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QIS Insights

Equity Multi-Factor Approaches: Sum of Factors vs. Multi-Factor Ranking

EFS Quantitative Investment Strategies (QIS)
16 September 2016

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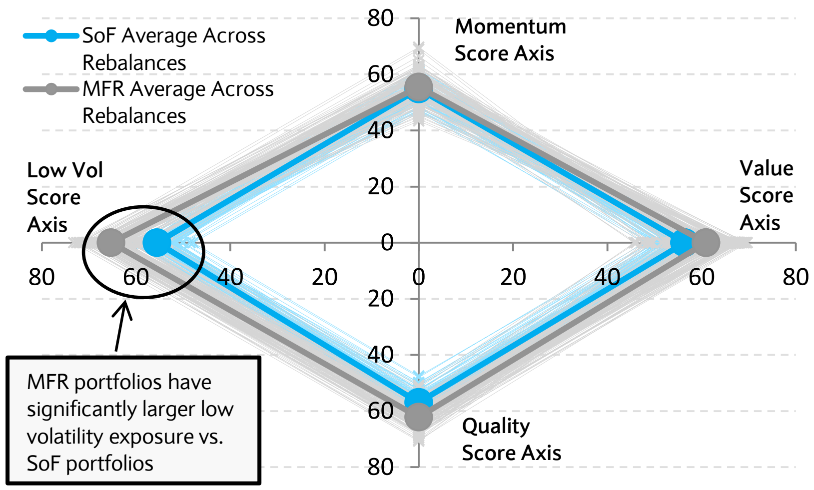
- There is a plethora of literature on the persistence and rationale of individual equity factor premia, which investors are often advised to extract through forming multi-factor portfolios – however, not so much attention is paid to the nuances of forming such portfolios and their implications

- There are generally two approaches for forming equity multi-factor portfolios:
  - Sum of Factors (SoF) – where separate respective factor portfolios are first formed which are then subsequently combined
  - Multi-Factor Ranking (MFR) – where individual stocks are selected based on a specified multi-factor ranking model

- In this paper, we empirically demonstrate the implications of the two approaches when allocating across four equity factors: Value, Momentum, Low Volatility and Quality. We do so in the context of two topical implementation considerations:
  - Portfolio size: Concentrated versus diversified portfolios
  - Factor exposure: Ex-ante versus ex-post factor exposure

- In summary when comparing the two approaches, we find:
  - MFR portfolios have historically outperformed SoF portfolios irrespective of portfolio size (see pages 12 and 13)
  - However, this has been historically driven by the persistently lower CAPM Beta of the MFR portfolios, which has not been by design and which is accentuated in concentrated portfolios
  - This lower CAPM Beta is from an implicit low volatility factor bias – see Figure 1
  - Such a bias comes with performance risk implications that investors should be mindful of

Figure 1: Average factor score at rebalances and through time for the simulated SoF and MFR portfolio approaches (see page 14 for further details)



Introduction

The nuances of Equity Multi-Factor portfolio construction are often overlooked. Providers commonly present different approaches without clarifying the differences. Investors are therefore led to think that despite the portfolio formation process, the resulting outcome for obtaining equity multi-factor exposure is the same. There are generally two methods for forming an equity multi-factor portfolio, as shown in Figure 2:[1]

1. **Sum of Factors (SoF) multi-factor portfolio:** Individual factor portfolios are first formed (through ranking stocks based on individual factor criteria), which are then subsequently combined

2. **Multi-Factor Ranking (MFR) portfolio:** Selecting stocks based on their ranking by a specified multi-factor model

In this paper we consider the pros and cons of each approach in the context of two specific implementation considerations.

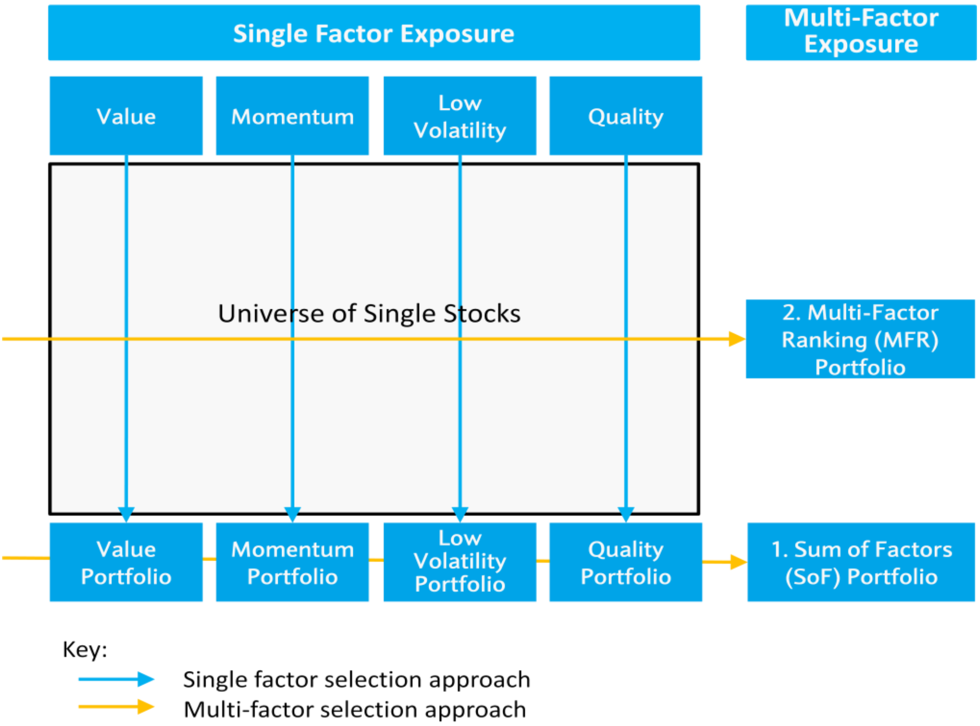
a. **Portfolio size: Concentrated versus diversified portfolios**

This is a topical question for equity factor investors: How many stocks should be in the factor baskets? We specifically look at the trade-offs when moving from concentrated to diversified long-only factor portfolios.

b. **Factor exposure: Ex-ante versus ex-post factor exposure**

The resulting factor loadings for the two approaches can be different and contrary to intuition. We highlight the effect of the resulting implicit factor exposure for the two approaches and the implications for expected returns in a long only context.

Figure 2: Schematic of the two main approaches to form an equity multi-factor portfolio



Before outlining the methodology for our study, we first comment on the two primary considerations when investing in equity factors:

1. Factor Identification & Justification

2. Multi-Factor Allocation

[1] A recent paper by Fitzgibbons et al. (2016) from AQR also looks at long-only equity multi-factor portfolio construction. For clarity, their "mix portfolio" is equivalent to our SoF portfolio, while their "integrated portfolio" is equivalent to our MFR portfolio. We draw comparisons from their work in our study given the relevance and timely nature of their work.

Factor Identification & Justification

This specifically means the process by which to demonstrate the empirical existence, sustainability and benefits of the factor premia together with establishing the rationale. As readers will know well, there is now a plethora of literature both academic and practitioner, on the persistence and rationale of individual equity factor premia such as size, value, momentum, quality and low volatility. An often cited seminal academic paper in this space being that of Fama and French (1993).

Academic work has generally focused on identifying and justifying new premia, whilst practitioners have focused on how best to harvest the respective premia, whether that be through use of different characteristics by which to pick stocks to form the factor baskets or through the use of differing weighting schemes applied to stocks within the factor basket, for example.

Whilst this is no doubt an important area of continuing research and debate, this is not the focus of this paper. Therefore, for completeness we briefly outline the research and justification for the factors under consideration, however our main focus is on the second consideration.

Multi-Factor Allocation

This pertains to how investors should form multi-factor portfolios given their factor investment objectives and risk/reward profiles. Indeed, Asness, Moskowitz & Pedersen (2013) and Asness et al. (2015) show that efficient allocation across risk premia can significantly enhance the benefits of investing in risk premia portfolios – our paper focuses on how to do this for equity factors.

In general, the diversification benefits of forming multi-factor portfolios are often motivated through:

- Low correlation between factor premia
- Factor premia go through different cycles
- Difficulty in timing the factor premia
- Improved historical probability of outperformance vs. the benchmark, in comparison to individual factor outperformance

Whilst our analysis follows suit in this regard – in that multi-factor portfolios allow investors to harvest equity factor premia in a more efficient manner – the focus of this paper is to highlight the unintended consequences of adopting different multi-factor portfolio formation approaches in order to help investors navigate the nuances.

In comparing the SoF and MFR approaches, we acknowledge the intuition and theoretical framework of Fitzgibbons et al. (2016) in that a MFR approach should generally avoid stocks with a high rank to one factor but low rank to other factors, in favour of stocks with good rankings across all the factors simultaneously. Indeed it seems sensible to posit that the simultaneous use of all factor information to build a MFR portfolio should produce a portfolio with a more balanced factor exposure. In this study, it is this that we empirically test to ascertain if the MFR portfolio is in fact well balanced across the factors.

The Factor Premia Under Consideration

This study is based on forming portfolios which contain exposure to four equity factors, namely: Value, Momentum, Low Volatility and Quality.[2] For completeness, we briefly describe the four equity factors and their economic rationale (with references for readers who wish to explore further), followed by the methodological specifics for our study.

Value

Value is arguably the best known of the factor premiums with significant backing in the academic literature. First qualified by Graham and Dodd (1934), the value premium is based on the outperformance of undervalued securities (relative to some benchmark) vs. overvalued securities (relative to the same benchmark) on average over time. Fama and French (1992) documented this premium in the cross-section of stocks using the book-to-market ratio as the criteria for "value", i.e. where a stock with a high book-to-market ratio (low price) versus its peers is seen as value stock in the cross-section of stocks.

The value premium is almost universally thought to be compensation for a non-diversifiable economic source of risk. It is likely that this perception stems from the Fama and French (1992) paper who

[2] We do not include the size factor in this study given the notable concerns of tradability of portfolios with small cap stocks which generally have low trading volumes. There is also a current debate on the existence of the size premium when accounting for other effects such as seasonality, as first documented by Keim (1983).

motivate the existence of the value premium from default risk: Whereby value firms are more exposed to a common default risk factor than non-value (growth) firms. However, there are possible behavioural explanations, such as by Daniel et al. (1997) in that value stocks are unglamorous and as such investors irrationally chase growth stocks, leading to the overpricing of growth and under pricing of value firms – an example of this being in 1997-2000 during the "dot-com bubble".[3] Despite the interesting nature of this debate in justifying the value premium, this is beyond the scope of this paper and so for brevity, we refer to the work by Asness et al. (2015) for the interested reader.

Momentum

Although first documented by Cowles and Jones (1937)[4] but formalised by Jeegadesh and Titman (1993), this factor premium is based on the empirical observation that securities which have performed well in the past tend to subsequently outperform those securities which have performed poorly over the same past – this relative assessment of security performance over a common past history being known as cross-sectional momentum.[5]

Contrary to value, the rationale of the momentum premium is widely thought to be behavioural – either to do with under reaction to news and/or bandwagon effects. The former being that information is incorporated into prices slowly, whilst the latter is to do with the herding behaviour of investors: buying (selling) the biggest winners (losers). However, there are also studies which attempt to justify the momentum premium as compensation for risk.[6] The two sides of this debate with accompanying references for the interested reader are well discussed in Myth #10 of Asness et al. (2014) paper on momentum investing. However, irrespective of the source, the premium for cross-sectional momentum exposure is undeniable, with many robustness tests performed in different regions (Rouwenhorst (1998), Fama and French (2012)) and within asset classes (Asness et al. (2013)).

Low Volatility

The low volatility factor which became particularly popular during the 2008 financial crisis, is based on the empirical observation that stocks with a lower realised volatility tend to subsequently outperform stocks with a higher realised volatility, on average over time. This is known as the "low volatility puzzle" mainly because financial economics is built on the premise that higher (systematic) risk (often proxied by volatility) implies higher expected return. Ang et al. (2006) was amongst the first academic pieces of work to show that historically for the US, low volatility stocks actually exhibited higher returns than high volatility stocks. Blitz and van Vliet (2007) then demonstrated that this volatility effect also existed in equity markets globally.[7]

The rationale for the low volatility factor is generally thought to be partially structural and partially behavioural in nature. Baker et al. (2011) established two symbiotic drivers of this phenomenon: investors' irrationality for lottery like payoffs (behavioural) and limits to arbitrage from leverage aversion/constraints and institutional mandates (structural). The former causing higher-volatility/beta stocks (lottery payoffs) to be bid up relative to fundamentals; and the latter explaining why investors do not offset this irrational demand – whereby leverage constraints and mandates cause investors to bypass investing into the higher risk-adjusted return low volatility portfolios in

[3] Note that we use the term "bubble" which is commonly used in describing the role of technology firms during equity market events of 1997-2000. However, just to clarify, we are not advocating (or ruling out) that this was in fact an asset pricing bubble, given the inherent difficulty in defining what an asset pricing bubble even is. For more on this see Cochrane (2011) or the following article for something more digestible: https://www.bloomberg.com/view/articles/2011-09-22/why-identifying-a-bubble-is-so-much-trouble-john-h-cochrane

[4] Cowles and Jones (1937) highlight the tendency of investments to exhibit persistence in price performance.

[5] This distinction on cross-sectional momentum is important as "momentum investing" is often used in a general sense to describe both absolute and cross-sectional momentum, which are not the same thing, albeit that they may be somewhat related. Absolute momentum is concerned with absolute price changes and is also known as trend-following; whereas as described above, cross-sectional momentum is based on the relative assessment of securities to each other.

[6] This is associated with the premium being compensation for bearing a source of economic risk which cannot be diversified away.

[7] We note that the low volatility anomaly is closely related to the *low beta* anomaly, the latter of which is also commonly used in forming "low volatility" factor portfolios. Recently, Blitz and Vidojevic (2016) in addition to Blitz and van Vliet (2007) observe a stronger mispricing for volatility than for beta, making it the more dominant phenomenon.

favour of higher *expected return* stocks (i.e. higher beta stocks in theory).[8]

Quality

Quality is arguably the "newest" of the factors which is topical in both academic and practitioner circles. Empirical research has demonstrated the higher risk-adjusted returns of high-quality stocks over low-quality stocks, however the current debate pertains to how to define quality – with there being a wide range of characteristics such as profitability, return on equity, earnings variability to name but a few. Indeed, Sloan (1996), although unknowingly at the time, was amongst the first to demonstrate the quality effect based on accounting accruals.[9] Novy-Marx (2013) more recently highlighted the use of gross profitability in demonstrating a similar effect – by this we mean notable average excess returns which are dissimilar in both characteristics and co-variances from the other well-known factors, such as value.[10] Such studies are now thought to be under the guise of the quality factor.

Indeed the more recent academic work done on this is by Fama and French (2015) who build on their classic 1993 3-factor model (market, size and value) with two additional factors, profitability and investment level, to create a 5-factor model.[11] Whilst Asness et al. (2014) find large and consistent average excess returns for a Quality Minus Junk portfolio using a variety of quality measures.

Despite the potential use of different characteristics to proxy for the quality factor, the evidence on the existence of a premium for this factor appears to be robust, whilst the rationale for its existence is currently being debated. Fama and French (2015) have certainly catalysed this debate by attempting to place two quality characteristics within an economic framework, whereby all systematic risks are economic risks which should earn a premium (for the investor who bears the risk), however they stop short of explaining why such a link exists – no doubt a topic for a future paper.

Data & Portfolio Construction

To empirically investigate the pros and cons of the two approaches to form equity multi-factor portfolios, we form such portfolios based on a US universe of stocks over the period from January 2003 to July 2016.

In the following section, we detail the data and stock characteristics used to define our factors, followed by the portfolio construction methodology for the two multi-factor approaches.

Data

We obtain single stock price, fundamental and sector data from FactSet. All other data is obtained from Bloomberg, such as the S&P500 total return price index and USD three-month Libor rate as proxy for the risk-free rate.[12]

On a monthly basis, we select the base universe of stocks listed on the New York Stock Exchange (NYSE) and NASDAQ indices excluding REITS, ADRs and closed-end funds.[13] In order for this study to be practically relevant for investors, we also impose liquidity and market capitalisation filters at a stock level for ease of tradability in terms of cost and volume: Specifically, we remove stocks with less than $50 million three-month average daily volume (ADV) by notional and/or less than $5 billion by market cap. This in effect removes the very small cap stocks from being selected.

Factor Characteristics

Table 1 details the characteristics used for each of the four factors considered in this paper and the signal construction/ranking process. Whilst the focus of the paper is not an investigation into the characteristics

[8] For the interested reader, such a finding is also demonstrated by Frazzini and Pedersen (2014) within the context of a structural model with leverage and margin constraints that can vary across investors and time.

[9] More specifically, Sloan (1996) finds a negative relationship between accounting accruals and subsequent stock returns.

[10] Indeed Novy-Marx (2013) demonstrates that profitability exhibits a negative correlation with the Fama-French value factor.

[11] For clarity, they find that stocks with high operating profitability tend to perform better, as do stocks with low investment levels as proxied by total asset growth.

[12] We note that all price data used is based on gross dividends reinvested on the ex-dividend date.

[13] We specifically exclude REITS securities given concerns around known biases in the underlying fundamental/accounting data which makes it hard to compare with non-REITS based securities: https://www.reit.com/sites/default/files/media/Portals/0/Files/Nareit/htdocs/policy/accounting/2002_FFO_White_Paper.pdf.

used to select stocks for the respective factor portfolios, we acknowledge that this is a topical question for investors.

Single versus Multiple Characteristics

The first thing readers will notice is the use of multiple characteristics for all but the low volatility factor. In our opinion, the need to be confined to one single characteristic is not theoretically justified. Asness et al. (2015) specifically look at this question for the value factor and find that portfolios constructed from different value characteristics produce highly correlated returns. Consider also that the use of a single characteristic comes with the risk of measurement error (e.g. mis-reporting of fundamental data, re-stated data, missing data, etc.).

Indeed, Israel and Moskowitz (2013) find that using more characteristics leads to more stable portfolios with more reliable predictability, as an average of characteristics approach reduces the measurement error. This is especially important when building tradable factor baskets with an eye on backtest over-fitting – as confirmed by Asness et al (2015): "A strategy's out-of-sample performance is usually better (i.e. more closely matched to the backtest) when we use an average of multiple measures."

Justification of the Factor Characteristics

As the use of different characteristics to identify respective factors is hotly debated, whilst not the focus of this paper, for completeness we justify our use of these specific characteristics for the respective factors under consideration. We also note in testing these factor characteristics, robustness tests have been performed across different geographies.[14]

Value

Whilst there are a plethora of different characteristics that one could use, we use the combination of price-to-earnings (P/E) and total yield.[15] We do so as P/E is

Table 1: Definition of equity factor characteristics

Factor	Factor Characteristics	Signal Construction and Ranking Process
Value	1) Price/Earnings (P/E) 2) Total yield: Div Yield + Net Buyback Yield	***P/E signal***: Rank by 1 in ascending order ***Total yield signal***: Rank by 2 in descending order <u>Value signal</u>: 0.5 x ***P/E signal*** + 0.5 x ***Total yield signal***
Momentum	1) 12m – 1m price momentum 2) Consistency: Number of days with positive returns (historical 6m to 1m window) 3) Confirmation: Sum of daily returns (historical 6m to 1m window) 4) Current price/price high reached in historical 6m to 1m window	***Macro signal***: Rank by 1 in descending order ***Persistency signal***: 1/3 x *a* + 1/3 x *b* + 1/3 x *c*, where *a*: Rank by 2 in descending order *b*: Rank by 3 in descending order *c*: Rank by 4 in descending order <u>Momentum signal</u>: 0.5 x ***Macro signal*** + 0.5 x ***Persistency signal***
Low Volatility	1) Realised volatility: 1-year realised volatility of daily returns	<u>Low Volatility Signal</u>: Rank by realised volatility signal in ascending order
Quality	1) Earnings variability: Volatility of the change in earnings (historical 6y window) 2) Return of Assets 3) Accruals ratio	***EV signal***: Rank by 1 in ascending order ***ROA signal***: Rank by 2 in descending order ***AR signal***: Rank by 3 in ascending order <u>Quality signal</u>: 1/3 x ***EV signal*** + 1/3 x ***ROA signal*** + 1/3 x ***AR signal***

[14] Results available from the authors upon request.

[15] Total yield is the sum of the dividend yield and buyback yield. This is intuitively a better measure of how companies actually distribute cash to shareholders, i.e. directly via cash dividends and indirectly via share buybacks.

used most often by research analysts and practitioners as an assessment of value; and the combination of the two provides a filter for value traps, i.e. being able to select undervalued companies that still distribute cash. We also note that as total yield is an actual cash number, whilst earnings is an accounting based number (which is open to manipulation), the combination mitigates to some extend any accounting biases.

We do acknowledge that whilst the most commonly used value characteristic is no doubt the book-to-market-equity ratio (Fama and French (1993)), we have found that such a measure is overused which can potentially lead to crowding in the "value" names selected. We therefore favour the P/E ratio to mitigate overuse effects as documented by Khandani and Lo (2011).[16,17]

Momentum

In order to enhance the quality of the momentum signal we blend both a macro signal and three persistency signals. The former is based on the traditional way to assess for momentum, defined as the past 12-month return, skipping the most recent month' to avoid microstructure and liquidity biases. The later is to strengthen the signal against reversal effects through the use of consistency, confirmation and breakdown signals as defined in Table 1.

The idea for such a blend was to keep the overall nature of the signal the same, but to enhance its stability. For example, the breakdown signal helps to remove those stocks which may have had strong momentum in the first six months, but have since then reversed and are not strong momentum stocks anymore. Indeed the persistency signals typically reduce the volatility and turnover of the momentum basket.

[16] Empirical tests revealed that for a set of different characteristics used to select value stocks, the B/M ratio was the weakest in terms of return predictability. Results are available from the authors on request.

[17] This being said, we find that the strategy returns from using the P/E ratio to select stocks is highly correlated to the returns from using the B/M ratio instead (0.94 over the period from January 2003 to July 2016) but have the confidence that such a measure is less at risk of overuse whilst still being able to characterise value stocks (Basu (1977), Fama and French (1996)).

Low Volatility

For the low volatility factor, we estimate the volatilities based on a 1-year window of daily returns. Whilst the sample window size could be optimised we decided to use a 1-year window to balance both reactivity of the signal and to ensure a full 1-year earnings cycle when comparing the cross-section of companies, in order to avoid noise around earnings season.

As noted earlier, we are also aware that one could use the characteristic of CAPM Beta to assess for low volatility stocks, however in order to avoid adding the element of estimation error of correlation to the benchmark and also that the two characteristics (sample volatility and CAPM Beta) are highly correlated, on this occasion we only use the sample volatility characteristic.

Quality

Similarly to that of the value factor, a range of characteristics could be considered for selecting quality stocks. Our approach is based on analysing and assessing the quality of a company from three different angles: An earnings variability factor is used to measure how stable the earnings are; return on assets (ROA) are used to assess the profitability of the business and accurals to analyse whether the earnings are generated based on real cash flow or potentially based on revenue from accounting practices.

While the use of the characteristics on their own do not necessarily have the best historical performance for a quality basket, we believe these are intuitively complimentary to each other when combined: For example, a stock could have negative stable earnings and rank high on earnings variability but the ROA will ensure that this stock is excluded. Or there could be companies with high ROA but potentially generated through non-standard accounting practices - this is where the accruals characteristic is a useful addition.

Factor Portfolio Construction

Following on from the definitions of the characteristics used for the respective factors, a final blended signal for each respective factor (except for the low volatility factor) is used to assign each stock with a unique rank, i.e. 1 to the number of eligible stocks in the universe, with 1 being the worst rank.

This being said, we outline the methodology for the two equity multi-factor portfolios below.

Sum of Factors (SoF) Portfolio Construction

This is based on a six-step procedure which is rebalanced monthly – see Figure 3. The reader will note that we have refrained from using sophisticated weighting schemes which require estimates of expected return and risk.[18] We do so in order to investigate the nuances of equity multi-factor portfolio construction without complicating the question through the use of different weighting schemes. We therefore adopt the simplest weighting scheme possible in order to perform our study: equal weight.

Figure 3: SoF Portfolio Construction

1. **Base Universe:**
All stocks from the NYSE and NASDAQ indices excluding REITS, ADRs and closed-end funds

2. **Apply Stocks Filters: Remove stocks with**
- **Liquidity: Less than $50 million 3m ADV**
- **Market Cap: Less than $5 billion**

3. **Individual Factor Ranks:**
Assign respective ranks to the stocks for each individual factor

4. **Form Individual Factor Portfolios:**
Select top 50 stocks by respective factor rank and weight equally subject to Step 5

5. **Sector Restrictions:**
No more than 20% sector exposure

6. **Final Portfolio:**
Equally weight across the individual factor portfolios

We impose sector restrictions for both approaches to form multi-factor portfolios in order to mitigate sector concentration effects from driving our conclusions.[19] As readers will no doubt be aware, in practice, sector concentration can have a significant impact on the risk and return of factor portfolios. Therefore, sector restrictions or sector neutrality are often imposed in order to control for such effects in tradable factor baskets, as we do so here.

Multi-Factor Ranking (MFR) Portfolio Construction

For this approach, the portfolio construction steps differ for steps 4, 5 and 6.

Figure 4: MFR Portfolio Construction

1. **Base Universe:**
All stocks from the NYSE and NASDAQ indices excluding REITS, ADRs and closed-end funds

2. **Apply Stocks Filters: Remove stocks with**
- **Liquidity: Less than $50 million 3m ADV**
- **Market Cap: Less than $5 billion**

3. **Individual Factor Ranks:**
Assign respective ranks to the stocks for each individual factor

4. **Average Factor Rank:**
Final rank across each stock is then based on the average of the ranks in step 3

5. **Final Portfolio:**
Select top X stocks by final rank and weight equally subject to Step 6

6. **Sector Restriction:**
No more than 20% sector exposure

We note that for step 5 of the MFR portfolio, we comment that the top X stocks will be selected. X is equal to the number of stocks in SoF portfolio outlined in Figure 3.[20]

[18] A subtle but important point here is not only the difficulty in estimating expected returns but in estimating *changes* in expected returns, given the importance of this within portfolio rebalancing. The acknowledgement of this was first mentioned by Black (1993): "Estimating expected return is hard. Daily data hardly help at all. Only longer time periods help. We need decades of data for accurate estimates of average expected return. We need such a long period to estimate the average that we have little hope of seeing changes in expected return."

[19] We implement this through asserting that each stock in the portfolio is equally weighted as per the number of stocks in the overall portfolio, in this case 50. Based on this, we are able to back out the maximum number of stocks per sector that would meet the 20% sector exposure, which in this case is 0.20/(1/50) = 10 stocks per sector.

[20] The number of stocks in the SoF portfolio will not necessarily equal 200 (4 x 50) as a respective stock is able to be selected for each factor portfolio, given they are formed separately.

Controlling for the number of stocks in each of the multi-factor portfolios is our approach to ensure comparability of the portfolios. We note that Fitzgibbons et al. (2016) approach this *without a stock selection stage*, instead assuming a fixed universe of stocks (e.g. S&P500) where stock-level expected factor returns can be embedded into a utility-based optimisation (e.g. mean-variance) which targets a level of risk (e.g. tracking error). Thus in order to ensure comparability in their setup, they target both multi-factor portfolio approaches to have the same tracking error – however, they also comment that this equivalent to holding the same number of stocks if a stock selection stage is employed.

Lastly, we assume a transaction cost of 5 basis points on the turnover (at a single stock level) for the returns to be reflective of the cost of execution for the factor portfolios.

Empirical Results

Descriptive Statistics of Individual Factors

We first look at the historical simulations of the individual factors over the sample period presented in Table 2.[21] As expected, all of the factors have positive outperformance versus the S&P500, with varying magnitude but momentum and quality have the highest outperformance. In terms of risk, value and momentum have the highest risk, tail risk (as proxied by CVaR) and drawdown. They also have the largest turnover of the factors, 37% and 84% respectively. Table 3 highlights the well-known result of a slightly

Table 2: Individual US factor portfolio simulations, January 2003 – July 2016

	Value	Momentum	Low Volatility	Quality	S&P 500 TR
Annual Average Return (%)	11.97%	12.03%	11.90%	12.20%	10.63%
Annualised Volatility (%)	20.06%	19.66%	13.52%	17.31%	19.40%
Sharpe ratio	0.51	0.52	0.75	0.60	0.46
Sortino	0.72	0.73	1.08	0.86	0.65
95% VaR – Monthly	6.48%	7.38%	3.60%	5.92%	6.12%
95% CVaR – Monthly	10.58%	9.62%	6.16%	7.67%	9.03%
Max Drawdown (%)	59.78%	53.12%	36.78%	43.03%	55.25%
Turnover - Monthly (%)	36.71%	83.77%	22.77%	22.02%	-
Relative Performance Statistics (to S&P500 TR)					
CAPM Beta	0.99	0.88	0.65	0.86	-
Annual Outperformance (%)	1.34%	1.40%	1.27%	1.56%	-
Beta-Adj Ann. Outperformance (%)	1.47%	2.68%	5.05%	3.02%	-
Tracking Error (%)	5.99%	10.04%	8.58%	5.14%	-
Information Ratio	0.22	0.14	0.15	0.30	-
Max Relative Drawdown	22.73%	32.24%	25.35%	11.12%	-
Historical Outperformance (1Y)	66.21%	58.90%	58.90%	55.40%	-
Historical Outperformance (3Y)	77.22%	58.95%	55.52%	52.44%	-
Historical Outperformance (5Y)	78.17%	54.34%	62.58%	63.03%	-

[21] See appendix for specific definitions.

negative correlation (on a beta-adjusted basis[22]) between value and momentum which has been documented by Asness et al. (2013).

The low volatility factor has the lowest outperformance over the sample period but the highest beta-adjusted outperformance of 5% – which is the more comparable statistic given the different CAPM betas across the factors. Given the defensive nature of this factor, it has the highest Sharpe ratio (as a result of the low volatility) and highest Sortino.

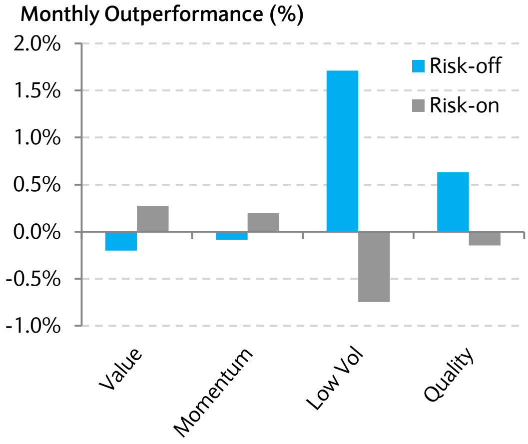
Conditional performance analysis in Figure 5 reveals the make-up of this factor versus the other factors in that it outperforms most significantly when there are downturns in market beta, i.e. risk-off states. Whereas during risk-on states, it tends to underperform the market highlighting the "defensive" nature of this factor. Interestingly, the quality factor displays similar characteristics to low vol.

Table 3: Sample correlation of the simulated individual factors

January 2003 – July 2016	Value	Mome-ntum	Low Vol
Long-only results			
Momentum	0.70	-	-
Low Vol	0.79	0.66	-
Quality	0.92	0.80	0.83
Beta-adjusted results			
Momentum	-0.26	-	-
Low Vol	-0.14	-0.11	-
Quality	0.21	0.20	0.08

Whilst these descriptive statistics highlight the nature of the factors, each will play a time-varying diversification role within a multi-factor portfolio which we will explore next.

Figure 5: Performance of the simulated individual factors during risk-off and risk-on states[23]



Descriptive Statistics of Multi-Factor Portfolios

Table 4 shows that the MFR portfolio has the same outperformance versus the S&P500, whereas on a beta-adjusted basis it significantly outperforms the SoF approach. It also has a higher Sharpe ratio of 0.65 versus 0.60 (for SoF) which comes from the lower volatility given that the annualised average returns are very similar. The latter two observations follow from the lower CAPM Beta of the MFR portfolio, which also contributes to the higher resulting tracking error. On the whole however, the MFR portfolio does appear better in performance terms than the SoF approach, as claimed by Fitzgibbons et al. (2016).

Note that unconstrained equity multi-factor portfolios will typically have a CAPM Beta of less than 1 when exposed to low volatility and quality, given the defensive nature of these factors – see Figure 5. This implicitly means that while such portfolios will tend to outperform during market sell-offs, they are subject to the risk of underperformance during risk-on periods. Investors would be wise to question this nuance of multi-factor portfolios to ensure the demonstrated historical performance is not solely coming from significant outperformance during risk-off periods, with mediocre outperformance during risk-on periods.

[22] By beta-adjusted we mean returns in excess of its respective CAPM Beta x returns of the S&P500.

[23] This conditional performance analysis is based on monthly returns in excess of the market returns, whereby negative monthly returns for the market characterise a risk-off state and positive monthly returns a risk-on state. We acknowledge that there are many risk-off and risk-on state definitions which could be used for such analysis.

Whilst the historical performance of the MFR approach appears better, interestingly the historical outperformance is slightly better for the SoF portfolio – indicating a higher historical outperformance frequency for the SoF approach. This potentially highlights a subtle bias in the MFR approach which is not being revealed by the performance figures – we explore this below.

Portfolio size: Concentrated versus diversified portfolios

An important ongoing debate is on how best to reap factor premia – be it via concentrated or more diversified portfolios. Amenc et al. (2016) interestingly found that the more concentrated factor portfolios did not noticeably increase the Sharpe or information ratios versus more diversified portfolios: In that any increase in the returns of the concentrated portfolios is accompanied by higher volatility and tracking error.

We offer another perspective in this debate in the context of multi-factor portfolios for concentrated versus diversified portfolios. Specifically we vary the number of stocks selected by the individual factor portfolios in Step 4 for the SoF portfolio from 25 – 200, and also create a comparable MFR portfolio as per Figure 4 which again sets X to be equal to the number of stocks in the respective SoF portfolio.

Figure 6 shows that in general as we increase the number of stocks in the portfolio, the outperformance increases, the Sharpe ratios marginally decrease which is mainly driven by the increase in the volatility of the portfolios, whilst the tracking error decreases – this is broadly in line with the findings of Amenc et al. (2016).

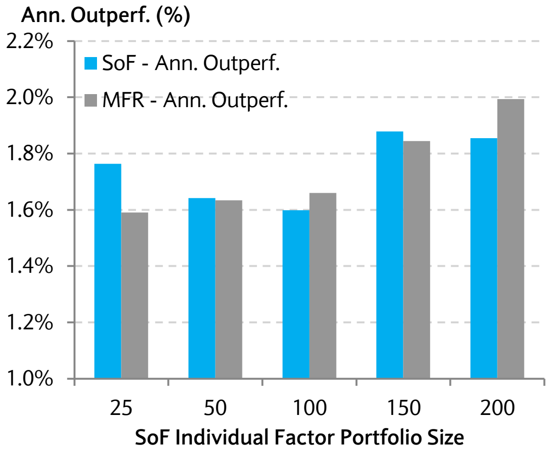
Before contrasting the SoF and MFR approaches, in general it appears from these results that diversified portfolios are better than concentrated portfolios in all aspects except for the increasing volatility.

Table 4: Multi-Factor US portfolio simulations, January 2003 – July 2016

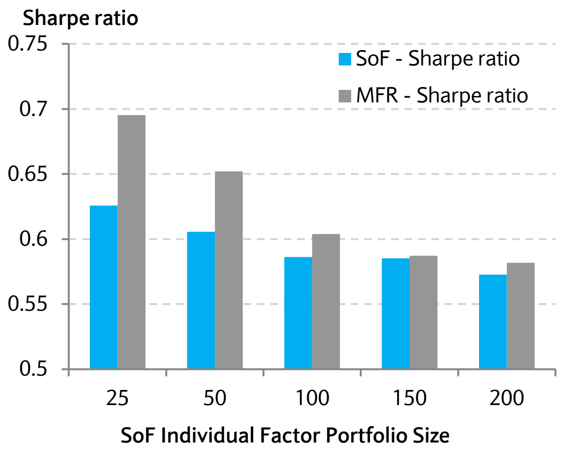
	Sum of Factors (SoF)	Multi-Factor Ranking (MFR)	S&P 500 TR
Annual Average Return (%)	12.27%	12.27%	10.63%
Annualised Volatility (%)	17.40%	16.15%	19.40%
Sharpe ratio	0.61	0.65	0.46
Sortino	0.85	0.92	0.65
95% VaR – Monthly	5.91%	5.65%	6.12%
95% CVaR – Monthly	8.38%	7.91%	9.03%
Max Drawdown (%)	50.02%	47.11%	55.25%
Turnover - Monthly (%)	36.66%	28.20%	-
Relative Performance Statistics (to S&P500 TR)			
CAPM Beta	0.88	0.81	-
Annual Outperformance (%)	1.64%	1.63%	-
Beta-Adj Ann. Outperformance (%)	2.93%	3.63%	-
Tracking Error (%)	4.22%	5.08%	-
Information Ratio	0.39	0.32	-
Max Relative Drawdown	6.13%	10.27%	-
Historical Outperformance (1Y)	75.80%	74.73%	-
Historical Outperformance (3Y)	83.18%	77.22%	-
Historical Outperformance (5Y)	84.41%	81.74%	-

Figure 6: Simulated SoF & MFR portfolios versus portfolio size

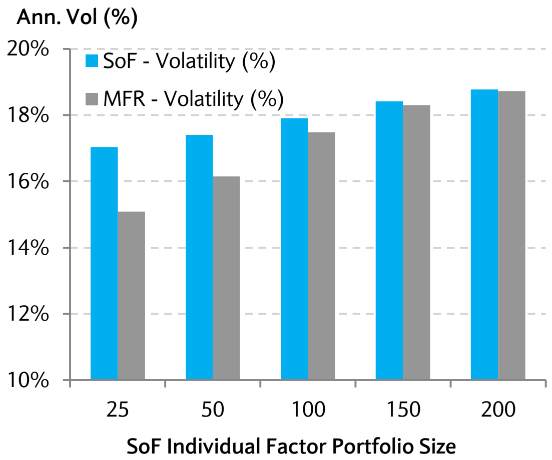
a. Annualised Outperformance



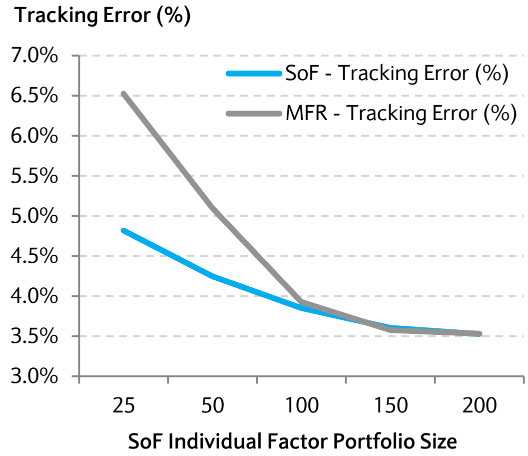
b. Sharpe ratio



c. Annualised Volatility

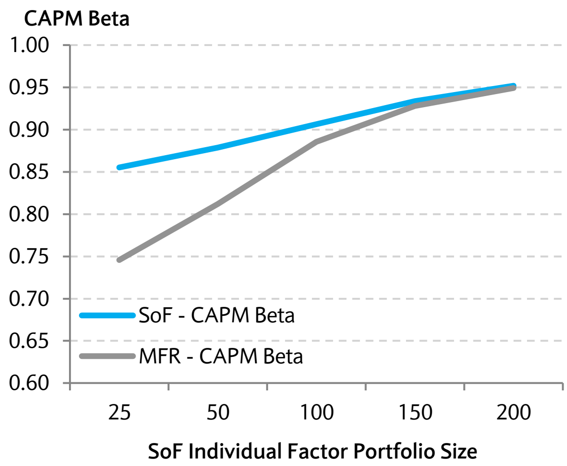


d. Tracking error



Whilst such a finding is counterintuitive at first glance, Figure 7 provides some insight: As the number of stocks increase, the CAPM Beta of both portfolios tends towards 1, hence one should rationally expect an increase in portfolio volatility towards that of the market portfolio. Such an observation should raise a question as to the importance of considering the CAPM Beta of the portfolio when comparing the efficacy of harvesting factor premia within concentrated or diversified portfolios.

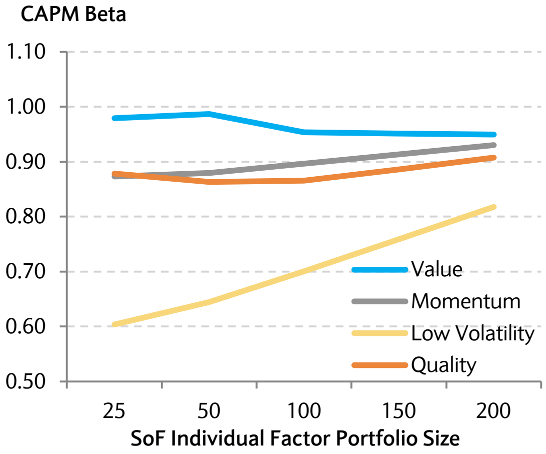
Figure 7: CAPM Beta of the simulated SoF & MFR portfolios versus portfolio size



The importance of CAPM Beta

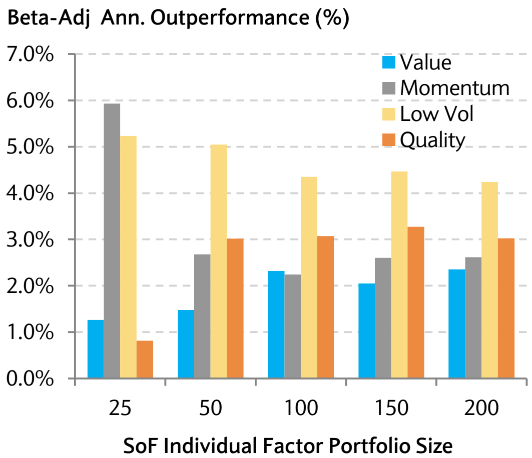
The need for such an examination is confirmed when looking at the CAPM Betas of individual factors as shown in Figure 8. Whilst we observe the same pattern as for the multi-factor portfolios (in that the portfolios tend to a CAPM Beta of 1 as the number of stocks is increased), the difference in CAPM Beta of a concentrated versus diversified portfolio can be very large for a respective factor, as demonstrated by all of the factors but especially so for the low volatility factor. Hence comparing portfolios without accounting for the CAPM Beta could be deemed unfair.

Figure 8: CAPM Beta versus portfolio size for the simulated individual factors



In results not displayed here, as for the multi-factor portfolios, we broadly agree with the findings of Amenc et al. (2016) for the respective individual factors when we do not adjust for the CAPM Betas of the portfolios with differing number of stocks.[24] However as can be seen from Figure 9, when adjusting for the CAPM Beta, the outperformance for momentum and low volatility concentrated portfolios are substantially higher than for the larger portfolios. As for value and quality, besides the jump in performance from 25 to 50 stocks, there is no convincing pattern from having 50 to 200 stocks in the portfolio.

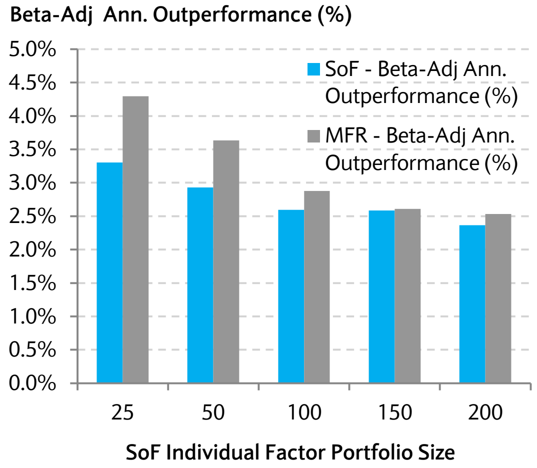
Figure 9: Beta-adjusted annualised outperformance for the simulated factors versus portfolio size



[24] These results are available upon request.

As for the multi-factor portfolios, Figure 10 displays the same CAPM Beta adjusted outperformance. In both cases, the outperformance decreases as the number of stocks in the portfolio increases. Thus on a beta-hedged basis, investors may be able to earn higher returns by forming concentrated portfolios.

Figure 10: Beta-adjusted annualized outperformance for the simulated multi-factor portfolios versus portfolio size



Turning back to contrasting the multi-factor portfolios, we observe also from Figure 10 that the magnitude of outperformance across the differently sized portfolios is larger for the MFR portfolio than for SoF. This observation is in addition to the generally better outperformance, Sharpe ratio and lower volatility of the MFR compared to that of the SoF shown within Figures 6a, 6b and 6c.[25] However, the noticeably higher tracking error of concentrated MFR portfolios is as a result of the persistently lower CAPM Beta as shown in Figure 7. We note that the gap in both Figures 6d and 7 reduce as we increase the number of stocks because of the liquidity and market cap level stock filters, which cause the overlap of names in the two portfolios to increase.[26]

Factor Correlation

Fitzgibbons et al. (2016) theoretical motivate that the benefits of MFR portfolios are particular high when

[25] This is the case for all observations except for the outperformance when the individual factor basket is composed of 25 stocks – where the SoF outperforms the MFR. We posit that this result is because of the prevailing idiosyncratic risk given the very small size of these portfolios.

[26] In results not displayed here, when we relax the stock-level filters to include all stocks in the S&P500 for the base universe, the gap between the tracking error and CAPM Beta curves remain as the number of stocks is increased.

factor correlation is negative. This intuition appears consistent with our empirical results above given the negative (beta-adjusted) correlations between value, momentum and low volatility (as shown in Table 3) and the resulting outperformance of the MFP over the SoF approach. We extend this intuition to also consider the resulting risk exposure taken by the MFR portfolio versus that of the SoF portfolio in order to outperform it.

Factor loadings: Ex-ante versus ex-post factor exposure

In order to further dissect the performance of the SoF and MFR portfolios, we look to the underlying factor exposure. Given the approach in Figures 3 and 4 to form the SoF and MFR portfolios, the ex-ante intention is to form portfolios that are well-balanced across the factor premia - investors should therefore be mindful if this is the case ex-post.

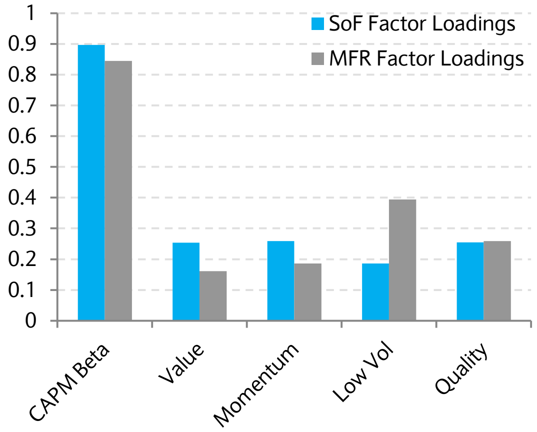
Table 5: Sample correlation of the simulated multi-factor portfolios versus each other and individual factors

January 2003 – July 2016	SoF	MFR
Long-only results		
SoF	-	0.92
Value	0.94	0.85
Momentum	0.88	0.90
Low Vol	0.86	0.96
Quality	0.97	0.99
Beta-adjusted results		
SoF	-	0.78
Value	0.32	0.17
Momentum	0.70	0.46
Low Vol	0.14	0.49
Quality	0.58	0.51

We firstly look at the sample correlations in Table 5 of the multi-factor portfolios to the separate individual factor portfolios. If a long-only multi-factor portfolio is harvesting the underlying factor premia to which it has exposure to, its returns should be somewhat positively correlated to each of the individual factor portfolios returns: This can broadly be seen to be the case for both the SoF and MFR portfolios. We also observe a correlation of 0.78 of the beta-adjusted SoF returns to that of the MFR which provides further comfort.

Figure 11 extends the analysis through regressing the excess returns of the multi-factor portfolios on the excess returns of the market and beta-adjusted individual factors.[27] Interestingly, a large factor loading to the low volatility factor can clearly be seen for the MFR approach, whilst a more balanced loading is seen for the SoF portfolio. Thus on a regression basis, it is clear that the MFR approach has relied heavily on the returns of the low volatility factor.[28]

Figure 11: Factor loadings on the simulated multi-factor portfolios



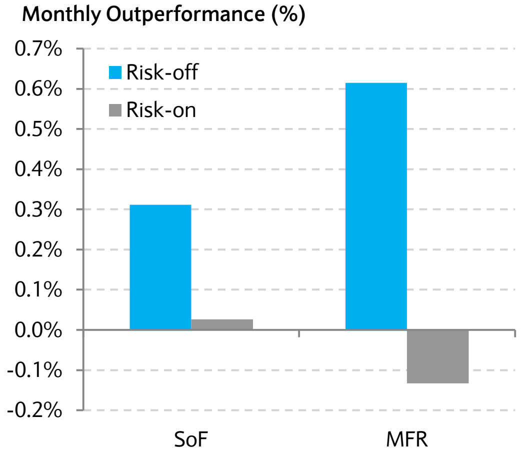
This large bias towards low volatility stocks can also be seen in Figure 1 which depicts the bottom-up average factor score of stocks in the multi-factor portfolios at each rebalance and through time. The favouring of stocks with high low volatility rankings by the MFR approach can clearly be seen from this chart. This is also emphasised in Figure 12 which highlights the risk-on/risk-off behaviour: The MFR portfolio actually underperforms the market on average during risk-on periods, with all of the outperformance coming from risk-off periods during the sample period studied. Whilst the SoF portfolio also does best during risk-off periods, it historically did not significantly underperform the market during

[27] The regression is performed based on monthly total returns where the market factor is the excess return of the S&P500 over the risk-free rate and the equity factors are the CAPM Beta-adjusted excess returns. The risk-free rate is based on the three-month US Treasury bill yield.

[28] In results not displayed, the coefficients of the regression are significant to a 1% level. Results are available on request.

risk-on periods, reflecting the more balanced nature of the underlying factor exposure.

Figure 12: Performance of the simulated SoF and MFR portfolios during risk-off and risk-on states[29]



Whilst one can indeed adjust the multi-factor ranking model to attempt to correct for this low volatility bias, we posit that doing so adds a layer of parameterisation with well-known implications on backtest overfitting (Harvey and Liu (2015)).[30]

We refrain from linking the occurrence of the bias to a correlation story and leave this as an area for future exploration. Thus irrespective of why for now, it is clear that such a bias will not only tilt the expected returns of MFR portfolios towards the expected returns of the low volatility factor; but the portfolio will also be subject to the risk of under-performance versus the more balanced approach of the SoF if the risk to low volatility stocks prevails. Such a risk and the implications for expected returns were recently discussed by Arnott et al. (2016) who posit an overvaluation of the low volatility factor and the increasing risk of a potential sell-off.

We also note that whilst investors may choose to accept this bias given the more defensive tilt of the MFR portfolio relative to the SoF portfolio (which has been rewarded over the sample period studied), the ex-ante intention of both approaches in the set up was to obtain balanced factor exposure, which ex-post is not the case. Therefore, on a forward looking basis, investors should also be mindful of the excess exposure to the low volatility factor.

Conclusion

In this study we empirically compare the different approaches that can be used to form equity multi-factor portfolios: Sum of Factors versus Multi-Factor Ranking. The former being based on the combination of separately formed factor portfolios whilst the latter directly selects stocks ranked by a specified multi-factor model, which in our case is the average of the individual respective factor scores.

We do so as investors are presented with the different approaches from different providers without justification – implicitly assuming that despite the portfolio formation process, the resulting outcome to obtain equity multi-factor exposure is the same. In this study we therefore empirically look into the nuances of the multi-factor construction process and implications.

We specifically compare the approaches in the context of two topical implementation considerations for equity factor investing – portfolio size and factor exposure.

For the first consideration we empirically found that increasing the number of stocks for both multi-factor portfolios did not necessarily translate to more efficiency in harvesting the factor premia. Indeed we highlighted an important nuance in accounting for CAPM Beta of the portfolios when comparing concentrated versus diversified portfolios. With such an adjustment, both concentrated multi-factor portfolios outperformed the more diversified portfolios by up to 1.5% per year inclusive of transaction costs, and thus despite the slightly higher turnover of concentrated portfolios.

We also found that across the size spectrum of the portfolio, MFR portfolios persistently outperform the SoF approach on a beta-adjusted basis, which was driven by the lower CAPM Beta of the MFR portfolio to that of the SoF.

Secondly, in assessing the underlying factor exposure of the two multi-factor portfolios, the lower CAPM Beta, higher Sharpe ratio and beta-adjusted

[29] This conditional performance analysis is conducted similarly to Footnote 23.

[30] Given the biased nature of the average estimator, we also test using the median in Step 4 of the MFR approach – our findings of a low volatility bias remain the same for the avoidance of doubt.

outperformance for the MFR portfolio came from a persistent bias to the low volatility factor – which naturally has a low CAPM Beta relative to the rest of the equity factors and has had good periods of outperformance over our sample period. This bias was confirmed by regression tests as well as assessing the bottom-up average factor score of stocks in the portfolios for the two multi-factor approaches.

Whilst we empirically demonstrate the performance benefits of a MFR approach, we also document a potential bias in the portfolio formation process. Such a bias comes with performance risk implications that investors should be made explicitly aware of when choosing between the different equity multi-factor portfolio construction approaches.

Appendix

Definition of Terms

- 95% VaR – Monthly: Defined as the percentage loss which will not be exceed over a monthly horizon with 95% confidence

- 95% CVaR – Monthly: Defined as the expected loss over a monthly horizon, conditional on the loss being within the 5th percentile of the return distribution

- Probability of Outperformance (xY): Defined as the performance of the respective portfolio above its benchmark over the specified period of x Years through rolling window analysis based on weekly returns with a 1 week step size; where at each step the geometric average returns of the portfolio to those of the benchmark are assessed. The statistic is then calculated as the number of times that the average portfolio returns outperform the benchmark average is the counted and divided by the total number of rolling year return comparisons. The intuition here is that it provides an assessment of the (historical) probability of outperforming the benchmark, when investing at any point in history (on a weekly basis) for a specified holding period of x Years

- Max Relative Drawdown: Defined as is the maximum loss between a peak and trough experienced by the strategy with respect to its benchmark over the sample period. It is typically used to assess the downside risk exposure of the strategy with respect to its benchmark

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