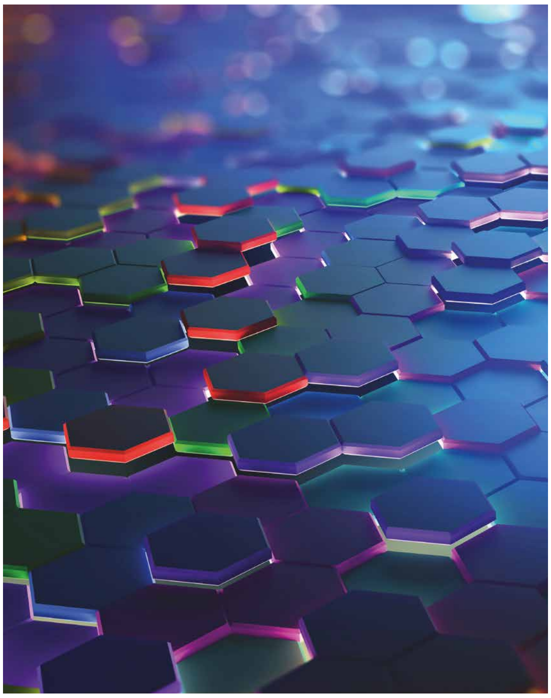
Economic versus statistical clustering in multi-asset multi-factor strategies

By Dr. Martin Kolrep, Dr. Harald Lohre, Erhard Radatz and Carsten Rother

In brief

Maximizing for diversification in the multi-asset multi-factor universe, the literature advances diversified risk parity strategies across economic clusters. For handling overly complex correlation matrices, hierarchical clustering techniques have recently been put forward to guide risk parity allocations. Indeed, such statistical clusters might be considered natural portfolio building blocks given that they automatically pick up the dependence structure and thus form meaningful ingredients to aid portfolio diversification. We explain the intuition and nature of hierarchical clustering techniques in the context of multi-asset multi-factor investing vis-à-vis the use of economic factors in diversified risk-based allocation paradigms such as 1/N, minimum-variance and diversified risk parity.



In an attempt to construct better, more efficient risk-managed portfolios, investors can diversify their portfolios through factors rather than traditional asset classes. Very often, however, this entails a correlation matrix so complex that it cannot be fully analyzed. In this study, we show how this problem can be addressed by using hierarchical clustering techniques and we investigate meaningful ways of generating a coherent multi-asset multi-factor allocation to harvest the associated asset and factor premia in a balanced fashion.

Standard portfolio theory suggests aiming for an optimal risk-return tradeoff by resorting to the seminal mean-variance paradigm of Markowitz (1952). Yet, given the notorious sensitivity of mean-variance portfolio optimization with regard to expected return inputs, one may disregard forecasting returns and focus on estimating risk instead. As a result, researchers have developed various risk-based allocation strategies in pursuit of portfolio diversification.

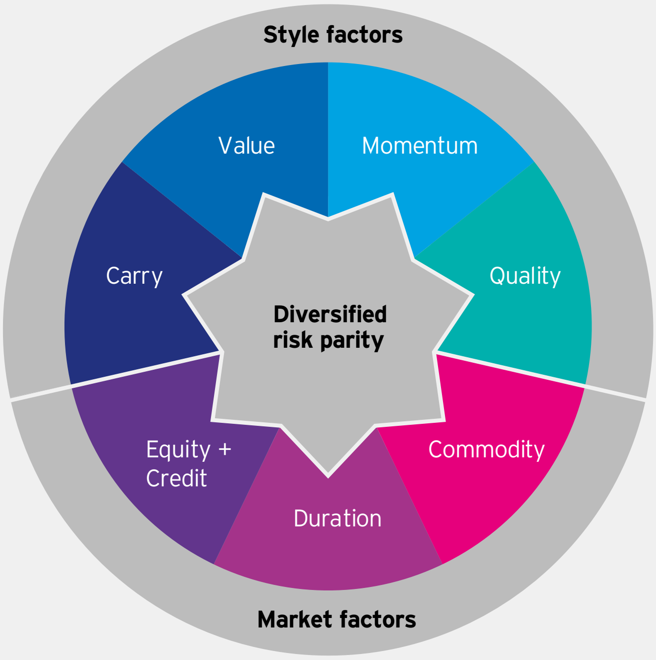
The literature has advanced diversified risk parity strategies designed to maximize diversification benefits across asset classes and style factors.

An innovative approach to managing diversification was introduced by Meucci (2009). Conducting a principal component analysis (PCA), he aims to identify the main risk drivers in a given set of assets. The ensuing principal components can be viewed as principal portfolios representing uncorrelated risk sources. A portfolio is considered well-diversified if the overall risk is distributed equally across these uncorrelated principal portfolios. Given the statistical nature of PCA, Meucci, Santangelo and Deguest (2015) propose a minimum-torsion transformation to derive uncorrelated risk sources that are economically more meaningful. Along these lines, the literature has advanced diversified risk parity strategies designed to maximize diversification benefits across asset classes and style factors; see Lohre, Opfer and Orszàg (2014), Bernardi, Leippold and Lohre (2018) and Dichtl, Drobetz, Lohre and Rother (2019).

Such an approach is dependent on designing an appropriate risk model, and it comes with several degrees of freedom. Accordingly, the recent literature presents risk parity allocation paradigms guided by hierarchical clustering techniques, prompting Lopez de Prado (2016) to label the technique 'hierarchical risk parity' (HRP). Given a set of asset class and style factor returns, the corresponding algorithm would cluster these according to some distance metric and then essentially allocate risk budgets equally along these clusters. Such clusters might be deemed more akin to natural building blocks than some aggregated factors in that they automatically pick up the dependence structure and are thus expected to form meaningful constituents to aid portfolio diversification.

In this article, we examine the mechanics and merits of hierarchical clustering techniques in the context of multi-asset multi-factor investing. We contrast these techniques with competing risk-based allocation paradigms, such as 1/N, minimum-variance and diversified risk parity. Hierarchical risk parity strategies generally build on two steps: first, hierarchical clustering algorithms uncover a hierarchical structure within the investment universe, represented in a tree-based map. Second, the portfolio weights are obtained by applying an allocation strategy along the hierarchy, which promises to deliver a meaningful degree of diversification.

Figure 1
Diversified risk parity across economic factors



Source: Invesco. For illustrative purposes only.

As estimates of covariance or correlation matrices are subject to estimation errors, filtering correlation-based clusters and networks are meaningful for constructing diversified portfolios.

As estimates of covariance or correlation matrices are subject to estimation errors, filtering correlation-based clusters and networks are meaningful for constructing diversified portfolios resulting in more reliable outcomes, see Tumminello (2010). In this vein, Lopez de Prado (2016) argues that a correlation matrix is too complex to be fully analyzed and lacks a hierarchical structure. Instead of analyzing the full correlation matrix, he suggests considering the corresponding 'minimum spanning tree' (MST) with N nodes (one node for each asset) and only N-1 edges, i.e. focusing on the most relevant correlations. Deriving the MST requires the definition of a distance measure, often referred to as a 'dissimilarity measure'. The MST is naturally linked to the hierarchical clustering algorithm, called single linkage. In a direct way, the MST reflects the hierarchical organization of the investigated assets, and the optimal portfolio weights can be derived by applying an allocation scheme to the hierarchical structure.

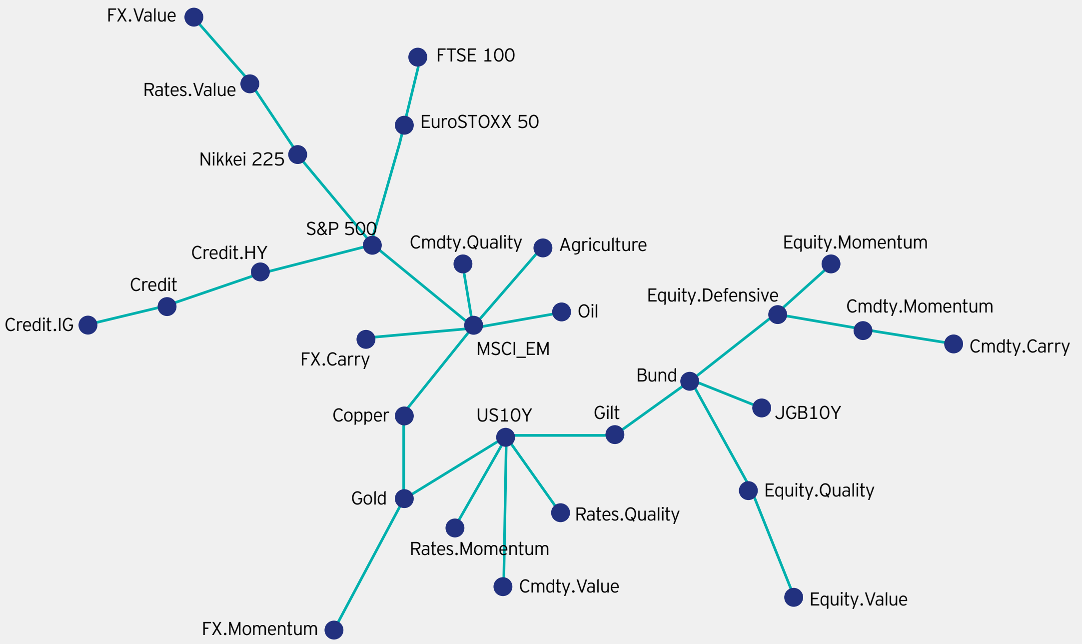
Economic factors in the multi-asset multi-factor universe

We consider a multi-asset multi-factor investment universe that combines the traditional asset classes equities, bonds (interest rates), commodities and credit, as well as different style factors. The monthly times series are available for the period from 31 January 2001 to 31 October 2018. The global equity and bond markets are represented by equity index futures for the S&P 500, Nikkei 225, FTSE 100, EuroStoxx 50, MSCI Emerging Markets and bond index futures for US 10Y Treasuries, Bund, 10Y Japanese Government Bonds (JGB) and UK gilts. The credit risk premium is captured by the Bloomberg Barclays US Corporate Investment Grade (Credit IG) and High Yield (Credit HY) Indices; both are interest rate duration hedged to synthesize pure credit risk. Gold, oil and copper indices are chosen to cover the commodity market.

In addition, we consider the four investment styles carry, value, momentum and quality (figure 1). Carry is based on the idea that high yield assets tend to outperform low yield assets, while momentum investors assume that recent winning assets outperform recent losing assets. Quality (or defensive) investing builds on the observation that high quality assets tend to have higher risk-adjusted returns than low quality assets. Value investing is based on the idea that cheap assets (according to a given valuation metric) tend to outperform expensive assets. We source the underlying return time series from Goldman Sachs (GS) and Invesco Quantitative Strategies (IQS). The factor definitions are given in the appendix.

To measure diversification, we consider an appropriate factor model encompassing suitable economic factors.

Figure 2
Minimum-spanning tree



Notes: The figure depicts the correlation network as a minimum spanning tree for the multi-asset multi-factor universe building on the variance-covariance matrix using monthly data from the full sample period from 31 January 2001 to 31 October 2018.
Sources: Bloomberg, Invesco, Goldman Sachs.

To benchmark the statistical clusters vis-à-vis economic factors, we include a parsimonious set of market factors: equity + credit, duration and commodity (figure 1). Further, taking a pure style factor investing perspective, we build aggregate style factors across asset classes, i.e. the aggregate momentum style factor is based on equity momentum, FX momentum, rates momentum and commodity momentum. In the same vein, we construct aggregate carry, value and quality factors.

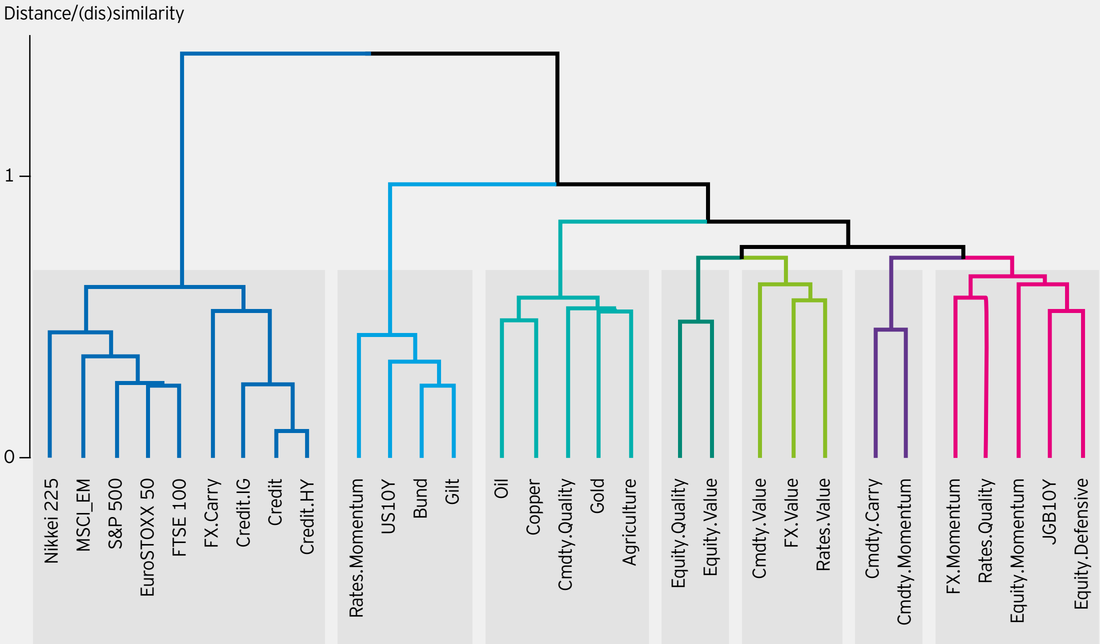
Diversified risk parity based on economic factors
Striving for a well-diversified portfolio, Meucci (2009) constructs uncorrelated risk sources embedded in the underlying portfolio assets. A well-diversified portfolio would follow a risk parity strategy applied to these uncorrelated risk sources; see Lohre, Opfer and Ország (2014). To construct uncorrelated risk sources, Meucci (2009) suggests using principal component analysis (PCA). Yet, follow-up research by Meucci, Santangelo and Deguest (2015) instead advocates a minimum-torsion transformation to derive the linear orthogonal transformation closest to the original assets (or a pre-specified factor model). Thus, we follow Dichtl, Drobetz, Lohre and Rother (2019) in using the minimum-torsions of the three market and four style factors introduced in figure 1.

The hierarchical structure of the multi-asset multi-factor universe
Portfolio optimization methods like the Markowitz mean-variance approach are sensitive to changes in input variables, and small estimation errors can lead to vast differences in optimal portfolio allocations. However, correlation and covariance matrices are quite complex, and they disregard the hierarchical structure of asset interactions. To reduce complexity, one wants to focus on relevant correlations only. In this regard, a well-known approach from graph theory is the minimum spanning tree (MST) that connects all entities (here: assets and factors) without cycles but with the minimum total edge weight. An algorithm for obtaining the MST was introduced by Prim (1957). Before applying this algorithm, one has to define a distance measure, which is often based on the correlation coefficient. We will refer to this measure as the dissimilarity measure, since it aims to measure the dissimilarity of the assets (and factors).[1] Applying the dissimilarity measure to the correlation matrix leads to the so-called 'dissimilarity matrix' and allows us to derive the MST (figure 2). When the MST is based on correlations, it is also often referred to as a correlation network.

The MST reflects essential information contained in the correlation matrix and introduces a hierarchical structure. Looking at the branches, one particularly identifies an equity risk-like cluster and a more defensive cluster, among others.

Graph theory is linked to unsupervised machine learning. In particular, the MST is naturally related to the hierarchical clustering algorithm called single linkage. In a direct way, the MST conveys the hierarchical organization of the investigated assets and style factors, which results in a tree structure as represented by the dendrogram in figure 3.[2] Moving up the tree, objects that are similar to each other are combined into branches, i.e. the higher the height of the fusion, the less similar the objects are. Note that one has to define how to use this information for measuring the (dis)similarity among

Figure 3
Dendrogram based on Ward's method



Notes: The figure depicts the dendrogram based on Ward's method for the multi-asset multi-factor universe building on the variance-covariance matrix using monthly data from the full sample period from 31 January 2001 to 31 October 2018.
Sources: Bloomberg, Invesco, Goldman Sachs.

clusters containing more than one element. This is done by the respective linkage criterion; we consider dendrograms based on Ward's method going forward.[3]

In the case of a large investment universe, it might make sense to consider the dendrogram only up to a certain level rather than taking the whole hierarchical structure into account. While this reduction leads to a loss of information, it makes finding the weight allocation faster. Cutting the dendrogram will partition the assets and style factors into clusters. There are different ways to determine an optimal number of clusters. One could simply choose a plausible number by looking at the dendrogram or apply a statistical criterion for determining the "optimal" number of clusters. An example is given in figure 3, where the number of clusters was deliberately chosen to be seven.

Portfolio allocation based on hierarchical clustering

Having determined the dendrogram, one has to decide how to allocate one's capital. Instead of using an algorithm based on recursive bisection as in Lopez de Prado (2016), Lohre, Rother and Schäfer (2020) propose investing along the nodes of the dendrogram to integrate the hierarchical information. Further, one has to choose an allocation technique within and across clusters – Lopez de Prado uses the inverse variance strategy in both cases, but there are various other alternatives. For instance, Papenbrock (2011) and Raffinot (2017) suggest a weighting scheme that allocates capital equally across cluster hierarchy and within clusters. In our study, we use a combination of risk parity based on equal risk contributions. The algorithm of Lohre, Rother and Schäfer is described

Box
Algorithm: Clustering-based weight allocation

1. *Perform hierarchical clustering and generate dendrogram*
2. *Assign all assets a unit weight* $\omega_i = 1 \;\forall\; i = 1,\ldots,N$
3. *For each dendrogram node (beginning from the top):*
   a. *Determine the members of clusters* C_1 *and* C_2 *belonging to the two sub-branches of the according dendrogram node*
   b. *Calculate the within-cluster allocations* $\widetilde{\omega}_1$ *and* $\widetilde{\omega}_2$ *for* C_1 *and* C_2 *according to risk parity (equal risk contributions)*
   c. *Based on the within-cluster allocations* $\widetilde{\omega}_1$ *and* $\widetilde{\omega}_2$ *calculate the across-cluster allocation* α *(splitting factor) for* C_1 *and* $1 - \alpha$ *for* C_2 *according to to risk parity (equal risk contributions)*
   d. *For each asset in* C_1 *re-scale allocation* ω *by factor* α
   e. *For each asset in* C_2 *re-scale allocation* ω *by factor* $1 - \alpha$
4. *For each cluster containing more than one element:*
   a. *Determine the members of the cluster*
   b. *Calculate the within-cluster allocation*
   c. *For each asset in the cluster re-scale* ω *by the within-cluster allocation*
5. *End*

Table 1
Performance statistics of multi-asset multi-factor strategies

Performance statistics	1/N	MVP	DRP	HRP	HRP Smooth
Gross return p.a. (%)	4.23	3.95	4.20	3.95	4.43
Net return p.a. (%)	3.96	3.33	3.78	3.22	3.76
Volatility p.a. (%)	3.45	1.38	1.51	1.57	1.63
Sharpe ratio	0.74	1.37	1.54	1.14	1.42
Maximum drawdown (%)	-8.62	-1.20	-1.20	-1.83	-2.03
Calmar ratio	0.46	2.77	3.16	1.77	1.85
Number of bets	3.15	4.35	7.00	6.02	6.17
Turnover (%)	1.55	5.61	3.72	17.22	12.99

Notes: The table provides simulated performance figures for risk-based multi-asset multi-factor strategies from the perspective of a US-dollar investor. This model does not factor in all of the economic and market conditions that can impact results.
Sources: Bloomberg, Invesco, Goldman Sachs. Period: January 2006 to October 2018. **The figures refer to simulated past performance and past performance is not a reliable indicator of future performance.**

in the box. It starts at the top of the dendrogram and assigns weights by going from node to node. Note that step 4 in the algorithm needs only be executed if an optimal number of clusters is used, i.e. not all remaining clusters are singleton clusters.

Hierarchical risk parity for multi-asset multi-factor allocations

In this section, we focus on examining hierarchical risk parity strategies in the multi-asset multi-factor domain vis-à-vis the alternative risk-based allocation strategies 1/N, minimum-variance (MVP) and diversified risk parity (DRP). The traditional risk-based allocation strategies are directly applied to the seven aggregated factors resulting from the imposed aggregate factor model. These seven factors can be viewed as "economic" clusters, providing a benchmark for the "statistical" hierarchical clustering. As for HRP, the allocation strategies used either within or across clusters are risk parity, based on equal risk contributions. For hierarchical clustering, we use Ward's method and the dissimilarity matrices are derived from the correlation matrix.[4]

Portfolio rebalancing is conducted on a monthly basis. The strategies are assumed to be implemented using futures and swaps with associated transaction costs of 10 basis points (futures) and 35 basis points (swaps), respectively. Furthermore, 8 basis points per month are considered for holding a given swap. A 5-year rolling window of monthly returns is used for estimation of the covariance matrix, and the resulting correlation-based dendrograms are updated every month. We perform backtests of the investment strategies from January 2006 to October 2018.[5]

Table 1 shows performance and risk statistics as well as the average strategy turnover. First, we note that the 1/N strategy suffers from the highest volatility, as well as the highest maximum drawdown, rendering its risk-adjusted performance sub par. The underlying lack of diversification is discernible from only 3.15 bets averaged over time. Minimum-variance optimization enables an increase of this number to 4.35. Unsurprisingly, MVP exhibits the lowest portfolio volatilities in the sample period (1.38%). Maximum drawdown figures and risk-adjusted returns are also improved relative to equal weighting.

Next, we examine the middle-ground solution in between 1/N and minimum-variance: diversified risk parity, which is designed to have a maximum of seven bets over time. Its gross return is almost as high as that of 1/N (4.20%) while its turnover is in between the one of 1/N and MVP. As a result, it has the highest net Sharpe ratio.

Having investigated the risk-based strategies for economic factors, we are eager to learn how the approach based on statistical clusters fares. From a volatility perspective, we note that HRP is almost on par with MVP and DRP (1.57%). Also, despite being grounded in statistical clusters, we note that HRP captures 6.02 bets on average. However, the HRP allocation exhibits rather high turnover (17.22%), bringing the net Sharpe ratio down to 1.14. Moreover, the HRP is characterized by a maximum drawdown of -1.83%, which is more severe than the respective figures for MVP (-1.20%) and DRP (-1.20%).

Of course, one would have hoped to enable competing particularly in this statistic when diversifying by statistical clusters. Presumably, the statistical nature of the HRP renders the strategy too active following changes in the correlation structure. As a remedy, we have examined a smoothed HRP variant that is anchored in the optimal HRP portfolio but subject to a transaction cost penalty to smooth the overall allocation and implicitly reduce the associated transaction costs.[6] The last column of table 1 highlights the efficacy of the transaction cost penalty. We observe an increase in returns, yet risk characteristics are hardly affected, rendering it roughly on par with the outcome of the diversified risk parity strategy.

Conclusions

The main motivation to base an allocation strategy on hierarchical clustering is that the correlation matrix is too complex to be fully analyzed and lacks the notion of hierarchy. Hierarchical clustering reduces complexity by focusing on the correlations that really matter. Hierarchical risk parity is an intuitive investment approach, allowing for a high degree of flexibility. Though conceptually appealing, our empirical study suggests that a pure HRP allocation creates substantial turnover when seeking to follow the ensuing dynamic clusters and hierarchy.

We consider a transaction cost penalty to be an effective means to smooth the HRP allocation, rendering its return similar to a diversified risk parity strategy based on economic factors, but not its diversification and downside risk.

Hierarchical clustering reduces complexity by focusing on the correlations that really matter.

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Appendix

Here, we briefly describe the single asset and style factor indices underlying the article's empirical analyses. The global equity and bond markets are represented by equity index futures for S&P 500, Nikkei 225, FTSE 100, EuroSTOXX 50, MSCI Emerging Markets and bond index futures for 10-year US Treasuries, German Bunds, 10-year JGBs and Gilts. The credit risk premium is captured by the Bloomberg Barclays US Corporate Investment Grade (Credit IG) and High Yield (Credit HY) indices (both duration-hedged to synthesize pure credit risk). To capture commodity markets, we consider total return indices of S&P GSCI for crude oil and gold as well as total return indices from Bloomberg for copper and agriculture.

All style factors are constructed in a long-short fashion and all non-equity style factors are sourced from Goldman Sachs (GS); see table 2 for the style factor indices used. For equity style factors, we utilize the Invesco Quantitative Strategies definitions as laid out in "Investing in a multi-asset multi-factor world", Risk & Reward, #3/2017. In particular, equity value, momentum and quality each follow a multi-factor approach that combines several metrics proxying for the respective style dimension. For equity defensive, we build on a long-short approach that is long a minimum-volatility portfolio while shorting a beta-adjusted market portfolio.

Table 2: **Overview of style factor series**

Style factor	Equity	Fixed Income	Commodity	FX
Carry	–	GS Interest Rates Carry 05	GS Macro Carry Index RP14	GS FX Carry C0115
Value	IQS Value	GS Interest Rates Value 05	GS Commodity COT Strategy COT3	GS FX Value C0114
Momentum	IQS Momentum	GS Interest Rates Trend	GS Macro Momentum Index RP15	GS FX Trend C0038
Quality	IQS Quality & IQS Defensive	GS Interest Rates Curve C0210	GS Commodity Curve RP09	–

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Notes

1 There are numerous ways of defining the dissimilarity measure, including Euclidean and Manhattan distances; in this article, we will consider

$$d : B \rightarrow [0,1]$$

$$d_{i,j} = d(X_i, X_j) = \sqrt{0.5(1-\rho_{i,j})}$$

where $\rho_{i,j} = \rho_{i,j}(X_i, X_j)$ is the Pearson correlation coefficient. One can verify that d is a dissimilarity measure; see for instance Lopez de Prado (2016). For perfectly positive correlated assets ($\rho_{i,j} = 1$), we have $d = 0$. For perfectly negatively correlated assets ($\rho_{i,j} = -1$), we have $d = 1$.

2 See Mantegna (1999) for early applications of MSTs in equity universes.

3 There are various criteria but the most common ones are single linkage, complete linkage, average linkage and Ward's method; see for instance Raffinot (2017). Ward's method minimizes the total within-cluster variance and results in compact clusters of similar size, making it a popular choice among researchers. Conversely, single linkage suffers from chaining, and the other methods are sensitive to outliers.

4 Lohre, Rother and Schäfer (2020) investigate HRP strategies based on tail-dependence clustering as opposed to standard correlation-based clustering. Such an approach might be particularly relevant given the elevated tail risk of some style factors.

5 The backtest is based on a rolling window estimation using the initial estimation window of 60 months starting in January 2001.

6 See Dichtl, Drobetz, Lohre and Rother (2019) for the implementation of such turnover penalties.

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