.4%	-4.4%	-3.5%	-3.0%	-2.6%	-2.2%	-1.9%	-1.1%	
Average number of names	200	300	400	500	600	700	800	900	1000	2410	
Average factor exposure	0.6	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.5	0.2	

We compare optimized VMQ portfolios with different concentration levels (from 200 to 1000 securities) with a rules-based VMQ portfolio that is built as an equal weighted combination of Value, Momentum and Quality rules-based factor portfolios described in previous section.

In both ARM and CRM cases, returns increase and active drawdowns decrease quite significantly as the number of names is increased from 200 to 1000. As expected, because of RI scores distribution, the specific risk is generally lower for RI portfolios than for Axioma's portfolios, Information ratios for the same concentration levels are better, and active drawdowns are significantly smaller.

Similar to single factor portfolios, diversified multi-factor portfolios produce better Information ratios than concentrated multi-factor portfolios (Exhibit 11).[8]

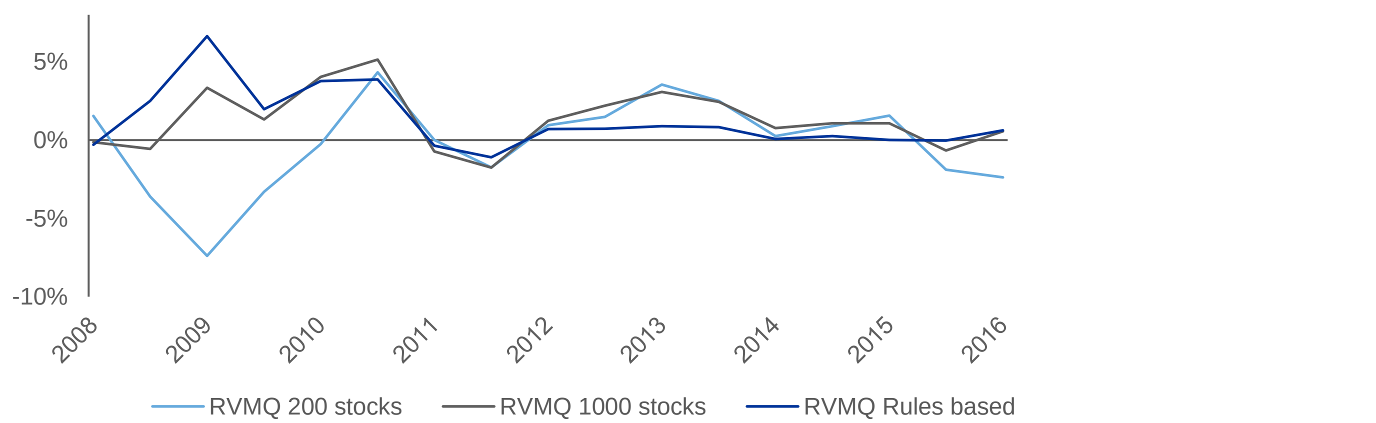
Exhibit 11: Information ratios for Global LC multi-factor portfolios (Axioma versus RI, dots labeled with corresponding turnover) [5]



We provide rolling excess returns for three multi-factor portfolios (RVMQ Rules-based, RVMQ 1000 and RVMQ 200) in Exhibit 12. We show the most concentrated portfolio for comparison. We continue to observe that during 2009, unintended bets overwhelmed the intended bets and a more concentrated multi-factor portfolio underperformed. All three concentrated single factor portfolios (Value, Momentum and Quality) underperformed during that time. The rules-based multi-factor portfolio had 2410 stocks. Comparing its performance to that of RVMQ 1000, we conclude that we can decrease the number of stocks in a rules-based multi-factor portfolio by more than 50% without materially deviating from its performance characteristics.

In contrast to single factor portfolios, the return pattern of rules-based multi-factor portfolios is slightly different from that of optimized multi-factor portfolios. This is mostly driven by the differences in composite scores and composite portfolio approaches (see Bennett and Gvozdeva, 2016).

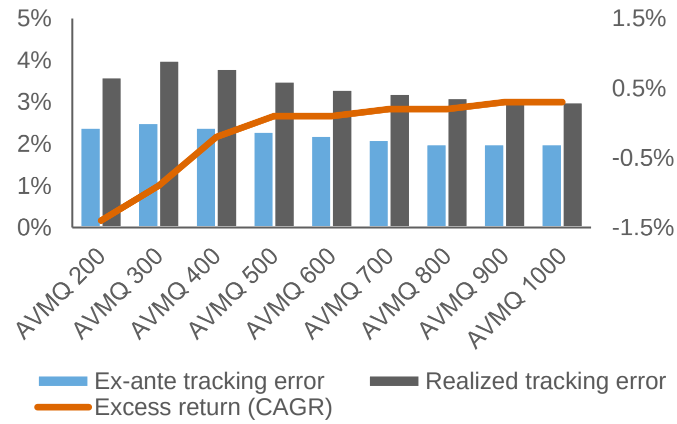
Exhibit 12: One year rolling excess returns vs. RGI LC Index for a subset of Global LC multi-factor portfolios [5]



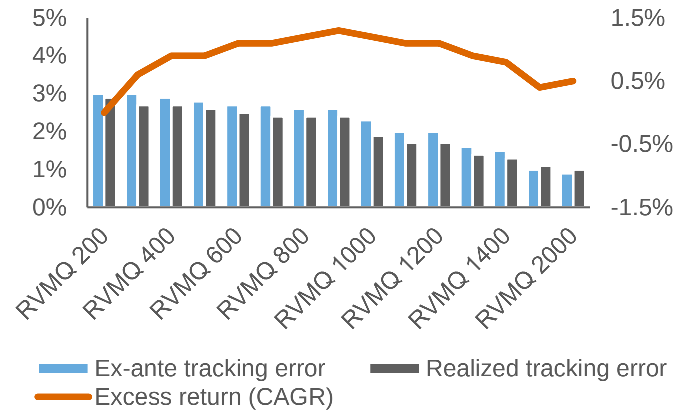
The ex-ante tracking error continues to predict realized tracking error better under the CRM (Exhibit 13) for multi-factor portfolios.

Exhibit 13: Ex-ante versus realized tracking errors for Global LC multifactor portfolios (Axioma versus RI, 2008-2017, tracking errors on LHS, excess return on RHS) [5]

Axioma risk model



Custom risk model



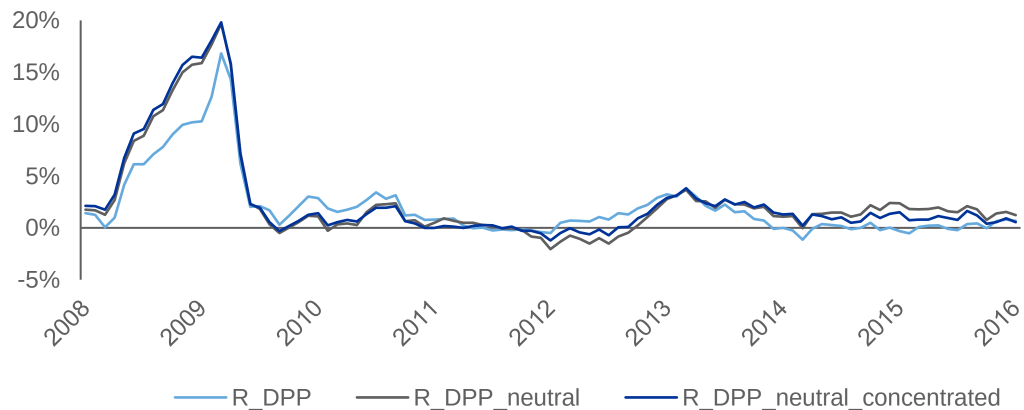
DPP portfolios after neutralization and concentration

After evaluating optimized factor exposures, the next step is to replicate the original factor-based Global LC Dynamic Preferred Positioning portfolio (DPP) and to build a concentrated and a non-concentrated version of that portfolio with neutral regional, country, sector and industry bets using the CRM. The objective function is to minimize tracking error to the original Global LC DPP portfolio while keeping exposures to Value, Momentum, Quality and Low volatility at the same level. We chose a limit of 1000 stocks in the concentrated portfolio based on the analysis in Part I, which demonstrated that we can decrease the number of stocks in a rules-based multi-factor portfolio by more than 50% without materially deviating from its performance characteristics. At the same time, we show that concentrating the portfolio further can increase active drawdowns and decrease Information ratios.

Exhibit 14: Performance characteristics for Global LC DPP dynamic portfolios (CRM, 2008-2017) [5]

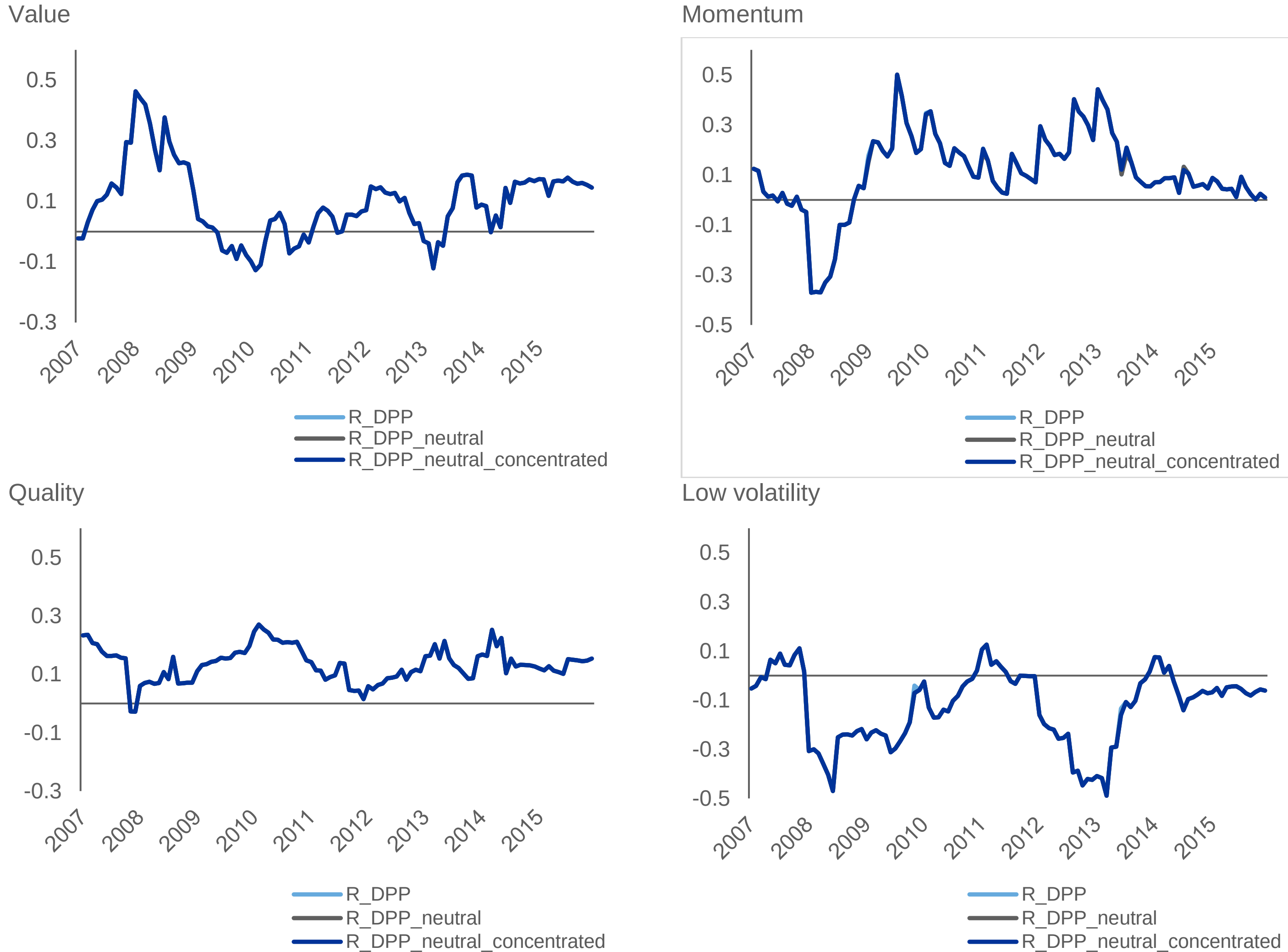
	R_DPP	R_DPP_NEUTRAL_ CONCENTRATED	R_DPP_NEUTRAL	BENCHMARK[6]
Return (CAGR)	5.5%	6.2%	6.1%	3.7%
Volatility	18.7%	18.6%	18.6%	17.7%
Excess return (CAGR)	1.8%	2.4%	2.4%	
Tracking error	2.4%	2.5%	2.5%	
Ex-ante tracking error	1.5%	1.8%	1.8%	
Ex-ante specific risk	0.4%	0.8%	0.8%	
Active share	29.4%	52.0%	51.3%	
Information ratio	0.78	0.98	0.97	
Max active drawdown	-1.9%	-1.2%	-1.4%	
Average number of names	3187	970	2492	

Exhibit 15: One year rolling excess returns vs. RGI LC Index for Global LC DPP dynamic portfolios



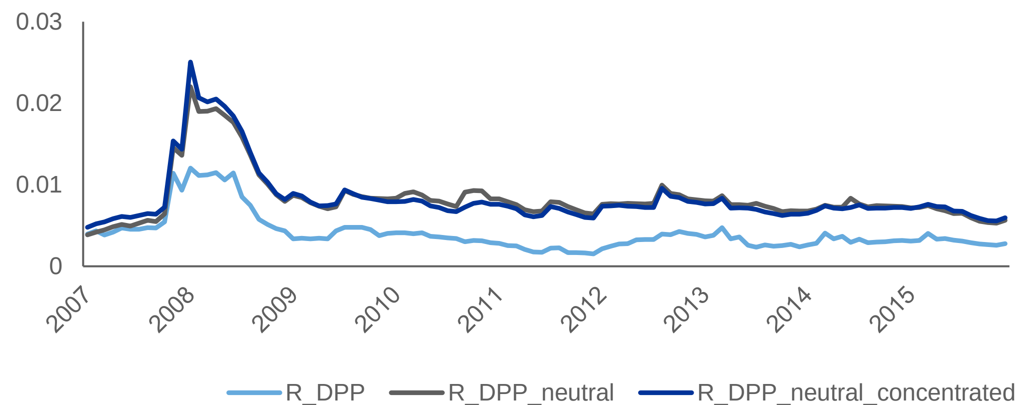
Generally, we expect portfolios with neutralization to be lower risk portfolios. We don't have any expectations with respect to returns. Interestingly, the return patterns of all the factor-based Global LC DPP Dynamic portfolios look very similar in this case. Volatilities and tracking errors don't change much. However, both neutral portfolios are more concentrated than the original Global LC DPP Dynamic portfolio. The active share of both neutral portfolios is almost twice that of the original portfolio. The exposures of the original portfolio, concentrated portfolios and non-concentrated portfolios with neutralization are at virtually the same levels as seen in Exhibit 16. Note, all three portfolios are plotted here, and one must look closely to see more than one line (e.g. Low volatility in 2011).

Exhibit 16: Factor exposures for Global LC DPP dynamic portfolios



Ex-ante specific risk is consistently slightly higher for portfolios with neutralization (Exhibit 17). So even though we can mitigate the risk along region/country/sector dimension, we slightly increase stock specific risk to match the factor exposures.

Exhibit 17: Ex-ante specific risk for Global LC DPP dynamic portfolios[5]



Based on the observations in this section, we cannot conclude that one approach is necessarily more beneficial than other approaches.

Replicating the full DPP process (including sector, country and region bets)

To replicate the full DPP process, we need to add region, country and sector bets. Currently we don't have the history of signals for those dimensions from DPP, so we will try a few different ad-hoc combinations and study the impact on tracking errors, active share, etc. Here we express our regional, country and sector views through constraints. We consider several independent specifications to deviate from the concentrated neutral Global LC DPP Dynamic portfolio described in the previous section.

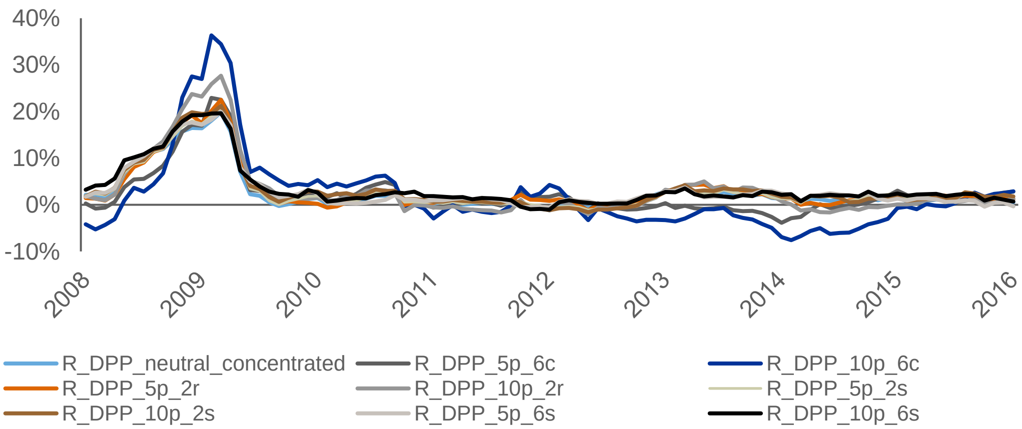
Table 1: Number of overweights/number of underweights/size of the bet for each portfolio

NAME	COUNTRY BETS	REGION BETS	SECTOR BETS
R_DPP_5p_6c	3/3/5%		
R_DPP_10p_6c	3/3/10%		
R_DPP_5p_2r		1/1/5%	
R_DPP_10p_2r		1/1/10%	
R_DPP_5p_2s			1/1/5%
R_DPP_10p_2s			1/1/10%
R_DPP_5p_6s			3/3/5%
R_DPP_10p_6s			3/3/10%

Exhibit 18: Performance characteristics for Global LC DPP dynamic portfolios with bets (CRM, 2008-2017) [5]

	R_DPP (NEUT, CONC)	R_DPP_ 5P_6C	R_DPP_ 10P_6C	R_DPP_ 5P_2R	R_DPP_ 10P_2R	R_DPP_ 5P_2S	R_DPP_ 10P_2S	R_DPP_ 5P_6S	R_DPP_ 10P_6S	BENCH-MARK[6]
Return (CAGR)	6.2%	5.8%	4.7%	6.4%	6.5%	6.5%	6.7%	6.4%	7.2%	3.7%
Volatility	18.6%	19.3%	20.8%	18.9%	19.3%	18.7%	18.7%	18.2%	18.0%	17.7%
Excess return (CAGR)	2.4%	2.0%	0.9%	2.6%	2.8%	2.8%	3.0%	2.7%	3.4%	
Tracking error	2.5%	3.0%	4.7%	2.6%	3.3%	2.5%	2.6%	2.5%	2.5%	
Ex-ante tracking error	1.8%	2.4%	3.6%	2.0%	2.6%	1.8%	1.9%	1.8%	1.8%	
Ex-ante specific risk	0.8%	1.1%	1.3%	0.8%	1.1%	0.9%	0.9%	0.9%	0.9%	
Active share	52.0%	58.6%	64.9%	53.0%	60.0%	53.0%	54.0%	56.2%	57.0%	
Information ratio	0.98	0.75	0.31	1.04	0.87	1.12	1.14	1.03	1.31	
Max active drawdown	-1.2%	-3.8%	-13.9%	-1.3%	-3.1%	-1.6%	-1.4%	-1.5%	-1.4%	
Average number of names	970	947	877	974	935	968	954	965	961	

Exhibit 19: One year rolling excess returns vs. RGI LC Index for Global LC DPP dynamic portfolios with bets[5]



Based on the analysis in Exhibit 18, it is prudent to expect tracking errors, active share and specific risk to increase when the bets are imposed. The factor exposures of all the portfolios with bets match those of the original DPP Dynamic portfolio.

When we combine a few different constraints, the results look similar. We consider the following specifications to deviate from concentrated neutral Global LC DPP Dynamic portfolios described in the previous section.

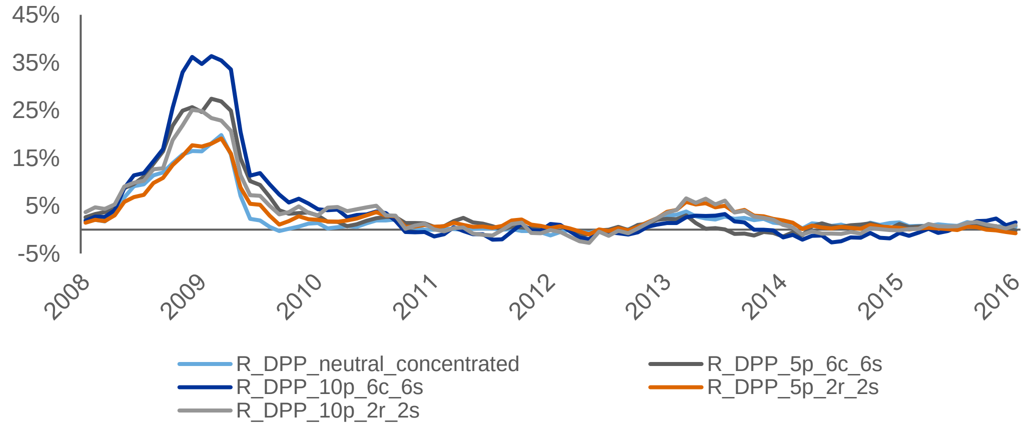
Table 2: Number of overweights/number of underweights/size of the bet for each portfolio

NAME	COUNTRY BETS	REGION BETS	SECTOR BETS
R_DPP_5p_6c_6s	3/3/5%		3/3/5%
R_DPP_10p_6c_6s	3/3/10%		3/3/10%
R_DPP_5p_2r_2s		1/1/5%	1/1/5%
R_DPP_10p_2r_2s		1/1/10%	1/1/10%

Exhibit 20: Performance characteristics for Global LC DPP dynamic portfolios with combinations of bets (CRM, 2008-2017) [5]

	R_DPP (NEUT, CONC)	R_DPP_5P_6C	R_DPP_10P_6C	R_DPP_5P_2R	R_DPP_10P_2R	BENCHMARK[6]
Return (CAGR)	6.2%	5.8%	4.7%	6.4%	6.5%	3.7%
Volatility	18.6%	19.3%	20.8%	18.9%	19.3%	17.7%
Excess return (CAGR)	2.4%	2.0%	0.9%	2.6%	2.8%	
Tracking error	2.5%	3.0%	4.7%	2.6%	3.3%	
Ex-ante tracking error	1.8%	2.4%	3.6%	2.0%	2.6%	
Ex-ante specific risk	0.8%	1.1%	1.3%	0.8%	1.1%	
Active share	52.0%	58.6%	64.9%	53.0%	60.0%	
Information ratio	0.98	0.75	0.31	1.04	0.87	
Max active drawdown	-1.2%	-3.8%	-13.9%	-1.3%	-3.1%	
Average number of names	970	947	877	974	935	

Exhibit 21: One year rolling excess returns vs. RGI LC Index for Global LC DPP dynamic portfolios with combinations of bets[5]



Based on this analysis, we conclude that we can express sector, country and region bets without significantly changing the performance pattern of the factor-based DPP portfolio.

APS strategies based on DPP framework

The optimization problem described in the prior section can be used for 100% factor managed portfolios. Next, we discuss adjusting the optimization to build APS strategies, which complement existing external managers' portfolios. For APS strategies, we start with the existing manager lineup holdings at a 75% allocation, set a 25% allocation to APS and choose the DPP Dynamic portfolio as an anchor portfolio for the fund. The objective function is to minimize the tracking error to the anchor portfolio. Some important constraints we use are holdings limits (e.g., active weight versus benchmark), which we set at 50 basis points for non-concentrated markets (e.g., Global LC example and 1% for concentrated markets (e.g., Australia example), max holdings of five times the benchmark weight, model deviation constraint versus benchmark and turnover constraints (e.g., transaction cost penalty and max turnover constraint). The asset holding levels are consistent with rules-based construction parameters for the rules-based Russell Investments Factor Portfolio suite.

We start with the Global LC universe. We consider a few different concentration levels: 300, 500 and 700 stocks in the APS sleeve. We first run the Global LC Fund with APS test with neutral regional, country, sector and industry bets constraints, and set range constraints for the factors to make sure that we are getting close to DPP factor exposures. In parallel, we run the same test with 100% allocated to a DI portfolio (Global LC DPP Dynamic concentrated neutral portfolio) with 1000 stocks (i.e., no managers included). This allows us to first make a direct comparison on the effects of using managers plus APS to achieve preferred factor exposures as opposed to 100% direct investment. We then run additional Global LC multi-manager portfolio with APS tests while expressing views on region, countries and sectors chosen at random (i.e., no forward-looking views). We consider the following region/country/sector specifications.

Table 3: Number of overweights/number of underweights/size of the bet at the fund level

NAME	COUNTRY BETS	REGION BETS	SECTOR BETS
R_APS_neut			
R_APS_2s			1/1/5%
R_APS_6s			3/3/5%
R_APS_2r		1/1/5%	
R_APS_6c	3/3/5%		
R_APS_2s_2r		1/1/5%	1/1/5%
R_APS_6s_6c	3/3/5%		3/3/5%

We introduce a couple of new measures to evaluate the efficacy of the APS strategies (Exhibits 22 and 24). To check whether the return pattern for the total fund is shifting towards the DPP return pattern, we calculate correlation of excess returns with DPP. For the Global LC universe, we find that correlation with DPP is positive for total portfolios with APS, while it is negative for the managers' portfolio. We also find that, the less concentrated the APS sleeves are, the higher the correlation with DPP. Because a larger portion is allocated to the manager lineup from the start (75%), the correlation with managers stays positive and high.

We also calculate the average differences between the exposures of managers and total portfolios with APS versus DPP portfolios (Average difference in X versus DPP). Even though correlation with managers of total portfolios with APS stays high for most factors, we can get the exposures half way close to DPP exposures. We are also able to decrease the exposure to high volatility but not to the same extent.

The risk characteristics (e.g., tracking error, specific risk, and active drawdowns) of total portfolios with APS look very reasonable as well. In Exhibits 23 and 25, we show backtested rolling excess performance for all the portfolios. Unsurprisingly, we notice that during some periods of time it is beneficial to be tilted towards a DPP portfolio while during other periods of time, it is beneficial to be tilted towards a managers' portfolio.[9]

Exhibit 22: Performance characteristics for Global LC DPP, manager and APS portfolios with 300 stocks in APS sleeve (CRM, 2008-2017) [5]

	R_DPP NEUT_ CONC	R_APS NEUT	R_APS _2S	R_APS _6S	R_APS _2R	R_APS _6C	R_APS _2S_2R	R_APS _6S_6C	R_MGR	BENCH-MARK[6]
Return (CAGR)	6.2%	4.8%	5.0%	5.2%	4.8%	4.7%	5.1%	5.1%	4.9%	3.7%
Volatility	18.6%	18.5%	18.5%	18.4%	18.6%	18.6%	18.6%	18.5%	18.7%	17.7%
Excess return (CAGR)	2.4%	1.1%	1.3%	1.4%	1.1%	1.0%	1.4%	1.4%	1.2%	
Tracking error	2.5%	2.0%	2.0%	2.0%	2.0%	2.0%	2.1%	2.0%	2.8%	
Ex-ante tracking error	1.8%	2.0%	2.0%	2.1%	2.0%	2.0%	2.0%	2.1%	2.8%	
Ex-ante specific risk	0.8%	1.2%	1.2%	1.2%	1.2%	1.2%	1.2%	1.2%	1.5%	
Active share	52.0%	62.5%	62.3%	62.7%	62.5%	62.6%	62.8%	62.8%	75.5%	
Information ratio	0.98	0.59	0.66	0.76	0.59	0.54	0.7	0.73	0.47	
Max active drawdown	-1.2%	-3.1%	-2.7%	-2.8%	-2.9%	-3.3%	-2.8%	-2.9%	-3.8%	
Average number of names	970	514	510	511	512	513	511	510	272	
Correlation with DPP	1	0.08	0.11	0.13	0.12	0.09	0.11	0.12	-0.11	
Correlation with managers	-0.11	0.90	0.91	0.90	0.88	0.89	0.89	0.90	1	
Aver. diff. in Value vs. DPP	0	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.16	
Aver. diff. in Momentum vs. DPP	0	-0.04	-0.04	-0.03	-0.04	-0.03	-0.03	-0.03	-0.1	
Aver. diff. in Quality vs. DPP	0	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01	-0.04	
Aver. diff. in Low volatility vs. DPP	0	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08	

Exhibit 23: One year rolling excess returns vs. RGI LC Index for Global LC DPP, manager and APS portfolios with 300 stocks in APS sleeve

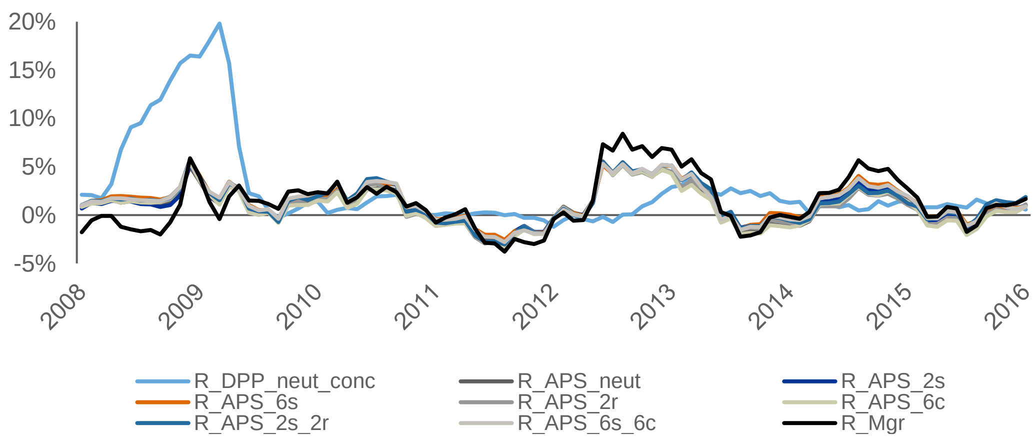
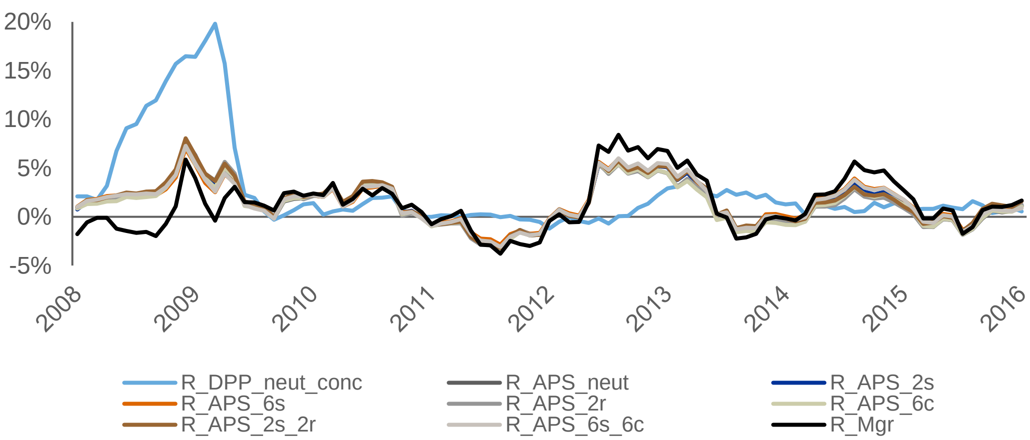


Exhibit 24: Performance characteristics for Global DPP, manager and APS portfolios with 700 stocks in APS sleeve (CRM, 2008-2017)[5]

	R_DPP NEUT_ CONC	R_APS NEUT	R_APS _2S	R_APS _6S	R_APS _2R	R_APS _6C	R_APS _2S_2R	R_APS _6S_6C	R_MGR	BENCH-MARK[6]
Return (CAGR)	6.2%	5.1%	5.2%	5.3%	5.1%	5.0%	5.3%	5.3%	4.9%	3.7%
Volatility	18.6%	18.6%	18.5%	18.5%	18.7%	18.6%	18.6%	18.5%	18.7%	17.7%
Excess return (CAGR)	2.4%	1.3%	1.5%	1.6%	1.4%	1.3%	1.6%	1.5%	1.2%	
Tracking error	2.5%	2.0%	2.0%	2.0%	2.0%	2.0%	2.1%	2.0%	2.8%	
Ex-ante tracking error	1.8%	1.9%	2.0%	2.0%	2.0%	1.9%	2.0%	2.0%	2.8%	
Ex-ante specific risk	0.8%	1.1%	1.2%	1.2%	1.1%	1.1%	1.2%	1.2%	1.5%	
Active share	52.0%	60.4%	60.3%	60.5%	60.4%	60.5%	60.7%	60.6%	75.5%	
Information ratio	0.98	0.73	0.77	0.82	0.73	0.7	0.81	0.79	0.47	
Max active drawdown	-1.2%	-3.1%	-2.7%	-2.8%	-2.9%	-3.3%	-2.8%	-3.1%	-3.8%	
Average number of names	970	868	863	863	866	867	865	863	272	
Correlation with DPP	1	0.18	0.16	0.14	0.19	0.16	0.19	0.15	-0.11	
Correlation with managers	-0.11	0.90	0.91	0.91	0.88	0.90	0.89	0.91	1	
Aver. diff. in Value vs. DPP	0	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07	-0.16	
Aver. diff. in Momentum vs. DPP	0	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.1	
Aver. diff. in Quality vs. DPP	0	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.04	
Aver. diff. in Low volatility vs. DPP	0	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.08	

Exhibit 25: One year rolling excess returns vs. RGI LC for Global DPP, manager and APS portfolios with 700 stocks in APS sleeve[5]



The portfolio construction test and results discussed previously have been applied in a diversified, multiple market universe (Global LC universe). To test the portfolio construction framework robustness and efficacy, we run the same APS tests in a concentrated, single market. The following results use the active managers from the Australian multi-manager portfolio, at varying concentration limits for the APS: maximum of 75 stocks, 100 stocks and 150 stocks.

We consider the following sector specifications.

Table 4: Number of overweights/number of underweights/size of the bet at the fund level

NAME	SECTOR BETS
R_APS_neut_AU	
R_APS_2s_AU	1 / 1 / 5%
R_APS_6s_AU	3 / 3 / 5%

In the case of Australia (unlike Global LC scenario), the correlation of managers' and DPP portfolios is positive and relatively high (Exhibits 26 and 28). The correlation of total portfolios with APS continues to stay at the same or slightly higher level. Similarly, because a larger portion is allocated to manager lineup from the start (75%), correlation with managers stays positive and high. Nonetheless, we can get the exposures of total portfolios with APS at least half way close to DPP exposures for all the factors.

The risk characteristics (e.g., tracking error, specific risk and active drawdowns) of total portfolios with APS look very reasonable in this concentrated market as well. In Exhibits 27 and 29, we show rolling excess performance for all the portfolios. Here we notice that sector bets have a slightly higher impact on the performance pattern of portfolios than in the case of the diversified multiple-market universe.

Exhibit 26: Performance characteristics for Australia DPP, manager and APS portfolios with 75 stocks in APS sleeve (CRM, 2008-2017) [5]

	R_DPP_AU	R_APS_NEUT_AU	R_APS_2S_AU	R_APS_6S_AU	R_MGR_AU	BENCHMARK[10]
Return (CAGR)	3.4%	3.4%	3.2%	3.7%	3.3%	2.4%
Volatility	25.8%	25.7%	25.7%	26.1%	25.7%	25.4%
Excess return (CAGR)	1.0%	1.1%	0.8%	1.3%	0.9%	
Tracking error	1.5%	1.7%	1.6%	2.4%	2.4%	
Ex-ante tracking error	1.4%	1.6%	1.6%	1.8%	2.2%	
Ex-ante specific risk	0.9%	1.1%	1.1%	1.2%	1.4%	
Active share	16.7%	20.2%	21.6%	22.4%	25.7%	
Information ratio	0.7	0.62	0.55	0.6	0.38	
Max active drawdown	-2.1%	-2.6%	-2.3%	-4.3%	-4.2%	
Average number of names	291	244	248	246	227	
Correlation with DPP	1	0.54	0.36	0.54	0.41	
Correlation with managers	0.41	0.86	0.77	0.84	1	
Aver. diff. in Value vs. DPP	0	0.02	0.01	0.02	0.09	
Aver. diff. in Momentum vs. DPP	0	-0.05	-0.06	-0.05	-0.12	
Aver. diff. in Quality vs. DPP	0	-0.04	-0.04	-0.04	-0.09	
Aver. diff. in Low volatility vs. DPP	0	-0.01	-0.03	-0.01	-0.01	

Exhibit 27: One year rolling excess returns vs. S&P/ASX 300 for Australia DPP, manager and APS portfolios with 75 stocks in APS sleeve[5]

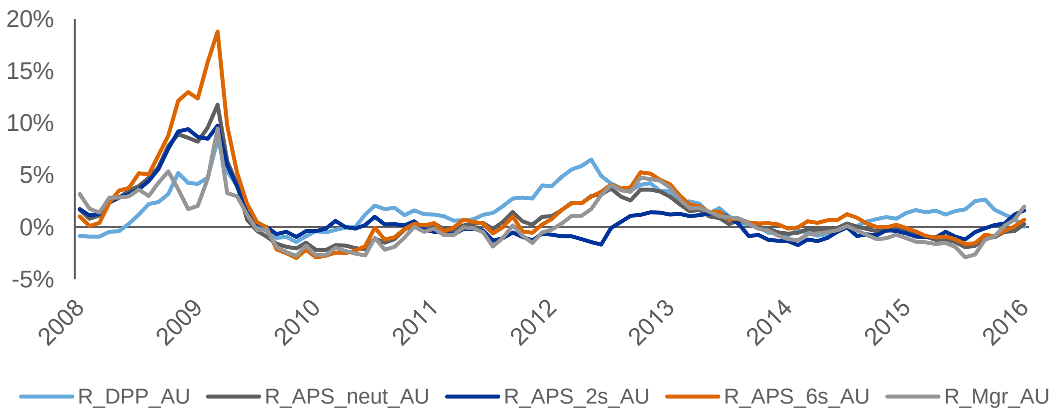
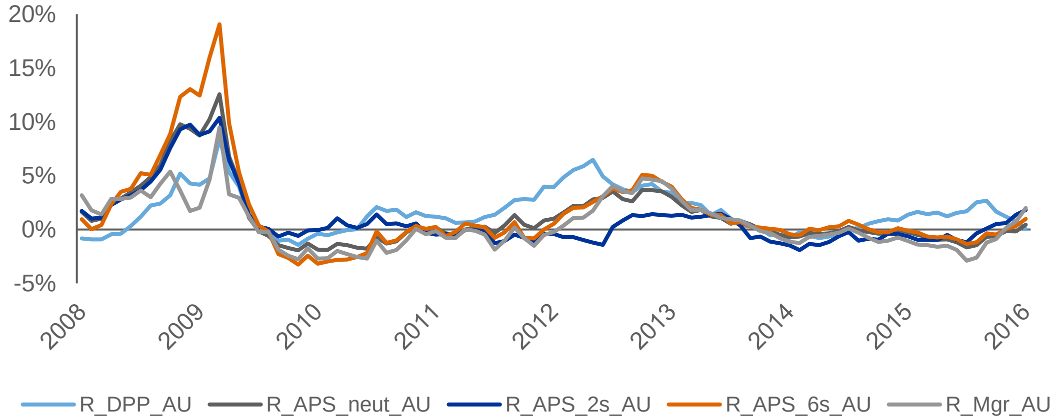


Exhibit 28: Performance characteristics for Australia DPP, manager and APS portfolios with 150 stocks in APS sleeve (CRM, 2008-2017) [5]

	R_DPP_AU	R_APS_NEUT_AU	R_APS_2S_AU	R_APS_6S_AU	R_MGR_AU	BENCHMARK[10]
Return (CAGR)	3.4%	3.5%	3.3%	3.6%	3.3%	2.4%
Volatility	25.8%	25.8%	25.8%	26.1%	25.7%	25.4%
Excess return (CAGR)	1.0%	1.1%	0.9%	1.2%	0.9%	
Tracking error	1.5%	1.8%	1.7%	2.5%	2.4%	
Ex-ante tracking error	1.4%	1.6%	1.6%	1.8%	2.2%	
Ex-ante specific risk	0.9%	1.1%	1.1%	1.2%	1.4%	
Active share	16.7%	19.9%	21.4%	22.2%	25.7%	
Information ratio	0.7	0.65	0.58	0.55	0.38	
Max active drawdown	-2.1%	-1.8%	-2.3%	-4.5%	-4.2%	
Average number of names	291	266	267	256	227	
Correlation with DPP	1	0.56	0.37	0.54	0.41	
Correlation with managers	0.41	0.87	0.77	0.85	1	
Aver. diff. in Value vs. DPP	0	0.02	0.02	0.02	0.09	
Aver. diff. in Momentum vs. DPP	0	-0.05	-0.06	-0.06	-0.12	
Aver. diff. in Quality vs. DPP	0	-0.04	-0.04	-0.04	-0.09	
Aver. diff. in Low volatility vs. DPP	0	-0.01	-0.03	-0.01	-0.01	

Exhibit 29: One year rolling excess returns vs. S&P/ASX 300 for Australia DPP, manager and APS portfolios with 150 stocks in APS sleeve[5]



Conclusion

From the series of empirical portfolio construction tests, we've confirmed key hypotheses around using the CRM and concentration in equity factor portfolios. From the two stage research, we've found:

- evidence that we can concentrate our factor portfolios (especially multi-factor portfolios) to some extent but overconcentrating can be detrimental to the performance due to concentrated portfolios being exposed to higher level of unrewarded stock-specific and other risks.
- an approach to incorporate DPP model output (factor/sector/country/region views) using APS strategies, which works in both broad and concentrated universes.
- robustness of portfolio construction is improved when using CRM in comparison to ARM, in terms of achieving high factor exposures in a diversified way without imposing any additional constraints in the optimization problem.
- initial evidence that CRM improves the accuracy of portfolio risk forecasts for factor-based strategies in comparison to ARM.

Developing a CRM that better aligns with Russell Investments' views on factors, both the definition and the distribution, is an important evolution in the investment process. This paper proves the efficacy of using the CRM in factor portfolio construction. Additionally, it provides the empirical testing of Russell Investments' APS 2.0 investment framework, demonstrating that constraints and views beyond factors can be applied in a robust way, which is an equally important evolution in how factor views are built into funds.

[1] See Eggins and Zylkowski (2014) for the original APS definition.

[2] See Maslov and Rytchkov (2013) and Bennett et al. (2014)

[3] As measured by z-scores using Axioma Risk Model and NLP scores using Russell Investments' Custom Risk Model

[4] Optimized factor portfolios can be constructed using mean-variance optimization. The expected return in this setup is proportional to a factor exposure. We can maximize factor exposure either under a tracking error or model deviation constraint (which places an upper limit on the distance between the portfolio's holdings and the specified benchmark's holdings; the distance is measured as the square root of the sum of the squared differences between the portfolio weights and the benchmark weights).

[5] Hypothetical performance data provided for informational purposes to indicate historical performance that theoretically may have been achieved had the strategy/portfolio been available over the relevant period.

[6] Russell Global Large Cap Index

[7] Average factor exposure in this multi-factor case is the average exposure to Value, Quality and Momentum.

[8] We see slightly higher levels of turnover for RI scores. This is likely due to the fact that RI composite scores are more similar for a group of stocks than Axioma's composite scores and it is easier to substitute one stock with another in the group. Also, it is easier to make trade-offs. This level of turnover can be controlled during implementation.

[9] The main goal here is to bring the total fund performance pattern closer to the DPP performance pattern while maintaining high correlation with managers' performance pattern and reasonable risk characteristics. We acknowledge that running more scenarios with simulated manager portfolios will give us a more robust evaluation. Unfortunately, this type of exercise is computationally infeasible at the moment.

[10] S&P/ASX 300

REFERENCES

Amenc, N., Ducoulombier, F., Goltz, F., Lodh, A., and S. Sivasubramanian, 2016, “Diversified or concentrated factor tilts?”, Journal of Portfolio Management, Winter 2016

Bennett, S. and E. Gvozdeva, 2016, “Comparison of multi-factor portfolios”, Investment Division Research Note

Bennett, S., Gvozdeva, E., Smith, S. and P. Velvadapu, 2014, “Russell Investment Concept strategies: Research and methodology summary”, Investment Division Research Note

Canova, C., Brown, M. and A. Steffanus, 2013, “Enhancing the investment process with a Custom Risk Model: a case study”, Axioma Case Study

Eggins, J. and Zylkowski, N., 2014, “Russell Investments active positioning strategies”, Investment Division Research Note

Ghayur, K., Heaney, R. and S. Platt, December 2016, “Constructing long-only multi-factor strategies: portfolio blending versus signal blending”, SSRN

Maslov, D. and O. Rytchkov, 2013, “Robustness and Monotonicity of Asset Pricing Anomalies”, Working paper

ABOUT RUSSELL INVESTMENTS

Russell Investments is a global asset manager and one of only a few firms that offers actively managed multi-asset portfolios and services, which include advice, investments and implementation. Russell Investments stands with institutional investors, financial advisors and individuals working with their advisors—using our core capabilities that extend across capital market insights, manager research, asset allocation, portfolio implementation and factor exposures to help investors achieve their desired investment outcomes.

FOR MORE INFORMATION:

Call Russell Investments at **800-426-8506** or
visit **russellinvestments.com/institutional**

First used: July 2018 AI-26712-07-21