DIVERSIFICATION DASHBOARD

Research Insights from Outside the Box

February 2021

Why the Most Diversified Portfolio is the Real Multi-Factor Portfolio
Original research, actionable insight

A note from the Research desk…

Recent years witnessed a significant increase in interest from investors in factor and multi-factor investing. 2020, however, turned out to be an unpleasant year for many investors in factor-based strategies. This includes the widely cited value factor drawdowns, but also multi-factor strategies themselves, particularly those that are put forward to investors as providing a diversified exposure to risk factors, which many did not.

The dismay of (multi-)factor investors in 2020 caught wider attention in the financial media. Unfortunately, the perceived failure of factor-based fund managers this year was promulgated as the failure of the entire spectrum of quantitative fund managers by the financial media. "A terrible, horrible, no good year for quants" (FT Nov 3rd 2020) and "Why 2020 has been rotten for quant funds" (The Economist Nov 19th 2020) to quote a few headlines from the press.

While these headlines portray a failure of the entire quantitative industry, looking at the performance of TOBAM's maximally diversified quantitative portfolios, we beg to differ. 2020 was not such a terrible year for quantitative investing, even with markets achieving new highs of concentration. Hence, we decided to pen our thoughts on factor investing and their implications for risk diversification. While we are very sympathetic to the underlying economic theory of asset pricing behind (multi-)factor investing, we take this opportunity to highlight the difficulties and potentially unintended consequences of some of the hidden biases that inadvertently come into play when trying to translate factor theory into live equity portfolios and how these problems also make it difficult to construct truly diversified multi-factor portfolios.

This Dashboard aims at contributing to a deeper understanding of why factor investing in its common form and in particular multi-factor portfolios may not deliver investors the balanced risk exposures and diversification effects, that they typically hope to achieve or are promised to obtain by spreading their investments across multiple factors. We would like to reiterate our belief that the failures in this regard of several multi-factor portfolios are due more to the challenges in implementation rather than the potential lack of soundness in the underlying economic theory. Finally, we also contrast the recent performance of US multi-factor portfolios to that of the US Anti-Benchmark®, a portfolio designed with well-diversified exposures to *all* risk factors.

We hope you enjoy reading this note as much as we enjoyed writing it.

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out-of-the-box thinking

noun. Thinking that moves away from established convention to incorporate alternative perspectives and which sometimes leads to novel ideas and solutions.

Why the Most Diversified Portfolio is the Real Multi-Factor Portfolio

The most widely applied theoretical foundation for factor models, as they are used in the financial industry today, is the Arbitrage Pricing Theory (APT) going back to Ross (1976)[1]. The economic idea formalized in his model is that of a homogenous set of assets, where differences in returns only arise because of different exposures to common components that make the returns of different assets take different paths over time. Idiosyncratic effects are assumed to be fully diversifiable. This, back in 1976, revolutionary way of thinking about asset pricing also had consequences for security selection, transforming it to include the potential for capturing a broad set of premia rather than solely making idiosyncratic bets. It is also important to remember that an important consequence of this new way of looking at performance and risk prepared the ground for a better understanding of portfolio characteristics and investor outcomes. Further, this sets the groundwork for risk and exposure optimization at a time when computation power was making it possible to directly monitor and optimize portfolios with hundreds of lines using huge covariance matrices.

We have a lot of sympathy with this way of describing asset pricing and with the associated conclusion that an efficient way to select assets and construct a portfolio is to capture a diversified set of effective risk exposures. However, one major issue with Ross' theory is that it leaves us in the dark about how this can be implemented in a real portfolio. In subsequent decades, a plethora of papers were written about factors that could be used, and over the last 20 years almost as many factors have been proposed by banks and asset managers to their clients. The dispersion of outcomes of these factors is huge, even if they share the same names. A recent paper by Kessler et al. (2020)[2] highlights that even slight changes to specifications of variable definitions, weighting methods and other implementation related constraints led to wide ranging risk-return profiles. Consequently, tracking errors among strategies that supposedly follow the same factor can be very high.

In an interview in 2019, Eugene Fama, one of the figureheads of factor-based investing, highlighted the issue of factor construction. He said:

> "*Lots of these [factors] are just manifestations of the same thing. So, value can be measured in many different ways: you can use the book-to-market ratio and you can use cash flow to price. I can use lots of different variables to identify what is basically the same thing. And there are thousands of finance professors out there, who all want to get tenure. They have to publish to do that, so they're… all just kind of searching through the data, finding stuff that may be there only on a chance basis — that won't be there on a sample. So, there's lots of work being done and that remains to be done on what we call robustness.*"

Referencing a range of single factors, multi-factor portfolios are designed to deliver a diversified exposure to what is believed to be the most relevant risk factors such that they do not have to worry anymore about how to construct their portfolio. Unfortunately, multi-factor portfolios are built with factors subject to the issues described above and, as we will illustrate, this fundamental challenge – when left unaddressed – leads to hidden biases and to poor diversification. Furthermore, combining several factor strategies that are potentially subject to specification issues, exacerbates the single factor problem and multiplies it exponentially[3].

Of course, investors can choose to introduce such biases consciously into their portfolio. However, if these biases arise unintentionally, they carry the potential for significant adverse consequences for the return and risk characteristics of the portfolio.

In this Dashboard we contribute to a deeper understanding of why factor investing, in its common form and in multi-factor portfolios, might not deliver to investors what they expect to receive. This happens not because of errors at the level of the economic theory, but rather because implementating multi-factor portfolios that span all relevant risk factors is a very difficult task. Especially when only considering a limited and predefined set of widely known long-

[1] Ross, Stephen A., 1976, *The Arbitrage Theory of Capital Asset Pricing*, Journal of Economic Theory, 13, pp. 341-360.
[2] Kessler, Stephan, Scherer, Bernd and Harries, Jan Philipp, 2020, *Value by Design?*, Journal of Portfolio Management, Quantitative Special Issue, pp. 25-43.
[3] Novy-Marx highlights that creating multi-signal strategies makes the issue of signal identification even more severe. He shows that when combining the best k out n strategies, this is almost as bad as making the choice of these n^k strategies (Novy-Marx, Robert, 2015, *Backtesting Strategies Based on Multiple Signal*, NBER Working Paper No 21329)

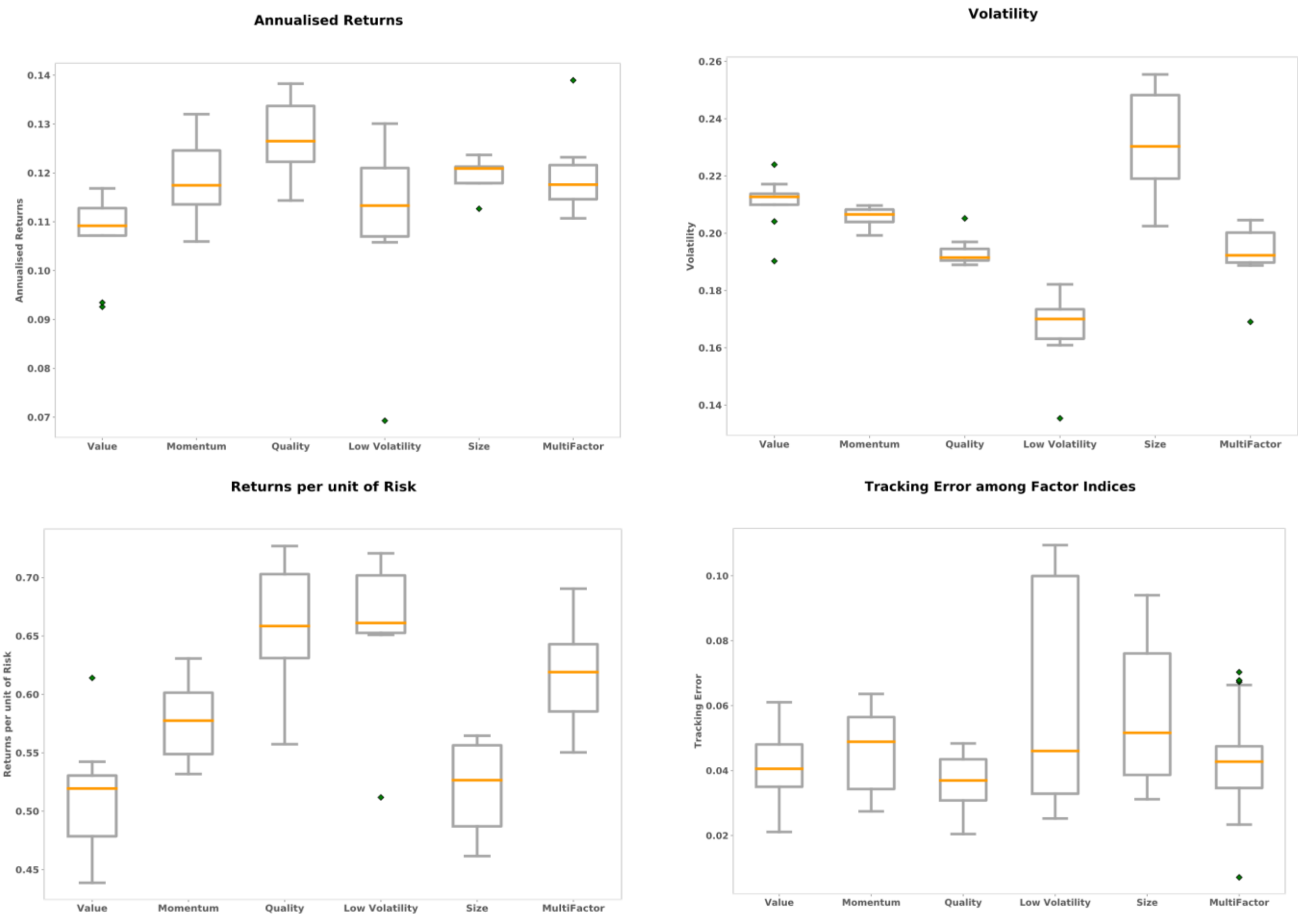
only portfolios. We also highlight the unintended consequences of these hidden biases, using 2020 as a case study, and contrast the recent performance of US multi-factor portfolios to that of the US Anti-Benchmark®, arguably a portfolio with well-diversified factor exposures to *all* risk factors.

I. Examining the Robustness of Factor Indices

In this section, we document the dispersion in risk and return characteristics of a range of widely used, publicly available factor and multi-factor indices produced by well-known financial industry participants. We note these indices all purport to be representative of the same core factors.

Figure 1 plots different risk and return measures of a range of single factor indices alongside the multi-factor indices. We note that risk and return characteristics vary to some extent between differing implementation of the same factor but are relatively consistent within each factor family. However, the presence of significant outliers (green diamonds outside the box plots) indicates how high the dispersion can be within a factor – even for those that seem straightforward in construction (such as Low Volatility). To put this into perspective, a 1% difference in annualized returns over a period of 30 years is roughly equivalent to a difference of 33% of the terminal value of the investments.

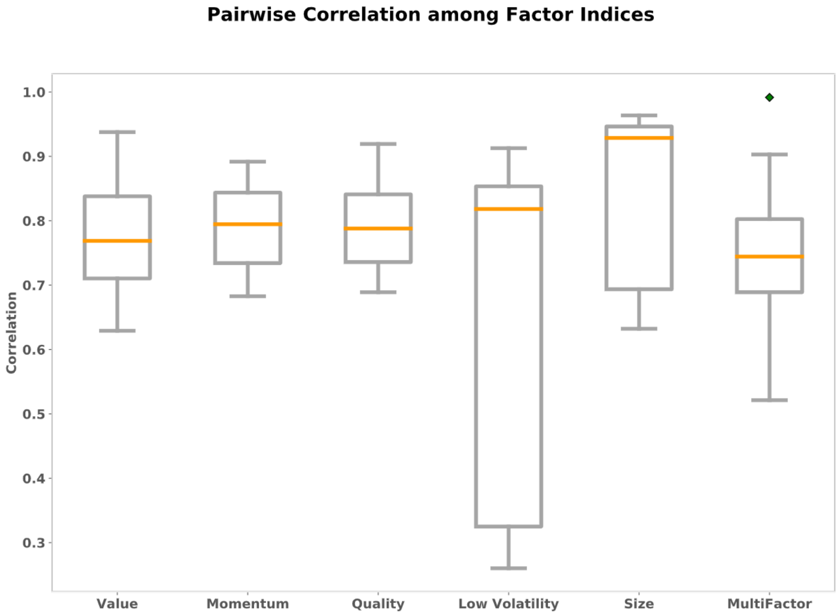
Figure 1: Risk and Return Characteristics across different Factors (long-only factor indices, 2005-2020)



Source: Bloomberg, TOBAM. Universe: USA. Period: December 2005 to December 2020. Daily total returns in USD are used in the analysis. Full period risk-return characteristics of all the peer indices chosen in each of the factor category are plotted in the above box plot. Tracking error is computed pairwise in each factor category. Please refer to the note page 13 of this document for a detailed description of the factor indices that were used.

Another way of looking at how disparate these factors are is to measure their average pairwise correlation for within each factor. Figure 2 summarizes these correlations. While factors exhibit relatively high correlations on average, these can be as low as 0.6 for most factors, thus inducing large dispersion within both single and multi-factor portfolios.

Figure 2: Average Pairwise Correlation among Factor Indices
December 2005 – December 2020



Source: Bloomberg, TOBAM. Universe: USA. Period: December 2005 to December 2020. Daily total returns in USD are used in the analysis. Full period pair-wise correlation of market beta adjusted returns of all the peer indices chosen in each of the factor category are plotted in the above box plot. Please refer to the note page 13 of this document for a detailed description of the factor indices that were used.

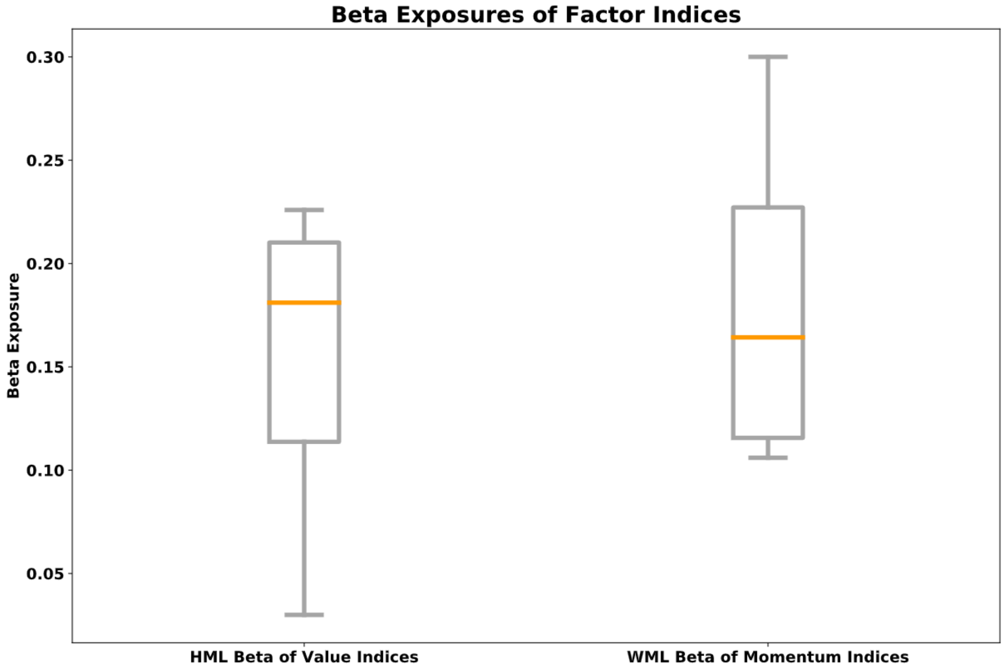
From the above analysis we conclude that long-only factor strategies deliver performances that are relatively consistent within each factor family, however the presence of significant outliers indicates that their construction is not straightforward. While a level of consistency can be expected as the factor indices referenced are long-only and thus incorporate a degree of non-factor specific beta exposure (limiting differentiation amongst them), given the context it is still surprising that they exhibit such non-negligible dispersion of their correlations. Separately, a long-only structure is a further potential implementation challenge as such factor indices, as we will see in the next section, may struggle to deliver an exposure to their reference long-short factors at all.

II. Hidden Biases of Single Factor Strategies

What are the potential drivers responsible for the dispersion of single – or multi-factor returns? Our hypothesis is that the difficulty in implementation of the theoretical concept may lead to factor portfolios that entail hidden biases.

In support of this hypothesis, when looking at, for example, the Value and Momentum factor indices (Figure 3), we observe a wide range of exposures to their reference (long/short) factors, Fama-French Value and Carhart Momentum factors. Indeed, we observe that some long-only value indices near zero value exposures. Momentum factors also seem to have a lot of additional - and very different - risk exposures rather than being representative of what had been once established as the reference Momentum factor.

Figure 3: Beta Coefficients
December 2005 – September 2020



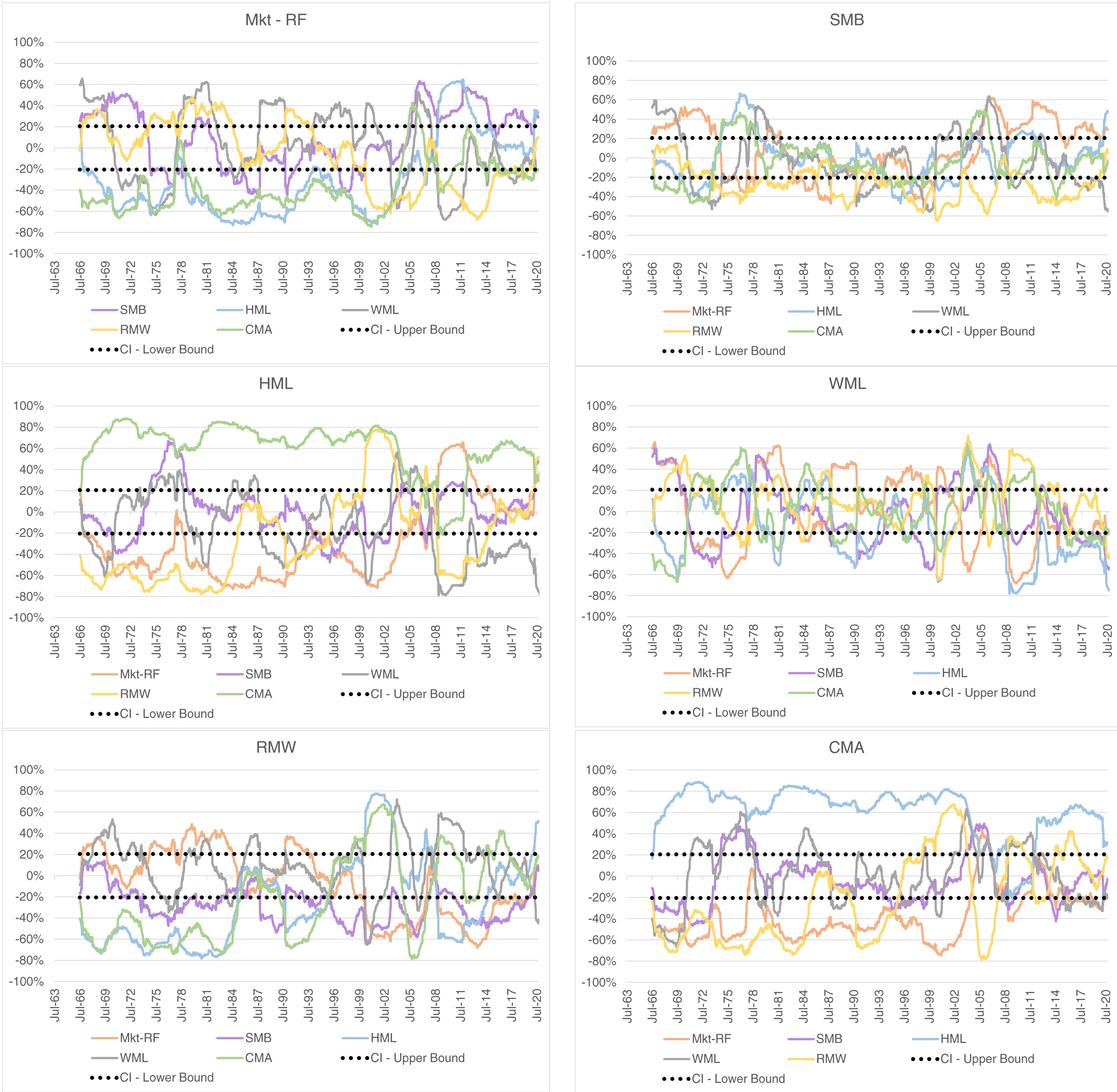
Source: Bloomberg and Kenneth French Data Library. Universe: USA. Period: December 2005 to September 2020. At the time of writing this dashboard, the latest date till which data was available at the public data library of Kenneth French was September 2020. Please refer to the note page 13 of this document for a detailed description of the factor indices that were used. HML beta of Value indices and WML beta of Momentum indices are reported from the Fama-French 5-Factor regression.

Even seemingly simple and robust academic empirical factors that are widely used as benchmarks to evaluate factor strategies can significantly violate the fundamental assumption behind APT - that factors explaining the cross-section of stock returns are to be uncorrelated.

In reality, even well-constructed empirical long-short factors such as the widely adopted Fama-French factors may be significantly correlated to one another, with correlations that are highly dynamic over time. We illustrate this point in Figure 4 below, using 3-year rolling window correlations among Fama-French factors. The pairwise correlations swing wildly through time from positive to negative, with high and low values that are significant, well beyond 99% thresholds.

Figure 4: 3-Year Rolling Window Correlations among Fama-French Long/ Short Factors

July 1963 – September 2020



Source: Kenneth French's Data Library available here. Period: July 1963 to September 2020. At the time of writing this dashboard, the latest date till which data was available at the public data library of Kenneth French was September 2020. Mkt-Rf, SMB, HML, WML, RMW and CMA represent Market, Size, Value, Momentum, Profitability, and Investment factors. 3-Year rolling correlation based on weekly returns of each factor against every other factor is depicted. These are long/short factors and the factor definitions and construction methodology is available here. The dotted lines represent the 99% confidence interval for zero correlation.

We conclude from the above two illustrations that commonly used long-only factors do not necessarily deliver a positive exposure to their reference counterparts (Fama-French, Cahart factors), and that the reference counterparts themselves are not independent through time.

This means that constructing a long-only portfolio that is uniquely exposed to a unique Fama-French or Cahart Momentum factor is a difficult task. Indeed, constructing a single factor portfolio entails an unavoidable exposure through time to other factors or, in other words, to hidden biases. By implication, therefore, multi-factor portfolios **rely** on time varying and highly correlated single factor building blocks for portfolio construction. This makes it challenging to obtain factor exposures that are diversified - and remain so - through time.

III. Multi-Factor Strategies are not fully Diversified across Factors

We now turn to the problem of allocating capital across equity factors drawn from the so called "Factor Zoo"[4].

As shown in Choueifaty et al. (2013)[5], the Maximum Diversification Portfolio© (MDP) maximizes its number of effective risk factor exposures, where the corresponding risk factors do not need to be identified. To do this we use a proprietary measure of diversification, the Diversification Ratio® (DR). By construction, and hence endogenously, the MDP maximizes the number of risk factor exposures and as such has very high effective number of risk factors (as measured by DR^2).

By construction, the MDP avoids the challenging task of, first, identifying relevant factors, then building a portfolio that achieves a balanced exposure to these and, finally, managing that exposure across time. In contrast, allocating risk equally to a given set of factors (a common industry practice), is certain to result in biased risk exposures. As illustrated in previous sections, factors are not independent, particularly in the long-only context. In this way, a multi-factor approach can give a false sense of security to investors, who may believe they are well diversified when, in reality, they remain subject to unintended hidden biases. Hence, in eliminating the many choices that necessarily underlie factor construction and allocation, the MDP is a more robust method of portfolio construction to achieve a diversified risk exposure through time.

To illustrate this point empirically, we first rely on a statistic called '*Effective number of bets*', introduced in Meucci et al. (2015) [6], that measures the degree of diversification in terms of how dispersed the portfolio risk exposures are, using statistical factors provided by a Principal Component Analysis (PCA). Since these factors are uncorrelated by construction, a portfolio's "*Effective number of bets*' can alternatively be thought of as the number of independent risk factors to which it is exposed, in much the same spirit as the DR^2.

The Effective number of bets is computed from the principal components of the universe of stocks and is defined as follows:

$$Effective\ Number\ of\ Bets = e^{-\sum_{k=1}^{K} p_k \ln p_k}$$

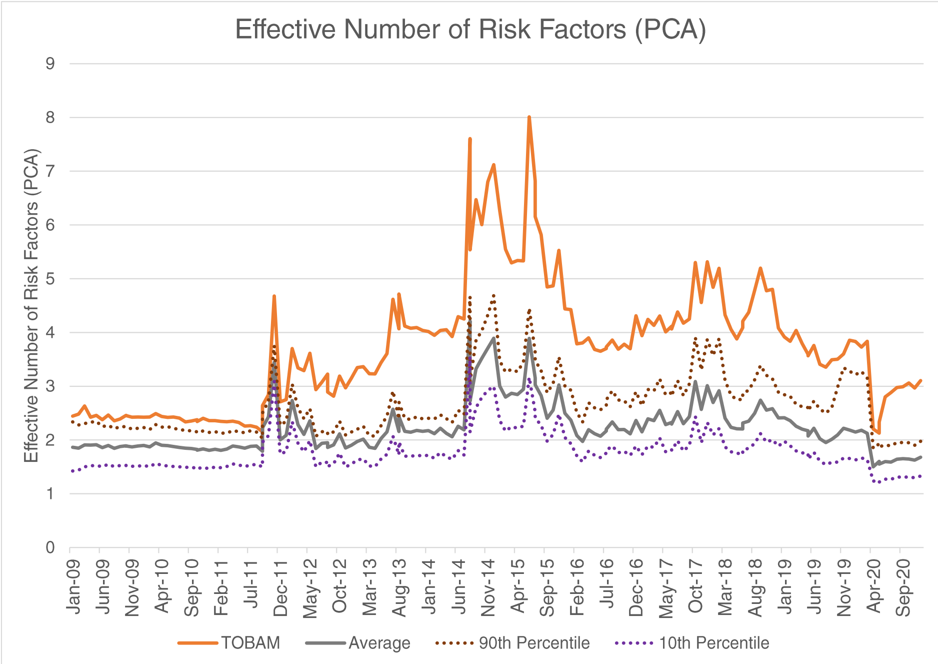
where K is the number of principal components, and p_k is the relative risk contribution of the kth principal component to the portfolio concerned. If all portfolio risk is driven by just one PCA factor, the number of bets (principal components) will be 1, whereas if all the PCA factors equally contribute to the risk of the portfolio then its number of bets will be equal to the total number of PCA factors chosen. Thus the higher the Effective number of bets, the better balanced the portfolio, in terms of its risk exposures.

In Figure 5 below, for a US equities universe the number of PCA factors[7] to which the real-life version of the MDP (Anti-Benchmark® US strategy) is exposed over time, compared to the average number of PCA risk factors along with the 10% and 90% quantiles, to which the multi-factor strategies in our sample are exposed[8].

Strikingly, the majority of multi-factor indices are exposed to less than 2 PCA factors. The risk concentration comes entirely from only one or two factors for most of these strategies. In contrast the Anti-Benchmark® US strategy (an implemented MDP) always exhibits a significantly higher number of PCA risk factors to which it is exposed. This shows that a more effective way to construct a balanced risk multi-factor portfolio is to make sure that endogenously, the portfolio is constructed in a well-diversified way, not to bundle together a number of potentially poorly pre-identified factors.

[4] Harvey, Campbell R. and Liu Yan, 2020, *A Census of the Factor Zoo*, Working Paper available on SSRN https://ssrn.com/abstract=3341728
[5] Choueifaty, Yves, Froidure, Tristan and Reynier, Julien, 2013, *Properties of the Most Diversified Portfolio*, Journal of Investment Strategies, 2(2), pp. 1-22.
[6] Meucci, Attilio, Santangelo, Alberto and Deguest, Romain, 2015, Risk Budgeting and Diversification Based on Optimized Uncorrelated Factors, Working Paper available on SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2276632

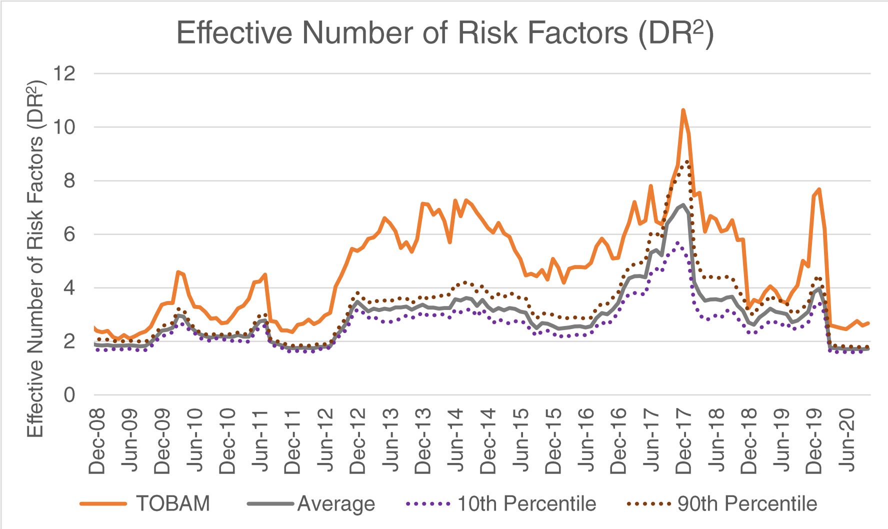
Figure 5: Effective Number of PCA Risk Factors – TOBAM Anti-Benchmark® US Strategy vs Multi Factor Indices



Source: Bloomberg and TOBAM. Universe: USA. Period: December 2005 to December 2020. Effective number of bets of TOBAM Anti-Benchmark US fund vs the average, 10th and 90th percentile values of the peer multi-factor indices are reported over time. The Effective number of bets are computed using on a rolling 3-year with monthly step size. The statistical PCA risk factors are computed from MSCI USA universe. Please refer to the note page 13 of this document for a detailed description of the factor indices that were used. TOBAM Anti-Benchmark US data reflects back-tested data from Dec 31, 2005 to Sep 26, 2006, plus live data for the TOBAM AB US strategy (AB) from Sep 26, 2006 to date (Dec 31, 2020).

We consider the diversification of multi-factor indices and the Anti-Benchmark® portfolio from another angle in Figure 6, where we estimate their daily one year rolling Diversification Ratios, using observed returns only, as described in Froidure et al (2019)[9]. We find a qualitatively comparable result, where multi-factor indices remain significantly below the level of diversification achieved by the Anti-Benchmark® portfolio.

Figure 6: Effective Number of Risk Factors (DR^2):
TOBAM Anti-Benchmark® US Strategy vs Multi Factor Indices



Source: Bloomberg and TOBAM. Universe: USA. Period: December 2005 to October 2020. DR^2 – the square of the Diversification Ratio - of TOBAM Anti-Benchmark US fund vs the average, 10^{th} and 90^{th} percentile values of the peer multi-factor indices are reported over time Please refer to the note page 13 of this document for a detailed description of the factor indices that were used. TOBAM Anti-Benchmark US data reflects back-tested data from Dec 31, 2005 to Sep 26, 2006, plus live data for the TOBAM AB US strategy (AB) from Sep 26, 2006 to date (Oct 31, 2020).

We conclude from the above exercise that even if some of the multi-factor strategies within our sample maintain that they invest in up to six factors, they are only effectively exposed to between two to three factors on average, depending on the measure considered. Importantly, they are less diversified across all time periods, according to either metric. This could either be a design choice, for example for strategies seeking to market time their factor exposures, or an unintentional characteristic coming from the hidden biases identified in the previous section.

[9] Froidure, Tristan, Jalalzai, Khalid and Choueifaty, Yves, 2019, Portfolio Rho-Presentativity, International Journal of Theoretical and Applied Finance, 22(7) 1950034. We use here an improved method that allows estimating DRs over periods that contain less observations than the number of assets in the investment universe.

IV. Unintended Consequences of Hidden Biases – The Case of 2020

To illustrate the dangers or unintended consequences of hidden biases within conventional multi-factor products, we use market data from the Covid crisis in 2020, which triggered many discussions about the effectiveness of factor investing.

Since the onset of the Covid crisis, market uncertainty has remained elevated. As is characteristic during times of high uncertainty, correlation among factors increased significantly.

Indeed, as detailed in Table 1, the average absolute correlation of Fama-French factors in 2020 was 35%, more than twice its long-term average of 16%.

Table 1: Correlation among Fama-French Long/Short Factors
September 1963 – September 2020

PANEL A: Full Period: September 1963 – September 2020

	Market	*Size*	*Value*	*Momentum*	*Profitability*	*Investment*
Market	100.0%					
Size	-9.2%	100.0%				
Value	-15.3%	12.0%	100.0%			
Momentum	-12.0%	-3.0%	-32.5%	100.0%		
Profitability	-19.1%	-26.3%	-1.8%	8.8%	100.0%	
Investment	-36.0%	2.2%	53.2%	0.3%	8.4%	100.0%

PANEL B: Year 2020: December 2019 - September 2020

	Market	*Size*	*Value*	*Momentum*	*Profitability*	*Investment*
Market	100.0%					
Size	20.9%	100.0%				
Value	34.6%	58.9%	100.0%			
Momentum	-15.7%	-54.1%	-83.2%	100.0%		
Profitability	19.7%	8.1%	45.5%	-49.5%	100.0%	
Investment	-5.1%	-4.6%	40.0%	-35.8%	41.6%	100.0%

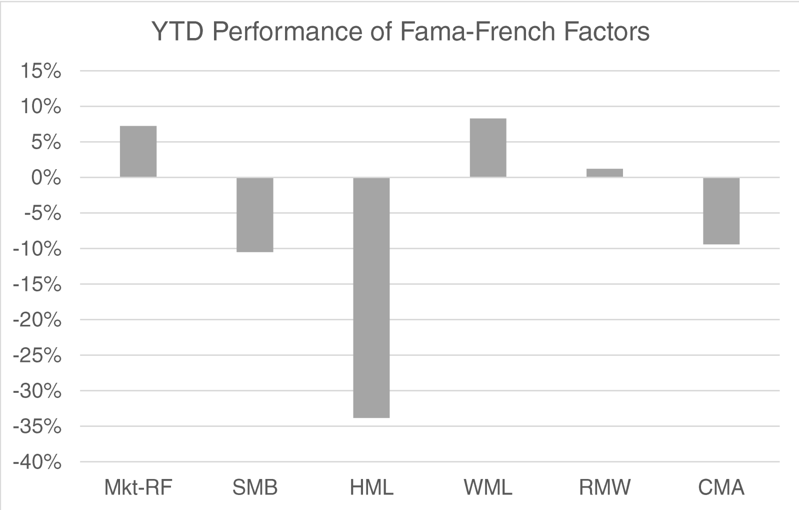
Source: Kenneth French's Data Library available here. Period: July 1963 to September 2020. At the time of writing this dashboard, the latest date till which data was available at the public data library of Kenneth French was September 2020. Mkt-Rf, SMB, HML, WML, RMW and CMA represent Market, Size, Value, Momentum, Profitability, and Investment factors. These are long/short factors and the factor definitions and construction methodology is available here.

Of particular note is the strongly negative correlation factor pair: Value (HML) – Momentum (WML). Over the long-term, this factor pair exhibited one of the most negative correlations (-32%), making the pair a good candidate for inclusion in multi-factor portfolios, who generally seek to control for their overall portfolio volatility, a structural feature of these portfolios.

In 2020, however, even if the pair enjoyed a negative 83% correlation, the overall absolute return of the Value factor - at three times that of the Momentum factor - dominated, despite having comparable volatility. This dramatic divergence was broadly discussed in the financial press, and is shown, alongside the range of Fama-French factors, in Figure 7.

More generally, we note that *all* the Fama-French factors have exhibited a negative correlation to the Carhart factor in 2020 (refer the highlighted yellow boxes on Table 1), with *all* of them underperforming the Momentum factor which performed similarly to the market.

Figure 7: 2020 Performances of Fama-French Long/Short Factors
December 2019 – September 2020



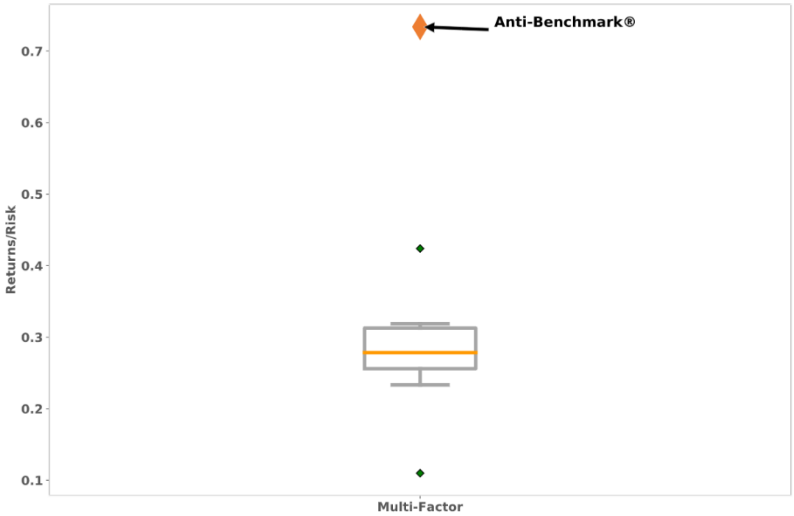
Source: Kenneth French's Data Library available here. Period: December 2019 to September 2020. At the time of writing this dashboard, the latest date till which data was available at the public data library of Kenneth French was September 2020. Mkt-Rf, SMB, HML, WML, RMW and CMA represent Market, Size, Value, Momentum, Profitability, and Investment factors. These are long/short factors and the factor definitions and construction methodology is available here.

As a result, performance of multi-factor portfolios in 2020 was disappointing for many investors. We surmise that this weak performance can be linked to likely structural exposures to the Value/Momentum pair and a lack of diversification more generally.

Indeed, many of these strategies invest by design in only a limited few, pre-identified factors. As such, they fail to diversify away from all possible risk factors other than traditional Fama-French factors (or their equivalents), of which all – with the exception of the Carhart Momentum factor - underperformed the market in 2020.

Comparing the performance of the multi-factor portfolios in our sample to the Maximum Diversification© based portfolio in Figure 8, highlights that a portfolio aiming to maximize diversification did comparatively well, seeking by design a homogenous exposure to *all* risk factors.

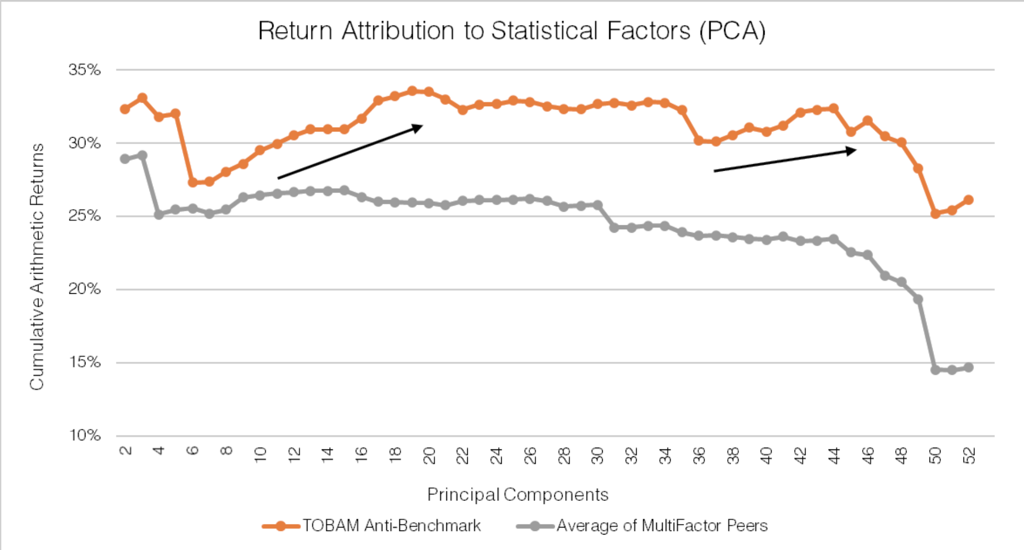
Figure 8: 2020 Risk adjusted Returns of Anti-Benchmark® vs Multi-Factor Indices
December 2019 – December 2020



Source: Bloomberg, TOBAM. Universe: USA. Daily total returns in USD gross of tax and exclude costs of transactions and fee assumptions is used in this analysis. Period: December 2019 to December 2020. Please refer to the note page 13 of this document for a detailed description of the factor indices that were used. ***Warning:*** *Past performance is not an indicator or a guarantee of future performance. The value of shares in the strategy and income received from it can go down as well as up, and investors may not get back the full amount invested. Performance details provided include the reinvested dividends.*

Further scrutiny of the sources of performance of both Anti-Benchmark® and multi-factor strategies during 2020 using the uncorrelated statistical factors (PCA factors) sheds more light on this observed performance dispersion. Figure 9 illustrates the cumulative return contribution of the statistical factors to both Anti-Benchmark® and multi-factor indices.

Figure 9: 2020 Performance Attribution of Anti-Benchmark® vs Multi-Factor Indices to PCA Risk Factors
December 2019 – December 2020



Source: Bloomberg, TOBAM. Universe: USA. Daily total returns in USD gross of tax and exclude costs of transactions and fee assumptions is used in this analysis. Period: December 2019 to December 2020. Please refer to the note page 13 of this document for a detailed description of the factor indices that were used. ***Warning:*** *Past performance is not an indicator or a guarantee of future performance. The value of shares in the strategy and income received from it can go down as well as up, and investors may not get back the full amount invested. Performance details provided include the reinvested dividends. PCA factors are constructed from MSCI USA universe of stocks. The performance of each of the multi-factor peer and TOBAM Anti-Benchmark are attributed to these PC factors and cumulative sum of PC attributed returns of TOBAM Anti-Benchmark and the average of the peers are plotted.*

As we saw in Table 1, many of the popular factors the multi-factor strategies aimed to exploit became highly correlated to each other in 2020, consequently much of the performance of the multi-factor strategies came from the first three PC factors. However, looking at the Anti-Benchmark® portfolio we see that a truly diversified portfolio with exposure to multiple uncorrelated sources of risk derived its performance from a diverse set of PC factors.

V. Conclusion

While factor investing is but one family within a broad spectrum of quant strategies, it triggered much discussion in recent months about the usefulness of quant strategies due to the rather choppy performance of many multi-factor portfolios.

In this note we show that common implementations of multi-factor strategies suffer from unwanted biases, then highlight the unintended consequences of these hidden biases. We outline that the MDP can overcome these issues, seeking by design an homogenous exposure to all risk factors, in an endogenous manner.

Despite seeking a similar goal, the MDP stands in contrast to common multi-factor approaches that limit themselves to a fixed set of widely known long-only factors. As these specific factors underperformed or matched the market's performance, it is of no surprise that common multi-factor approaches underperformed in 2020.

Quant investing will no doubt be again targeted for attack or called into question much more likely in such situations compared to fundamental strategies because humans prefer humans over machines, even if this might be the least rational thing to do. While we continue to believe – and the evidence suggests - that investing in a systematic, economically as well as mathematically founded way is key. We are, however, also aware that a lot of things can go wrong in defining such a strategy. Still, diversified across more factors, the MDP generally outperformed multi-factor strategies, showing that quant investing might have been worthwhile in 2020, after all.

<u>Note about the factor indices that are mentioned in this document:</u>

Value Factor Indices used in this document are: MSCI USA Value Index, MSCI USA Enhanced Value Index, FTSE RAFI USA 1000 Index, JP Morgan US Value Index, S&P 500 Value Index, Fidelity US Value Index, Credit Suisse Holt US Value Index, Scientific Beta US Value Multi-Strategy Index and Scientific Beta US 4-Strategy High Factor Intensity Value Index.

Momentum Factor Indices used are: FTSE Russell 1000 Momentum Index, MSCI USA Momentum Index, JP Morgan USA Momentum Index, S&P 500 Momentum Index, Fidelity US Momentum Index, Credit Suisse Holt US Momentum Index and Scientific Beta USA High Momentum Multi-Strategy Index.

Quality indices used are: Russell 1000 Quality Index, MSCI USA Quality Index, JP Morgan USA Quality Index, S&P 500 Quality Index, Fidelity US Quality Index, Credit Suisse Holt US Quality Index and Barclays US Quality Index.

Low Volatility indices used are: Russell 1000 Low Volatility Index, MSCI USA Minimum Volatility Index, FTSE US Risk Premium Long Only Low Volatility Index, JP Morgan US Minimum Volatility Index, S&P 500 Low Volatility Index, SSGA Large Cap Low Volatility Index and Scientific Beta USA Low Volatility Multi-Strategy Index.

The Size factor indices used are: Russell 2000 Index, MSCI USA Small and Mid-Cap Index, FTSE US Mid and Small Cap Index, CRSP US Small and Mid-Cap Index, S&P US 600 SmallCap Index and Scientific Beta US Mid Cap Multi-Strategy Index.

Multi-factor Indices used are: Credit Suisse Holt US Multi-factor Index, MSCI USA Diversified Multiple-factor Index, Invesco US QVM Multi-factor Index, S&P 500 Quality, Value and Momentum Multi-factor Index, RAFI US Dynamic Multi-factor Index, Scientific Beta US 4-Factor Multi-beta Multi-strategy Equal Weighted Index, Scientific Beta US 6-Factor Multi-beta Multi-strategy Equal Weighted Index, Robeco US Multi-factor Equity Index, Stoxx US 500 Ax Multi-factor Index and FTSE USA Qual/Vol/Yield Multi-factor 5% Capped Index.

For more information

TOBAM is an asset management company offering innovative investment capabilities designed to increase diversification. Its mission is to provide rational and professional solutions to long term investors in the context of efficient markets.

The Maximum Diversification® approach, TOBAM's flagship investment process founded in 2006, is supported by original, patented research and a mathematical definition of diversification and provides clients with diversified core exposures, across equity and fixed income markets.

In line with its mission statement and commitment to diversification, TOBAM also launched a separate activity on cryptocurrencies in 2017.

As at December 2020, TOBAM manages US$10.2 billion on behalf of clients globally. TOBAM's team is composed of 48 professionals.

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