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When Should I Use a Linked Model?

Case Studies: Axioma Worldwide Equity Linked Factor Risk Model

Simon Bell, Analytics Research Director, Qontigo

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1. Testing, Testing, One Two...

Throughout this document, we make use of the Axioma Worldwide Equity Linked Factor Risk Model - Medium Horizon (WWLM4-MH), which is derived from the three sub-models:

- US4-MH (US medium-horizon equity model)
- DMxUS4-MH (Developed Markets ex-US medium-horizon equity model)
- EM4-MH (Emerging Markets medium-horizon model)

We carry out a variety of tests comparing the performance of the Linked Model against the sub-models and against the Axioma Worldwide Medium-Horizon Equity Factor Risk Model (WW4-MH).[1]

The WWLM4 model spans the same equity universe as WW4 (over 47,000 assets at time of writing) as well as the same time span. It contains over 430 factors, making the model approximately half as large again as WW4. For more details on the model construction and choices, see the separate Linked Model Handbook.

For our tests we use up to 20 years of (mostly monthly) data from 2000 to 2020, with asset universes appropriate to the models being tested. Portfolios are either 'off-the-shelf' or constructed using a variety of strategies, which fall broadly into these categories:

- Market benchmarks - both regional and single-country
- ETFs - especially those based on a particular investment style
- Country buckets - sort the asset universe into its respective country groups
- Sector or Industry Group buckets - as above, but for GICS Sector or Industry Group buckets
- Style tilt portfolios - quintile portfolios with high or low exposure to third party style factors
- Style top-minus-bottom portfolios - as above but we go long the top quintile, short the bottom
- FMP portfolios - using a model's style factor-mimicking portfolio[21] as a long-short benchmark
- Mean-variance portfolios - using third party or risk model factors as alphas and active risk constraint of 3%; plus the following parameters:
  - Maximizing or minimizing exposure
  - Turnover constraints
  - Long-only or long-short
- Minimum-variance portfolios - both long-only and long-short, but with no other constraints or conditions

1 For brevity, we henceforth drop the '-MH' and refer to these models as WWLM4, US4, etc.

2 The factor-mimicking portfolio is a long-short portfolio with unit exposure to a particular factor, zero exposure to all else

Portfolios may be either equal or cap-weighted. Other variants or parameters will be introduced as needed.

Typical portfolio metrics we investigate include:

- Proportion of active factor to active model risk
- Bias statistics
- Average absolute deviation of the bias statistic from one (BSAD) [2]
- Benchmark factor exposures
- Benchmark risk and return attribution results
- Portfolio performance statistics: realized risk, Sharpe Ratio, turnover, transfer coefficient

Results may be either time-series, point-in-time or averaged over time depending on the situation. In addition, we often aggregate results across portfolio families to get a handle on the bigger picture.

2. Sanity Check: Comparison with the Sub-Models

In this section we confirm that, over a broad selection of portfolios, the performance of the WWLM4 model matches each of the sub-models when the initial universe is a broad benchmark appropriate to the sub-model in question. In other words, we compare the following:

- WWLM4 with US4 using a US market benchmark
- WWLM4 with DMxUS4 using a developed ex-US benchmark
- WWLM4 with EM4 using an emerging markets benchmark

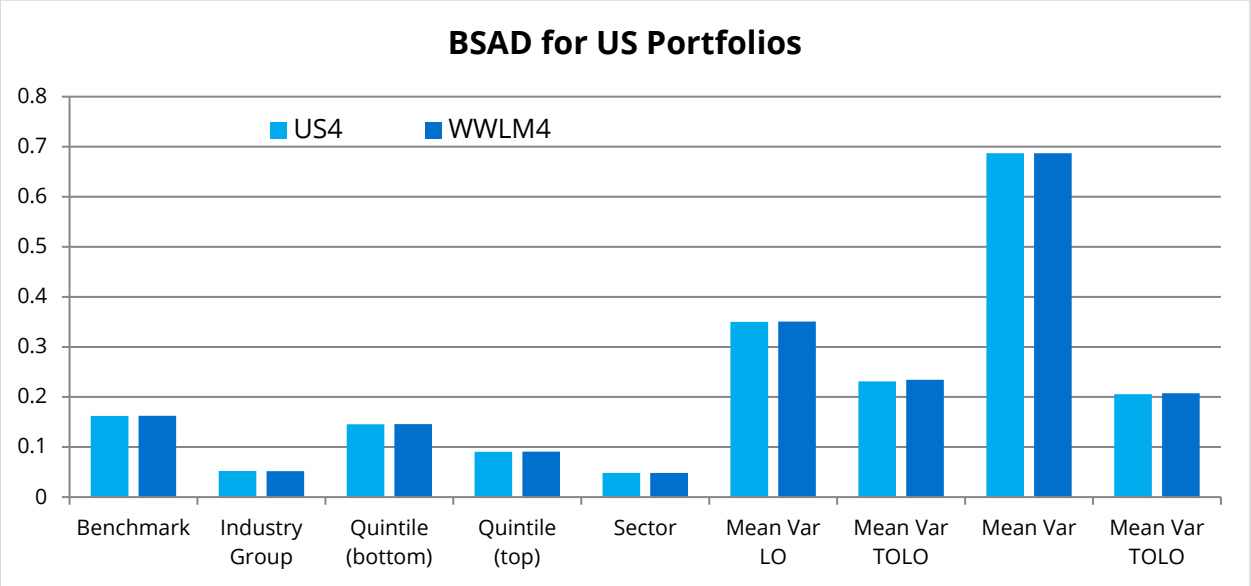
Note that, for reasons mentioned in the Linked Models Handbook, we do not necessarily expect the results to match exactly across models, but they should be very close.

Figures 1, 2 and 3 show the average active BSAD scores for various classes of portfolios; typical benchmarks, country, sector, quintile and industry group buckets, and mean-variance.

We see that, so far as risk accuracy is concerned, there is almost nothing to choose between the two models in each case. This, of course, is exactly as it should be.

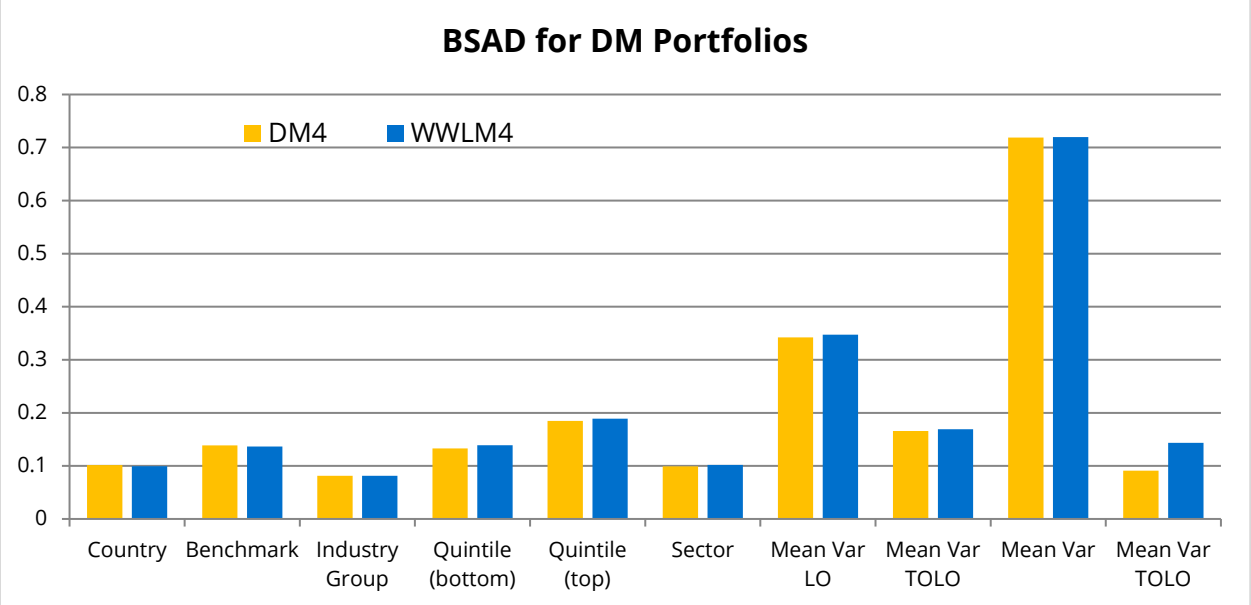
[2] 3 If our bias statistics are bt, t = 1, . . . T , then BSAD = 1 T |bt − 1|

Figure 1: Active BSAD for portfolios based on a US Universe



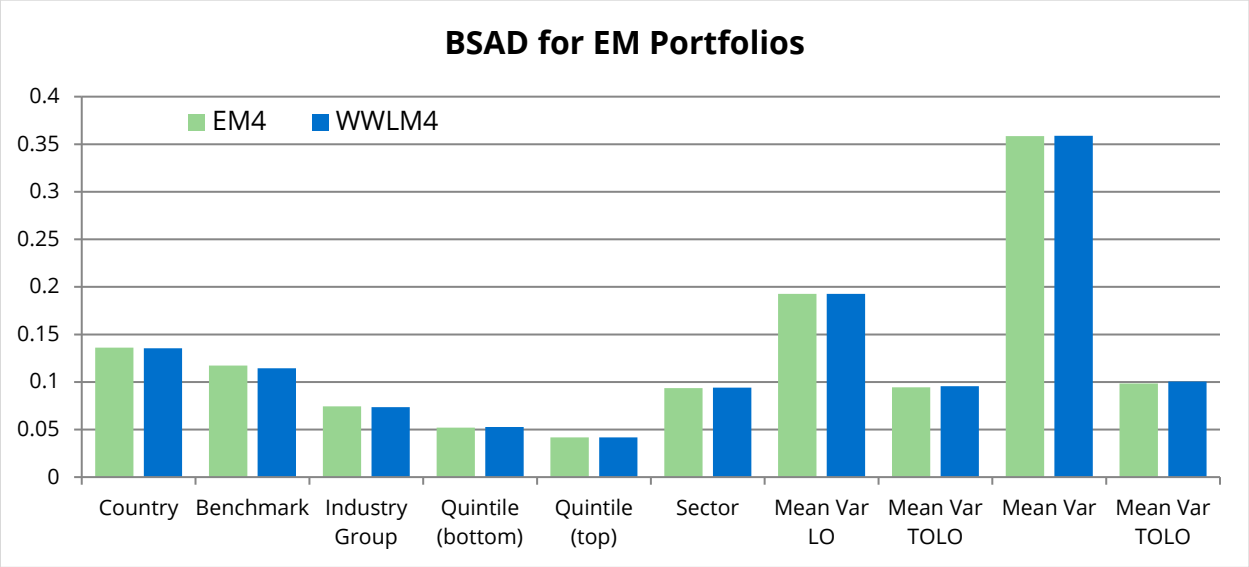
Source: Qontigo

Figure 2: Active BSAD for portfolios based on the DMxUS Universe



Source: Qontigo

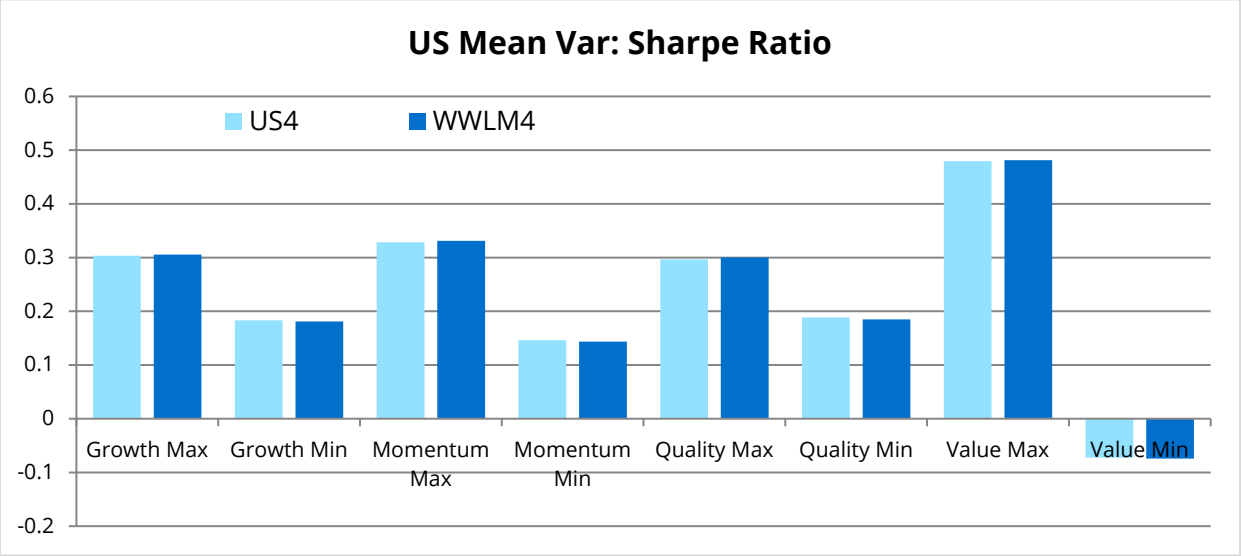
Figure 3: Active BSAD for portfolios based on the Emerging Markets Universe



Source: Qontigo

As a final check, we pick the results of the long-short mean variance tests and examine the Sharpe Ratios for each portfolio.

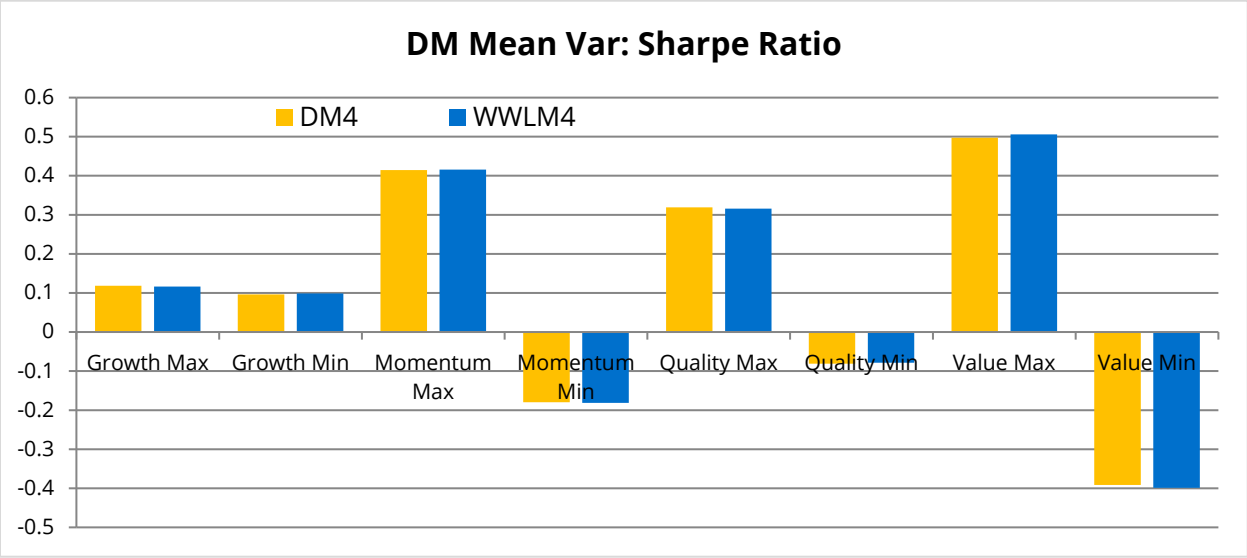
Figure 4: Sharpe Ratio for Long-Short US Mean Variance portfolios



Source: Qontigo

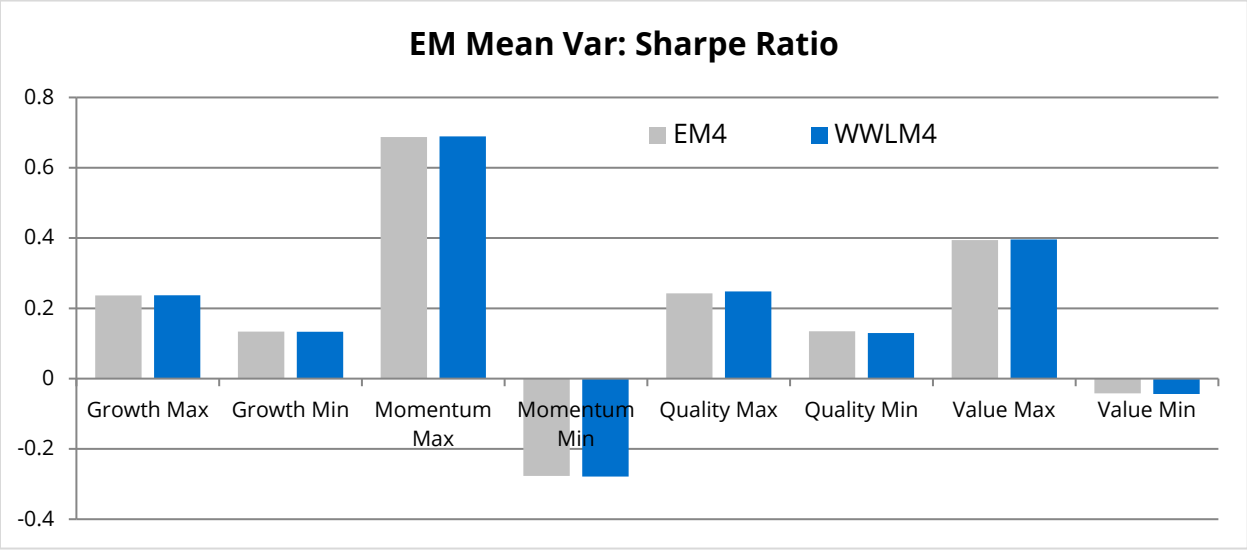
Figures 4, 5 and 6 show the Sharpe Ratios for strategies based on four third-party alpha signals.

Figure 5: Sharpe Ratio for Long-Short DMxUS Mean Variance portfolios



Source: Qontigo

Figure 6: Sharpe Ratio for Long-Short Emerging Market Mean Variance portfolios



Source: Qontigo

We see that in each case, model performance is almost identical. And so, our sanity check is over.

When the universe is restricted to that of one of the sub-models, the Linked Model yields almost identical performance as the sub-models.

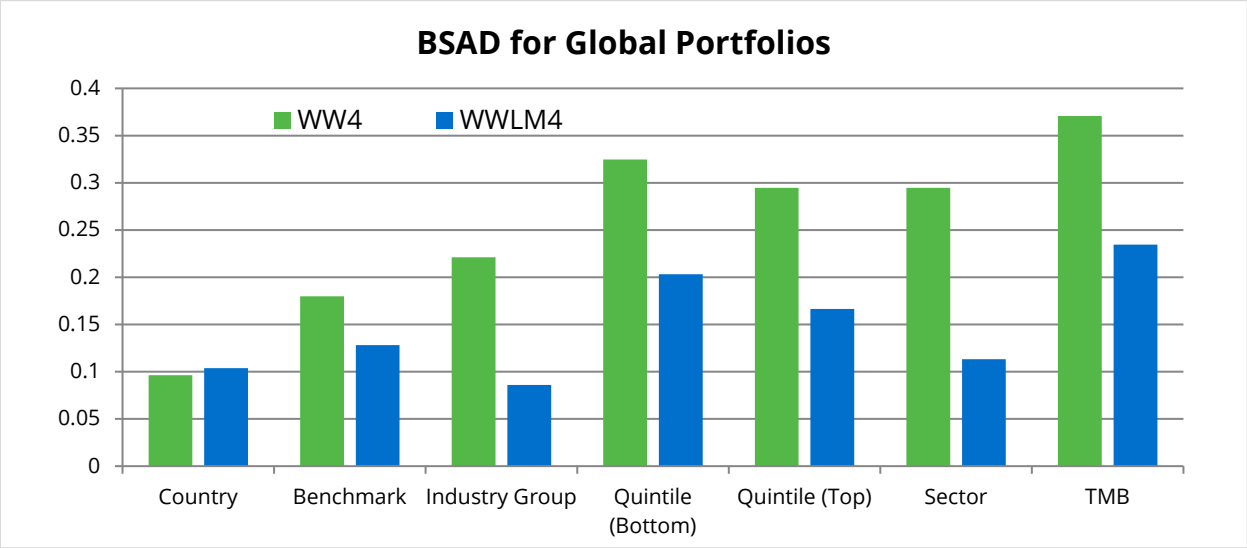
As already mentioned, none of this should come as a surprise; it is in fact the raison d'être of the Linked Model. The more interesting and useful cases occur when we widen our investment universe beyond that of any one of the sub-models. Henceforth, our model of comparison will be the standard global model, WW4.

3. Global Portfolio Tests

3.1 Overall Risk Accuracy and Factor Contribution

Here, we investigate portfolio classes whose holdings span a global investment universe; this being where we expect the extra granularity of the Linked Model to pay dividends. Beginning, as before, at the top; we produce aggregate BSAD numbers for a variety of portfolio types. Now, however, our investment universe is a broad global benchmark and our comparison model is the WW4 medium-horizon fundamental model.

Figure 7: Active BSAD for portfolios based on a global universe



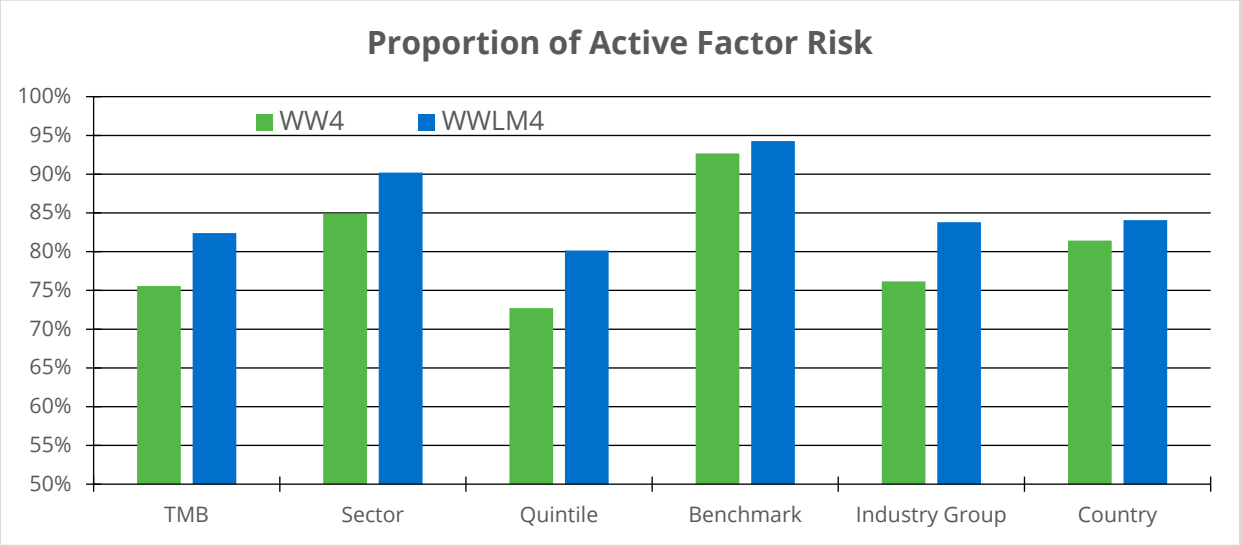
Source: Qontigo

Figure 7 shows that, with one exception, we see unambiguous improvement in forecast accuracy across portfolio classes.

Corresponding to this improvement in accuracy is an increase in the proportion of active predicted risk explained by the factors (Figure 8). The Linked Model, WWLM4, exhibits a higher proportion of factor risk for all portfolio types.

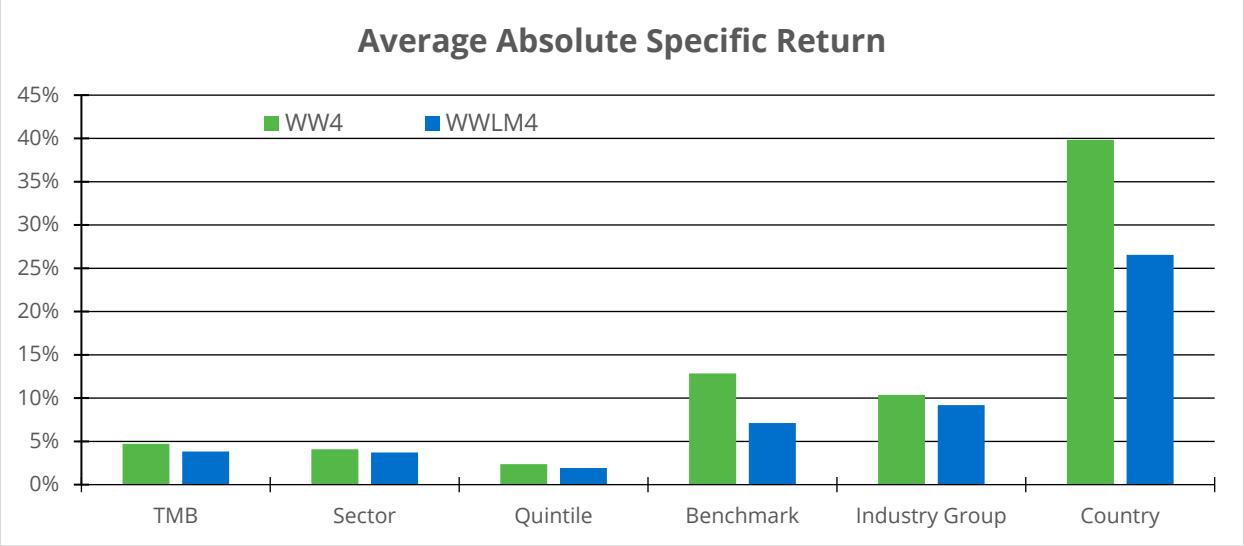
Finally, Figure 9 gives the absolute active specific return averaged over global portfolio classes. We see that WWLM4 has consistently lower magnitude specific returns.

Figure 8: Proportion of active factor risk for portfolios based on a global universe



Source: Qontigo

Figure 9: Average absolute active specific return for portfolios based on a global universe



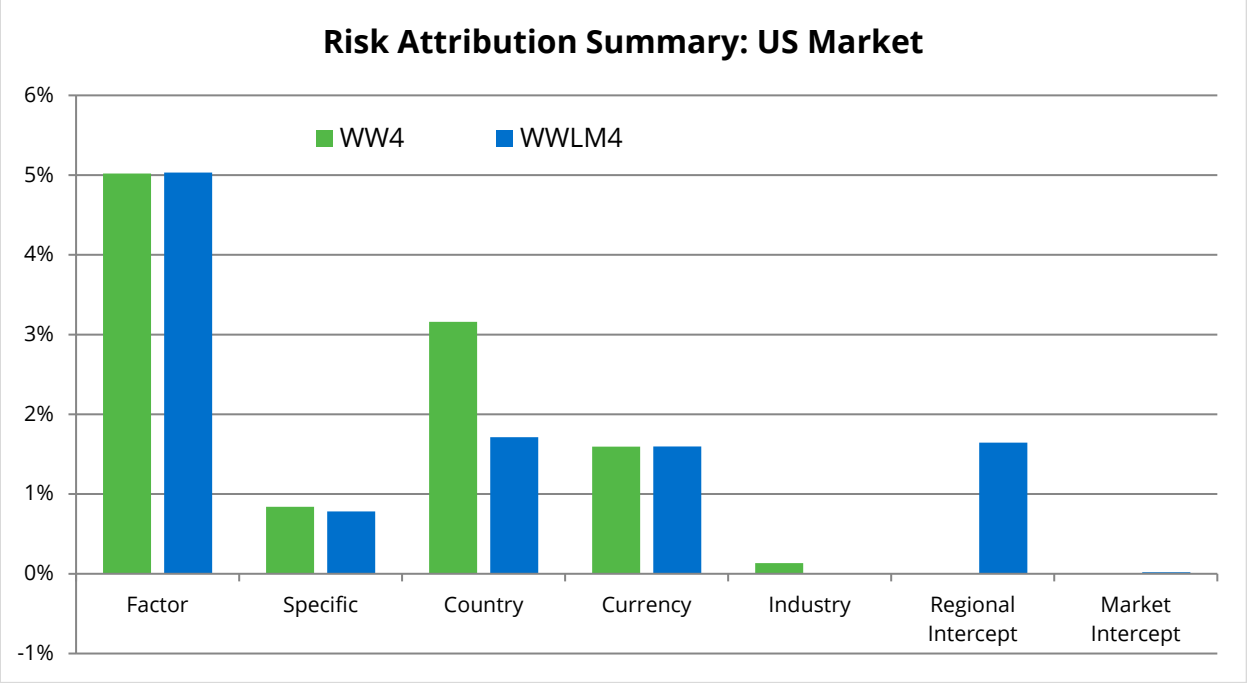
Source: Qontigo

3.2 Country Risk

Returning to the BSAD numbers, the only portfolio class to show little difference between models is the 'Country' type. These portfolios are market capitalization-weighted country buckets derived from the global universe. Their active returns and risks tend to be dominated by country-like factors in either model.

To illustrate what we mean, consider Figures 10 and 11. These show, respectively, the active risk and return decompositions for a US country portfolio versus a global benchmark.

Figure 10: Active risk decomposition for US country portfolio



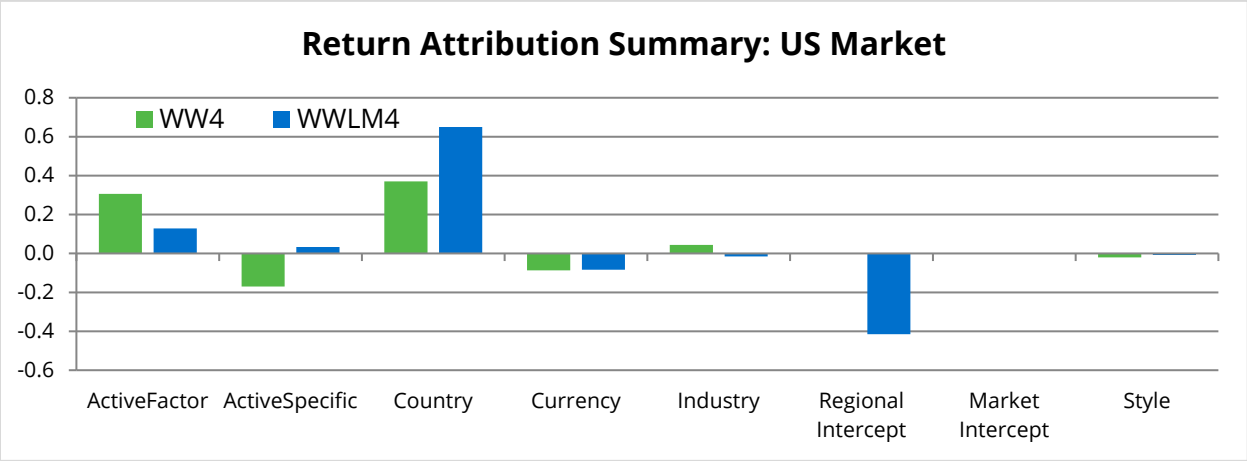
Source: Qontigo

We see that WW4's (non-currency) active factor risk is dominated by the model's US Country factor.

For WWLM4, the picture is a little more complex. The so-called country risk for this model is in fact the Market Intercept from the US4 model, now playing the part of a country factor. There is also a contribution of roughly the same size from the 'Regional Intercept' factors. These are a combination of the intercept factors from DMxUS4 and EM4, which are not true intercepts in the context of the Linked Model.

This underlines an important aspect of linked models: there is typically no longer a true intercept; rather a set of regional binary factors, which we refer to as 'Regional Intercepts' for convenience.

Figure 11: Active return decomposition for US country portfolio



Source: Qontigo

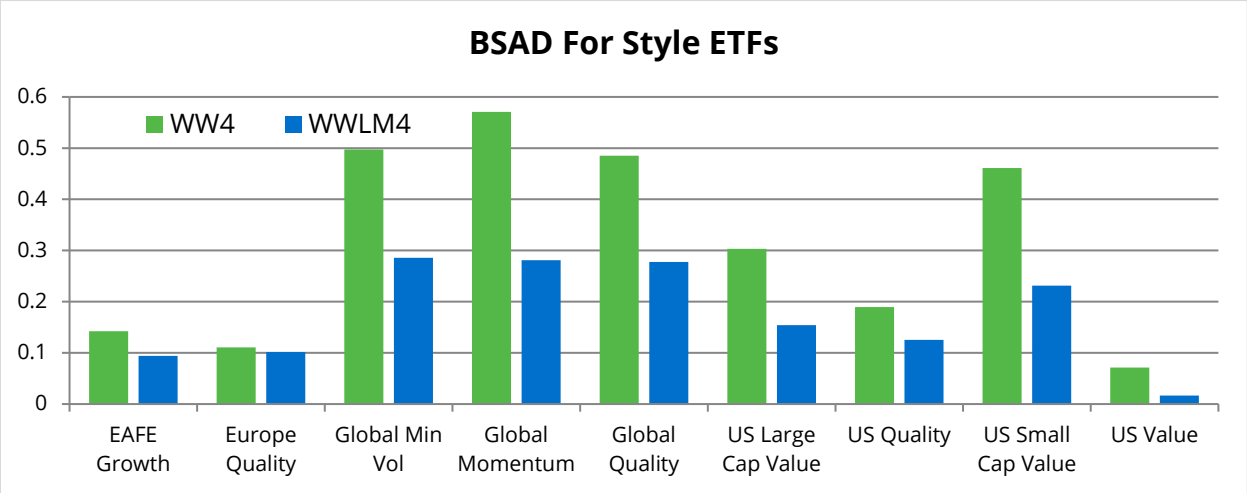
Figure 11 shows that we are effectively long the US4 country factor and short the DMxUS4 and EM4 market factors in the WWLM4 model results. Since this is not dissimilar to the definition of the US Country factor in the WW4 model, we should not be surprised at the overall risk results being close.

To summarize then, where the factor decomposition of a portfolio is dominated by country risk, we should not expect to see a consistent granularity premium. Where the Linked Model's more granular structure does come into play is when we construct portfolios whose weights are not simply proportional to the constituent markets.

3.3 Style Portfolios

Figure 12 shows the BSAD figures for a selection of global and regional ETFs with a 'style-flavor'. We see that the global and US-oriented ETFs show significantly greater accuracy under WWLM4.

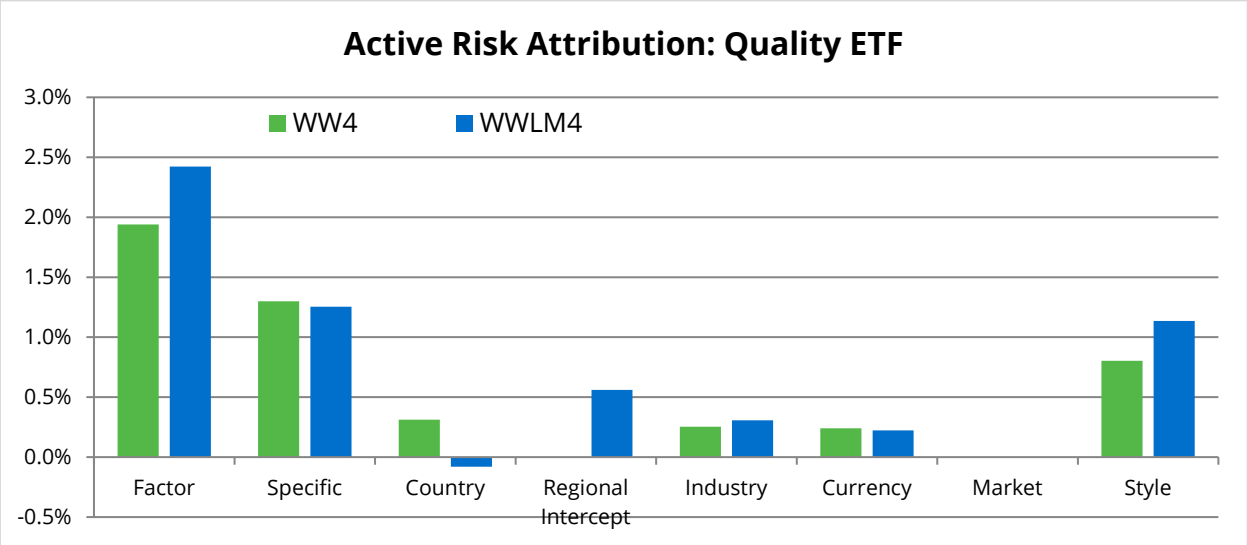
Figure 12: Active BSAD for style ETFs



Source: Qontigo

Drilling down into one of these, the Global Quality ETF, Figure 13, indicates that differences in risk attribution arise from two sources: the market/country structure, and the styles.

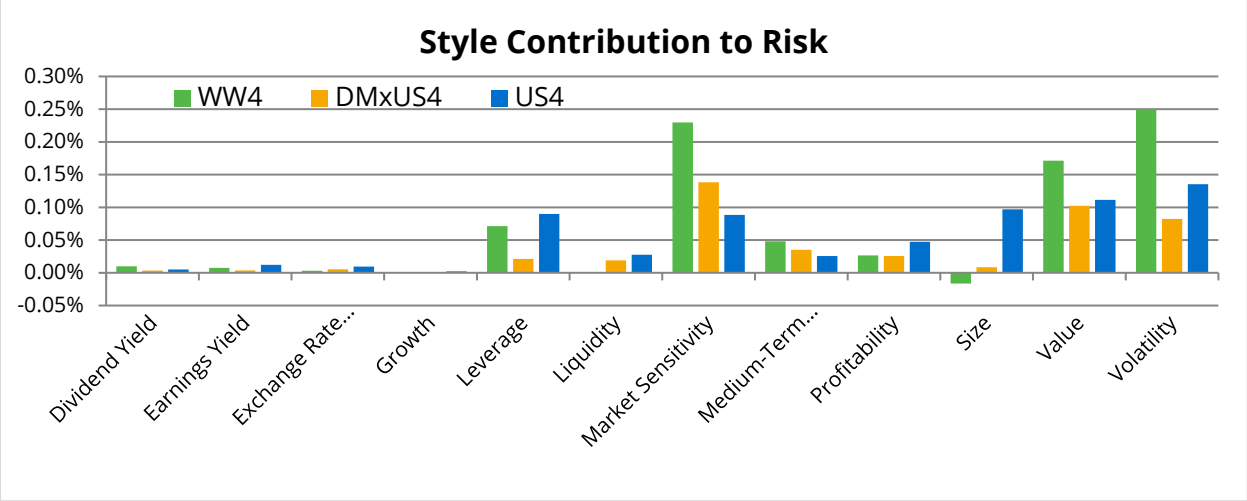
Figure 13: Active Risk Attribution for Global Quality ETF



Source: Qontigo

Figure 14 breaks down style risk into the contributions from either WW4 factors or WWLM4's constituent US4 and DMxUS4 components (the EM4 styles contributed little). While many style contributions may be roughly equal (mentally combining those for the Linked Model), one that does stand out is for Size. We see a negligible contribution to Size from WW4, while that for WWLM4 is approximately 10bps.

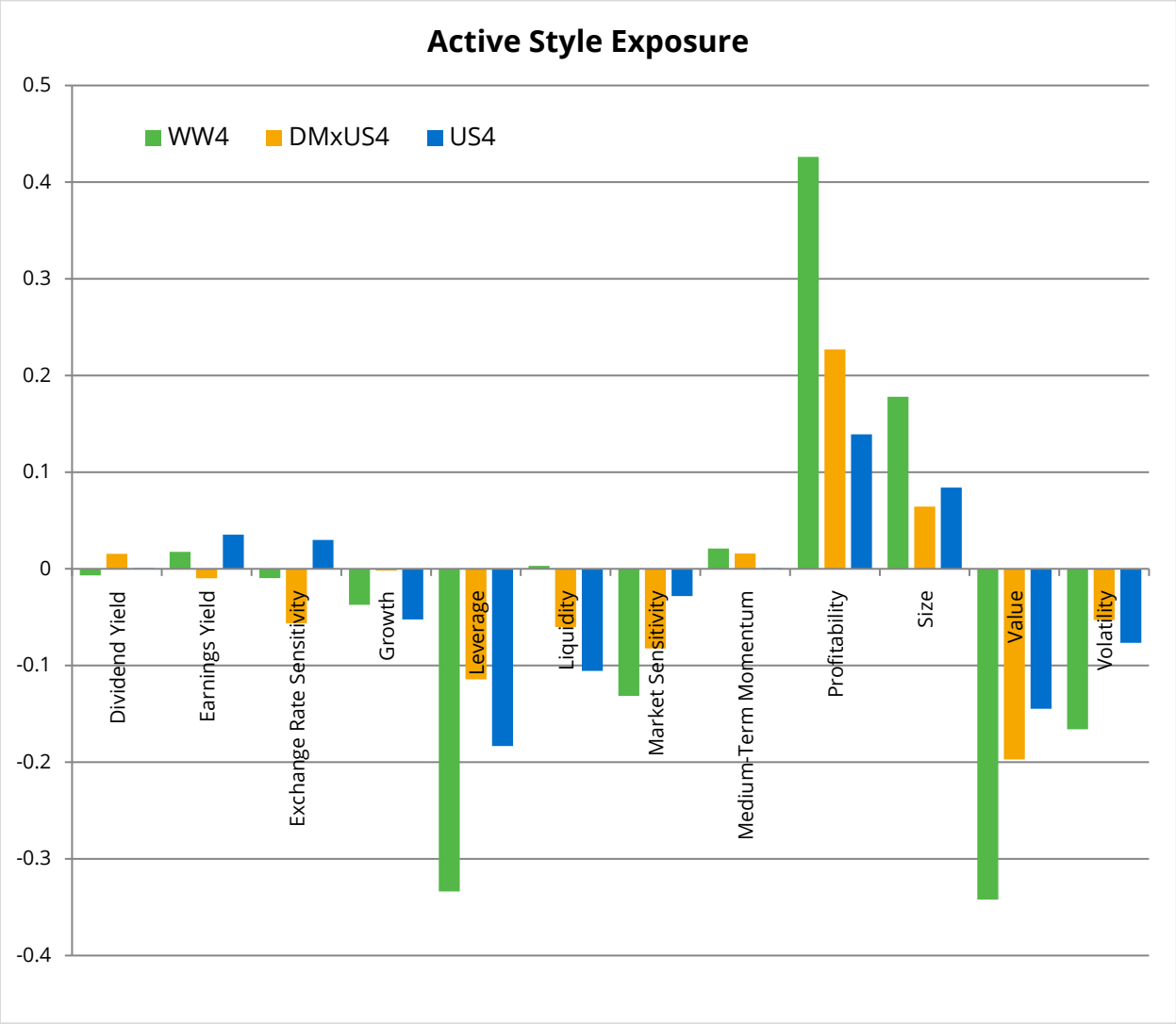
Figure 14: Active Style Risk Attribution for Global Quality ETF



Source: Qontigo

Considering the exposures to these styles (Figure 15) we see little difference in the overall contributions.

Figure 15: Active Style Exposure for Global Quality ETF

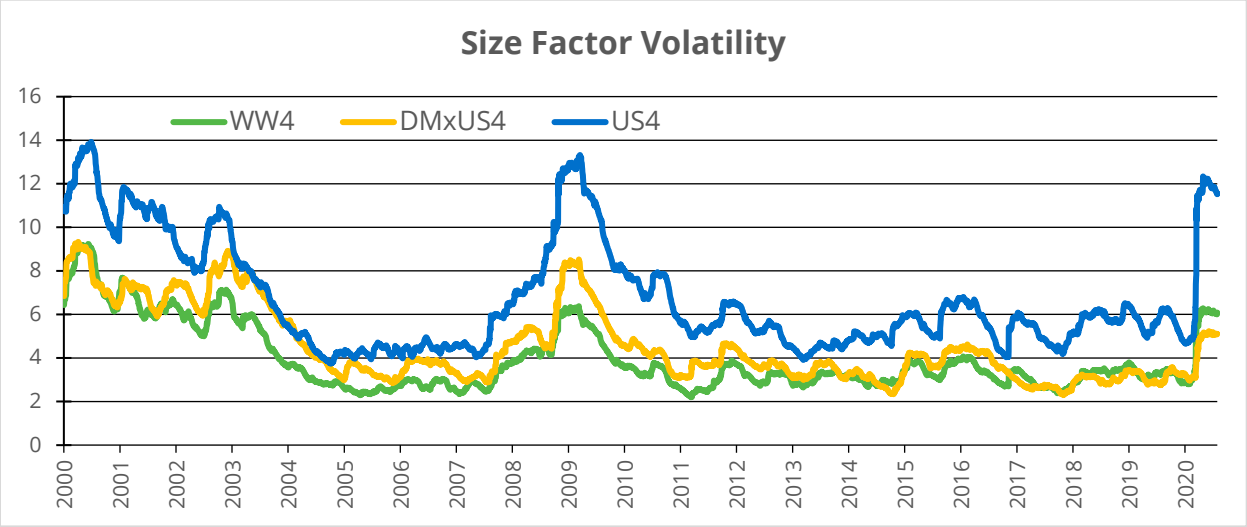


Source: Qontigo

The difference does, in fact, come from the significantly different behavior of US4 Size in comparison with global Size.

Figure 16 gives the volatilities of the Size style factors for WW4, DMxUS4 and US4. Size volatility in the US4 model (and hence the US contribution to the WWLM4 model) has typically been twice that of both the DMxUS market and the overall global market as evinced by WW4. This, in turn, drives the increased factor risk contribution to the Quality ETF, and hence, its improved risk forecast.

Figure 16: Size factor volatility over time



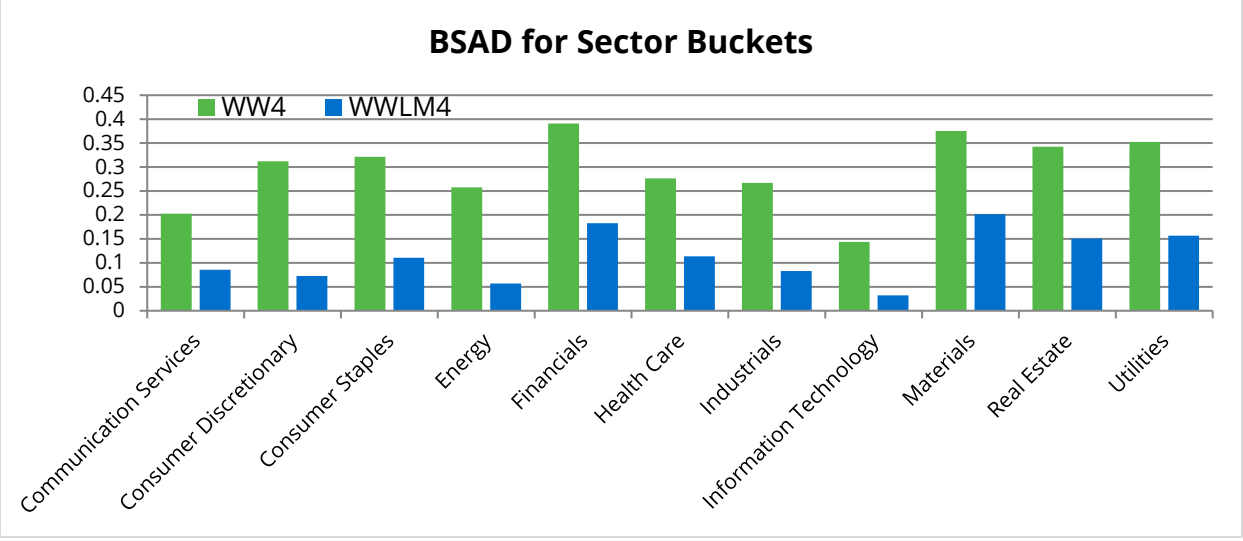
Source: Qontigo

3.4 Sector Portfolios

As a final example for this section, we look at global (market cap-weighted) sector buckets.

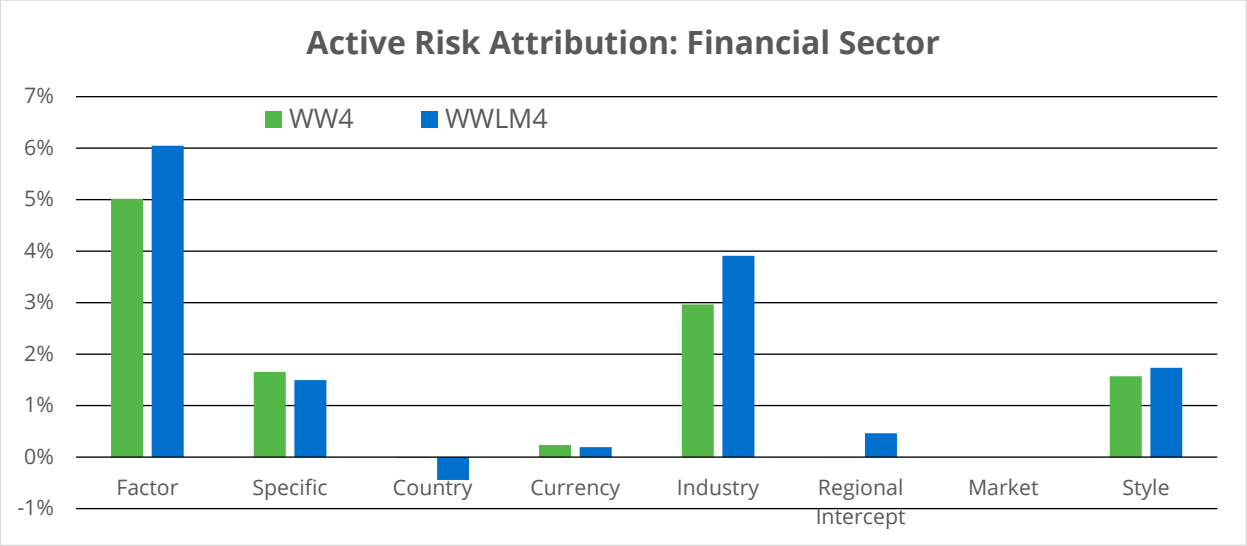
Figure 17 indicates vastly improved risk accuracy for such portfolios: clearly there is a great advantage in the WWLM4 model's extra granularity, and its (roughly) three times as many industry factors. Figure 18 demonstrates that, rather as one might expect, the difference in performance is driven by the industry factor contribution.

Figure 17: Active BSAD for global sector bucket portfolios



Source: Qontigo

Figure 18: Active risk attribution for Financial Sector portfolio



Source: Qontigo

4. Global Mean Variance Portfolios

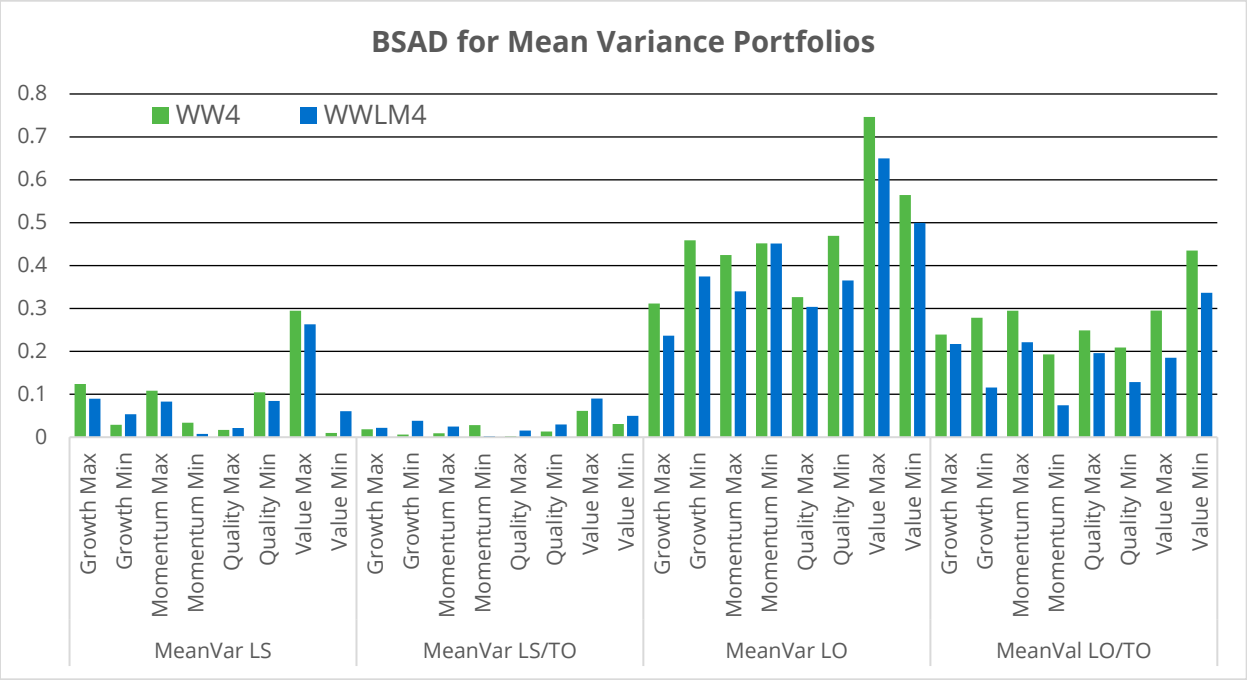
All portfolios considered so far could be described as 'ready-made', meaning that they have been generated independently of the model(s); these models being used merely to analyze their properties and performance. To take testing a step further, we next examine portfolios also generated by one of the two models, WW4 and WWLM4.

As described in the introduction, we generate a number of optimized mean-variance portfolios, Long- Only (LO) and Long-Short (LS) using third-party alpha signals. We are interested in three important comparisons between the Linked Model and WW4:

- Risk accuracy and attribution
- Realized performance (Sharpe Ratios, realized risk)
- Optimizer performance (turnover, time-taken)

4.1 Overall Accuracy

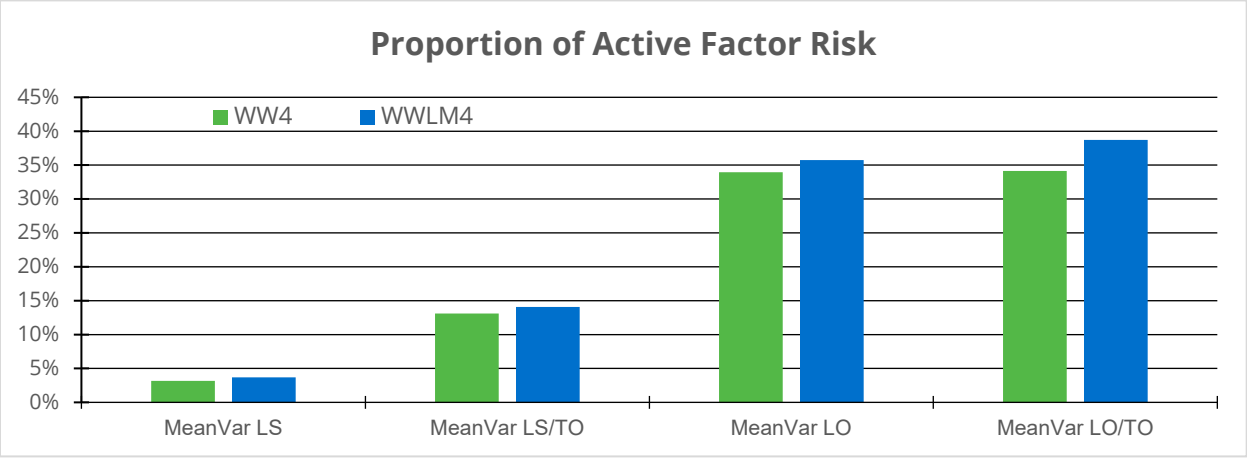
Figure 19: BSAD for global Mean Variance portfolios



Source: Qontigo

Figure 19 shows BSADs for each portfolio. Note that 'TO' denotes a turnover constraint and that the long-short results are total, rather than active, BSADs. We see that, in the long-only portfolio space, WWLM4 provides significantly greater accuracy. For long-short portfolios, the results are mixed, with no clear winner.

Figure 20: Proportion of Active Factor Risk for global Mean Variance portfolios



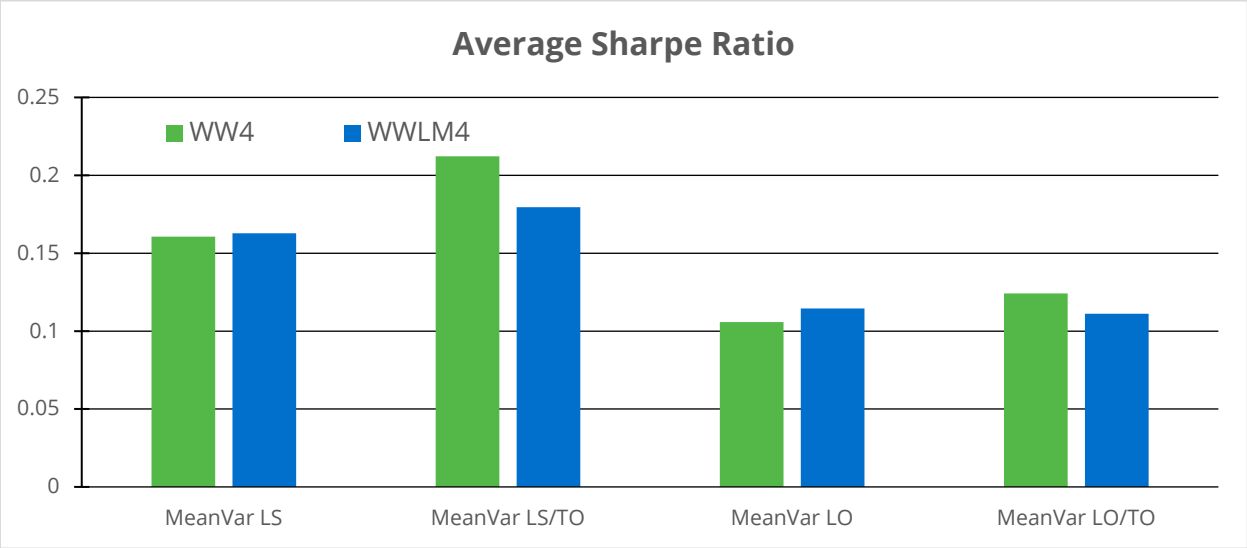
Source: Qontigo

Figure 20 exhibits the proportion of active factor risk per portfolio type. Again, the WWLM4 model accounts for higher proportion of factor risk amongst portfolios.

4.2 Portfolio Performance

Moving to realized portfolio results, we look at the Sharpe Ratios (averaged across strategy) for our Mean Variance Portfolios (Figure 21).

Figure 21: Average Sharpe Ratio for global Mean Variance portfolios



Source: Qontigo

It would appear that, where turnover is controlled in this case, WW4 yields slightly better results; when relaxed, WWLM4 is marginally better, but the differences are not large.

Generally, what we can say, is that the size of the Linked Model – i.e. its greater number of factors – does not 'break' the optimizer. We are still able to generate solutions reliably and in good time, though the outcomes are not guaranteed to be significantly better.

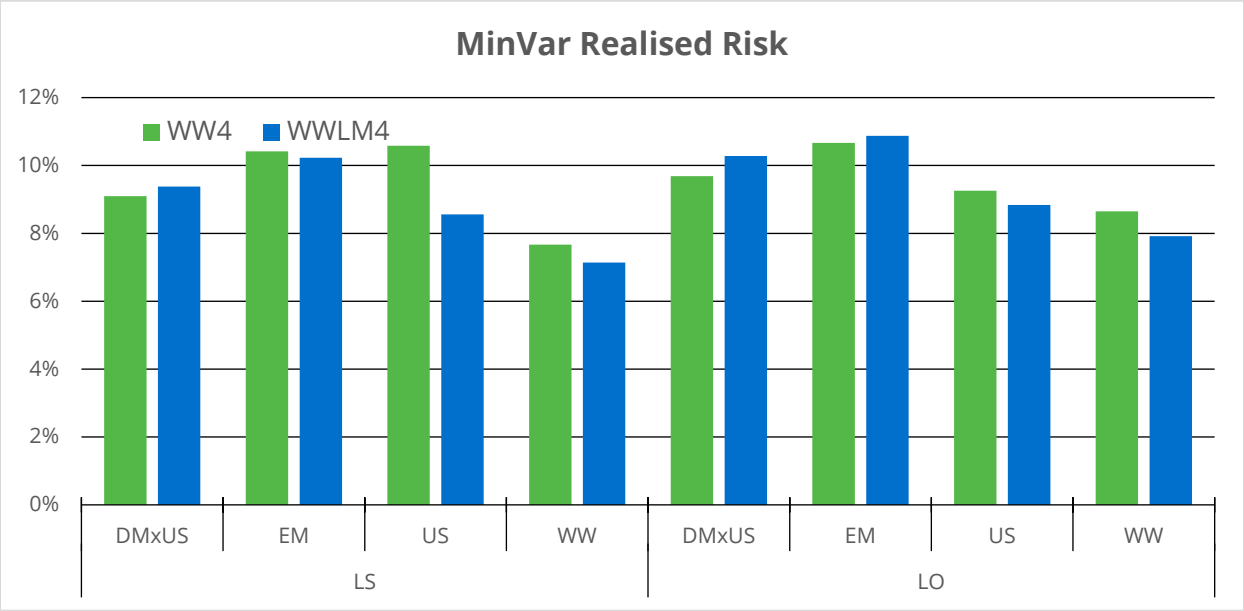
5. Global Minimum Variance Portfolios

Another important class of optimized portfolios are Minimum Variance portfolios. We again use a global benchmark, optimize monthly, and generate both Long-Only and Long-Short portfolios using WW4 and WWLM4.

Sharpe Ratios are of less interest here, as the portfolio return of a Minimum Variance portfolio is something of an 'accident'. Rather, we are concerned with their realized risk: can the optimizer navigate the Linked Model's more extensive factor structure to arrive at a reasonable solution?

5.1 Portfolio Outcome

Figure 22: Realized risk for Minimum Variance portfolios



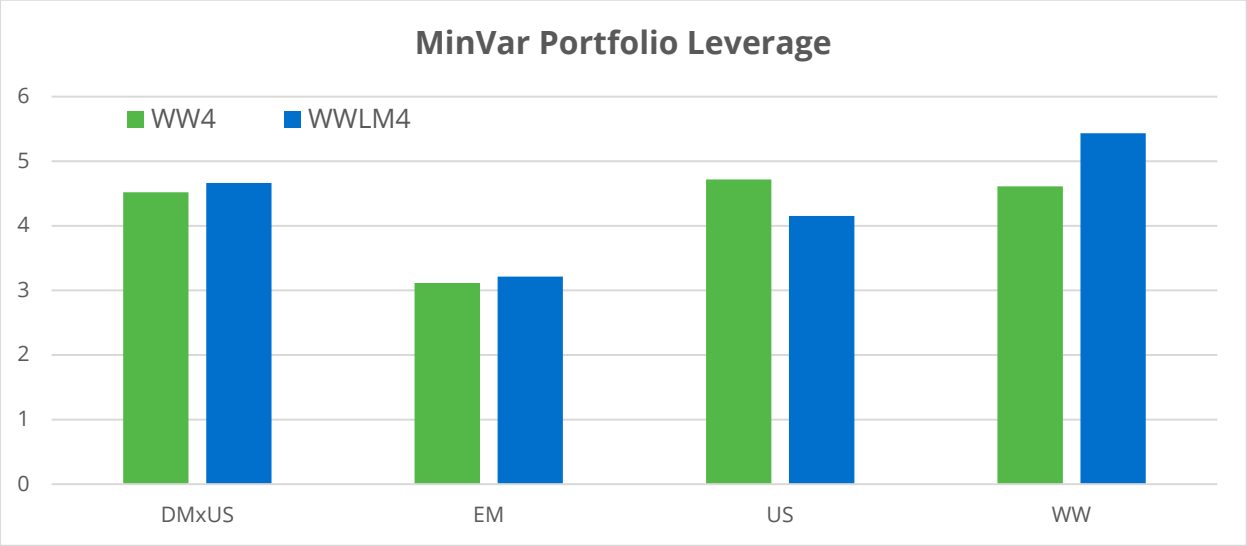
Source: Qontigo

In Figure 22 we show the realized risk for Long-Short and Long-Only Minimum Variance strategies using four different regions respectively as our investment universe:

- Developed Markets ex-US (DMxUS)
- Emerging Markets (EM)
- US Market (US)
- Global Market (WW)

Overall, the results are not vastly different: sometimes one model wins out, sometimes the other. Arguably, the US market favors using WWLM4, which seems reasonable: for other markets, there is less of an advantage to be gained from its extra granularity.

Figure 23: Leverage for Long-Short Minimum Variance portfolios



Source: Qontigo

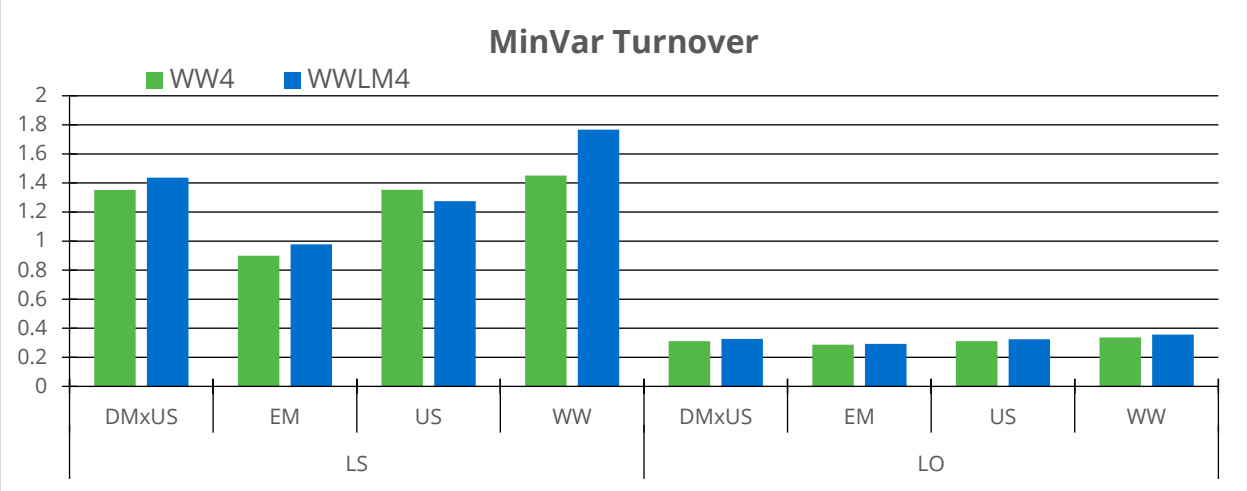
From Figure 23 we see the corresponding average portfolio leverage for the Long-Short strategies. Again, results for the US universe favor WWLM4 slightly, and those for the global (WW) universe favor WW4 a little more.

6. Optimizer Performance

Given the various outcomes, the next question is, how much work did it take each model to arrive at a solution?

Figure 24 shows the average turnover for each strategy: most show little difference. Only the Long-Short global strategy points to slightly worse performance for the WWLM4 model.

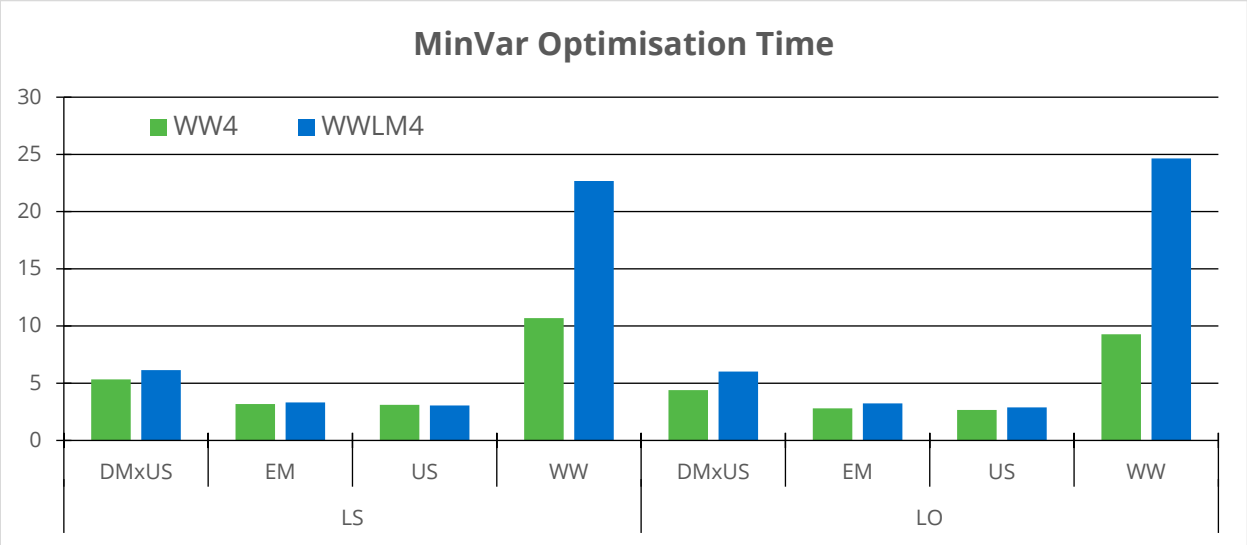
Figure 24: Turnover for Minimum Variance portfolios



Source: Qontigo

Finally, in the time taken (in minutes) for each strategy to run its course (the total optimization time), we see a clear advantage for WW4 over WWLM4 (Figure 25).

Figure 25: Optimization time for Minimum Variance portfolios



Source: Qontigo

The WWLM4 model took roughly twice as long to solve the optimization for the global universe. Smaller universes exhibited little difference between models.

Overall, therefore, the Linked Model exhibits portfolio performance similar or better to that of the WW4 model, except when the universe becomes large and spans most or all the Linked Model's factors. In such cases, the turnover may increase, and optimization time will certainly increase.

7. A 9:1 US:DM Universe

Many investors have a mandate for a particular region, with perhaps a permitted five to ten percent weighting of stocks outside this region. An investor for instance, may have a US-mandate for his or her portfolio, but be able to hold ten percent of its value in other developed market assets.

Currently, such an investor would be best-served by the WW4 model, since the US4 model lacks the necessary non-US coverage (obviously). However, the WW4 model is constructed over the entire global (estimation) universe of assets, where the US accounts for approximately 40% of the weight by market capitalization; large admittedly, but there are more non-US than US assets by any measure.

It is no fault of the WW4 model that it will not, in general, model US assets as well as the US4 model: that is a consequence of fitting a model to a more or less homogenous set of assets. The ideal solution for our investor would use US4 to model the US assets, and DMxUS4, say, to model the smaller proportion of Developed Market holdings.

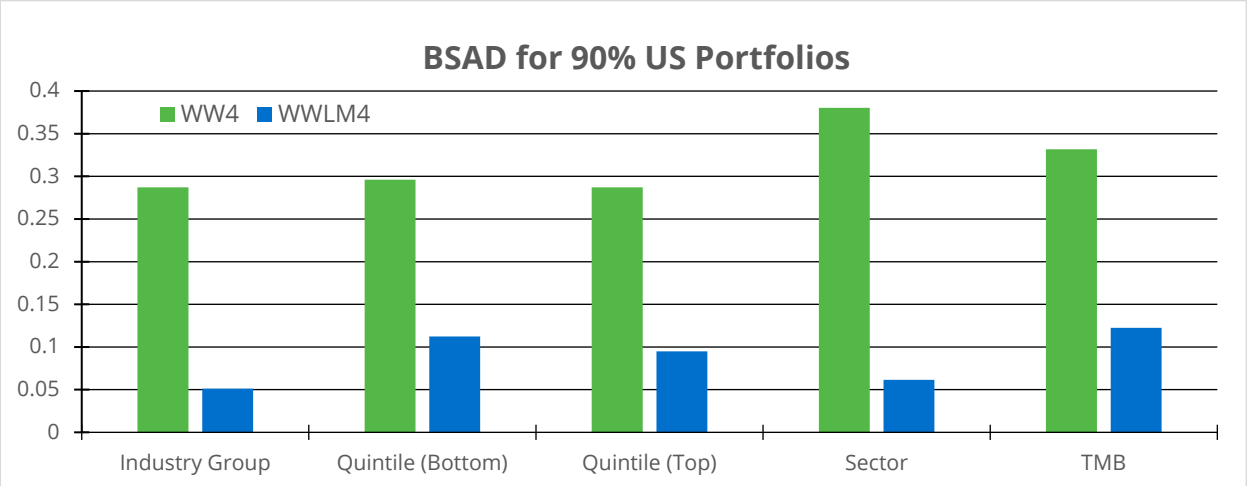
This precise situation is one of the purposes of the global Linked Model.

To compare the performance over a range of portfolios with such a strong US-bias, we take a global market cap-weighted universe, and upweight the US assets en masse so they account for roughly 90% of the total universe weight. We use this to construct various classes of ready-made Developed Market (inc. US) portfolios, all now heavily tilted towards the US market.

7.1 Ready-Made Portfolios

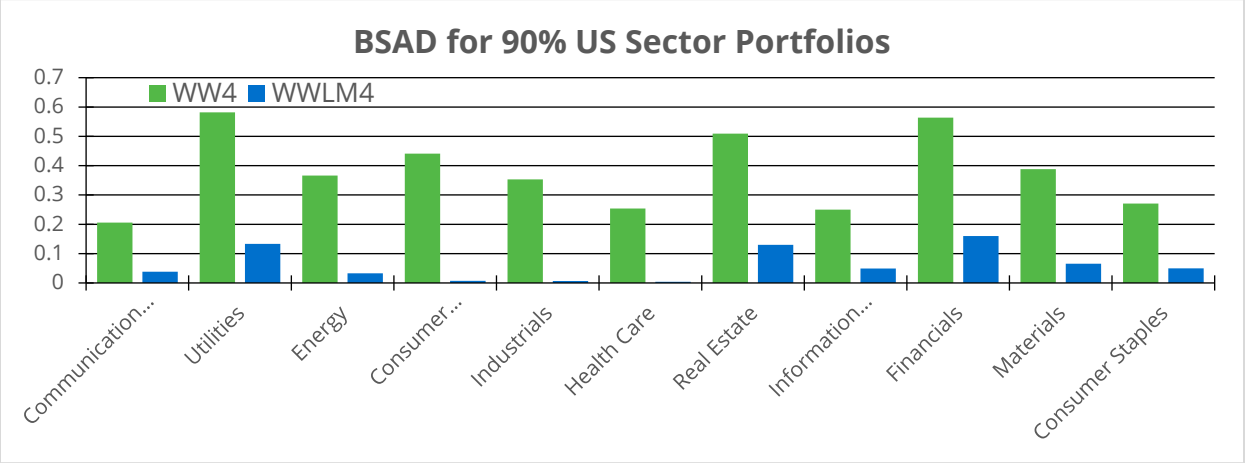
Figure 26 gives the BSAD figures averaged over classes of portfolio constructed on our custom US-centric universe. We see that the Linked Model yields vastly more accurate forecast risk for all portfolio classes. This improvement is consistent over portfolios within each class (e.g. Figure 27) and over time.

Figure 26: BSAD for 90% US Developed Portfolios



Source: Qontigo

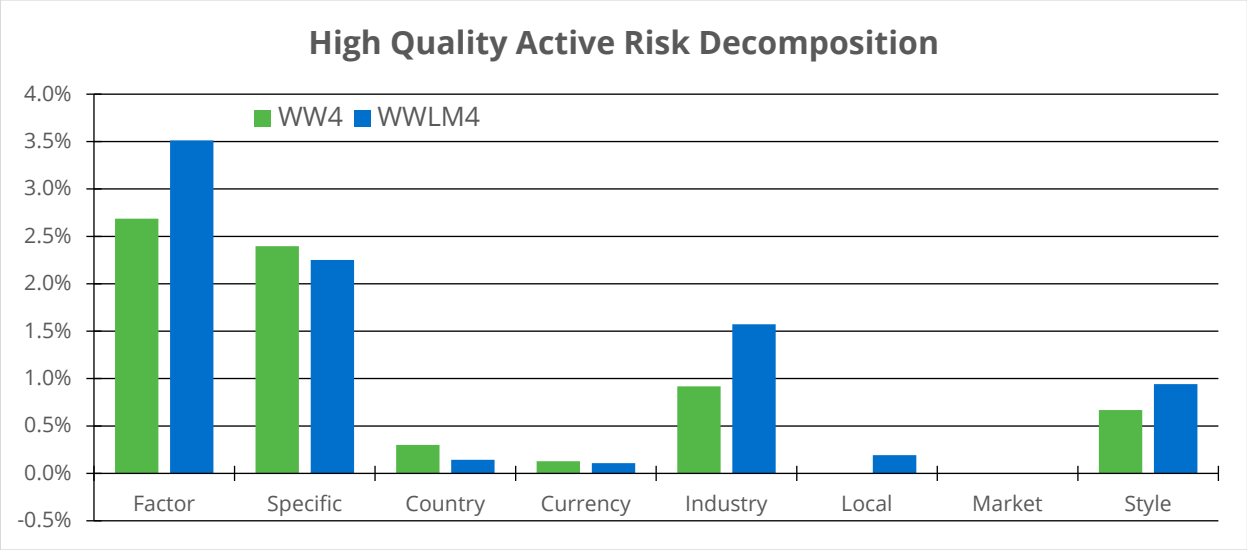
Figure 27: BSAD for 90% US Developed Sector Portfolio



Source: Qontigo

Drilling into the High Quality quintile portfolio, to take an example at random, we see that the improvement is driven by the increased granularity in both styles and industries (Figure 28).

Figure 28: Proportion of Active Factor Risk for High Quality Quintile Portfolio

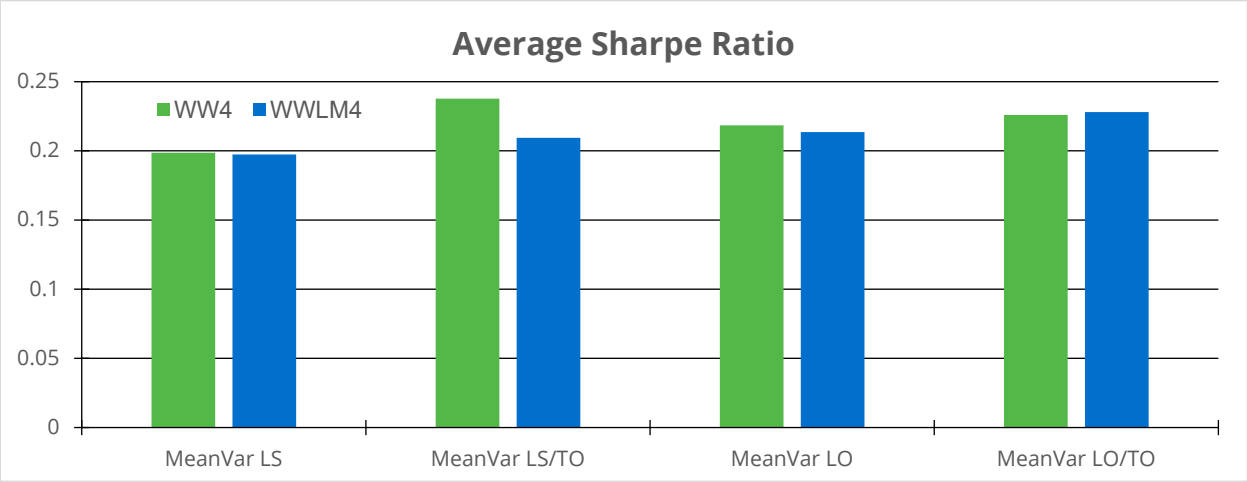


Source: Qontigo

7.2 Optimized Portfolios

To avoid belaboring points made earlier, we present a few summary results for Mean Variance portfolios, using the same parameters as previously discussed, and our custom asset universe.

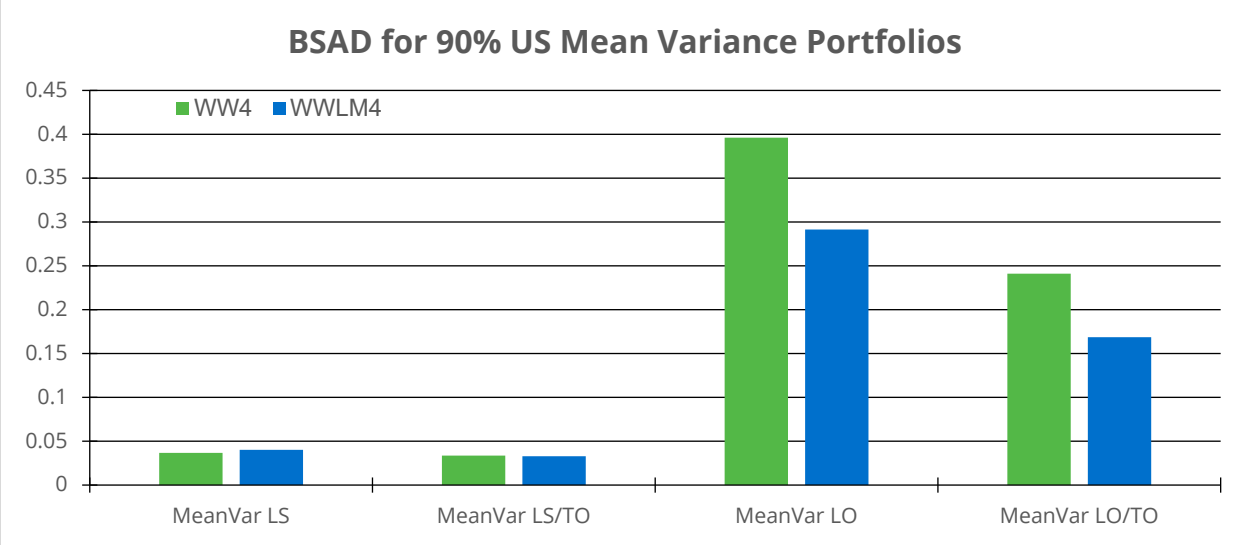
Figure 29: Average Sharpe Ratio for 90% US Developed Mean Variance portfolios



Source: Qontigo

Portfolio performance, at least as measured by Sharpe Ratio, is comparable for most strategy types, the exception being, as before, Long-Short with turnover constraint (Figure 29).

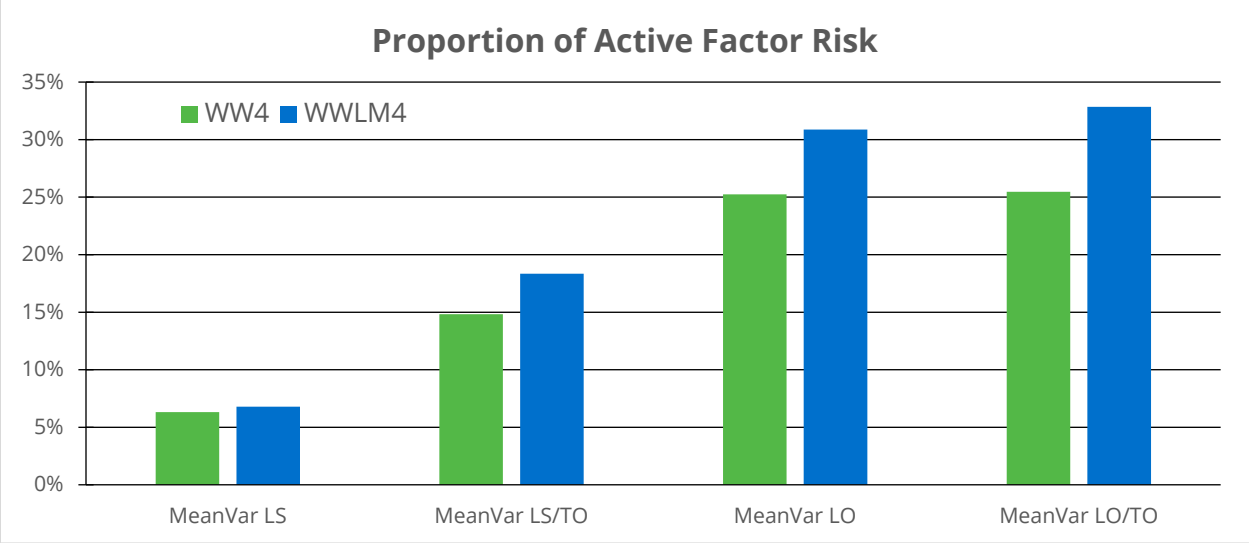
Figure 30: BSAD for 90% US Developed Mean Variance portfolios



Source: Qontigo

Also as previously seen, risk accuracy and proportion of active factor risk were improved for portfolios generated using WWLM4 (Figures 30 and 31).

Figure 31: Proportion of Active Factor Risk for 90% US Developed Mean Variance Portfolios



Source: Qontigo

In conclusion, use of the Linked Model in these cases can give substantially better forecast accuracy and risk attribution, with similar realized performance outcomes.

8. Q: Is Momentum the Same Everywhere?

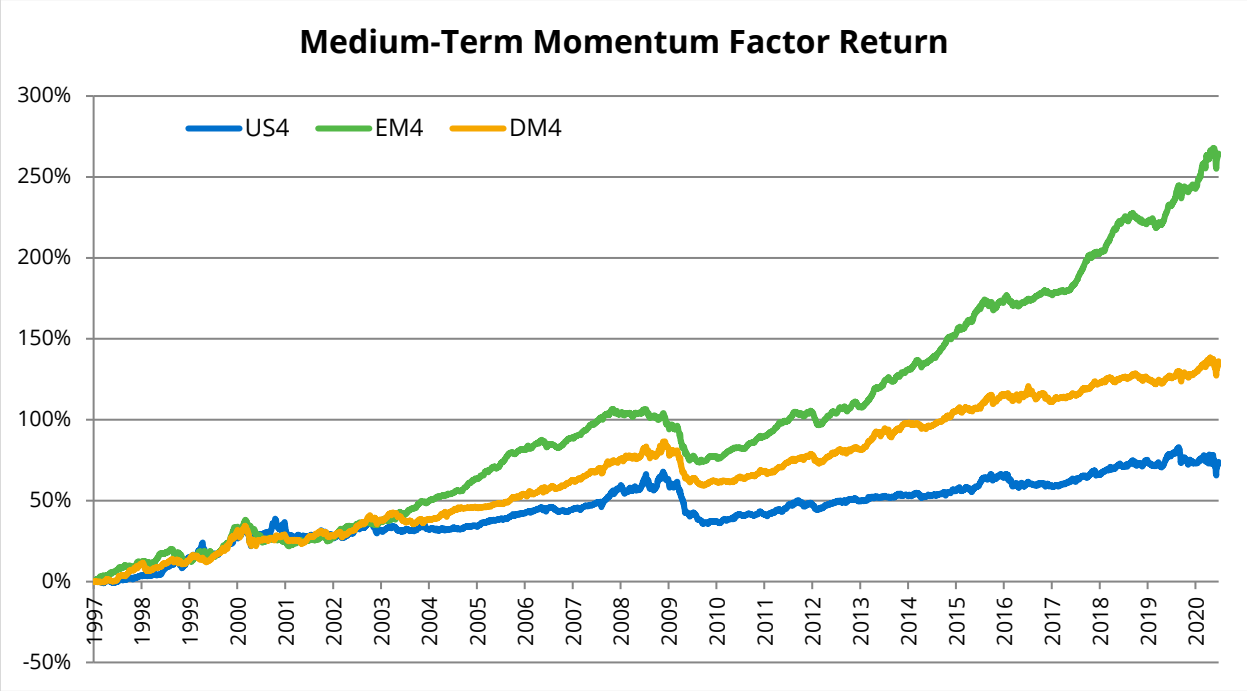
A: No.

However, for those demanding proof, we create an instructive case study.

By adopting a single global set of factors for styles, a model such as WW4 is making a structural assumption. It assumes that, for instance, Momentum in the US is essentially identical to Momentum in Europe. More precisely, if one were to construct a portfolio with exposure to US Momentum and no exposure to anything else at all, and a corresponding portfolio for European Momentum, their return and risk would be identical – one could use the one to hedge against the other.

In reality, while there do tend to be high degrees of commonality among markets, there are also significant areas of difference: US Momentum and European Momentum are not clones of one another.

Figure 32: Cumulative Return for three Medium-Term Momentum factors



Source: Qontigo

Figure 32 shows the cumulative returns of the momentum factors in, respectively, the US4, EM4 and DMxUS4 models. While they all exhibit the same general long-term trends, they are obviously not the same. In fact, the correlation between weekly returns (to reduce the impact of temporal artifacts) over the period in the figure is:

- US4 / EM4 correlation: 37%
- US4 / DMxUS4 correlation: 60%

These are quite some way from identical. Taking a snapshot of correlations between US4 and DMxUS4 style factors from the respective models' covariance matrices, we get Figure 33.

Figure 33: Model Correlation Between US4 and DMxUS4 Style Factors

		US4											
		Value	Leverage	Growth	Size	Market Sensitivity	Liquidity	MTM	Volatility	Earnings Yield	Dividend Yield	ERS	Profitability
DM4	Value	**0.418**	0.017	-0.375	-0.022	0.307	-0.051	-0.488	0.350	0.222	0.196	0.011	0.222
	Leverage	0.270	**0.397**	0.013	-0.173	0.215	0.150	-0.070	0.121	0.137	0.248	0.093	-0.166
	Growth	-0.227	0.103	**0.407**	-0.006	0.055	0.180	0.273	0.036	-0.191	-0.151	-0.040	-0.295
	Size	0.087	-0.161	-0.185	**0.228**	0.295	-0.077	-0.303	0.266	0.144	0.092	-0.248	0.206
	Market Sensitivity	0.460	0.371	-0.068	-0.085	**0.808**	0.252	-0.376	0.501	0.454	0.290	-0.285	-0.190
	Liquidity	0.161	0.309	0.154	-0.188	0.455	**0.414**	-0.145	0.363	0.166	0.210	-0.034	-0.272
	MTM	-0.419	0.033	0.544	0.112	-0.268	0.029	**0.753**	-0.377	-0.357	-0.356	0.058	-0.218
	Volatility	0.321	0.236	0.047	-0.065	0.643	0.324	-0.304	**0.664**	0.165	0.213	-0.116	-0.226
	Earnings Yield	0.239	0.217	-0.186	0.048	0.188	0.057	-0.174	-0.061	**0.437**	0.078	-0.201	-0.031
	Dividend Yield	0.385	0.289	-0.305	-0.257	0.256	0.055	-0.443	0.133	0.417	**0.444**	0.054	-0.118
	ERS	0.189	0.155	0.052	0.035	0.256	0.113	-0.141	0.115	0.091	-0.041	**-0.378**	-0.068
	Profitability	-0.037	-0.206	-0.077	0.104	-0.149	-0.097	-0.054	-0.102	-0.040	-0.032	-0.058	**0.318**

Source: Qontigo

We see from the block's diagonal that correlations between like factors from different models exhibit a wide range of values, with one, Exchange Rate Sensitivity (ERS), showing strong negative correlations.

This, then motivates our next and final study: if we construct a portfolio that is, say, long US Momentum and short DMxUS Momentum the WW4 model should see this as hedged – the two momentum contributions should cancel. However, the Linked Model, WWLM4, with separate US4 and DMxUS4 factors, should capture the actual differences between the long and short legs of the portfolio and produce a more accurate prediction of its risk.

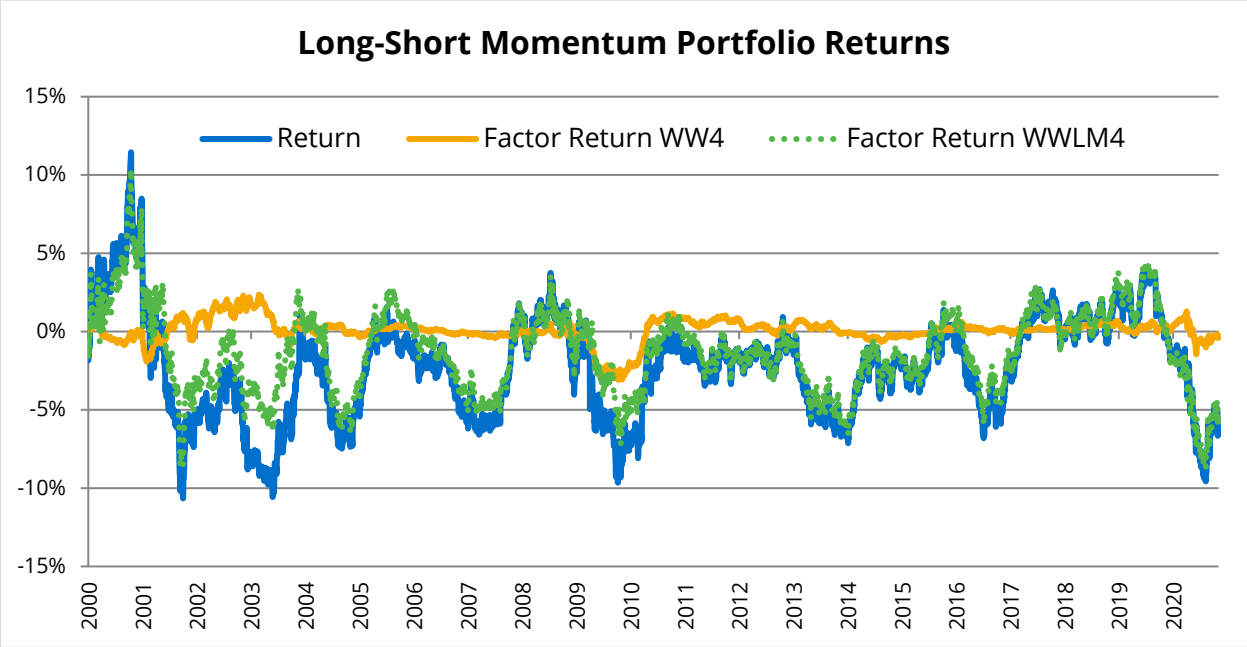
As so happens, we have ready-made long-short factor-bet portfolios in the form of factor mimicking portfolios. A factor-mimicking portfolio (FMP) arises from the model's cross-sectional regression, and is a long-short portfolio with unit exposure to a given factor, and zero exposure to all other factors. The return of said portfolio is the model's factor return. It is thus the ideal laboratory in which to examine the behavior of a factor in isolation.

Our test portfolio is a long-short portfolio whereby:

- The long-leg consists of the US4 medium-term Momentum FMP.
- To this we add −1× the DMxUS4 momentum FMP to form the short leg.

Because of the WW4 model's global view of Momentum, we expect that it should consider that the long and short legs of the portfolio offset one another, and the portfolio is neutral to Momentum. We analyze our portfolio using both the WW4 and WWLM4 models.

Figure 34: Long-Short Momentum Portfolio Return and Factor Return

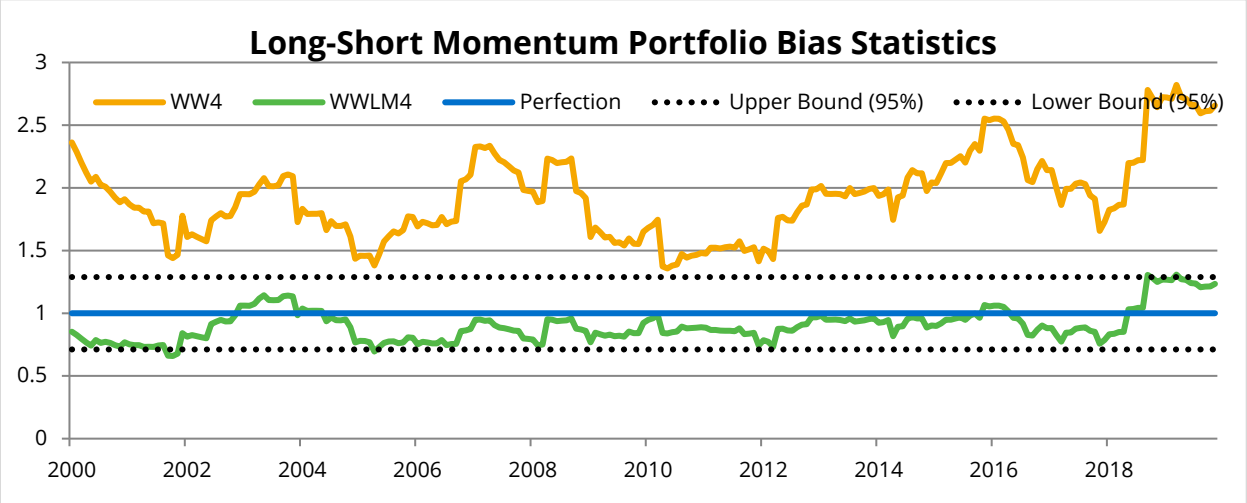


Source: Qontigo

Figure 34 shows the one-year rolling cumulative returns according to the two models. We see that WW4 is indeed largely factor neutral: it does consider US momentum to be a hedge for DMxUS momentum. WWLM4, on the other hand, explains the portfolio's total return as almost entirely factor-driven.

And how does this translate to risk accuracy?

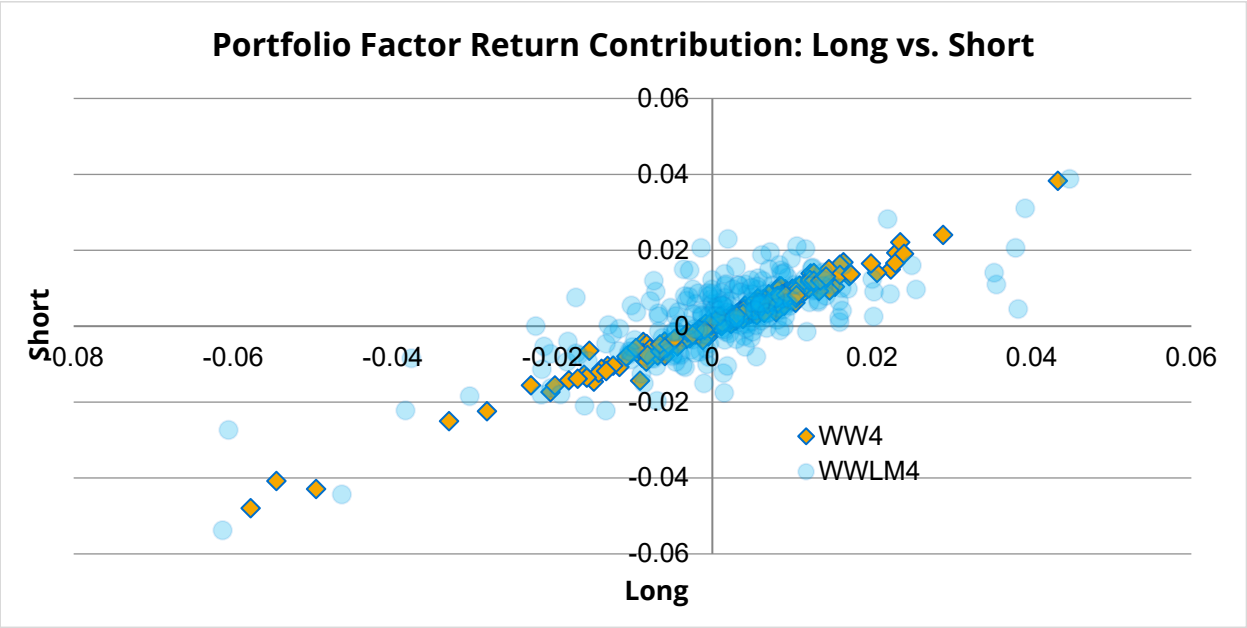
Figure 35: Long-Short Momentum Portfolio Bias Statistics



Source: Qontigo

Figure 35 shows the rolling 24-month bias statistics for the two models along with 95% confidence intervals. The differences could hardly be more stark: WWLM4 remains comfortably within its confidence intervals over the entire period. WW4, on the other hand, consistently under-estimates the portfolio risk by a large margin: all because it considers that US momentum can perfectly hedge DMxUS momentum.

Figure 36: Long versus short factor return contributions for each model



Source: Qontigo

Just to finally drive the point home, Figure 36 details the long versus short factor monthly factor return contributions according to the two models. We see that WW4's contributions are an almost perfect match.

We freely admit that this example is, to a certain extent, artificial. An investor will not tend to use an FMP as his or her portfolio. Rather, the point is to show how, isolating from the effect of other factors, an investment style in one region will not act as a perfect hedge in another. By taking account of the differences between the two, the Linked Model provides far more accurate risk estimates, and reduces the chance of spurious hedging for the user.

9. Contacts & Information

Learn more about how Qontigo can help you better manage risk and enhance your investment process.
Qontigo.com

Europe

Frankfurt
Mergenthalerallee 61
65760 Eschborn, Germany
+49 69 2 11 0

Geneva
Rue du Rhone 69, 2nd Floor
1207 Geneva, Switzerland
+41 22 700 83 00

London
11 Westferry Circus
London E14 4HE, United Kingdom
+44 20 7862 7680

Paris
19 Boulevard Malesherbes
75008, Paris, France

+33 1 55 27 38 38
Futurama Business Park Building F
Sokolovska 662/136b
186 00 Prague 8, Czech Republic

Zug
Theilerstrasse 1A
6300 Zug, Switzerland
+41 43 430 71 60

Americas

Atlanta
400 Northridge Road, Suite 550
Atlanta, GA 30350
+1 678 672 5400

Buenos Aires
Corrientes Avenue 800, 33rd Floor
Office 101
Buenos Aires C1043AAU, Argentina
+54 11 5983 0320

Chicago
1 South Wacker Drive, Suite 200
Chicago, IL 60606
+1 224 324 4279

New York
17 State Street, Suite 2700
New York, NY 10004 USA
+1 212 991 4500

San Francisco
201 Mission Street, Suite #2150
San Francisco, CA 94105
+1 415 614 4170

Asia Pacific

Hong Kong
28/F LHT Tower
31 Queen's Road Central
Hong Kong
+852 8203 2790

Singapore
80 Robinson Road, #02-00
Singapore 068898, Singapore
+852 8203 2790

Sydney
9 Castlereagh Street, Level 17
Sydney, NSW 2000, Australia
+61 2 8074 3104

Tokyo
27F Marunouchi Kitaguchi Building,
1-6-5 Marunouchi Chiyoda-ku
Tokyo 100-0005, Japan
+81 3 4578 6688

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