The Frontier Line

Thought leadership and insights from Frontier

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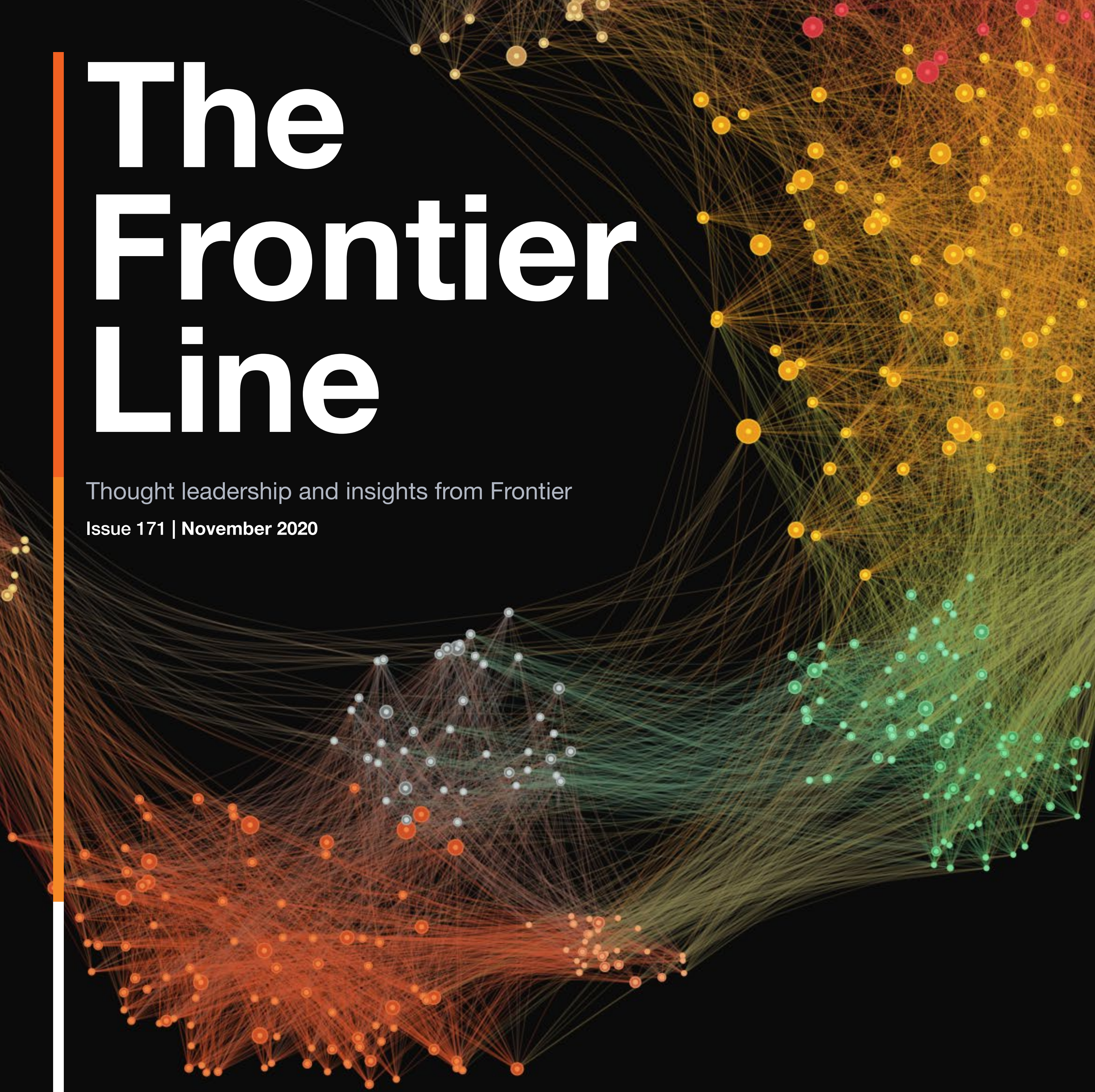

Cluster analysis. Do your diversifiers diversify?

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About us

Frontier has been at the forefront of institutional investment advice in Australia for over twenty five years and provides advice over more than $400 billion of assets across the superannuation, charity, public sector, insurance and university sectors.

Frontier's purposeis to empower our clients to advance prosperity for their beneficiaries through knowledge sharing, customisation, technology solutions and an alignment and focus unconstrained by product or manager conflict.

AUTHOR

Donna Davis

Associate

Donna Davis joined Frontier as an Associate in 2019. She works with the Alternatives and Derivatives team providing quantitative analytics support. She also assists with manager and investment research. Prior to joining Frontier, Donna worked for AustralianSuper in their Options Management Team. She also has 9 years banking experience with the Commonwealth Bank and ANZ in Corporate and Commercial Lending. Donna holds a Bachelor of Quantitative Finance from the University of South Australia and is currently completing the CFA program.

AUTHOR

Joe Clark

Senior Consultant

Joe joined frontier in 2020 as Senior Consultant. His responsibilities include derivatives, alternatives, and insurance linked strategies. Prior to joining Frontier Joe was at QIC in Brisbane for 9 years, working as a Senior Portfolio Manger for volatility and insurance linked strategies. Prior to this, Joe was a Portfolio Manager for the Tyndall/Suncorp Global Macro Fund for 5 years, specialising in commodity volatility strategies. Joe holds a PhD in Economics from the University of Queensland where he lectured Macroeconomics and Mathematical Economics, and a first class honours degree in Econometrics.

INTRODUCTION

Cluster analysis. Do your diversifiers diversify?

Constructing a diversified portfolio requires an understanding of how fundamental strategies, managers and investments relate to each other in different market conditions.

Often this involves sizable amounts of data, making identification of these relationships challenging and complex. This makes it difficult to understand:

- is the portfolio as diversified as expected?
- is there "hidden beta"?
- how do relationships change in different market conditions?

Cluster analysis is one tool to assist in better comprehending these relationships to get visibility of true portfolio diversification.

Best practice asset managers have already incorporated this into their portfolio construction process. In our view, the uses of this machine learning technique include:

- assessing which new strategy is the best addition to an existing portfolio
- identifying how "true to label" a strategy, manager or product is
- understanding existing portfolio diversification in relation to targeted portfolio diversification.

Background

This edition of *The Frontier Line* summarises and expands on the recent Frontier Conference presentation *'Liquid Alternatives: Ensuring diversifiers don't cluster together'*. This paper expands on that research and incorporates several interesting ideas suggested in the Q & A part of that conference session.

View link ⟶

What is cluster analysis?

Cluster analysis looks for similarities and differences within a set of data. It identifies relationships which may not be easily identified due to the complexity or volume of data present.

Figure 1: Cluster analysis takes a complex set of data and finds groups and natural order

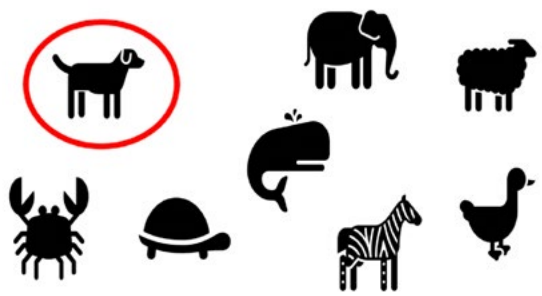
Consider Figure 1 where the image of a mess of books represents a large set of data. Here it is very difficult to understand what books are present, or to find the book you are looking for or to distinguish or discern relationships or clusters between various groups of books. What cluster analysis does can be considered akin to the image on the right - it creates order by creating groups of similar data called clusters.

This can highlight similarities and differences within our data which might not otherwise be intuitively evident. In one form of this analysis, rather than the groupings being preordained by a person or specific predetermined relationships being tested, a machine algorithm assesses from a clean slate what those relationships are.

Cluster analysis is one of many different machine learning techniques. Machine learning is a buzz word at the moment. Machine learning refers to calculations completed, generally with repetition, by a computer algorithm or set of instructions. This algorithm learns from the data, along the lines of 'see a pattern, learn from the pattern'. There are two main types:

- Supervised - the user instructs the algorithm in regard to the intended outcome or information being sought. Data is labelled and you have identifiable dependent and independent variables.
- Unsupervised - the user does not provide instructions regarding desired outcomes and the data is unlabelled.

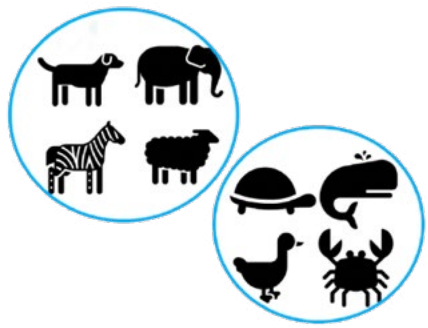
Figure 2: Supervised machine learning



A simplified visual example of these differences is shown in Figure 2 and Figure 3. In this example, the data is represented by this collection of animals. With supervised machine learning, we specify what we are looking for; in this scenario, we identify we are looking for a dog. Cluster analysis utilises the data set to identify similarities and differences, like the image on the right. Maybe the algorithm will identify the clusters in blue: animals which live in water and animals which are found on land.

It is obvious that cross over exists in these identified clusters: the crab can walk on land and when it is warm elephants and dogs will definitely head into water for a swim! This is just one of the groupings the cluster analysis may identify. This is a strength of the algorithm: it may help the end user to look beyond existing grouping biases, to identify groupings or relationships in the data which they may not have previously noticed.

Figure 3: Unsupervised machine learning



How cluster analysis works

In its simplest form, cluster analysis looks at the distance between a single data point and every other data point within the data set.

Consider a data set consisting of eight data points. The algorithm may start with data point 1 and measure the distance between every other data point. Chart 1 shows the distance to point 2 is 1.25 units, to point 3 is 0.75 units, to point 4 is 4.29 units and so on. It does this distance calculation for each and every data point. It then compares all distance calculations and ranks them, grouping points which are closest together thereby creating clusters.

Chart 2 highlights some of the groups or clusters the algorithm identified:

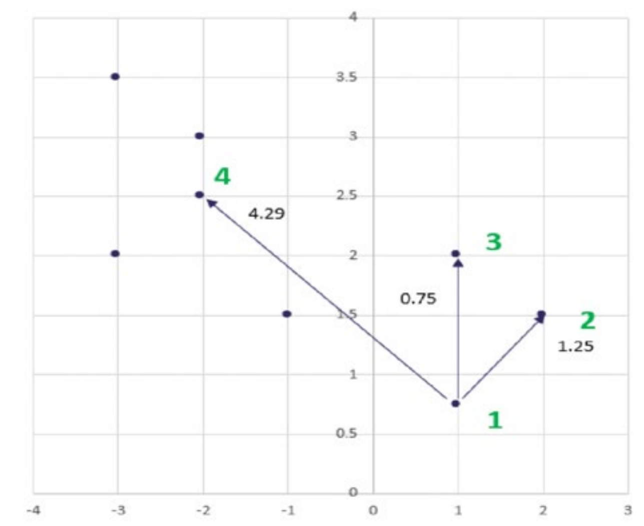
- Two high level clusters in red of four points within each cluster
- Two second level clusters of two points within each cluster (four two-point clusters overall).

The algorithm doesn't require clusters to all contain the same number of points – a cluster can contain a single data point or as many as all data points from the data set.

While this is considered a machine learning technique, it is by no means a fully systematic or automated analysis. User input is required to designate the number of clusters sought and to interpret the implications of identified clusters. The algorithm is run multiple times for a range of cluster numbers and results compared to the number of clusters which best explains the relationships in the data.

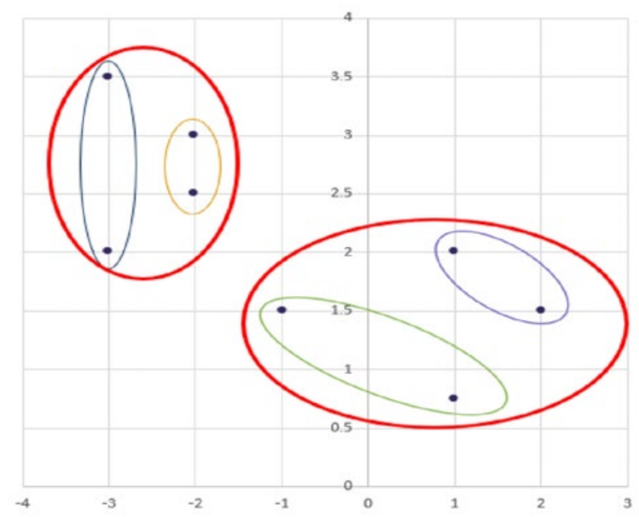
It is this sheer volume of required calculations which is where machine learning has allowed this process to be applied to financial data. In the above simple example, there are 28 distance calculations required. Running the algorithm three times, for maybe two, three and four clusters, results in over 80 calculations. One can imagine how many calculations are required for a portfolio of even 20 individual strategies, or even 100…

Chart 1: Raw data



Source: Frontier

Chart 2: Clustered data

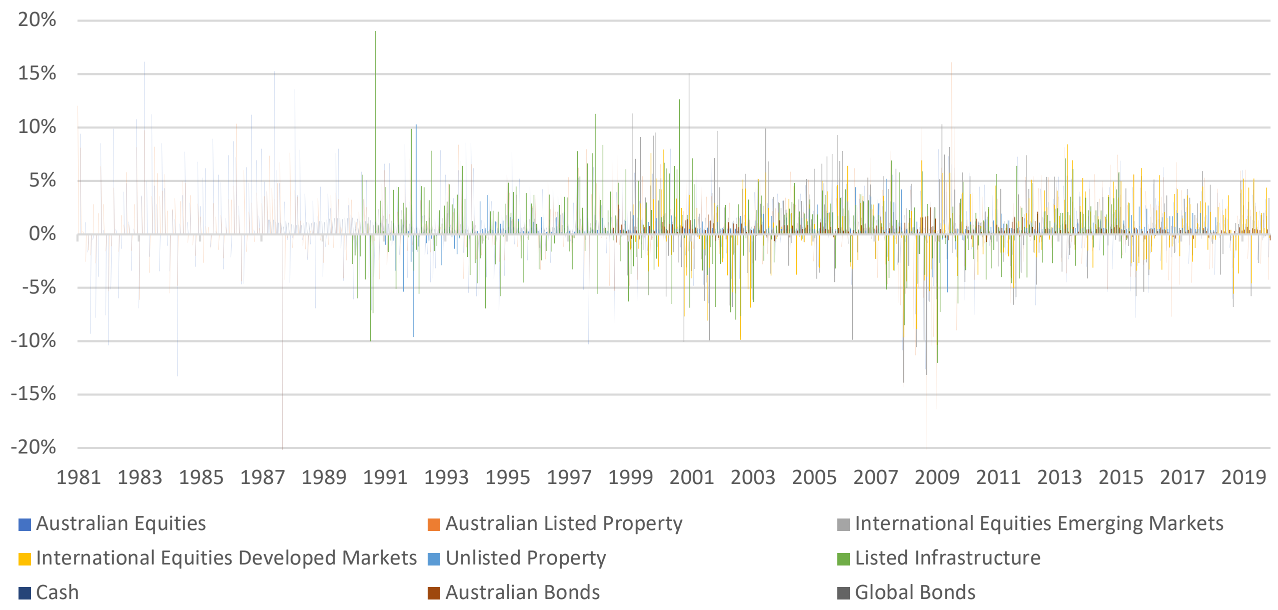


Source: Frontier

Cluster analysis and financial data

In the previous simple eight data point example, it was visually easy to identify relationships. The data used to assist in portfolio construction decision making is far larger and more complex, making identifying these connections and relationships extremely difficult.

Chart 3: Time series of major asset class index returns



Source: Frontier, Bloomberg. Data covers the period 1981 to 2019, showing monthly returns

In a portfolio, analysing interaction between asset classes is frequently completed. When viewed as historic time series returns, visually identifying the relationships and interactions is virtually impossible as Chart 3 highlights.

One technique frequently used to analyse these relationships is a correlation matrix. Visually this is easier to interpret than the previous chart, with colour coding aiding in identifying where strong similarities and differences exist. For example, in Table 1 the strong positive correlation between Australian and international equities is easy to identify (with a correlation of 0.52).

Table 1: Correlation matrix of index returns

	Australian equities	Australian listed property	Global equities EM	Global equities DM	Unlisted property	Listed infra	Cash	Australian bonds	Global bonds
Australian equities	1.00								
Australian listed property	0.62	1.00							
Global equities emerging markets	0.64	0.30	1.00						
Global equities developed markets	0.52	0.37	0.67	1.00					
Unlisted property	-0.04	-0.01	0.02	0.03	1.00				
Listed infrastructure	0.17	0.27	0.13	0.53	0.05	1.00			
Cash	0.00	-0.02	-0.09	-0.16	-0.17	-0.01	1.00		
Australian bonds	-0.24	0.06	-0.30	-0.17	-0.08	0.12	0.34	1.00	
Global bonds	0.10	0.25	-0.17	-0.26	-0.18	0.22	0.23	0.49	1.00

Source: Frontier, Bloomberg. Data covers the period 1981 to 2019

To rank and interpret relationships is quite a manual process, computationally slow and cumbersome – especially in a portfolio of 20, 50 even 100 assets. This is where cluster analysis can assist in not only identifying relationships, similarities and differences, but also ranking these relationships for the data categories being considered. One visual representation used in cluster analysis is presentation via a 'dendrogram', also known as a tree diagram.

To interpret the dendrogram, one needs to consider both horizontal and vertical elements:

- Vertical stems represent the distance between clusters. The longer the stem, the greater the distance and hence the differentiation or diversification between clusters.
- Horizontal branches represent which group or cluster a data group belongs to.

In Chart 4, there is a long vertical stem on the Cash / Aus bonds / global bonds branch, highlighting differentiation from the branch on the right. Horizontally, there are two distinct branches representing a two-group clustering, identified in the chart with orange boxes. As perhaps would be expected, these show groupings of traditional defensive assets and more growth style assets.

The shorter the vertical length of the stem, and the closer the horizontal branch, the greater the similarity. A few have been highlighted in purple in the chart– the branch length for say Australian and global bonds are short and horizontally on the same branch. This indicates these two data groups are part of the same cluster and in terms of our portfolio, would provide the least diversification benefit from each other.

The visual presentation of the ranked relationships can help with better understanding of portfolio relationships and interactions.

When interpreting output, two limitations need to be taken into consideration.

Cluster analysis is a relative analysis.

It measures the difference relative to the specific data set under consideration. What this means is showing two strategies close together horizontally on the same branch may not necessarily indicate those two strategies are similar. It simply indicates those strategies are most similar when compared with all other data categories.

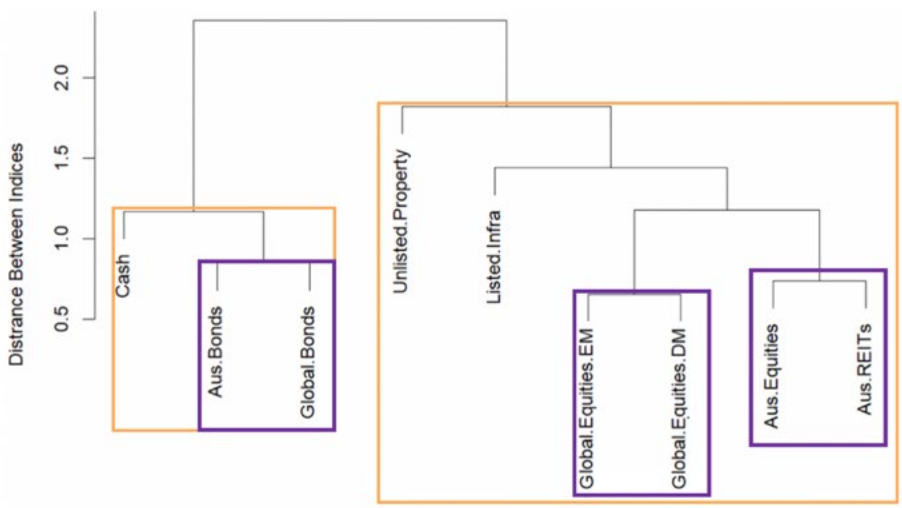
When interpreting clusters, the breadth of data under consideration needs to be understood and front of mind.

Cluster analysis is static.

Relationships are calculated for a fixed point in time, and these relationships change over time. What this means is diversification benefits identified in one time period e.g. an equity market rally, will not necessarily hold true during other market conditions e.g. a sharp equity market drawdown. Analysis needs to be completed over multiple time periods to understand how these relationships and diversification benefits dynamically shift. One method [which has been utilised in this paper] is to run analysis over different sub-sets of historic data covering time periods replicating different market conditions. Another strategy could be to simulate[1] forward looking returns using varying correlations reflective of your conviction in certain market scenarios and then complete analysis on the simulated data.

Robust analysis includes scenarios run across multiple time periods, whether based off historic proxy or forward-looking simulation data to understand how relationships change.

Chart 4: Dendrogram of major asset class index returns correlations



Source: Frontier, Bloomberg. Dendrogram is based on correlation matrix of asset class index returns from 1981 to December 2019

[1] Using Monte Carlo simulations or similar

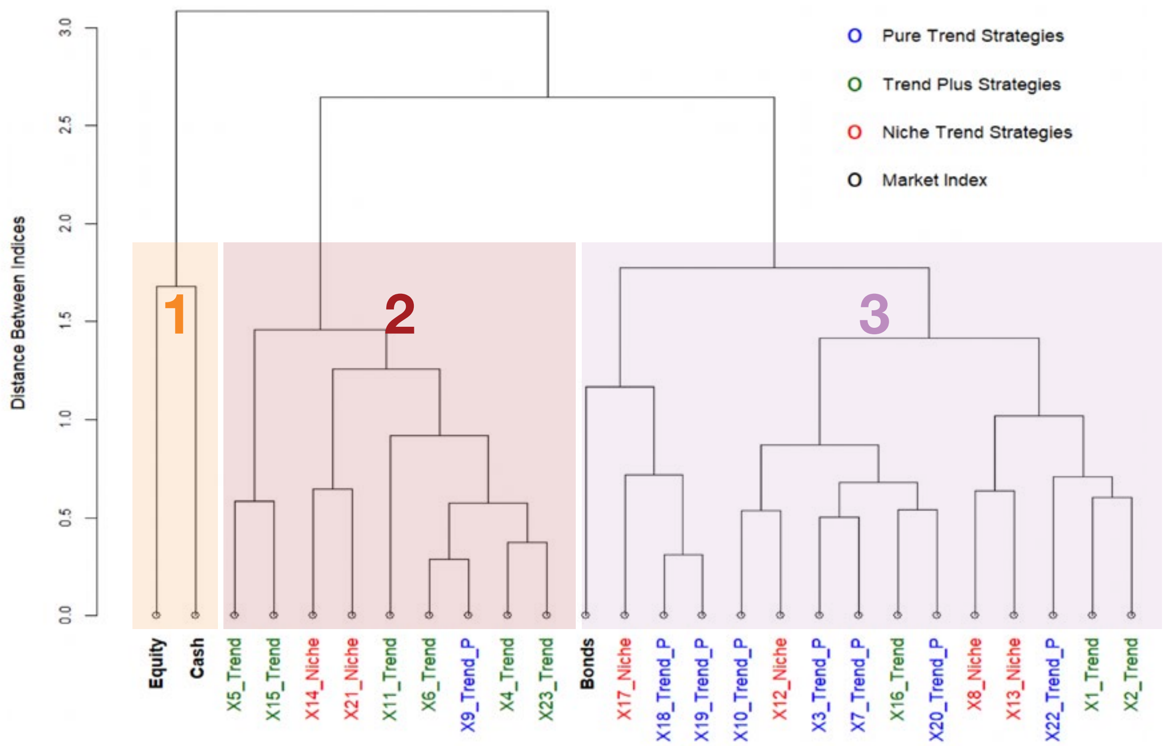
Case studies

CASE STUDY 1

Selecting a new manager product

This case study considers the application of cluster analysis to assist in selecting a new manager product to add to an existing portfolio. Specifically, the inclusion of two new CTA products which will provide diversification from existing equity, bond and cash holdings[2].

Chart 5: Dendrogram of manager product correlation



Source: Bloomberg, Frontier, Managers. Data 2000 (or since inception) to May 2020

This analysis is aimed at understanding how true to label each manager product is. This is to make sure that when included in the portfolio it brings the desired diversification characteristics.

At Frontier, we consider the CTA sector to have three sub-sectors:

- *Pure trend* strategies based solely on price trend following models
- *Trend plus* strategies which incorporate additional signals into their models such as carry
- *Niche* strategies which trade in lesser known markets.

The dendrogram of over 20 CTA managers in Chart 5 highlights three clear groups across the horizontal axis with varying degrees of height on the vertical axis.

There are several interesting observations which can be made from analysis of this dendrogram. Firstly, there are three clear groups present which interestingly do not align to the CTA sub-sectors groups identified earlier; there is quite a mix of sub-sector managers within each group.

Secondly, cash and equities appear within the same branch or cluster in this chart. As mentioned earlier, this does not necessarily mean they are "similar". It simply means they are very distinct from the other data categories in the analysis and almost like a process of elimination, result in being the most similar in respect to the data being considered. This is further supported by the larger height of the vertical stems of these branches.

Given our stated purpose in this case study was to find products which diversify from our existing equity, cash and bond holdings, the next step is to select a sub-set of this data, being cluster 2 in Chart 5.

[2] Equities, bonds and cash holdings have been proxied via indices

Chart 6 shows the analysis re-run on sub-set cluster two. This rather complicated looking chart is called a 'cluster plot'. It provides a two-dimensional visualization of clusters in respect to the first two principal components. It provides a different visualisation of the clustering within the data.

As mentioned earlier, the identification of the optimal data grouping or number of clusters for a particular data set is determined with a combination of mathematical calculation and human interpretation. In the cluster plot, computationally the first two principal components help explain 81.56% of data variability[3]. This means there is a reasonable level of similarity within this sub-set of the CTA managers – the higher the percentage, the greater the similarity.

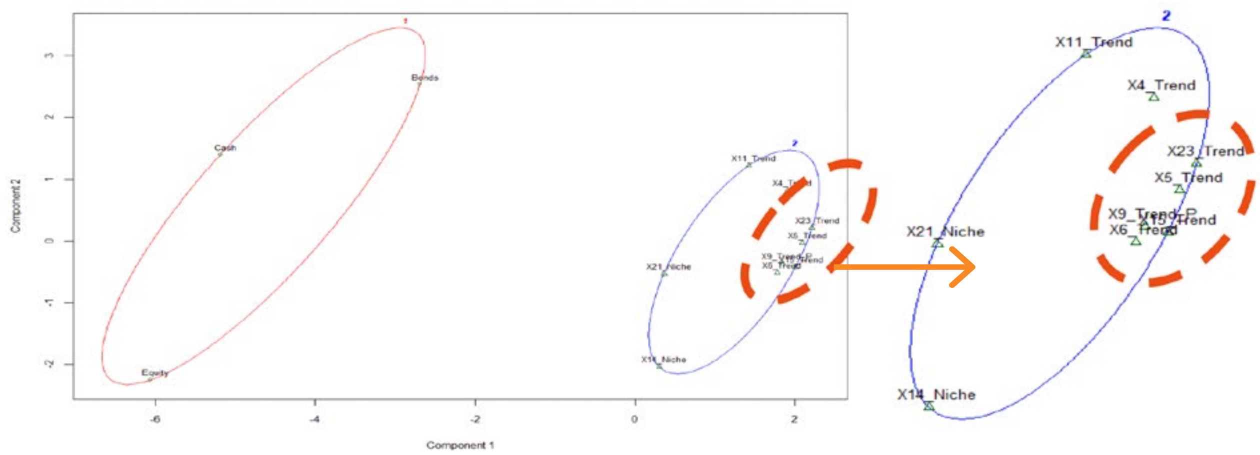
Visually, a number of interpretations can be made.

- There is a large differentiation between our existing portfolio holdings (cluster 1 in red in Chart 6) and the manager products under consideration (cluster 2 in blue in Chart 6), which is highlighted by how far apart are the two ellipses or clusters.
- There is varying differentiation within the manager products under consideration.

Expanding this second cluster we can see a tight grouping of mainly trend managers within the highlighted red ellipse. If the objective is to have a strong level of similarity within the added strategies, the two manager products should be selected from this group. If the objective was to maintain a level of diversification within the new portfolio sub-sector then selecting maybe one of the niche manager products and one of the trend manager products would be the best fit.

This cluster on the right is an expansion of cluster 2 in the cluster plot on the left to make it visually easier to see the groupings

Chart 6: Cluster plot based on dual component variance



Source: Bloomberg, Frontier, Managers. Data 2000 (or since inception) to May 2020

[3] Principal components analysis (PCA) is a statistical technique which aims to identify the main drivers of variability or predictability in a statistical series. In our case, the series is manager returns. PCA helps with understanding how diversified are the return drivers across the CTA manager group. If most of the variability in returns is explained by a small number of principal components, then this indicates that most managers had similar drivers for their returns.

CASE STUDY 2

Portfolio diversification. Is it in line with expectations?

This case study incorporates cluster analysis into the portfolio construction process. The portfolio is analysed top down to ascertain if targeted asset class expectations are being achieved.

In this example we have used a portfolio with the target beta, asset allocation, objectives in Table 2[4]. To form our portfolio 22 manager products have been selected and allocation is based on the product stated asset class.

This case study is targeted at understanding:

- Is the actual portfolio reflecting the stated portfolio objectives?
- Or is there hidden beta?

Table 3 shows the power of cluster analysis in understanding portfolio relationships. It is difficult to fully grasp the level of interaction between portfolio elements, to distinguish how closely they resemble their stated asset class groupings or to rank relationships in any kind of meaningful order for a data set of this size.

Table 2: Target portfolio asset class allocation

Asset class	Target allocation
Australian equities	25.0%
International equities	35.0%
Credit	10.0%
Fixed income	15.0%
Alternatives	10.0%
Cash	5.0%

Source: Frontier

Table 3: Correlation matrix of 22 manager products and 6 index returns

	1_AEQ	2_AEQ	3_AEQ	4_AEQ	5_AEQ	6_IEQ	7_IEQ	8_IEQ	9_IEQ	10_IEQ	11_IEQ	12_CRE	13_CRE	14_FI	15_FI	16_FI	17_FI	18_ALT	19_ALT	20_ALT	21_CASH	22_CASH	AEQ_Ind	IEQ_Ind	CRE_Ind	FI_Index	ALT_Ind	CASH_In
1_AEQ	100%																											
2_AEQ	91%	100%																										
3_AEQ	82%	78%	100%																									
4_AEQ	78%	83%	81%	100%																								
5_AEQ	71%	78%	77%	91%	100%																							
6_IEQ	48%	57%	54%	64%	62%	100%																						
7_IEQ	49%	58%	52%	64%	61%	97%	100%																					
8_IEQ	63%	70%	60%	70%	68%	83%	83%	100%																				
9_IEQ	59%	66%	53%	65%	59%	81%	81%	88%	100%																			
10_IEQ	59%	62%	54%	59%	57%	77%	77%	89%	86%	100%																		
11_IEQ	64%	72%	60%	71%	68%	83%	83%	96%	91%	92%	100%																	
12_CRE	-9%	-15%	-12%	-20%	-22%	-32%	-34%	-38%	-21%	-28%	-31%	100%																
13_CRE	42%	47%	52%	51%	50%	57%	54%	68%	48%	58%	63%	-26%	100%															
14_FI	-8%	-15%	-9%	-16%	-20%	-33%	-35%	-38%	-19%	-27%	-30%	97%	-26%	100%														
15_FI	-14%	-19%	-19%	-23%	-27%	-40%	-41%	-44%	-25%	-35%	-36%	95%	-33%	96%	100%													
16_FI	20%	24%	16%	26%	25%	68%	68%	43%	53%	53%	49%	3%	21%	1%	-4%	100%												
17_FI	7%	14%	8%	18%	16%	53%	53%	29%	39%	36%	36%	18%	11%	16%	10%	88%	100%											
18_ALT	6%	10%	4%	5%	3%	1%	3%	-5%	15%	7%	6%	29%	-22%	33%	36%	19%	23%	100%										
19_ALT	12%	14%	10%	10%	7%	2%	6%	6%	20%	14%	16%	28%	-12%	30%	35%	17%	15%	73%	100%									
20_ALT	10%	9%	14%	12%	11%	8%	10%	7%	13%	12%	8%	5%	-6%	6%	5%	14%	9%	25%	17%	100%								
21_CASH	7%	0%	8%	2%	12%	10%	5%	7%	8%	11%	4%	26%	11%	27%	20%	17%	8%	8%	3%	25%	100%							
22_CASH	-3%	-9%	-7%	-8%	-1%	-2%	-6%	-4%	0%	1%	-5%	26%	-2%	25%	21%	12%	10%	2%	2%	19%	80%	100%						
AEQ_Index	95%	97%	82%	84%	78%	58%	59%	68%	63%	61%	69%	-15%	48%	-15%	-19%	27%	17%	7%	10%	12%	2%	-9%	100%					
IEQ_Index	70%	74%	63%	71%	66%	77%	77%	96%	87%	91%	95%	-36%	64%	-35%	-40%	35%	17%	3%	13%	6%	5%	-7%	72%	100%				
CRE_Index	24%	23%	19%	24%	18%	35%	35%	18%	30%	23%	25%	46%	22%	46%	41%	59%	62%	37%	30%	4%	18%	8%	26%	17%	100%			
FI_Index	0%	-2%	-6%	-3%	-9%	0%	1%	-20%	1%	-9%	-9%	66%	-16%	66%	65%	40%	51%	48%	37%	2%	7%	7%	0%	-18%	87%	100%		
ALT_Index	11%	9%	7%	7%	3%	4%	7%	2%	18%	11%	14%	32%	-12%	35%	37%	17%	18%	79%	89%	23%	8%	2%	6%	11%	39%	47%	100%	
CASH_Index	0%	-7%	-5%	-6%	0%	-2%	-5%	-4%	0%	0%	-5%	29%	-1%	28%	24%	11%	10%	1%	3%	20%	80%	99%	-6%	-6%	9%	9%	2%	100%

Source: Frontier, Bloomberg. Correlation data is based on time series returns for the period 2011 to 2019

[4] This is not a Frontier view on the optimal portfolio strategic asset allocation. These allocations have simply been used for example purposes only

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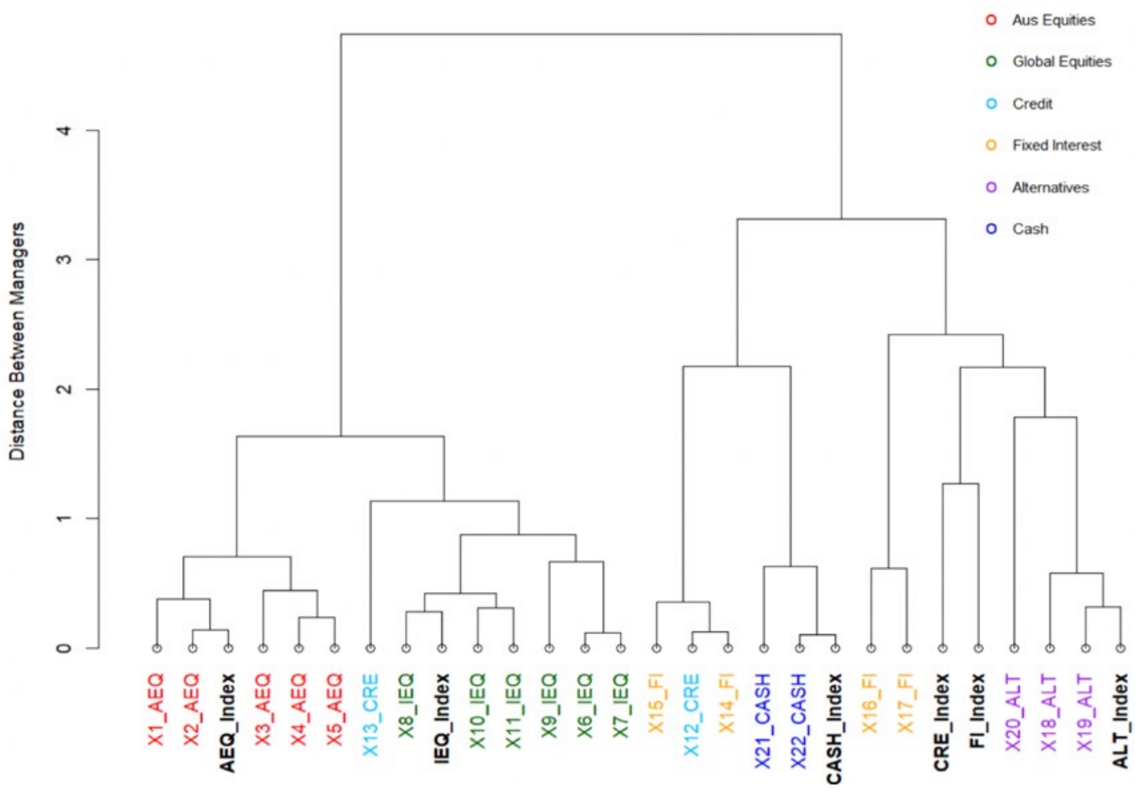
Chart 7: Dendrogram of correlation of portfolio manager products and beta indices



Source: Frontier, Bloomberg. Correlation data is based on time series returns for the period 2011 to 2019

Completing cluster analysis and presenting findings as a dendrogram assists in better interpretation of portfolio interactions In Chart 7 it is visually easy to identify how various strategies are grouping or clustering on the horizontal axis, and the magnitude of diversification by the heights of the stems on the vertical axis.

Chart 7 confirms some manager products are reflecting beta characteristics true to label. For example, the equities managers, cash and alternative managers are within the same branch or clusters as the targeted beta index proxies with short stems. This indicates a higher degree of similarity with these proxies than other data elements.

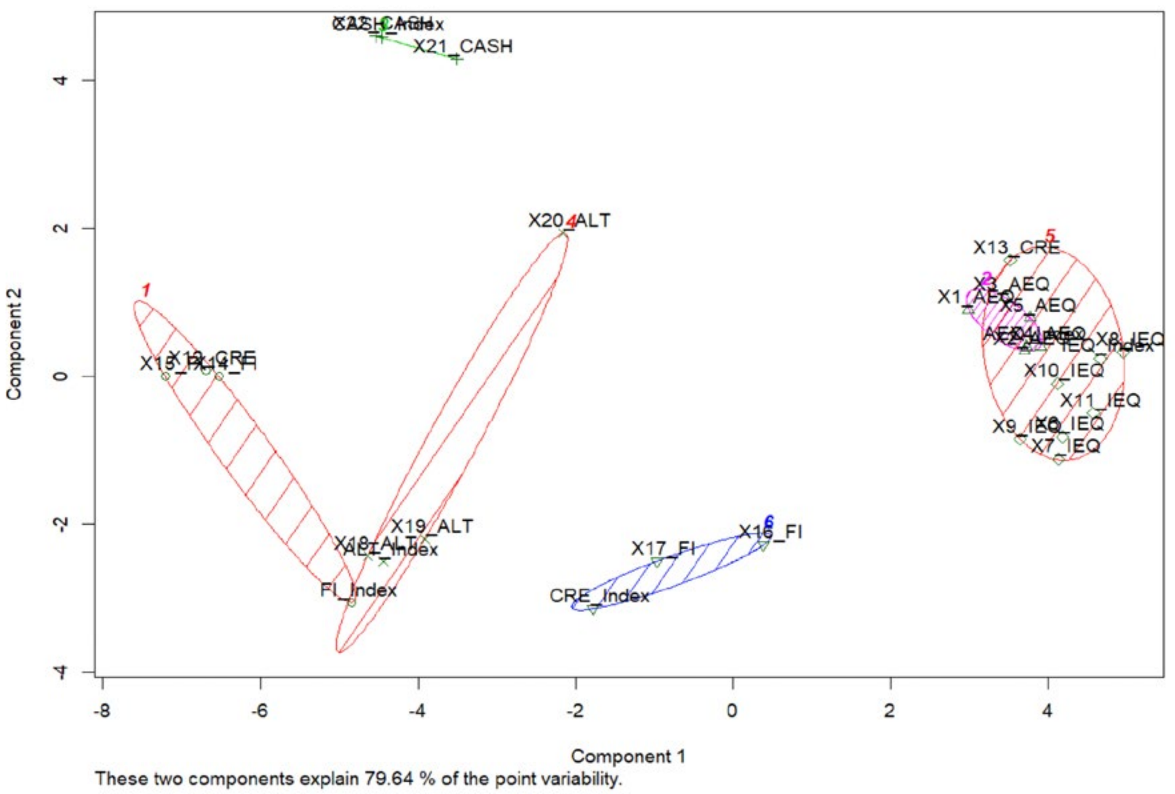
Chart 7 also highlights several managers which may not be as true to label or aligned to the asset class proxies as we maybe had first initially thought. The best example of this is manager product X13. X13 was initially allocated as part of the credit asset class. Chart 7 shows it is exhibiting characteristics most similar to the international equities managers given that it is horizontally located on the same branch as the international equities managers. The vertical height of the stem is marginally larger than other elements of this branch.

Manager products X12, X14 and X15 in the middle of Chart 7 are not showing similarity to any beta index. This highlights a shortfall of this visual representation of this analysis – based on this diagram alone it is difficult to determine with any degree of certainty to which cluster these managers belong.

Similarly X16 & X17 are not part of a branch with a beta index, but horizontally they are located directly next to the credit index.

This dendrogram has been a great first starting point to understand relationships and diversity in the portfolio but further analysis is required to better understand portfolio beta composition.

Chart 8: Cluster plot based on dual component variance



Source: Frontier, Bloomberg. Correlation data is based on time series returns for the period 2011 to 2019

Chart 8 provides a different perspective on portfolio grouping, with six clear clusters identified. Each different colored ellipse represents a cluster. The distance between each ellipse provides insight into the level of differentiation between clusters.

The cluster composition is as follows.

- **Cluster 1** | Fixed income cluster
  Fixed income index and manager products X12 (initially classified as a credit asset class manager), X14-15 (fixed income).
- **Cluster 2** | Australian equities cluster
  Australian equities index and manager products X1-5 (all initially classified as Australian equities).
- **Cluster 3** | Cash cluster
  Cash index and manager products x21-22 (both initially classified as cash).
- **Cluster 4** | Alternatives cluster
  Alternatives index and manager products X18-20 (all initially classified as alternatives).
- **Cluster 5** | International equities cluster
  International equities index and manager products X7-11 (initially international equities) and X13 (initially credit).
- **Cluster 6** | Credit cluster
  Credit index and manager products X16-17 (initially fixed income).

Several managers which we had initially allocated based on their stated asset class are exhibiting characteristics more aligned to a different asset class. This results in a different beta exposure for the portfolio than initially targeted.

Table 4: Expected portfolio risk and return

Asset class	Target allocation	Actual allocation based on cluster attribution	Difference
Australian equities	25.0%	25.0%	0.0%
International equities	35.0%	40.0%	5.0%
Credit	10.0%	7.5%	-2.5%
Fixed income	15.0%	12.5%	-2.5%
Alternatives	10.0%	10.0%	0.0%
Cash	5.0%	5.0%	0.0%
1 year return	4.0%	3.9%	-0.1%
1 year risk	15.0%	15.7%	0.7%
3 year return	5.4%	5.5%	0.1%
3 year risk	10.0%	10.4%	0.4%
5 year return	4.8%	5.1%	0.3%
5 year risk	8.9%	9.3%	0.4%

Source: Frontier, Bloomberg. Correlation data is based on time series returns for the period 2011 to 2019

The cluster analysis has helped us calculate beta exposure to several asset classes which is inconsistent with initial portfolio objectives.

- International equity exposure targeted 35%, but is actually 40%.
- Credit exposure targeted 10%, but is actually 7.5%.
- Fixed Income exposure targeted 15%, but is actually 12.5%.

This impacts the expected portfolio risk and return. Table 4 shows the portfolio is expected to have higher risk over all time horizons.

Cluster analysis provided additional understanding of how manager products relate both to each other and the targeted beta indices. Using cluster analysis to re-define the asset class of each manager product and allocating to these asset classes can be a way of creating a portfolio more in line with targeted asset class objectives.

Table 5: Actual portfolio return with allocation by stated asset class and cluster analysis

Asset class	Asset class allocation	Cluster allocation	Difference
Australian equities	25.0%	25.0%	0.0%
International equities	35.0%	35.0%	0.0%
Credit	10.0%	10.0%	0.0%
Fixed income	15.0%	15.0%	0.0%
Alternatives	10.0%	10.0%	0.0%
Cash	5.0%	5.0%	0.0%
1 year return	1.9%	3.9%	2.0%
1 year risk	15.8%	14.6%	-1.2%
3 year return	4.6%	4.7%	0.1%
3 year risk	10.2%	9.6%	-0.7%
5 year return	4.9%	5.0%	0.1%
5 year risk	9.0%	8.4%	-0.6%

Source: Frontier, Bloomberg. Correlation data is based on time series returns for the period 2011 to 2019

Table 5 compares portfolio metrics calculated based on realised manager product returns for allocation both by stated asset class and by cluster analysis. Actual portfolio risk is lower and return is higher over all time horizons. More importantly, realised risk and return is closer to the original portfolio targeted risk and return expectations in column one of Table 4.

Cluster analysis has provided additional information on the portfolio, but it is by no means meant to replace other tools and techniques already in place. It provides a different perspective from which to consider portfolio relationships, providing additional information which has the potential to assist in creating a portfolio more in line with the diversification and other objectives initially intended.

CASE STUDY 3

ARP sleeve selection

Frontier recently completed a ‘deep dive’ review of alternative risk premia (ARP) strategies, to better understand performance of the sub-sector in both the short to medium term *The Frontier Line: Alternative risk premia COVID-19 deep dive*.

In this case study, ARP sleeve level strategies were analysed to visualise how diversification changes in different market environments. The hypothesis for this analysis was that diversification of these strategies changed significantly in 2020. A selection of 28 risk premia styles were selected from across six asset classes and seven styles.

Initially the five-year period 2015 – 2019 was analysed as this provides an indication of strategy performance during a predominantly positive growth equity market. The number of branches and vertical distances between these branches suggests good levels of diversification across all of the alternative risk premia. Analysis appears to indicate that five clusters best describe the groupings within the data.

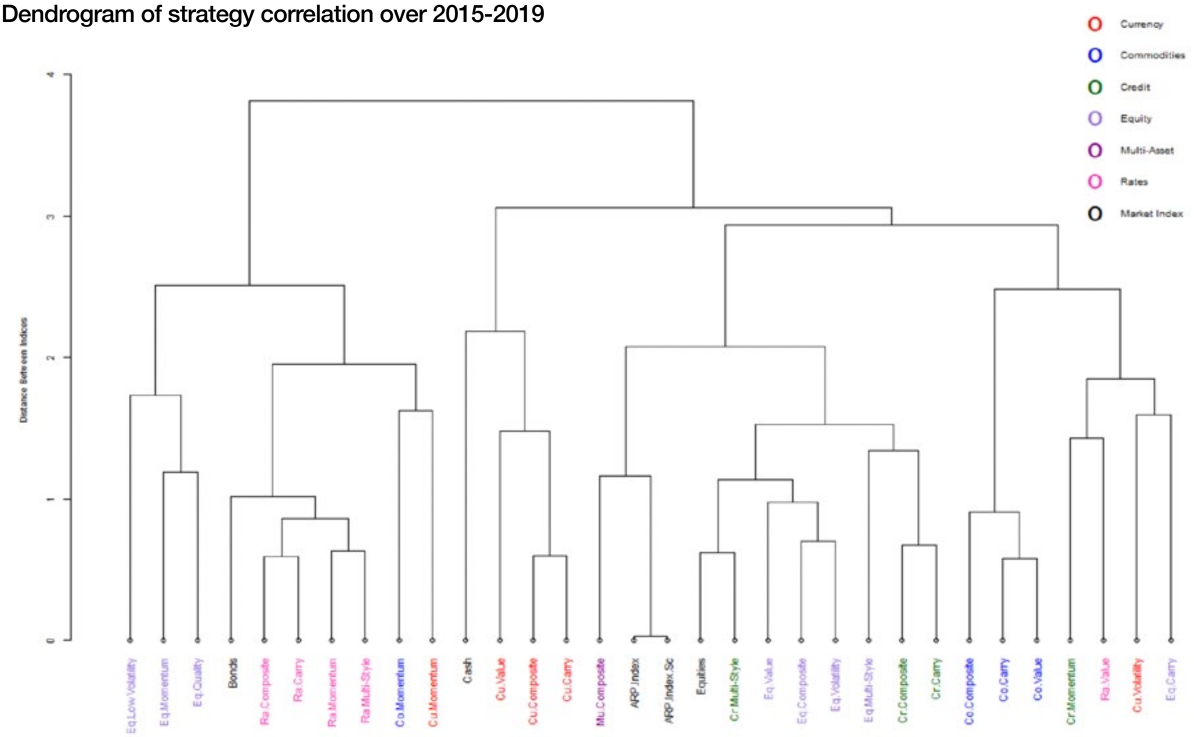
Table 6: Risk premia asset class

Asset Class
Currency
Commodity
Credit
Equity
Multi Asset
rates

Table 7: Risk premia style

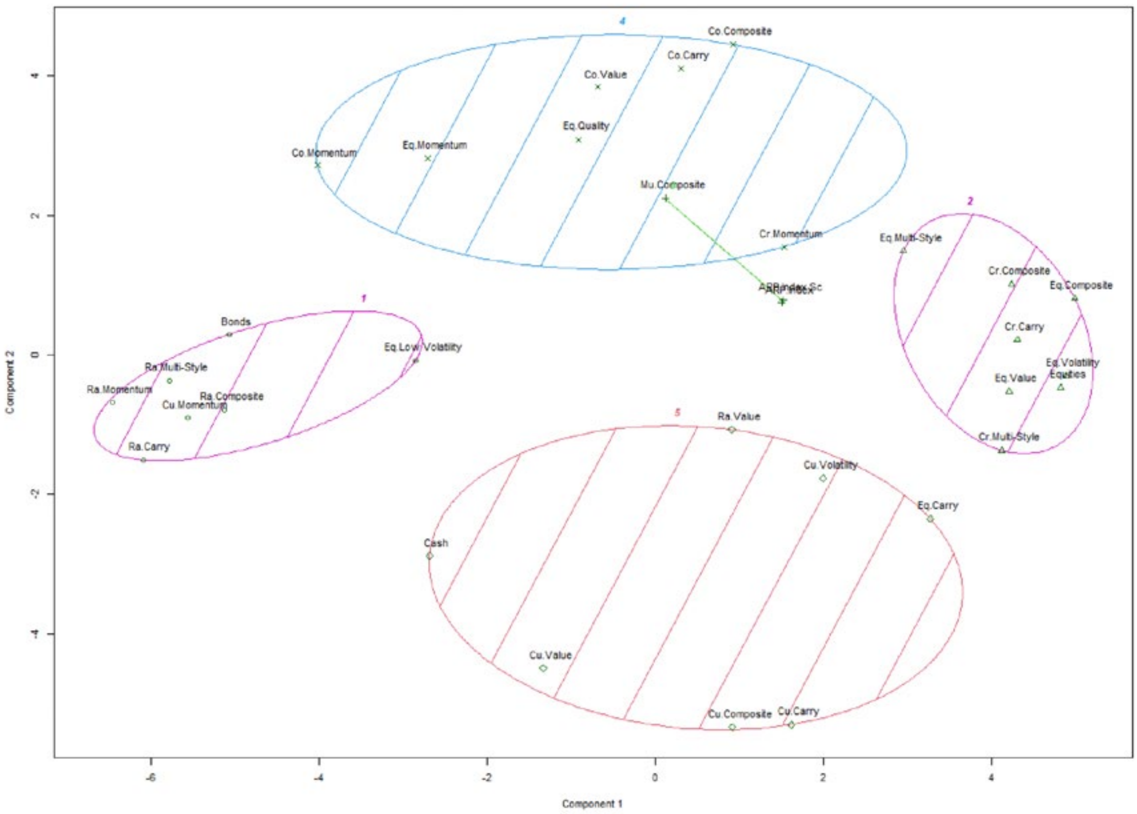
Style
Composite
Carry
Low volatility
Momentum
Multi-style
Value
Volatility

Chart 9: Dendrogram of strategy correlation over 2015-2019



Source: Frontier, HFR. Correlation data is based on time series returns for 2015 to 2019

Chart 10: Cluster plot of strategy correlation over 2015-2019



Source: Frontier, HFR. Correlation data is based on time series returns for 2015 to 2019

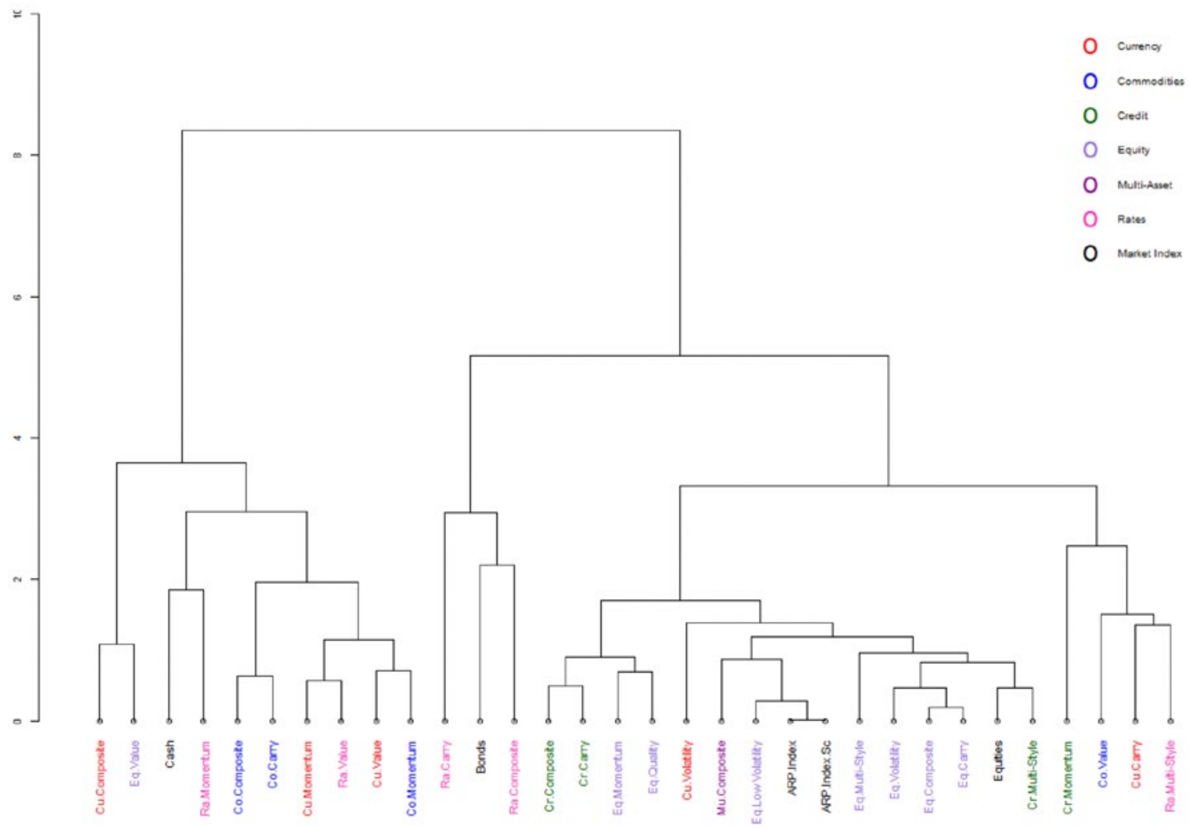
Some strategies appear to cluster broadly in line with defined asset classes (e.g. rates and currency), regardless of strategy. Grouping of other strategy styles are less clear. Strategies which provide the greatest diversification during this time period from the market proxies are those in cluster 4 in Chart 10. These strategies all sit in different cluster groupings to any market proxy and have the longest stem length to those proxies when the analysis is viewed in dendrogram form (per Chart 9).

As anticipated in the hypothesis of this analysis, cluster groupings changed significantly during 2020, indicating strategy diversification changed, as highlighted in Chart 11. How these clusters changed, and the magnitude of change in some instances was somewhat of a surprise with several sub-strategies not providing the diversification benefits initially anticipated.

As an example, currency and rate strategies no longer clustered together but equity strategies did appear within the same cluster. This suggests diversification from different styles of equity premia reduced while diversification between different styles of currency and rate strategies increased.

The distance between clusters also increased and increased significantly for some strategies – almost double the stem lengths evident in the prior five year period (refer Chart 9). This indicates a significant increase in the magnitude of diversification provided by certain strategies. For example, the horizontal and stem distance increased materially between rates momentum and rates carry. To illustrate this change, the stem distance increased from just under one unit in Chart 9 to over 8 units in Chart 11. This suggests a significant increase in the magnitude of diversification between these strategies during 2020.

Chart 11: Dendrogram of strategy correlation during 2020



Source: Frontier, HFR. Correlation data is based on time series returns for January to August 2020

In other strategies, this diversification reduced significantly. As an example the stem distance between equity low volatility and equity carry reduced materially from under four units in Chart 9 to around one unit in Chart 11. This indicates that these strategies provided very little diversification benefits from each other during the shorter 2020 period.

Analysis of the selection of ARP sub-strategies confirmed the initial hypothesis the diversification benefits of the strategies varied during 2020. What was surprising from the analysis was the magnitude of some of the changes, along with the way certain cluster groupings changed. This change in diversification was a contributing factor in unforeseen tail losses within some blended ARP products. This re-iterated the importance of understanding dynamic diversification in multiple market scenarios (i.e. there are time periods, particularly when measured over short time periods, where correlations break down or relationships behave differently to what has been assumed or what has occurred historically).

Frontier supports the creation of bespoke portfolios of alternative risk premia strategies which allows the investor to exclude some premia which exist within a manager's product.

For example, an investor may wish to exclude equity-driven alternative risk premia (e.g. equity value) given an allocation to equities elsewhere in the investor's broader portfolio. When considering bespoke or tailored portfolios, it is important to view how the diversification benefits vary, both in size and magnitude during different market conditions. We note that additional analytical techniques are required to better understand these impacts on portfolio construction.

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The final word

At Frontier, cluster analysis is already being used by the alternatives and derivatives strategies research team to:

- better understand the alternatives sub-sectors and how they interact both with each other and other asset classes
- dig into how true to label products are, identifying where there is potential for hidden beta or similarities with other strategies which may not initially be identified
- assess portfolios of strategies to analyse diversification and understand how new strategies will assimilate into the portfolio.

While cluster analysis has been widely used in social sciences, with advances in technology and improved computer processing power it is more and more being used within investments and finance. Frontier views the benefits of cluster analysis are broad, as detailed.

It's smarter

Machine based learning

It does look past data, and is complementary to fundamental and forward looking analysis

Examines relationships

Contemplates a wider range of explantory relationships than typically assumed in portfolio construction or asset allocation

Presents opportunites

Are investments "true to label"

Hidden beta

Deepen understanding in different market conditions

Different portfolio designs

Deliver superior outcomes

Want to learn more?

We hope this paper has generated lots of ideas of where you see cluster analysis being applied for your own portfolios. If this is the case, please reach out to Frontier to discuss how we can work with you to use this powerful tool.

Frontier

Level 16, 222 Exhibition Street, Melbourne, Victoria 3000

Tel +61 3 8648 4300

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